Learning and Inference for Clause Identification

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## Outline

- Clause Identification.
- Inference Scheme.
- Learned Functions.
- Experimentation.
- Conclusions.

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We want to identify **clauses** in a **sentence**.

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Clauses in a sentence form a hierarchical structure.
We do not consider clause types (main, relative, noun, adverbial, ...).

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\* Overlapping of clauses is not permitted:
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3

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• **Output:** a bracketing codifying the hierarchical clause structure, in which:

★ A clause is codified by its boundaries:
w w (words within the clause) w w w √
★ Overlapping of clauses is not permitted:
w w ( w w ( w w w ) w w ) w ×
★ Clauses are possibly embedded.
( ( w w ) w w ( w w w ( w w w ) ) ) √

# **Syntactic Parsing**

Clause Identification  $\in$  **Syntactic Parsing**  $\in$  NLP

- Grammar-based methods:
  - ★ Grammars: manually constructed, inferred, . . .
  - ★ Parsing Schemes: CKY, Early, . . .
  - ★ PCFG's, parameter estimation.
- No-Explicit-Grammar Parsers:
  - \* Usually, intensive use of learning techniques.
  - ★ Decision Trees, [Magerman 96]
  - ★ Maximum-Entropy parser, [Ratnaparkhi 98]
  - ★ Partial Parsing techniques, [Abney 91] [CoNLL tasks]

#### Learning and Inference for Partial Parsing

Local classifiers: solve dependent partial decisions, e.g.:

Whether a word opens and/or closes a constituent.
 Whether a word starts or continues a constituent.

 Inference is made on the outcome of local classifiers to produce a global solution, coherent wrt. the problem constraints. [Roth ECML'02]

 Much work in chunking, for plain structures (non-overlapping & non-embedding) [CoNLL'00]
 We propose an inference scheme for clausing (non-overlapping & embedding) [CoNLL'01]

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# **Our Approach**

• Learned Functions (classifiers):

Start of a clause: spoint
End of a clause: epoint
Score of a clause: score

• Algorithm: Recursively from the bottom-up . . .

- ★ Generate clause candidates.
- ★ Select best split of clauses.

 $w_1 \ w_2 \ w_3 \ w_4 \ w_5 \ w_6 \ w_7 \ w_8 \ w_9 \ w_{10} \ spoints \ oldsymbol{s_1} \ oldsymbol{s_2} \ oldsymbol{s_6} \ oldsymbol{s_6}$ 

	$w_1$	$w_2$	$w_3$	$w_4$	$w_5$	$w_6$	$w_7$	$w_8$	$w_9$	$w_{10}$
spoints	$s_1$	$s_2$				$s_6$				
epoints								$e_8$		$e_{10}$







	$w_1$	$w_2$	$w_3$	$w_4$	$w_5$	$w_6$	$w_7$	$w_8$	$w_9$	$w_{10}$
spoints	$s_1$	$s_2$				$s_6$				
epoints								$e_8$		$e_{10}$
	(	(				(		))		١
								))		)

	$w_1$	$w_2$	$w_3$	$w_4$	$w_5$	$w_6$	$w_7$	$w_8$	$w_9$	$w_{10}$
spoints	$s_1$	$s_2$				$s_6$				
epoints								$e_8$		$e_{10}$
	(	(				(		))		)
	(	(						)		))







#### **Clause Score**

Each clause candidate (s, e) is scored by a function:

 $score(s, e) \to \mathbb{R}$ 

Given the score of (s, e):

• The sign tells whether (s, e) is a clause or not.

• The magnitude codifies the confidence of the decision.

# **Optimal Clause Split**

 $\Delta:$  set containing all possible splits.

S: a split, i.e. a coherent set of clauses,  $\{(s_i, e_i)\}_{i=1}^l$ .

$$S^* = \arg \max_{S \in \Delta} \sum_{(s,e) \in S} score(s,e)$$

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The optimal clause split can be efficiently found . . .

- Using dynamic programming techniques.
- Exploring the sentence from the bottom-up.

 $w_s w w w w_e \dots$ 





internal split 1 internal split 2

$w_s$	w	w	w	$w_e$
$w_s$	w	W	W	$w_e$



internal split 1
internal split 2
internal split 3

$w_s$	w	W	w	$w_e$
$w_s$	w	w	w	$w_e$
$w_s$	w	w	w	$w_e$



internal split 1 internal split 2 internal split 3 internal split 4

$w_s$	w	w	w	$w_e$
$w_s$	w	w	W	$w_e$
$w_s$	w	w	w	$w_e$
$w_s$	$\overline{w}$	W	w	$w_e$



internal split 1
internal split 2
internal split 3
internal split 4

(s,e) clause ?

$w_s$	$\mid w \mid$	w	w	$w_e$
$w_s$	w	W	w	$w_e$
$w_s$	W	w	w	$w_e$
$w_s$	W	w	W	$w_e$
$w_s$	$\overline{w}$	$\overline{w}$	$\overline{w}$	$w_e$

# **General Algorithm**

function optimal\_clause\_split (s, e) if  $(s \neq e)$  then optimal\_clause\_split(s, e-1) optimal\_clause\_split(s + 1, e)  $\Delta := \{ \texttt{BestSplit}[s, r] \cup \texttt{BestSplit}[r+1, e] \mid s \le r < e \}$  $S^* := \arg \max_{S \in \Delta} \sum_{(k,l) \in S} \operatorname{Score}[k, l]$ if (spoint(s) and epoint(e)) then Score[s, e] := score(s, e)if (Score[s, e] > 0) then  $S^* := S^* \cup \{(s, e)\}$  $BestSplit[s, e] := S^*$ end function

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#### **Spoints and Epoints**

- Example to be classified: word.
- Decide whether a word Starts and/or Ends a clause.
- Use of a sliding window to codify the local context with binary features:

					?				
form	$w_{i-4}$	$w_{i-3}$	$w_{i-2}$	$w_{i-1}$	$w_i$	$w_{i+1}$	$w_{i+2}$	$w_{i+3}$	$w_{i+4}$
PoS	$p_{i-4}$	$p_{i-3}$	$p_{i-2}$	$p_{i-1}$	$p_{i}$	$p_{i+1}$	$p_{i+2}$	$p_{i+3}$	$p_{i+4}$
chunk	$c_{i-4}$	$c_{i-3}$	$c_{i-2}$	$c_{i-1}$	$C_i$	$c_{i+1}$	$c_{i+2}$	$c_{i+3}$	$c_{i+4}$

## **Score Function**

Example: clause candidate (i.e. sequence of words)
Clause candidates are represented by patterns:

Verb PhrasesConjunctionsAdverbsPunctuationRelative Pronouns. . .

• Example:

(( When ( you don't have any other option )) , it's easy ( to fight ) . ) When  $\sim$  VERB  $\sim$  ,  $\sim$  VERB  $\sim$  VERB .

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#### • Problem: clauses can be very long.

( Not everyone believes ( that
 ( the good times are over for shippers) ) .)

it.1 [...that ( the good times are over for shippers ).

( Not everyone believes ( that
 ( the good times are over for shippers) ) .)

it.1 ...that ( the good times are over for shippers ).  $\implies$  CLAUSE

( Not everyone believes ( that
 ( the good times are over for shippers) ) .)

it.1 ...that ( the good times are over for shippers ).  $\implies$  CLAUSE it.2 ...one believes ( that the good ... shippers ).

it.1	that ( the good times are over for shippers ).
	$\implies$ CLAUSE
it.2	one believes ( that the good shippers ).
	one believes ( that CLAUSE ).

it.1	that ( the good times are over for shippers ).
	$\implies$ CLAUSE
it.2	one believes ( that the good shippers ).
	one believes ( that CLAUSE ).
	$\implies$ CLAUSE

it.1	$ \ldots$ that ( the good times are over for shippers ).
	$\implies$ CLAUSE
it.2	one believes ( that the good shippers ).
	one believes ( that CLAUSE ).
	$\Longrightarrow \text{CLAUSE}$
it.3	(Not everyone believes that shippers . )

it.1	that ( the good times are over for shippers ).
	$\implies$ CLAUSE
it.2	one believes ( that the good shippers ).
	one believes ( that CLAUSE ).
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it.3	(Not everyone believes that shippers . )
	( Not everyone believes CLAUSE . )

it.1	that ( the good times are over for shippers ).
	$\Longrightarrow \text{CLAUSE}$
it.2	one believes ( that the good shippers ).
	one believes ( that CLAUSE ).
	$\Longrightarrow \text{CLAUSE}$
it.3	( Not everyone believes that shippers . )
	( Not everyone believes CLAUSE . )
	$\implies$ CLAUSE

it.1 (Sapporo gained 80 to 1,050) and Kirin ...

it.1 (Sapporo gained 80 to 1,050) and Kirin  $\dots \longrightarrow CLAUSE$ 

it.1 (Sapporo gained 80 to 1,050) and Kirin  $\dots$  $\implies$  CLAUSE it.1 ...1,050 and (Kirin added 60 to 2,000).

it.1( Sapporo gained 80 to 1,050 ) and Kirin ... $\implies$  CLAUSEit.1...1,050 and ( Kirin added 60 to 2,000 ) . $\implies$  CLAUSE

it.1	Sapporo gained 80 to 1,050 ) and Kirin
	$\implies$ CLAUSE
it.1	1,050 and ( Kirin added 60 to 2,000 ) .
	$\implies$ CLAUSE
it.2	(Sapporo gained and to 2.000 . )

it.1	( Sapporo gained 80 to 1,050 ) and Kirin
	$\implies$ CLAUSE
it.1	1,050 and ( Kirin added 60 to 2,000 ) .
	$\implies$ CLAUSE
it.2	(Sapporo gained and to 2,000 . )
	( CLAUSE and CLAUSE . )
	$\implies$ CLAUSE

### **Scoring Functions**

- Plain Scoring: No reduction of previously identified clauses. Consists of one classifier.
- Structured Scoring: Reduction of the optimal split identified inside the current candidate. The function is a composition of three specialized classifiers:
  - ★ Base clauses.
  - ★ Recursive clauses, assuming complete split.
  - ★ Recursive clauses, assuming partial split.

# Learning Algorithm: AdaBoost

real AdaBoost with confidence-rated predictions.
 [Schapire & Singer '99]

•  $f(x) = \sum_{t=1}^{T} \alpha_t h_t(x)$ 

The sign codifies the predicted class.
The magnitude is a confidence score of the prediction.

• Weak Rules  $(h_t)$ : Decision Trees of small depth (3-4).

• Good performance in NLP domains.

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# **CoNLL 2001 Setting**

#### Data Set:

\* Penn Treebank: Wall Street Journal
\* Words, POS tags, chunks.
\* Training Set: sections 15-18 (8,936 sentences).
\* Development Set: section 20 (2,012 sentences).
\* Test Set: section 21 (1,671 sentences).

• Evaluation: precision, recall,  $F_{\beta=1}$ 

#### **Results on the Development Set**

	prec.	rec.	$F_{eta=1}$
Plain Scoring	88.33%	83.92%	86.07%
Structured Sco.	92.53%	82.48%	87.22%

CoNLL'01 CM 87.18% 82.48% 84.77%

#### **Results on the Test Set**

	prec.	rec.	$F_{eta=1}$
Plain Scoring	85.25%	74.53%	79.53%
Structured Sco.	90.18%	72.59%	80.44%

CM01	84.82%	73.28%	78.63%
MP01	70.89%	65.57%	68.12%
TKS01	76.91%	60.61%	67.79%
PG01	73.75%	60.00%	66.17%
Dej01	72.56%	54.55%	62.77%
Ham01	55.81%	45.99%	50.42%



# Conclusions

- We have presented an inference scheme for recognizing hierarchical structure.
- All the decisions involved in the process are solved with learning techniques.
- Local decisions take advantage of the partial solution.
- On Clause Identification, our approach improves top-performing methods . . .
  - . . . but there is still room for improvement.