EDAN20
Language Technology
http://cs.lth.se/edan20/
Chapter 10: Partial Parsing

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ELIZA: Word Spotting and Template Matching

User	Psychotherapist
. . . I like X. . .	*Why do you like X?*
. . . I am X. . .	*How long have you been X?*
. . . father. . .	*Tell me more about your father*

Word Spotting in Prolog

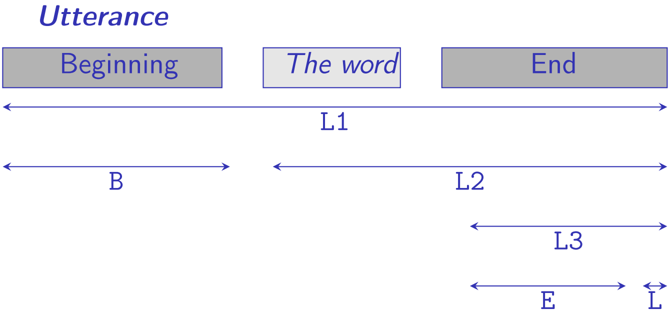
Model of the utterance:

```
utterance(U) --> beginning(B), [the_word], end(E).
```

Prolog equivalent:

```
utterance(U, L1, L) :-
  beginning(B, L1, L2),
  'C'(L2, the_word, L3),
  end(E, L3, L).
```

Representation of the Difference Lists



Linking the lists:

```
beginning(X, Y, Z) :- append(X, Z, Y).
end(X, Y, Z) :- append(X, Z, Y).
```

ELIZA in Prolog

```
eliza :-
  write('Hello, I am ELIZA. How can I help you?'), nl,
  repeat,
  write('> '),
  tokenize(In),
  process(In).

process([bye | _]) :-
  write('ELIZA: bye'), nl, !.
process(In) :-
  utterance(Out, In, []), !,
  write('ELIZA: '), write_answer(Out),
  fail.
```

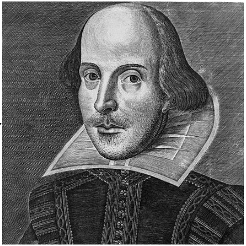
ELIZA in Prolog (II)

```
answer(['Why', aren, '''', t, you | Y]) -->
  ['I', am, not], end(Y).
answer(['How', long, have, you, been | Y]) -->
  ['I', am], end(Y).
answer(['Why', do, you, like | Y]) -->
  ['I', like], end(Y).
```

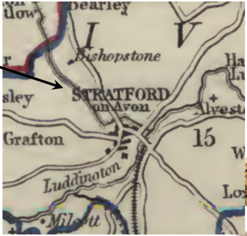
Multiwords

Type	English	French
Prepositions	*to the left hand side*	*À gauche de*
Adverbs	*because of*	*à cause de*
Conjunctions		
Names	*British gas plc.*	*Compagnie générale d'électricité SA*
Titles	*Mr. Smith*	*M. Dupont*
	The President of the United States	*Le président de la République*
Verbs	*give up*	*faire part*
	go off	*rendre visite*

Named Entities: Proper Nouns



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



Multiword Annotation

The Message Understanding Conferences (MUC), a benchmarking competition organized by the US military, defined an annotation scheme.

The MUC annotation restricts the annotation to information useful to the funding source: names (named entities), time expressions, and money quantities.

The annotation scheme defines an XML element for three classes: `<ENAMEX>`, `<TIMEX>`, and `<NUMEX>` with which it brackets the relevant phrases in a text.

The phrases can be real multiwords, consisting of two or more words, or restricted to a single word.

<ENAMEX>

The <ENAMEX> element identifies proper nouns and uses a TYPE attribute with three values to categorize them: ORGANIZATION, PERSON, and LOCATION as in

- The <ENAMEX TYPE="PERSON">Clinton</ENAMEX> government
- <ENAMEX TYPE="ORGANIZATION">Bridgestone Sports Co.</ENAMEX>
- <ENAMEX TYPE="ORGANIZATION">European Community</ENAMEX>
- <ENAMEX TYPE="ORGANIZATION">University of California</ENAMEX> in <ENAMEX TYPE="LOCATION">Los Angeles</ENAMEX>

Modeling Multiwords

```
multiword(in_front) --> [in, front].
multiword(['<ENAMEX>', 'M.', Name, '</ENAMEX>']) -->
  ['M.'], [Name],
  {
    atom_codes(Name, [Initial | _]),
    Initial >= 65, % must be an upper-case letter
    Initial =< 90
  }.
multiword(['<NUMEX>', Value, euros, '</NUMEX>']) -->
  [Value], [euros],
  {
    number(Value)
  }.
```

Longest Match

Multiwords:

```
multiword(in_front_of) --> [in, front, of].
multiword(in_front) --> [in, front].
```

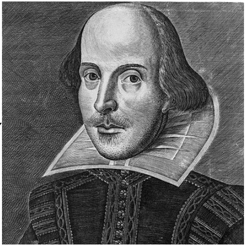
Sentence:

```
word_stream(Beginning, Multiword, End) -->
  beginning(Beginning),
  multiword(Multiword),
  end(End).
```

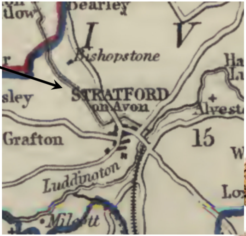
Running the rules:

```
multiword_detector(In, [Head | Out]) :-
  word_stream(Beginning, Multiword, End, In, []),
  append(Beginning, [Multiword], Head),
  multiword_detector(End, Out).
multiword_detector(End, End).
```

Named Entities: Proper Nouns



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



Others Entities: Common Nouns

☺

Meeting with our guest on the landing at lunchtime

Noun Groups

English	French	German
The waiter *is bringing* ***the very big dish*** *on* ***the table***	***Le serveur*** *apporte* ***le très grand plat*** *sur* ***la table***	***Der Ober*** *bringt* ***die sehr große Speise*** *an* ***den Tisch***
Charlotte *has eaten* ***the meal*** *of* ***the day***	***Charlotte*** *a mangé* ***le plat*** *du* ***jour***	***Charlotte*** *hat* ***die Tagesspeise*** *gegessen*

Verb Groups

English	French	German
*The waiter **is bringing** the very big dish on the table*	*Le serveur **apporte** le très grand plat sur la table*	*Der Ober **bringt** die sehr große Speise an den Tisch*
*Charlotte **has eaten** the meal of the day*	*Charlotte **a mangé** le plat du jour*	*Charlotte **hat** die Tagesspeise **gegessen***

Noun Groups

```
nominal([NOUN | NOM]) --> noun(NOUN), nominal(NOM).
nominal([N]) --> noun(N).

noun(N) --> common_noun(N).
noun(N) --> proper_noun(N).

noun_group([PRO]) --> pronoun(PRO).
noun_group([D | N]) --> det(D), nominal(N).
noun_group(N) --> nominal(N).
```

Adjectives

```
adj_group_x([RB, A]) --> adv(RB), adj(A).
adj_group_x([A]) --> adj(A).

adj_group(AG) --> adj_group_x(AG).
adj_group(AG) -->
  adj_group_x(AGX),
  adj_group(AGR),
  {append(AGX, AGR, AG)}.
```

Participles

```
adj(A) --> past_participle(A).
adj(A) --> gerund(A).
```

We must be aware that these rules may conflict with a subsequent detection of verb groups. Compare *detected words* in

> *the detected words*

and

> *The partial parser detected words.*

```
noun_group(NG) -->
  det(D), adj_group(AG), nominal(N),
  {append([D | AG], N, NG)}.
```

The Vocabulary

```
% Determiners
det(the) --> [the].
det(a) --> [a].

% Nouns
common_noun(problems) --> [problems].
common_noun(solutions) --> [solutions].

% Adverbs
adv(relatively) --> [relatively].
adv(likely) --> [likely].

% Adjectives
adj(small) --> [small].
adj(big) --> [big].
...
```

Group Bracketing

```
group(NG) -->
  noun_group(Group),
  {append(['<NG>' | Group], ['</NG>'], NG)}.
group(VG) -->
  verb_group(Group),
  {append(['<VG>' | Group], ['</VG>'], VG)}.
```

Group Detector

```
group_detector(In, [Group | Out]) :-
  word_stream(Beginning, Group, End, In, []),
  group_detector(End, Out).
group_detector(_, []).

word_stream(Beginning, Group, End) -->
  beginning(Beginning),
  group(Group),
  end(End).
```

Example

Critics question the ability of a relatively small group of big integrated prime contractors to maintain the intellectual diversity that formerly provided the Pentagon with innovative weapons. With fewer design staffs working on military problems, the solutions are likely to be less varied. (LA Times, December 17, 1996)

```
?- group_detector([critics, question, the, ability, of, a,
relatively, small, group, of, big, integrated, prime,
 ...], L).
L = [[<NG>, critics, </NG>], [<VG>, question, </VG>],
[<NG>, the, ability, </NG>], of, [<NG>, a, relatively, small,
group, </NG>], of, [<NG>, big, integrated, prime, contractors,
</NG>], [<VG>, to, maintain, </VG>], [<NG>, the, intellectual,
diversity, </NG>], that, ...]
```

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 ,/I *non-communists*/I *parties*/I ./O

Other Chunking Schemes

Tjong and Venstra (1999) created 3 other schemes: IOB1, IOB2, IOE1, and IOB2:

IOB1 : Inside, Outside, Between

IOB2 : Begin, Inside, Outside

IOE1 : Inside, Outside, End (between two chunks)

IOE2 : Inside, Outside, End

Other Chunking Schemes

IOB1 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, non-communists/I parties/I

IOB2 Even/O Mao/B Tse-tung/I 's/B China/I began/O in/O 1949/B with/O a/B partnership/I between/O the/B communists/I and/O a/B number/I of/O smaller/B, non-communists/I parties/I

IOE1 Even/O Mao/I Tse-tung/E 's/I 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, non-communists/I parties/I

IOE2 Even/O Mao/I Tse-tung/E 's/I China/E began/O in/O 1949/E with/O a/I partnership/E between/O the/I communists/E and/O a/I number/E of/O smaller/I, non-communists/I parties/E

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.

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
.	O

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

Chunking Algorithms

We can apply statistical and symbolic methods to chunking:

1. Brill's method with templates adapted to groups.
2. Stochastic methods similar to POS tagging.

The maximum of likelihood estimator determines the optimal sequence of gap tags $G = g_2, g_3, ..., g_n$ given a sequence of part-of-speech tags $T = t_1, t_2, t_3, ..., t_n$ and of words $W = w_1, w_2, w_3, ..., w_n$.

$$P(G) = \prod_{i=2}^{n} P(g_i | w_{i-1}, t_{i-1}, w_i, t_i).$$

We can also use machine-learning techniques with logistic regression, support vector machines, or decision trees.

Feature Engineering (I)

CoNLL 2000 baseline: Use t_i to predict $chunk\_tag_i$

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

F-measure: 77.07

Feature Engineering (II)

Second experiment: Use t_{i-1}, t_i to predict $chunk\_tag_i$

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

F-measure: 81.88

Feature Engineering (III)

Third experiment: Use t_{i-2}, t_{i-1}, t_i to predict $chunk\_tag_i$

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

F-measure: 82.84

Dynamic Features

So far, we used "static" features extracted from a first annotation, for example, the words and their part of speech: $w_{i-1}, t_{i-1}, w_i, t_i$

We can add dynamic features that will reuse the value of the preceding (and just obtained) chunk brackets.

It is possible to reuse chunk tags to the left in case of left-to-right parsing and to the right in case of right-to-left parsing

Feature Engineering (IV)

Fourth experiment: Use $w_i, t_{i-1}, t_i, t_{i+1}, chunk\_tag_{i-1}$ to predict $chunk\_tag_i$. All words with a frequency less than ∼100 mapped onto a unique symbol (RARE_WORD).

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

F-measure: 90.17

Kudoh and Matsumoto (2000)

Kudoh and Matsumoto (2000) won the CoNLL-2000 shared task.

They used static and dynamic features in the Yamcha system

Typically, a feature vector consists of 10 static parameters:

$w_{i-2}, t_{i-2}, w_{i-1}, t_{i-1}, w_i, t_i, w_{i+1}, t_{i+1}, w_{i+2}, t_{i+2}$

And two dynamic parameters: $chunk\_tag_{i-2}, chunk\_tag_{i-1}$

Kudoh and Matsumoto (2000) experimented various feature vectors, forward and backward parsing, as well as the four annotation schemes.

Their classifiers used support vector machines.

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	

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

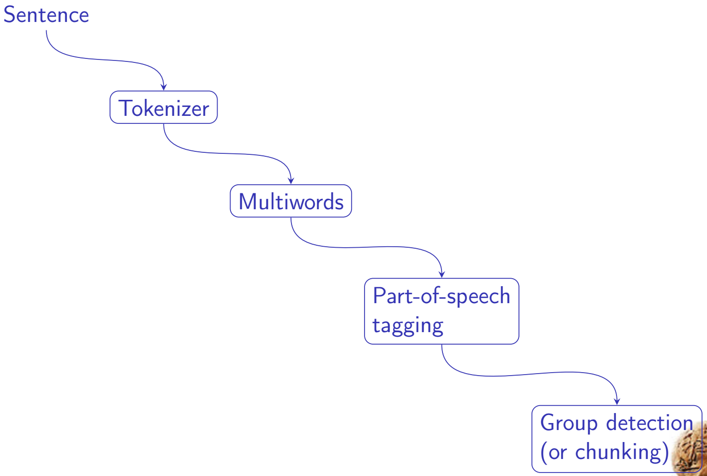
FASTUS uses partial parsers that are organized as a cascade of finite-state automata.

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.

FASTUS' Architecture



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:

$$F = \frac{2}{\frac{1}{P} + \frac{1}{R}} = \frac{2PR}{P + R}.$$