Artificial Intelligence
EDAF70
Lecture 9.1: Natural Language Processing

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Applications of Language Processing

- Spelling and grammatical checkers: *MS Word*
- Text indexing and information retrieval on the Internet: *Google*, *Microsoft Bing*, *Yahoo*
- Telephone information that understands some spoken questions: *SJ* (trains in Sweden) or *Tellme.com* in the United States
- Speech dictation of letters or reports
- Translation: *Google Translate*, *SYSTRAN*

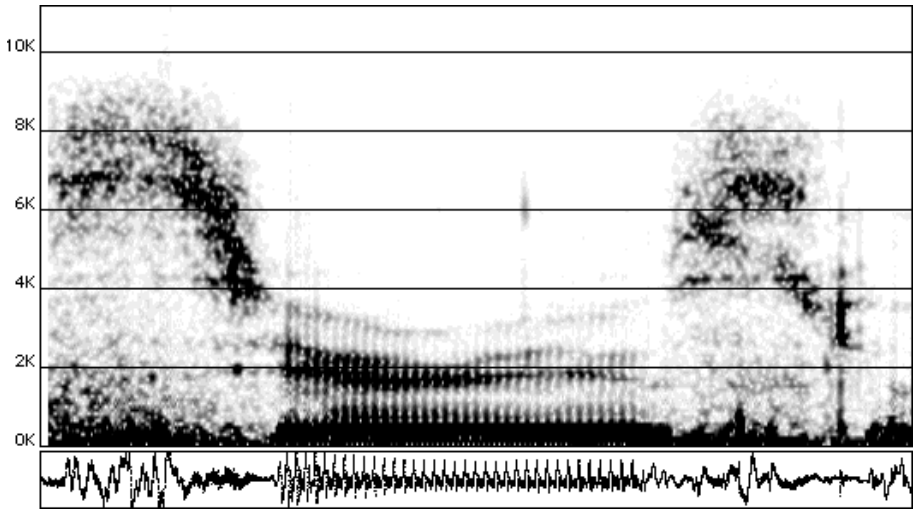
Applications of Language Processing (ctn'd)

- Direct translation from spoken English to spoken Swedish in a restricted domain: *SRI* and *SICS*
- Voice control of domestic devices
- Conversational agents able to dialogue and to plan
- Spoken navigation in virtual worlds: *Ulysse*, *Higgins*
- Generation of 3D scenes from text: *Carsim*
- Question answering systems: *IBM Watson*

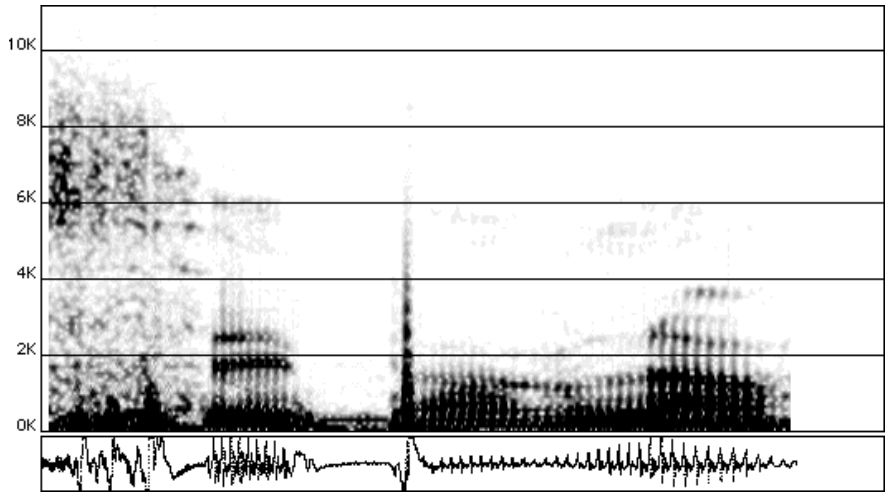
Linguistics Layers

- Sounds
- Phonemes
- Words and morphology
- Syntax and functions
- Semantics
- Dialogue

Sounds and Phonemes



Serious



C'est par là 'It is that way'

Lexicon and Parts of Speech

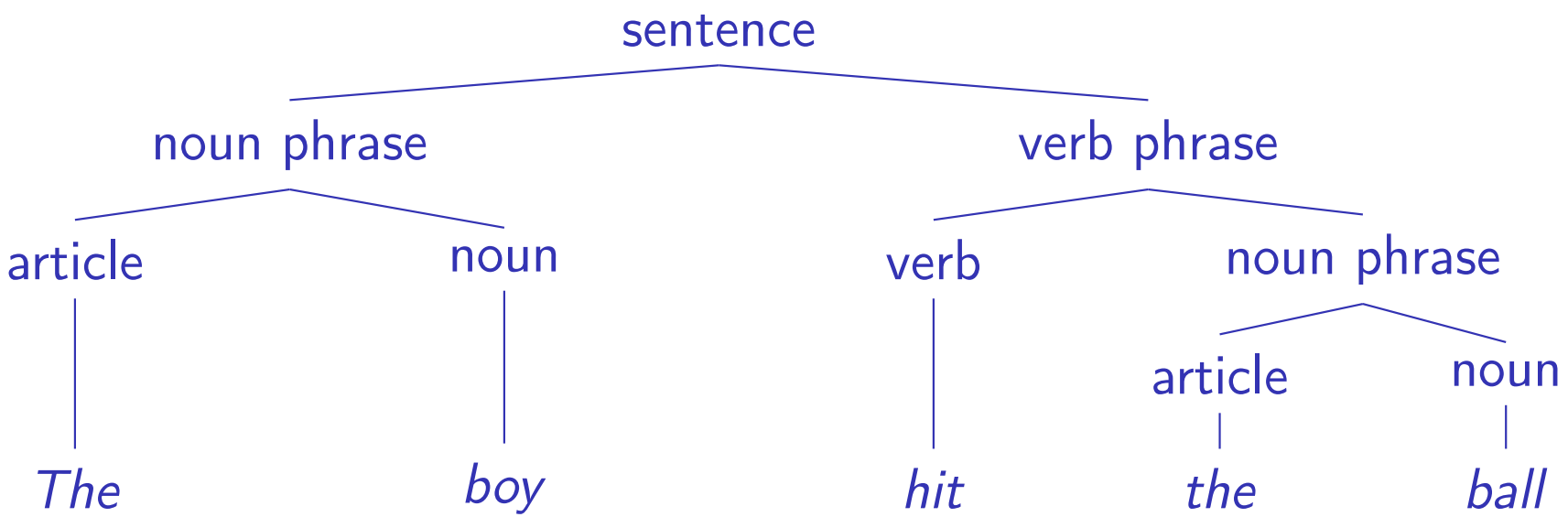
The big cat ate the gray mouse

The/article *big*/adjective *cat*/noun *ate*/verb *the*/article *gray*/adjective *mouse*/noun
Le/article *gros*/adjectif *chat*/nom *mange*/verbe *la*/article *souris*/nom *grise*/adjectif
Die/Artikel *große*/Adjektiv *Katze*/Substantiv *ißt*/Verb *die*/Artikel *graue*/Adjektiv *Maus*/Substantiv

Morphology

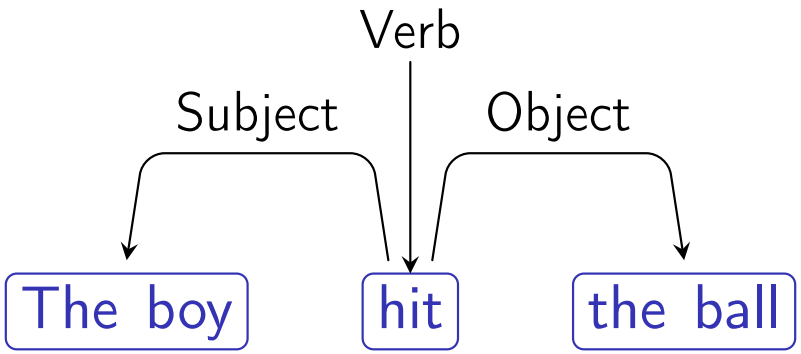
Word	Root form
worked	*to work* + verb + preterit
travaillé	*travailler* + verb + past participle
gearbeitet	*arbeiten* + verb + past participle

Syntactic Tree



Syntax: A Classical View

A graph of dependencies and functions



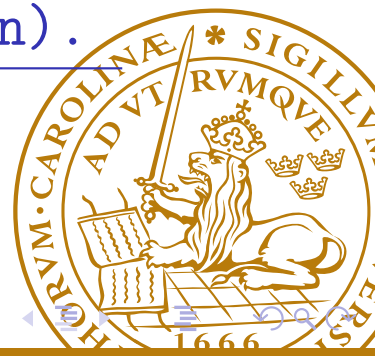
Semantics

As opposed to syntax:

1. Colorless green ideas sleep furiously.
2. *Furiously sleep ideas green colorless.

Determining the logical form:

Sentence	Logical representation
Frank is writing notes	`writing(Frank, notes).`
François écrit des notes	`écrit(François, notes).`
Franz schreibt Notizen	`schreibt(Franz, Notizen).`

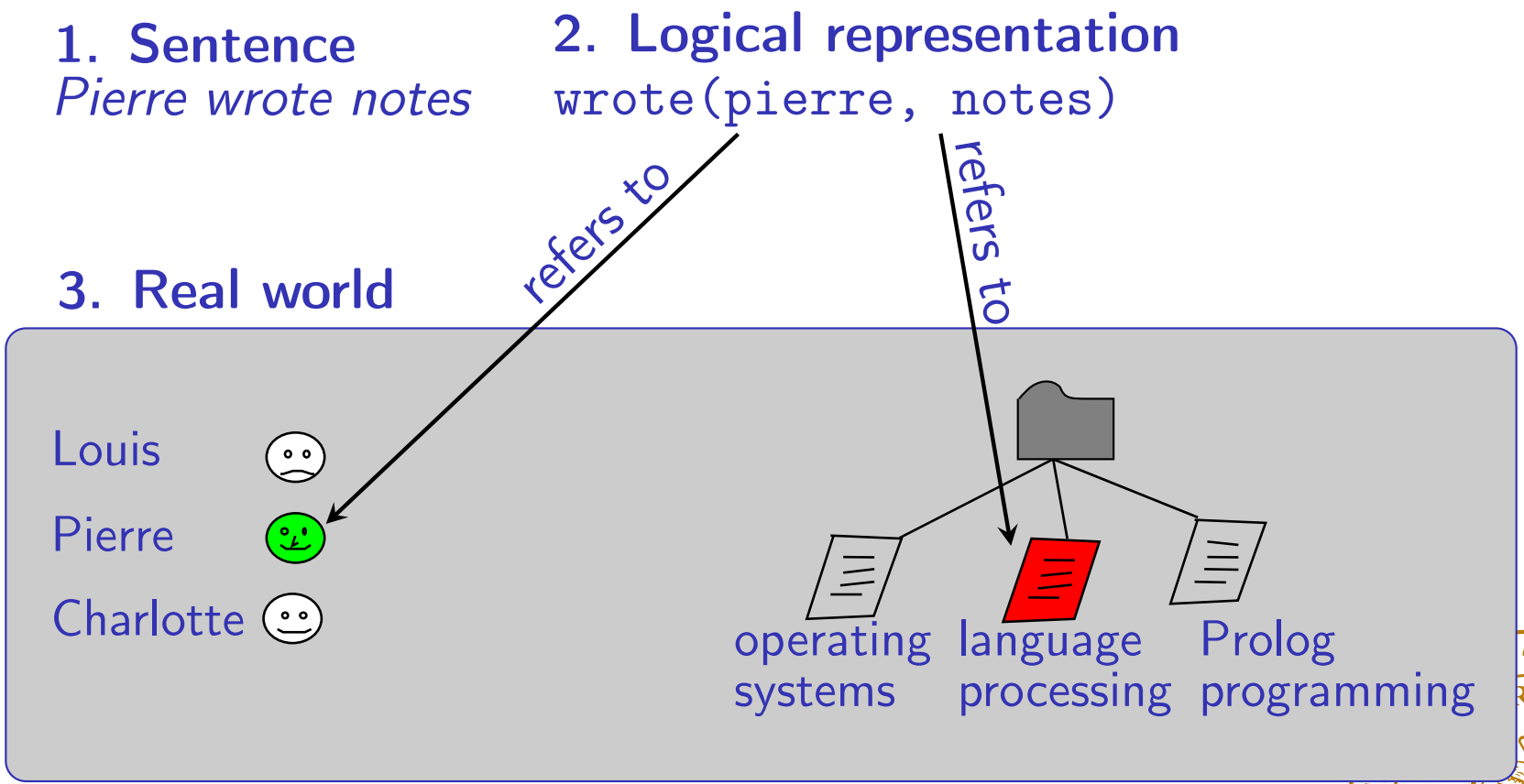


Lexical Semantics

Word senses:

1. **note** (*noun*) short piece of writing;
2. **note** (*noun*) a single sound at a particular level;
3. **note** (*noun*) a piece of paper money;
4. **note** (*verb*) to take notice of;
5. **note** (*noun*) of note: of importance.

Reference


1. Sentence
Pierre wrote notes
2. Logical representation
wrote(pierre, notes)
refers to
refers to
3. Real world
Louis
Pierre
Charlotte
operating systems
language processing
Prolog programming

Communication

Exchange of information between two parties
A dialogue is a set of linguistic interactions to carry out this exchange for instance to ask, inform, command, accept, etc.
It involves the generation of phrases/sentences by the speaker and their analysis by the hearer
Generation can be modeled as logical terms and then converted into sentences
Analysis involves the perception of the message, its syntactic and semantic parsing, and a pragmatic interpretation

Ambiguity

Many analyses are ambiguous. It makes language processing difficult.
Ambiguity occurs in any layer: speech recognition, part-of-speech tagging, parsing, etc.
Example of an ambiguous phonetic transcription:
The boys eat the sandwiches
That may correspond to:
The boy seat the sandwiches; *the boy seat this and which is*; *the buoys eat the sand which is*

Models and Tools

Linguistics has produced an impressive set of theories and models
Language processing requires significant resources
Models and tools have matured. Resources are available.
Tools involve notably finite-state automata, regular expressions, rewriting rules, logic, statistics and machine learning.

The Carsim System: A Text-to-Scene Converter

Texts	XML Templates	3D Animation

Véhicule B venant de ma gauche, je me trouve dans le carrefour, à faible vitesse environ 40 km/h, quand le véhicule B, percute mon véhicule, et me refuse la priorité à droite. Le premier choc atteint mon aile arrière gauche,

```
// Static Objects
STATIC [
ROAD
TREE
]
// Dynamic Objects
DYNAMIC [
VEHICLE [
ID = vehicule_b;
```

Corpora

A corpus is a collection of texts (written or spoken) or speech
Corpora are balanced from different sources: news, novels, etc.

	English	French	German
Most frequent words in a collection of contemporary running texts	*the*	*de*	*der*
	of	*le* (article)	*die*
	to	*la* (article)	*und*
	in	*et*	*in*
	and	*les*	*des*
Most frequent words in Genesis	*and*	*et*	*und*
	the	*de*	*die*
	of	*la*	*der*
	his	*à*	*da*
	he	*il*	*er*

Characteristics of Current Corpora

Big: The Bank of English (Collins and U Birmingham) has more than 500 million words
Available in many languages
Easy to collect: The web is the largest corpus ever built and within the reach of a mouse click
Parallel: same text in two languages: English/French (Canadian Hansards), European parliament (23 languages)
Annotated with part-of-speech or manually parsed (treebanks):

- Characteristics/N of/PREP Current/ADJ Corpora/N
- (NP (NP Characteristics) (PP of (NP Current Corpora)))

Corpora as Knowledge Sources

Short term:

- Describe usage more accurately
- Assess tools: part-of-speech taggers, parsers.
- Learn statistical/machine learning models for speech recognition, taggers, parsers

Longer term:

- Semantic processing and knowledge extraction
- Texts are the main repository of human knowledge

Counting Words and Word Sequences

Words have specific contexts of use.
Pairs of words like *strong* and *tea* or *powerful* and *computer* are not random associations.
Psychological linguistics tells us that it is difficult to make a difference between *writer* and *rider* without context
A listener will discard the improbable *rider of books* and prefer *writer of books*
A language model is the statistical estimate of a word sequence.
Originally developed for speech recognition
The language model component enables to predict the next word given a sequence of previous words: *the writer of books, novels, poetry*, etc. and not *the writer of hooks, nobles, poultry*, ...

N-Grams

The types are the distinct words of a text while the tokens are all the words or symbols.

The phrases from *Nineteen Eighty-Four*

War is peace
Freedom is slavery
Ignorance is strength

have 9 tokens and 7 types.

Unigrams are single words

Bigrams are sequences of two words

Trigrams are sequences of three words

Trigrams

Word	Rank	More likely alternatives
We	9	*The This One Two A Three Please In*
need	7	*are will the would also do*
to	1	
resolve	85	*have know do. . .*
all	9	*the this these problems. . .*
of	2	*the*
the	1	
important	657	*document question first. . .*
issues	14	*thing point to. . .*
within	74	*to of and in that. . .*
the	1	
next	2	*company*
two	5	*page exhibit meeting day*
days	5	*weeks years pages months*

Probabilistic Models of a Word Sequence

$$\begin{aligned} P(S) &= P(w_1, ..., w_n), \\ &= P(w_1)P(w_2|w_1)P(w_3|w_1, w_2)...P(w_n|w_1, ..., w_{n-1}), \\ &= \prod_{i=1}^{n} P(w_i|w_1, ..., w_{i-1}). \end{aligned}$$

The probability $P(\textit{It was a bright cold day in April})$ from *Nineteen Eighty-Four* corresponds to
It to begin the sentence, then *was* knowing that we have *It* before, then *a* knowing that we have *It was* before, and so on until the end of the sentence.

$$\begin{aligned} P(S) &= P(It) \times P(was|It) \times P(a|It, was) \times P(bright|It, was, a) \times ... \\ &\times P(April|It, was, a, bright, ..., in). \end{aligned}$$

Approximations

Bigrams:

$$P(w_i|w_1, w_2, ..., w_{i-1}) \approx P(w_i|w_{i-1}),$$

Trigrams:

$$P(w_i|w_1, w_2, ..., w_{i-1}) \approx P(w_i|w_{i-2}, w_{i-1}).$$

Using a trigram language model, $P(S)$ is approximated as:

$$\begin{aligned} P(S) \quad \approx \quad & P(It) \times P(was|It) \times P(a|It, was) \times P(bright|was, a) \times ... \\ & \times P(April|day, in). \end{aligned}$$

Maximum Likelihood Estimate

Bigrams:

$$P_{\text{MLE}}(w_i|w_{i-1}) = \frac{C(w_{i-1}, w_i)}{\sum_w C(w_{i-1}, w)} = \frac{C(w_{i-1}, w_i)}{C(w_{i-1})}.$$

Trigrams:

$$P_{\text{MLE}}(w_i|w_{i-2}, w_{i-1}) = \frac{C(w_{i-2}, w_{i-1}, w_i)}{C(w_{i-2}, w_{i-1})}.$$

Text Categorization

The objective is to determine the type of a text with a set of predefined categories, for instance: {spam, no spam}
The Reuters corpus contains 800,00 economic newswires (`http://trec.nist.gov/data/reuters/reuters.html`)
Each newswire is manually annotated with a topic selected from a set of 103 predefined topics, for example:

C11: STRATEGY/PLANS,

C12: LEGAL/JUDICIAL,

C13: REGULATION/POLICY,

C14: SHARE LISTINGS

etc.

Text Representation

Most categorizers use the **bag-of-word** technique that represents each document as a vector of words.
The vector parameters denote the presence or absence of a word.
The documents:

D1: Chrysler plans new investment in Latin America.

D2: Chrysler plans major investments in Mexico.

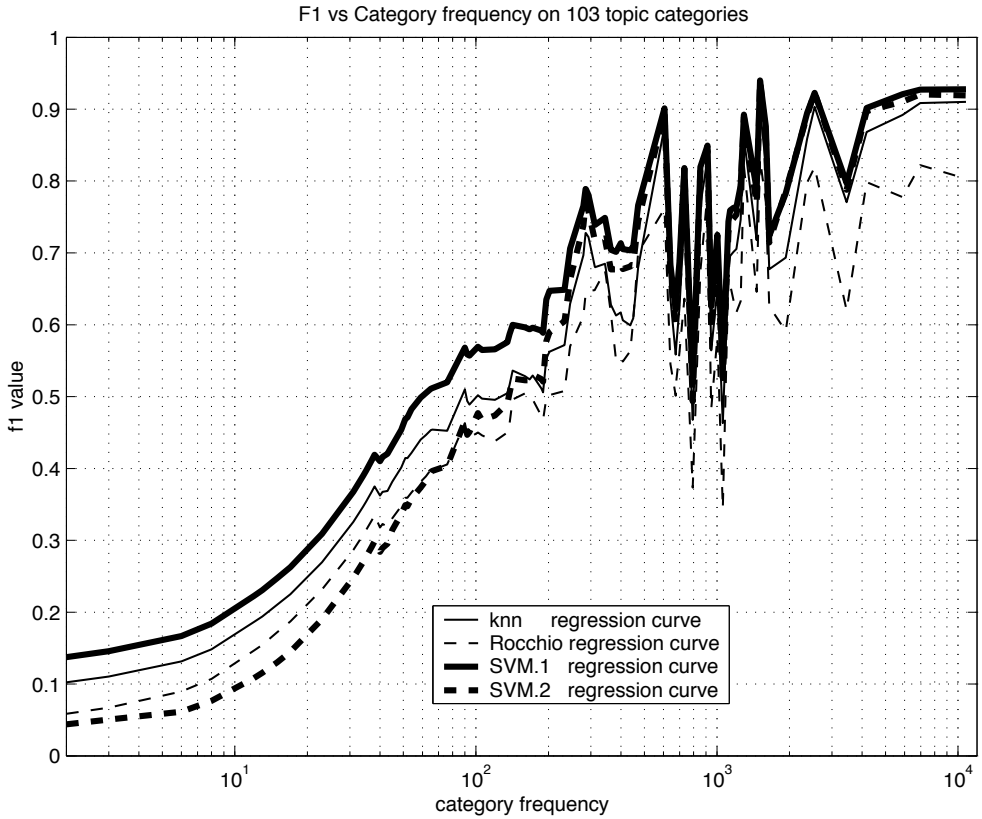
are represented as:

D\W	chrysler	plan	new	major	investment	latin	america	mexico
1	1	1	1	0	1	1	1	0
2	1	1	0	1	1	0	0	1

We can use supervised learning, where the classes are the categories and the features, the word vectors.

Algorithms for Text Categorization

The performance depends on the number of samples



David D. Lewis, Yiming Yang, Tony G. Rose, and Fan Li, RCV1: A New Benchmark Collection for Text Categorization Research, *Journal of Machine Learning Research* 5 (2004) 361-397.

Information Retrieval

Astronomic number of available documents
Search engines – Google, Yahoo – are examples of tools to retrieve information on the web
Usually, we have:

- A document collection
- A query
- A result consisting of a set of documents

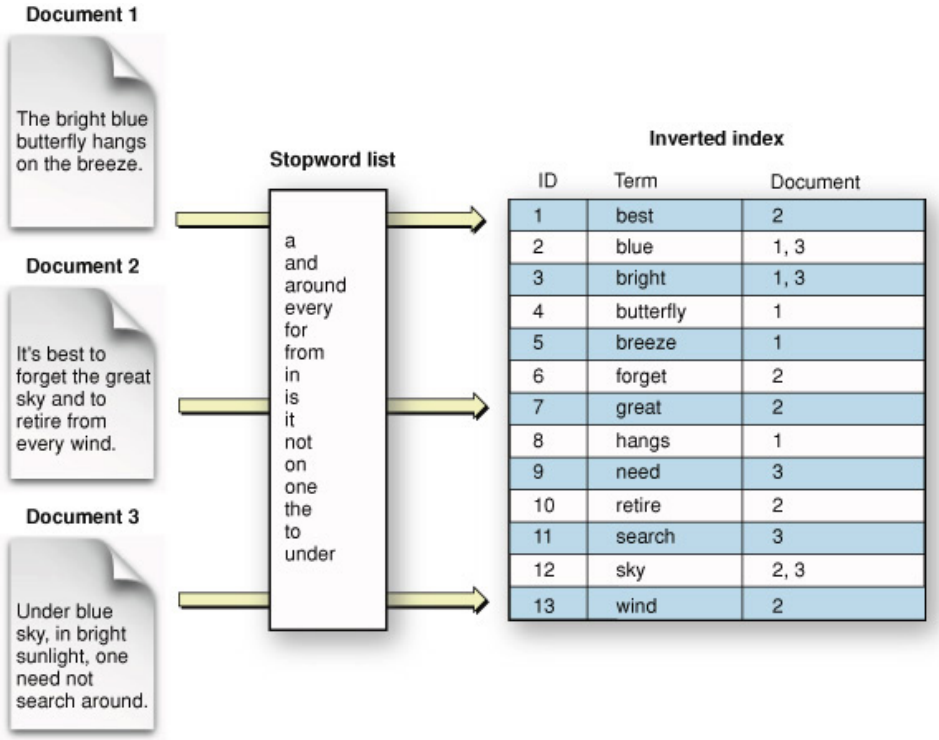
The simplest technique is to use a Boolean formula of conjunctions and disjunctions that will return the documents satisfying it.

The Vector Space Model

The vector space model represents a document in word space:

Documents \Words	w_1	w_2	w_3	...	w_m
D_1	$C(w_1, D_1)$	$C(w_2, D_1)$	$C(w_3, D_1)$	...	$C(w_m, D_1)$
D_2	$C(w_1, D_2)$	$C(w_2, D_2)$	$C(w_3, D_2)$	...	$C(w_m, D_2)$
...					
D_n	$C(w_1, D_n)$	$C(w_2, D_n)$	$C(w_3, D_n)$	...	$C(w_m, D_n)$

Inverted Index (Source Apple)



http://developer.apple.com/library/mac/documentation/UserExperience/Conceptual/SearchKitConcepts/index.html

Lucene is an outstanding program for document indexing and retrieval:

http://lucene.apache.org

Giving a Weight

Word clouds give visual weights to words

$TF \times IDF$

The frequency alone might be misleading

Document coordinates are in fact $tf \times idf$: Term frequency by inverted document frequency.

Term frequency $tf_{i,j}$: frequency of term j in document i

Inverted document frequency: $idf_j = \log(\frac{N}{n_j})$

Document Similarity

Documents are vectors where coordinates could be the count of each word:
$\vec{d} = (C(w_1), C(w_2), C(w_3), ..., C(w_n))$
The similarity of documents is their cosine:

$$\cos(\vec{q}, \vec{d}) = \frac{\sum_{i=1}^{n} q_i d_i}{\sqrt{\sum_{i=1}^{n} q_i^2} \sqrt{\sum_{i=1}^{n} d_i^2}}.$$

Evaluation

The Message Understanding Conferences have introduced a metric to evaluate the performance of information extraction systems using three figures.
They are borrowed them from library science

	Relevant documents	Irrelevant documents
Retrieved	A	B
Not retrieved	C	D

Recall, Precision, and the F-Measure

Recall measures how much relevant information the system has retrieved.

$$\text{Recall} = \frac{A}{A \cup C}.$$

Precision is the accuracy of what has been returned

$$\text{Precision} = \frac{A}{A \cup B}.$$

Recall and precision are combined into the **F-measure**, which is defined as the harmonic mean of both numbers:

$$F = \frac{2PR}{P + R}.$$

Implementation Details

Very frequent words (stop words) can be removed
Words can be stemmed or lemmatized, for instance *table*, *tables*, *tabled*, *tabling* would have the same representation
Search can be extended to synonyms
Some systems use spell checkers

Google's PageRank

Google's PageRank algorithm does not use word frequencies, but the page popularity through the "backlinks", the links pointing to a page.
Each backlink has a specific weight, which is related to the rank of the page it comes from.
The page rank is defined as the sum of the weights of all its backlinks:

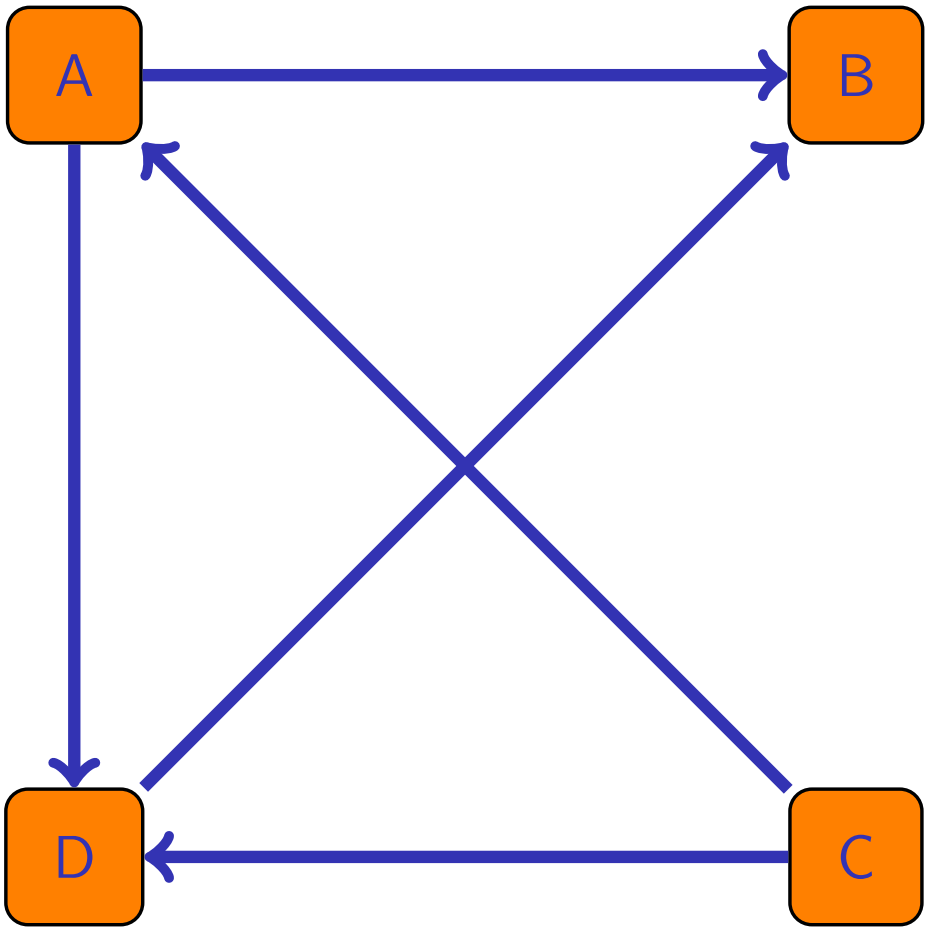
$$PR(p_j) = \frac{1-d}{N} + d \sum_{p_i \in Ref(p_j)} \frac{PR(p_i)}{C(p_i)}.$$

Google's PageRank (II)

The importance of a page is spread through its forward links and contributes to the popularity of the pages it points to.
The weight of each of these forward links is the page rank divided by the count of the outgoing links.
The ranks are propagated in a document collection until they converge:

$$PR(p_j, t+1) = \frac{1-d}{N} + d \sum_{p_i \in Ref(p_j)} \frac{PR(p_i, t)}{C(p_i)}$$

Pagerank Example



$$d = 0.85; \frac{1-d}{N} = \frac{0.15}{4} = 0.0375$$

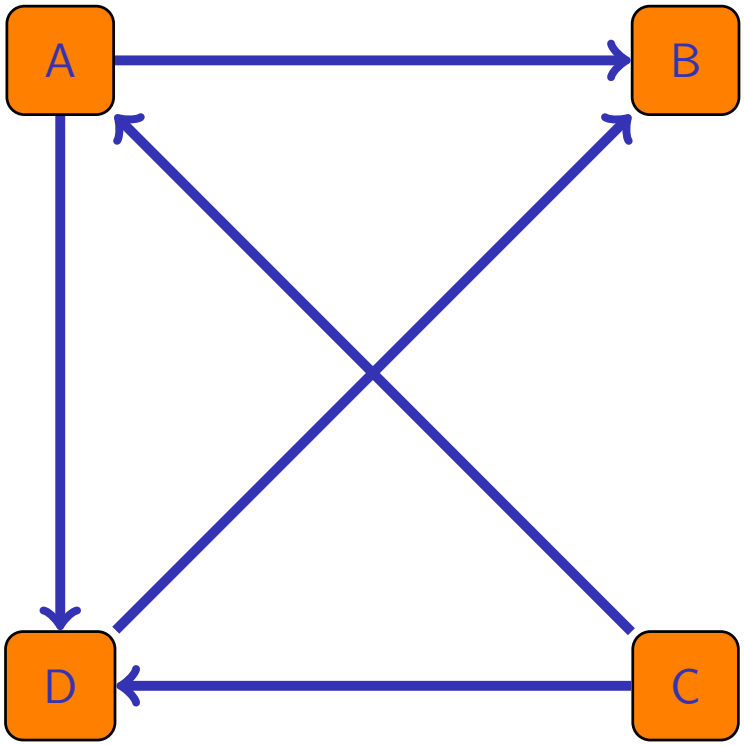
A	B	C	D
1	1	1	1

Table: Initial pageranks

$\rightarrow$	A	B	C	D
A	0	1	0	1
B	0	0	0	0
C	1	0	0	1
D	0	1	0	0

Table: Links

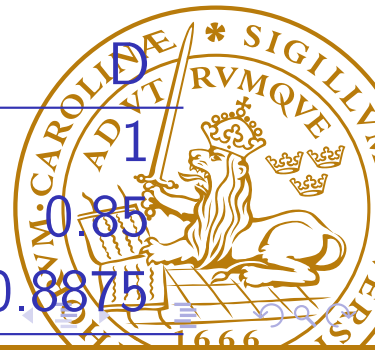
Pagerank Example



→	A	B	C	D
A	0	0.5	0	0.5
B	0	0	0	0
C	0.5	0	0	0.5
D	0	1	0	0
Sum	0.5	1.5	0	1

Table: Initial weighted links

	A	B	C	D
Sum	0.5	1.5	0	1
Damped = 0.85 × Sum	0.425	1.275	0	0.85
PR = 0.0375 + Damped	0.4625	1.3125	0.0375	0.8875



Message Understanding Conferences

The Message Understanding Conferences (MUCs) measure the performance of information extraction systems.
They are competitions organized by an agency of the US department of defense, the DARPA
The competitions have been held regularly until MUC-7 in 1997.
The performances improved dramatically in the beginning and stabilized then.
MUCs are divided into a set of tasks that have been changing over time.
The most basic task is to extract people and company names.
The most challenging one is referred to as information extraction.

Information Extraction

Information extraction consists of:

- The analysis of pieces of text ranging from one to two pages,
- The identification of entities or events of a specified type,
- The filling of a pre-defined template with relevant information from the text.

Information extraction then transforms free texts into tabulated information.

An Example

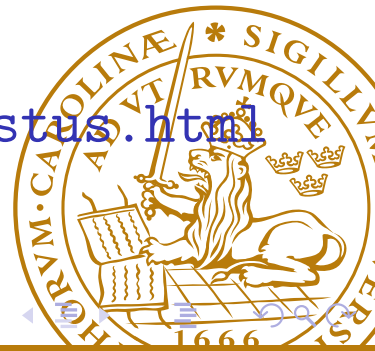
San Salvador, 19 Apr 89 (ACAN-EFE) – [TEXT] Salvadoran President-elect Alfredo Cristiani condemned the terrorist killing of Attorney General Roberto Garcia Alvarado and accused the Farabundo Marti National Liberation Front (FMLN) of the crime...
Garcia Alvarado, 56, was killed when a bomb placed by urban guerrillas on his vehicle exploded as it came to a halt at an intersection in downtown San Salvador...
Vice President-elect Francisco Merino said that when the attorney general's car stopped at a light on a street in downtown San Salvador, an individual placed a bomb on the roof of the armored vehicle...
According to the police and Garcia Alvarado's driver, who escaped unscathed, the attorney general was traveling with two bodyguards. One of them was injured.

The Template

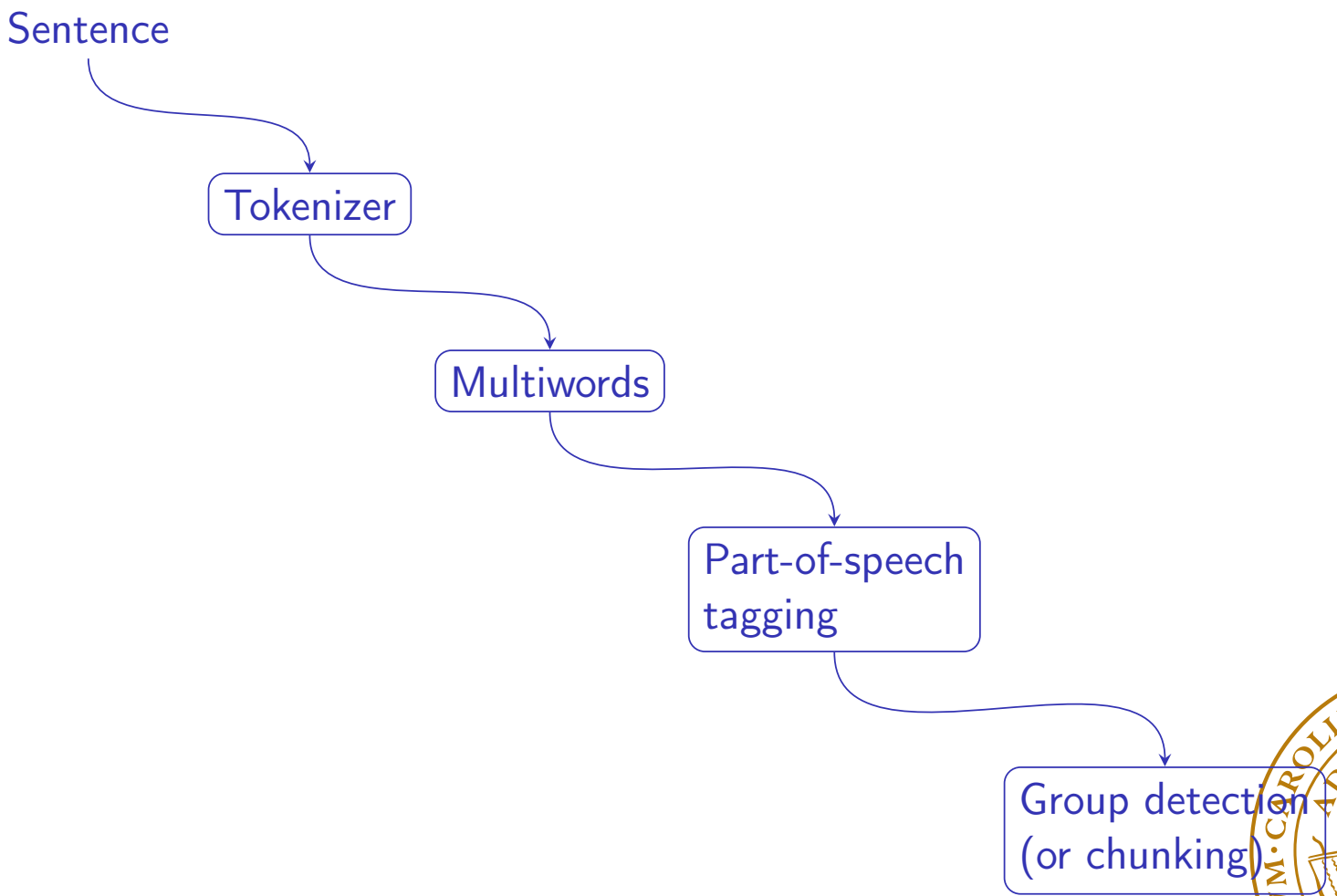
Template slots	Information extracted from the text
Incident: Date	19 Apr 89
Incident: Location	El Salvador: San Salvador (city)
Incident: Type	Bombing
Perpetrator: Individual ID	*urban guerrillas*
Perpetrator: Organization ID	*FMLN*
Perpetrator: Organization confidence	Suspected or accused by authorities: *FMLN*
Physical target: Description	*vehicle*
Physical target: Effect	Some damage: *vehicle*
Human target: Name	*Roberto Garcia Alvarado*
Human target: Description	*Attorney general*: *Roberto Garcia Alvarado* *driver* *bodyguards*
Human target: Effect	Death: *Roberto Garcia Alvarado* No injury: *driver* Injury: *bodyguards*

FASTUS

The FASTUS system has been designed at the Stanford Research Institute to extract information from free-running text
FASTUS uses partial parsers that are organized as a cascade of finite-state automata.
It includes a tokenizer, a multiword detector, and a group detector as first layers.
Verb groups are tagged with active, passive, gerund, and infinitive features.
Then FASTUS combines some groups into more complex phrases and uses extraction patterns to fill the template slots.
See
`http://www.ai.sri.com/natural-language/projects/fastus.html`



FASTUS' Architecture



Probabilistic Models for Information Extraction

It is possible to use statistical tagging techniques to carry out information extraction.
An example with three tapes corresponding to the text (input), speaker, and date (both output).
(From the textbook, Stuart Russell and Peter Norvig, *Artificial Intelligence*, 3rd ed., 2010, page 876.)

There	will	be	a	seminar	by	Andrew	McCallum	on	Friday
–	–	–	–	PRE	PRE	TARGET	TARGET	POST	–
–	–	–	–	–	–	–	–	PRE	TARGET

The speaker and date tapes are tagged by two separate hidden Markov models.
The procedure is similar to that of part-of-speech tagging.

Tagging Techniques to Extract Groups

Group detection – chunking – can be reframed as a tagging operation.

From: [$_{NG}$ The government $_{NG}$] has [$_{NG}$ other agencies and instruments $_{NG}$] for pursuing [$_{NG}$ these other objectives $_{NG}$] .

To: *The*/I *government*/I *has*/O *other*/I *agencies*/I *and*/I *instruments*/I *for*/O *pursuing*/O *these*/I *other*/I *objectives*/I ./O

From: Even [$_{NG}$ Mao Tse-tung $_{NG}$] [$_{NG}$'s China $_{NG}$] began in [$_{NG}$ 1949 $_{NG}$] with [$_{NG}$ a partnership $_{NG}$] between [$_{NG}$ the communists $_{NG}$] and [$_{NG}$ a number $_{NG}$] of [$_{NG}$ smaller, non-communists parties $_{NG}$] .

To: *Even*/O *Mao*/I *Tse-tung*/I *'s*/B *China*/I *began*/O *in*/O *1949*/I *with*/O *a*/I *partnership*/I *between*/O *the*/I *communists*/I *and*/O *a*/I *number*/I *of*/O *smaller*/I ...

IOB Annotation for Named Entities

CoNLL 2002	
Words	Named entities
Wolff	B-PER
,	O
currently	O
a	O
journalist	O
in	O
Argentina	B-LOC
,	O
played	O
with	O
Del	B-PER
Bosque	I-PER
in	O
the	O
final	O
years	O
of	O
the	O
seventies	O
in	O
Real	B-ORG
Madrid	I-ORG

CoNLL 2003			
Words	POS	Groups	Named entities
U.N.	NNP	I-NP	I-ORG
official	NN	I-NP	O
Ekeus	NNP	I-NP	I-PER
heads	VBZ	I-VP	O
for	IN	I-PP	O
Baghdad	NNP	I-NP	I-LOC
.	.	O	O

Multiple Categories of Chunks

Extendable to any type of chunks: nominal, verbal, etc.
For the IOB scheme, this means tags such as I.Type, O.Type, and B.Type,
Types being NG, VG, PG, etc.
In CoNLL 2000, ten types of chunks

Word	POS	Group	Word	POS	Group
He	PRP	B-NP	*to*	TO	B-PP
reckons	VBZ	B-VP	*only*	RB	B-NP
the	DT	B-NP	*£*	#	I-NP
current	JJ	I-NP	*1.8*	CD	I-NP
account	NN	I-NP	*billion*	CD	I-NP
deficit	NN	I-NP	*in*	IN	B-PP
will	MD	B-VP	*September*	NNP	B-NP
narrow	VB	I-VP	*.*	.	O

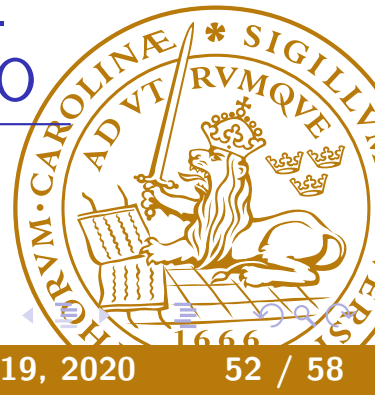
Noun groups (NP) are in red and verb groups (VP) are in blue.

Example from Kudoh and Matsumoto (2000)

Three lines or columns representing the words, the parts of speech, and the groups.

He	*reckons*	*the*	*current*	*account*	*deficit*	*will*	*narrow*
PRP	VBZ	DT	JJ	NN	NN	MD	VB
B-NP	B-VP	B-NP	I-NP	I-NP	I-NP	B-VP	I-VP

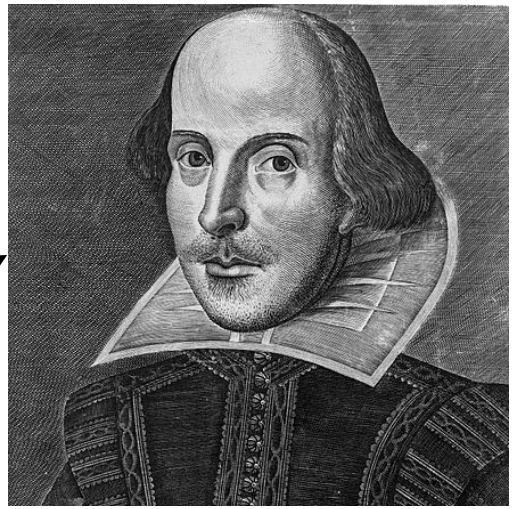
to	*only*	*#*	*1.8*	*billion*	*in*	*September*	.
TO	RB	#	CD	CD	IN	NNP	.
B-PP	B-NP	I-NP	I-NP	I-NP	B-PP	B-NP	O



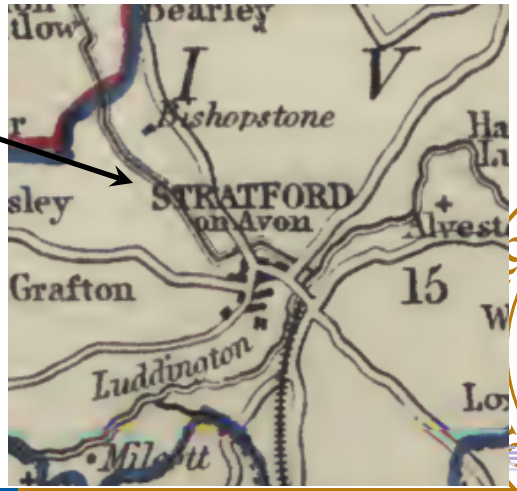
Example from Kudoh and Matsumoto (2000)

Words	POS	Groups	
BOS	BOS	BOS	***Padding***
BOS	BOS	BOS	
He	PRP	B-NP	
reckons	VBZ	B-VP	
the	DT	B-NP	
current	JJ	I-NP	
account	NN	I-NP	
deficit	NN	I-NP	***Input features***
will	MD	B-VP	
narrow	VB	I-VP	***Predicted tag***
to	TO	B-PP	↓
only	RB	B-NP	
£	#	I-NP	
1.8	CD	I-NP	
billion	CD	I-NP	
in	IN	B-PP	
September	NNP	B-NP	
.	.	O	
EOS	EOS	EOS	***Padding***
EOS	EOS	EOS	

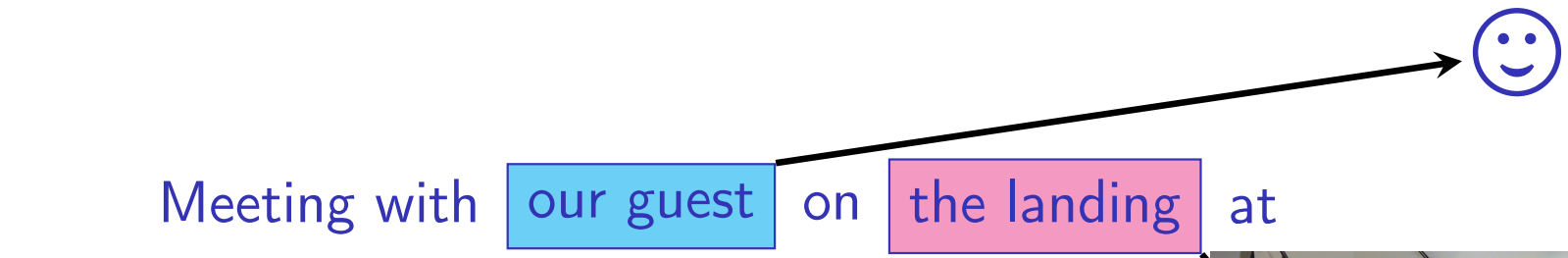
Named Entities: Proper Nouns



William Shakespeare was born and brought up in Stratford-upon-Avon



Others Entities: Common Nouns



Supervised Learning: A Summary

Needs a manually annotated corpus called the **gold standard**
The gold standard may contain errors (*errare humanum est*) that we ignore
A classifier is trained on a part of the corpus, the **training set**, and evaluated on another part, the **test set**, where automatic annotation is compared with the *gold standard*
N-fold cross validation is used avoid the influence of a particular division
Some algorithms may require additional optimization on a development set
Classifiers can use statistical or symbolic methods

Conditional Random Fields

To carry out named entity tagging, time or location extraction, it is possible to use discriminative models such as support vector machines. Conditional random fields are tools that take into account sequences. Let X_1^N be the words and Y_1^N, the tags:

$$P(Y_1^N|X_1^N) = \alpha e^{\sum_{i=1}^{N} F(Y_{i-1}, Y_i, X_1^N, i)}$$

F are feature functions:

$$F(Y_{i-1}, Y_i, X_1^N, i) = \sum_k \lambda_k f_k(Y_{i-1}, Y_i, X_1^N, i)$$

where:

$$f_1(Y_{i-1}, Y_i, X_1^N, i) = \begin{cases} 1 & Y_i = \text{SPEAKER and } X_i = \text{Andrew,} \\ 0 & \text{otherwise.} \end{cases}$$

(From the textbook, Stuart Russell and Peter Norvig, *Artificial Intelligence*, 3rd ed., 2010, page 879.)

Question Answering

Question parsing and classification: Syntactic parsing, entity recognition, answer classification

Document retrieval. Extraction and ranking of passages: Indexing, vector space model.

Extraction and ranking of answers: Answer parsing, entity recognition