Trade-off between incrementality and accuracy

Seminar on Incremental Processing

Benjamin Weitz

June 30, 2011

Outline

Introduction

Incremental Dialogue Systems:

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- Baumann et. al: Automatic Speech Recognition
- Kato et. al: Parsing

Baumann et al.

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Definitions

Hypothesis at time t:

$hyp_t = w_{hyp_t}$

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How to evaluate the quality of $\boldsymbol{hyp_t}$?

use **actually spoken input** as gold standard

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Why?

more meaningful:

- relates partial hypothesis to what can be expected from ASR
- correct interpretation might never be recognized

Relative Correctness

w_{gold}: final, non incremental hypothesis

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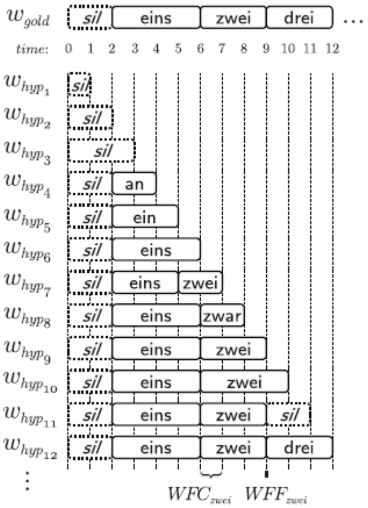

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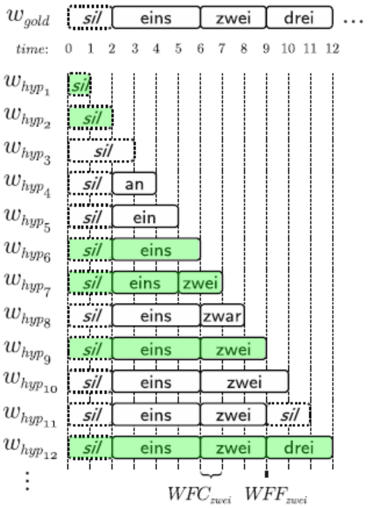

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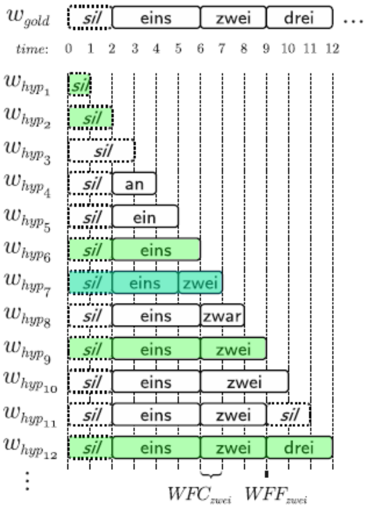

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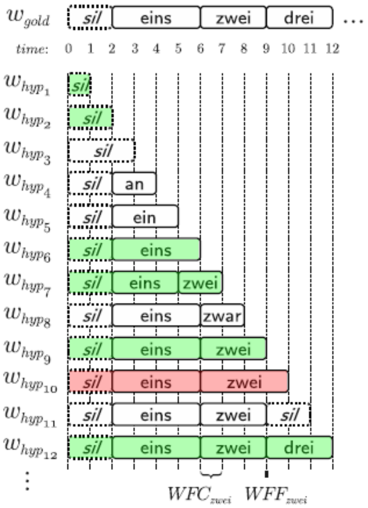

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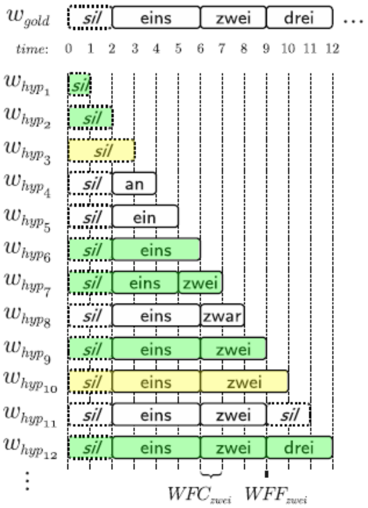

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Three ways for hyp_{t+1} to differ from hyp_t:

- extension
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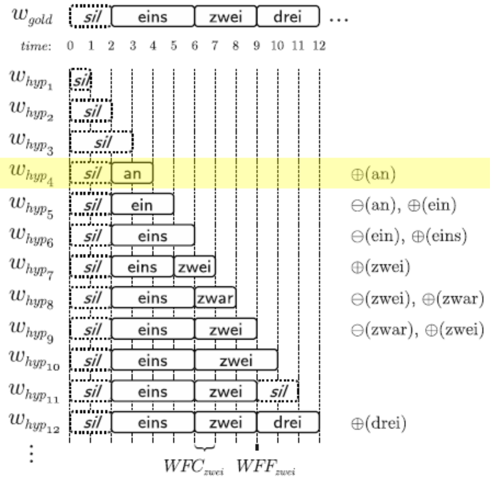

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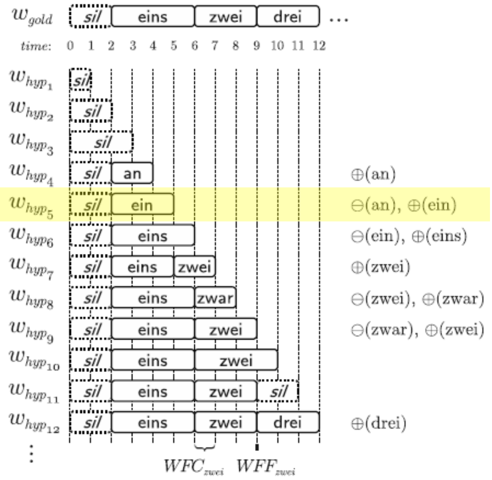

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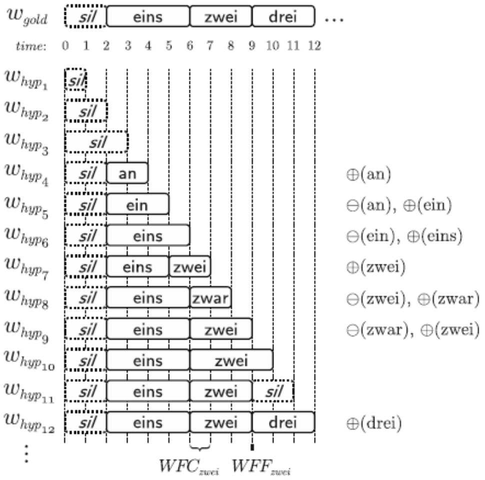

Perfect ASR-System:

1 extension for each word

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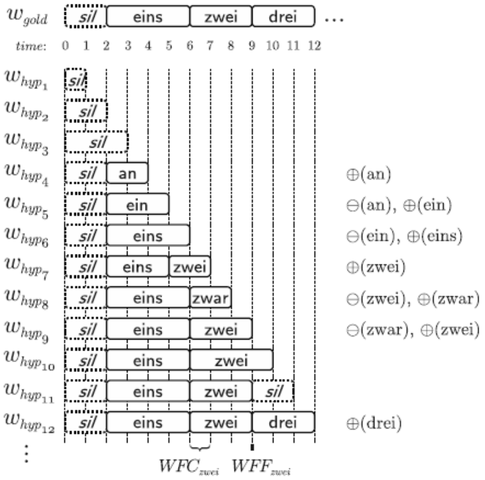

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rate of spurious edits

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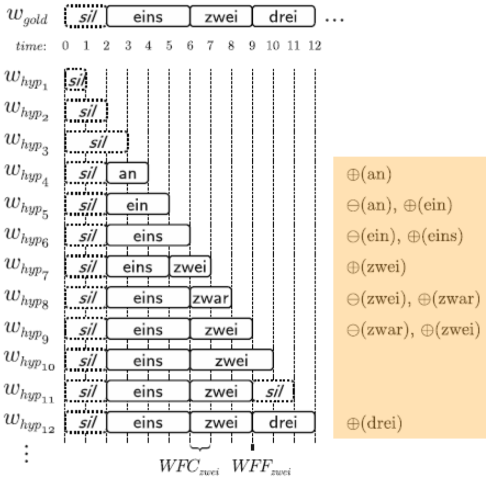

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11 edits

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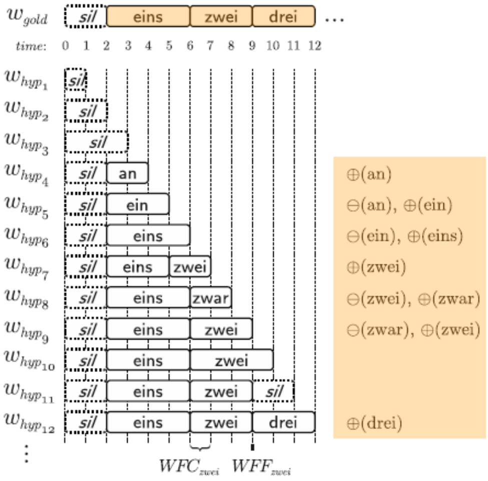

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11 edits, 3 words

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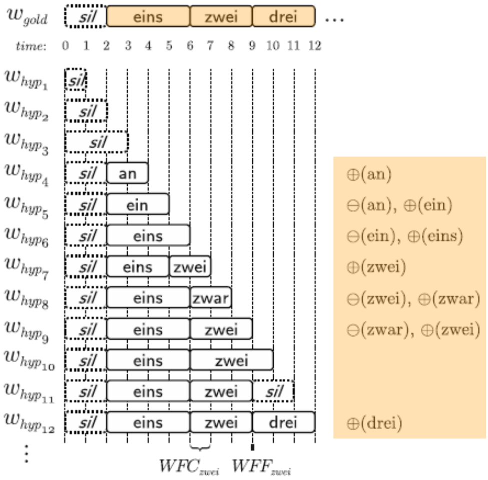

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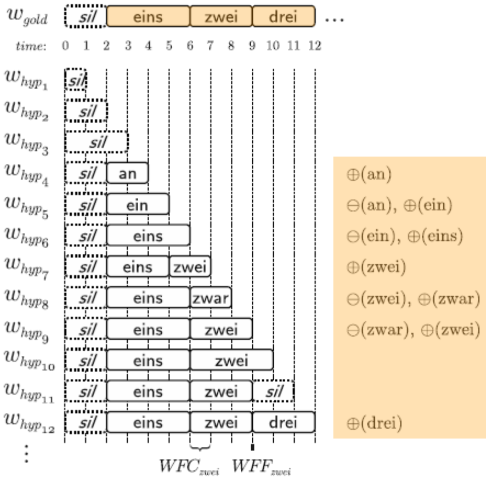

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$\Rightarrow EO = \frac{8}{11}$

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The first time a word appears in the correct position

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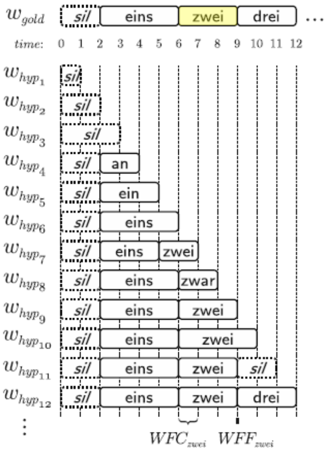

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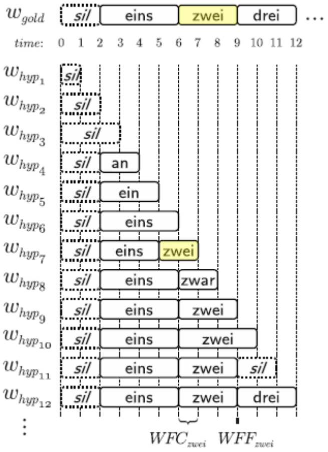

$WFC_{zwei} = 7$

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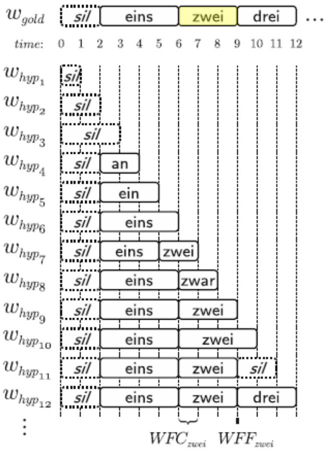

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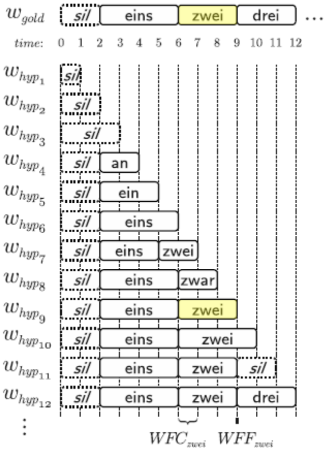

$$WFF_{zwei} = 9$$

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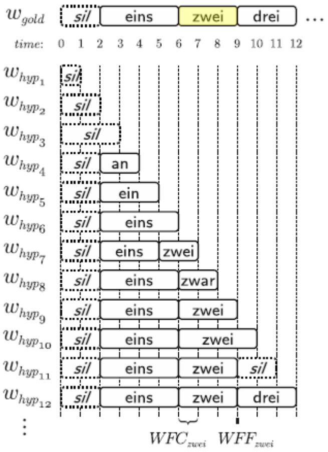

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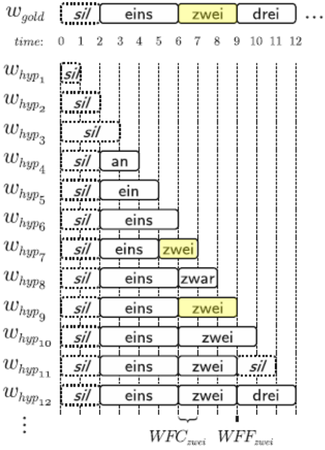

$$CT_{zwei} = 9 - 7 = 2$$

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Setup and Data

- continious speech framework *Sphinx-4*
- acoustic model
  - German
  - instructions in a puzzle domain
- trigram language model
- test data
  - 85 recodings
  - two speakers
  - sentence similar to training sentences

Measurements

SER	68.2%
WER	18.8%
r-correct	30.9%
p-correct	53.1%
edit overhead	90.5%
mean word duration	0.378 s
WFC	mean: 0.276 s
WFF	mean: 0.004 s
immediately correct	58.6%

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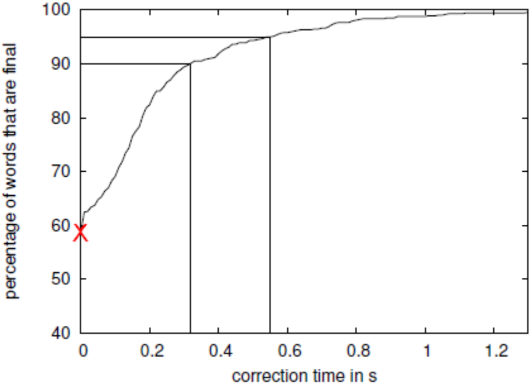

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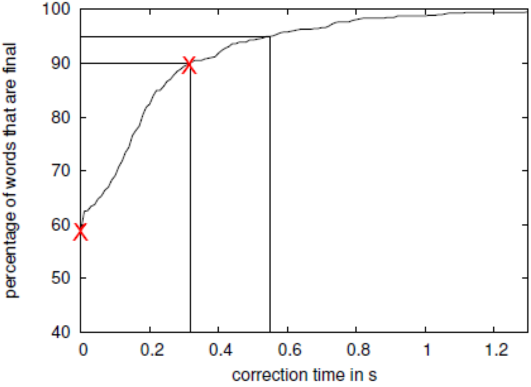

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90% correct after a correction time of 320 ms

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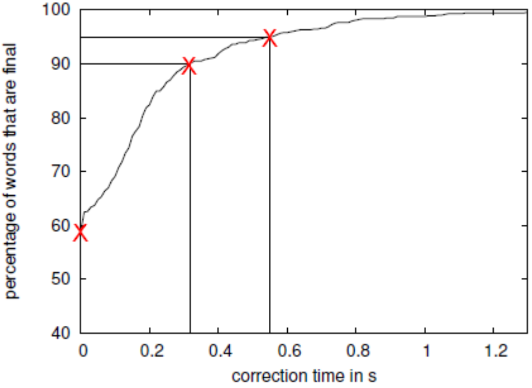

58.6% immediately correct

90% correct after a correction time of 320 ms

95% correct after a correction time of 550 ms

Independency of the measures?

Are the measures independent of specific settings?

- vary LM/AM-weight
- vary audio quality by adding white noise

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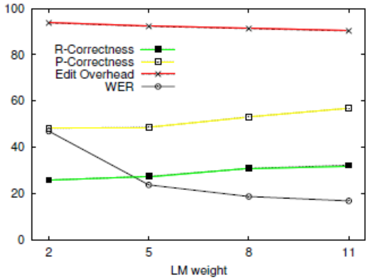

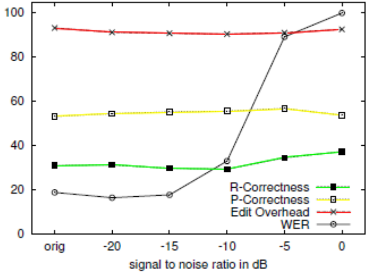

Baumann et al.

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Which improvements?

main goal: improve edit overhead

- reduce amount of wrong hypotheses
- still as quick as possible

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allow larger right context of size Δ:

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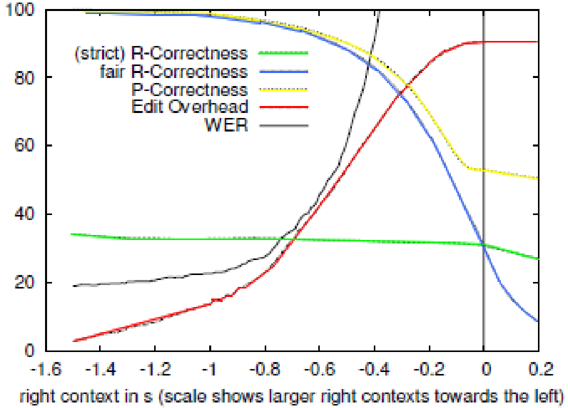
Fair R-Correctness

w_{hyp_t} is *fairly r-correct*, **iff** $w_{hyp_t}{}_{t-\Delta} = w_{gold}{}_{t-\Delta}$

Right Context



correctness and EO improve with more right context

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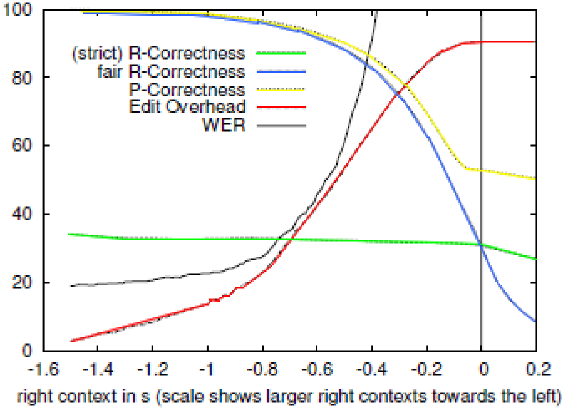

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timing measures increase with larger right context

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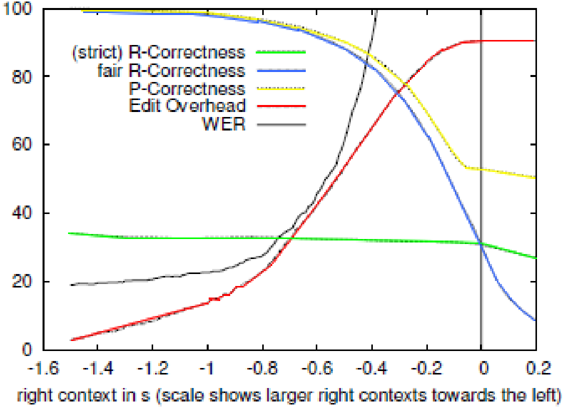

correctness and EO improve with more right context

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percentage of immediately correct hypotheses increases:
90% @ 580 ms
98% @ 1060 ms

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edit message must be result of N consecutive hypotheses before commitment

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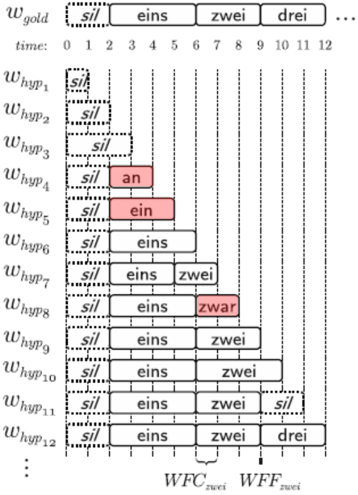
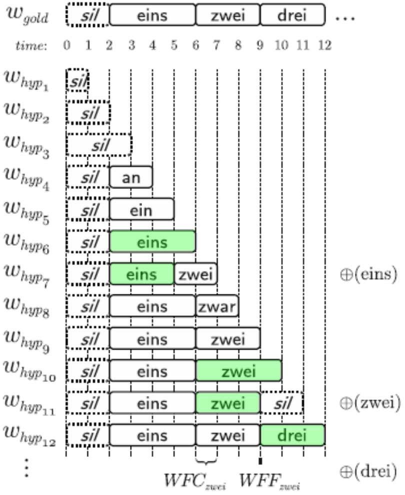


Message Smoothing

edit message must be result of N consecutive hypotheses before commitment

$N = 2$:

- *an*, *ein* and *zwar* would never be committed
- only 3 edit messages



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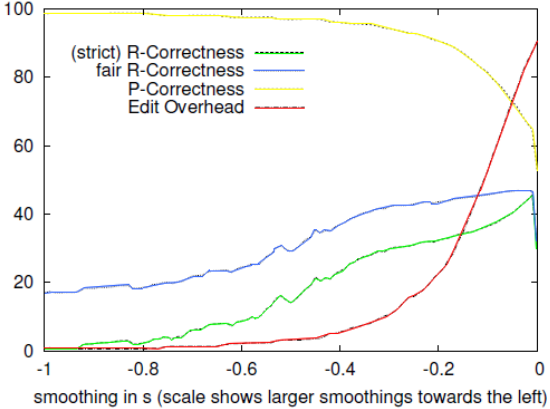

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50% after 110 ms

10% after 320 ms

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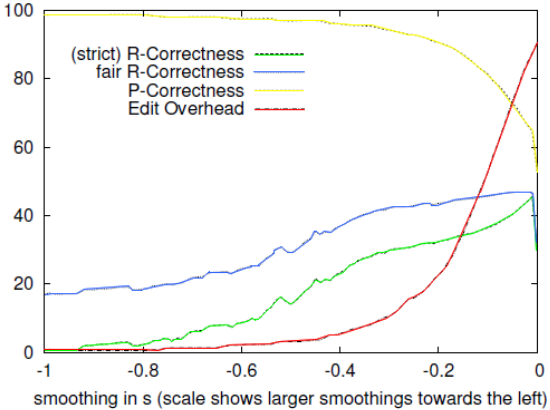

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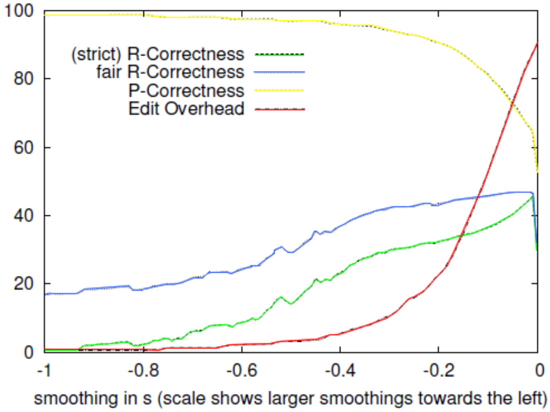

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Baumann et al.

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improvements with larger delays, increasing correctness

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could be combined to yield a good effect

Kato et. al

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   $X, X_1, \ldots, X_k$: nonterminal symbols

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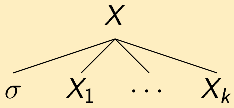

Elementary Trees

Initial Trees

must be *leftmost-expanded*:

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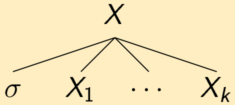

Auxiliary Trees

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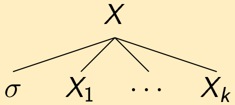

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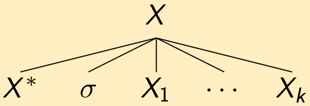

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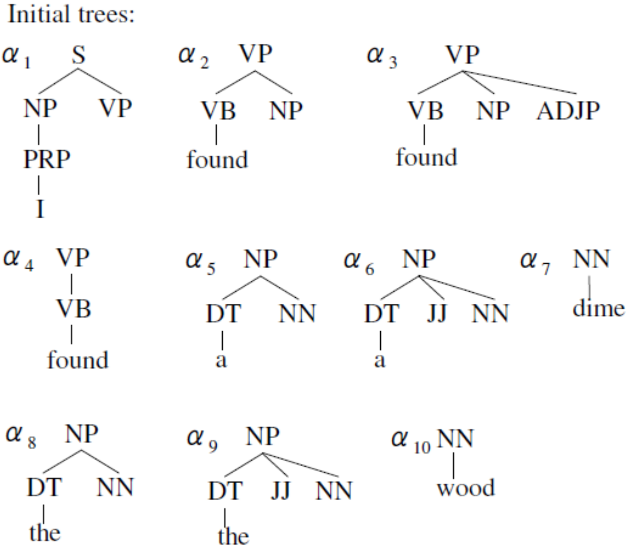

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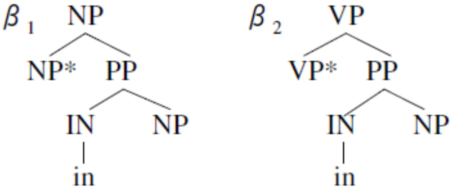

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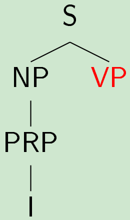

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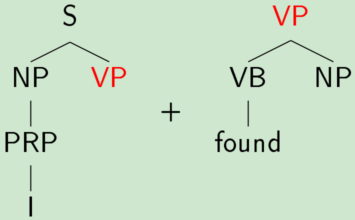

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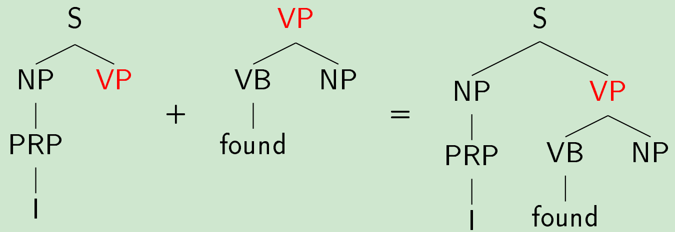

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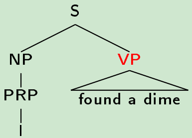

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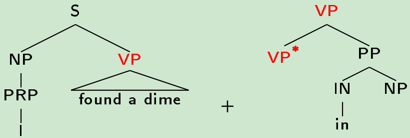

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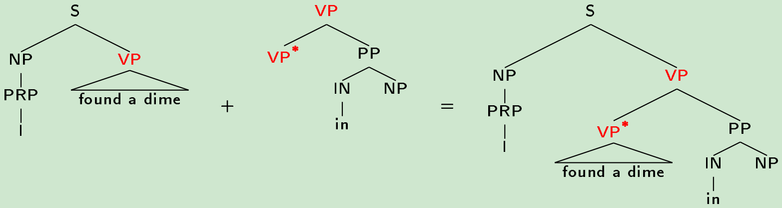

Parsing with ITAG

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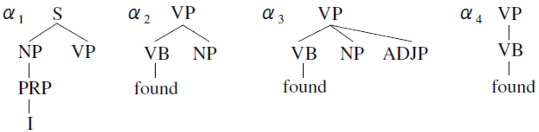
α1 S
NP VP
PRP
I
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VB NP
found
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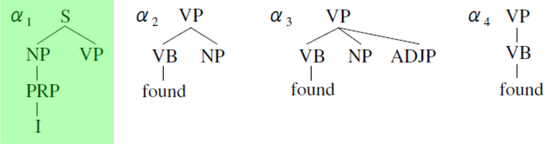
α4 VP
VB
found

S

Example

I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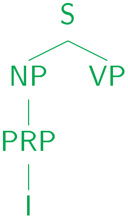
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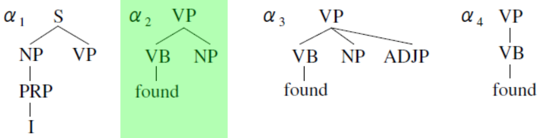
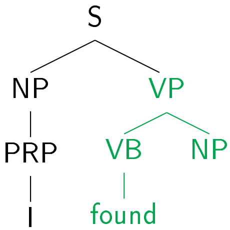


I found



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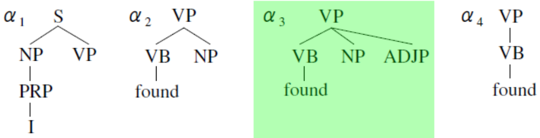

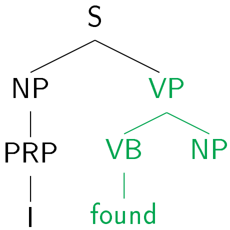

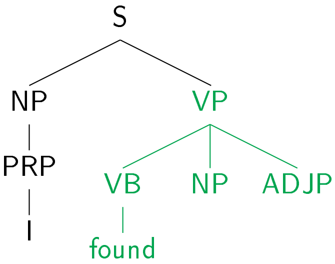

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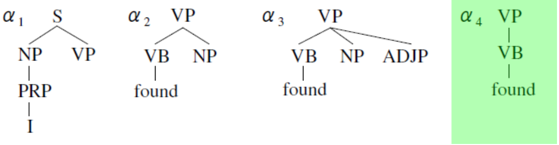

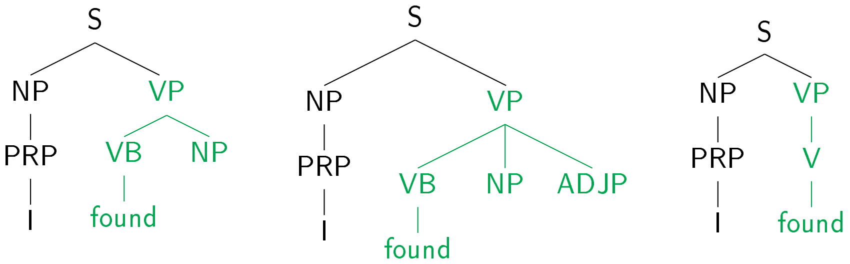

Example

word	#	partial parse tree
	1	s
I	2	$[[[I]_{prp}]_{np} vp]_s$
found	3	$[[[I]_{prp}]_{np}[[found]_{vb} np]_{vp}]_s$
	4	$[[[I]_{prp}]_{np}[[found]_{vb} np\ adjp]_{vp}]_s$
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	13	$[[[I]_{prp}]_{np}[[found]_{vb}[[[a]_{dt}[dime]_{nn}]_{np}[[in]_{in} np]_{pp}]_{np}]_{vp}]_s$
the	14	$[[[I]_{prp}]_{np}[[[found]_{vb}[[a]_{dt}[dime]_{nn}]_{np}]_{vp}[[in]_{in}[[the]_{dt} nn]_{np}]_{pp}]_{vp}]_s$
	15	$[[[I]_{prp}]_{np}[[[found]_{vb}[[a]_{dt}[dime]_{nn}]_{np}]_{vp}[[in]_{in}[[the]_{dt} jj\ nn]_{np}]_{pp}]_{vp}]_s$
	16	$[[[I]_{prp}]_{np}[[found]_{vb}[[[a]_{dt}[dime]_{nn}]_{np}[[in]_{in}[[the]_{dt} nn]_{np}]_{pp}]_{np}]_{vp}]_s$
	17	$[[[I]_{prp}]_{np}[[found]_{vb}[[[a]_{dt}[dime]_{nn}]_{np}[[in]_{in}[[the]_{dt} jj\ nn]_{np}]_{pp}]_{np}]_{vp}]_s$
wood	18	$[[[I]_{prp}]_{np}[[[found]_{vb}[[a]_{dt}[dime]_{nn}]_{np}]_{vp}[[in]_{in}[[the]_{dt}[wood]_{nn}]_{np}]_{pp}]_{vp}]_s$
	19	$[[[I]_{prp}]_{np}[[found]_{vb}[[[a]_{dt}[dime]_{nn}]_{np}[[in]_{in}[[the]_{dt}[wood]_{nn}]_{np}]_{pp}]_{np}]_{vp}]_s$

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constructing parse trees of initial fragments for every word input possible!

Tree Construction

How to get the elementary trees?

Tree Construction

How to get the elementary trees?

- Extraction from a treebank!

Kato et. al

- ITAG: incremental-parsing-oriented tree adjoining grammar
- PITAG: probabilistic ITAG
- Validity of Partial Parse Trees
- Experimental Results and Conclusions

Probabilities

probabilities for events combining an elementary tree and another tree by **substitution and adjunction**

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$$P(s_\alpha) = \frac{|s_\alpha| \text{ in the treebank}}{|\text{substitutions using other initial trees with root X}| \text{ in the treebank}}$$

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Probability of adjoining β

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probability of a parse-tree:

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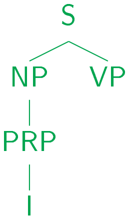

1.0

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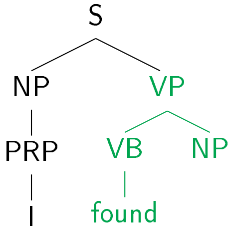

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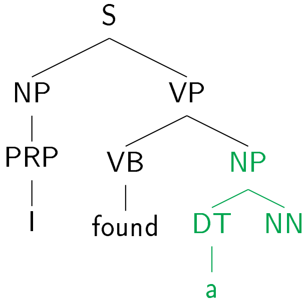

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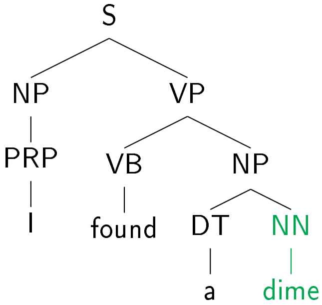

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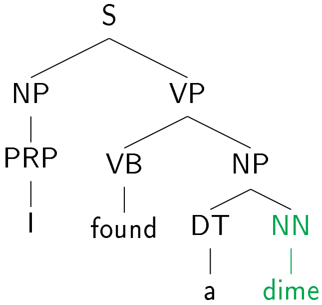

$1.0 \times 0.7 \times 0.3 \times 0.5 = 0.105$

Parsing with PITAG

Improve efficiency by:

- discard tree with lower probability when there are parse trees with same possible operations
- only keep n-best partial parse-trees

Kato et. al

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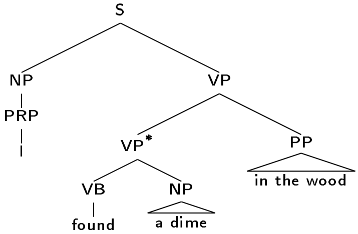
Validity

a partial parse tree is valid for an input sentence, **iff** it subsumes the correct parse tree for the input sentence

Example



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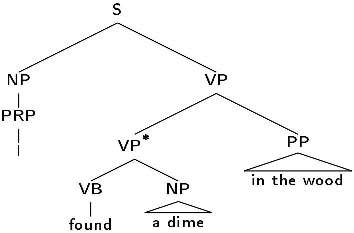
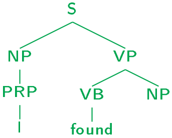

S
NP
VP
PRP
I
VP*
PP
in the wood
VB
NP
found
a dime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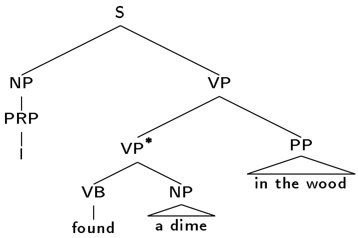
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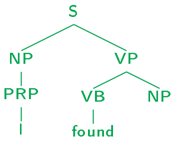
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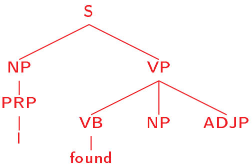
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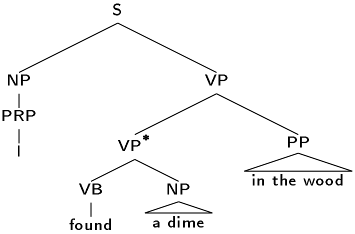
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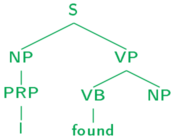
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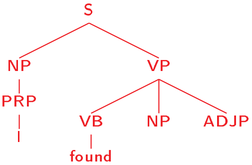
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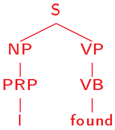
NP
ADJP


S
NP
PRP
I
VP
VB
found

Evaluating Validity

validity for a partial parse tree depends on the rest of the sentence

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σ: partial parse tree for initial fragment $w_1 \cdots w_i (i \leq j)$

Conditional Validity of partial parse tree σ

$$V(\sigma | w_1 \cdots w_j) = \frac{\sum(\text{Probabilities of partial parse trees at } w_j \text{ subsumed by } \sigma)}{\sum(\text{Probabilities of partial parse trees constructed at } w_j)}$$

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example: later

Output Partial Parse Trees

delay output until validity is high enough:

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Parse Tree to be returned

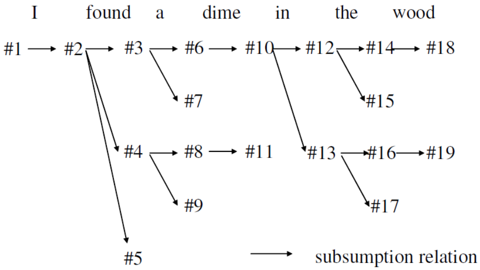
Parse Tree with the longest initial fragment whose validity is greater than threshold θ

θ: threshold between 0 and 1

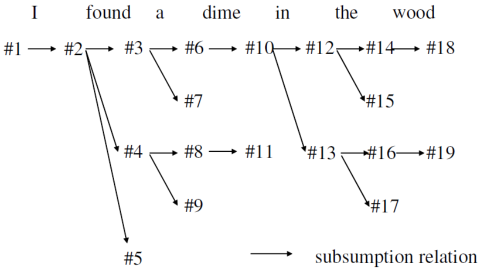
Example

word	#	partial parse tree
	1	s
I	2	$[[[I]_{prp}]_{np} vp]_s$
found	3	$[[[I]_{prp}]_{np}[[found]_{vb} np]_{vp}]_s$
	4	$[[[I]_{prp}]_{np}[[found]_{vb} np\ adjp]_{vp}]_s$
	5	$[[[I]_{prp}]_{np}[[found]_{vb}]_{vp}]_s$
a	6	$[[[I]_{prp}]_{np}[[found]_{vb}[[a]_{dt} nn]_{np}]_{vp}]_s$
	7	$[[[I]_{prp}]_{np}[[found]_{vb}[[a]_{dt} jj\ nn]_{np}]_{vp}]_s$
	8	$[[[I]_{prp}]_{np}[[found]_{vb}[[a]_{dt} nn]_{np} adjp]_{vp}]_s$
	9	$[[[I]_{prp}]_{np}[[found]_{vb}[[a]_{dt} jj\ nn]_{np} adjp]_{vp}]_s$
dime	10	$[[[I]_{prp}]_{np}[[found]_{vb}[[a]_{dt}[dime]_{nn}]_{np}]_{vp}]_s$
	11	$[[[I]_{prp}]_{np}[[found]_{vb}[[a]_{dt}[dime]_{nn}]_{np} adjp]_{vp}]_s$
in	12	$[[[I]_{prp}]_{np}[[[found]_{vb}[[a]_{dt}[dime]_{nn}]_{np}]_{vp}[[in]_{in} np]_{pp}]_{vp}]_s$
	13	$[[[I]_{prp}]_{np}[[found]_{vb}[[[a]_{dt}[dime]_{nn}]_{np}[[in]_{in} np]_{pp}]_{np}]_{vp}]_s$
the	14	$[[[I]_{prp}]_{np}[[[found]_{vb}[[a]_{dt}[dime]_{nn}]_{np}]_{vp}[[in]_{in}[[the]_{dt} nn]_{np}]_{pp}]_{vp}]_s$
	15	$[[[I]_{prp}]_{np}[[[found]_{vb}[[a]_{dt}[dime]_{nn}]_{np}]_{vp}[[in]_{in}[[the]_{dt} jj\ nn]_{np}]_{pp}]_{vp}]_s$
	16	$[[[I]_{prp}]_{np}[[found]_{vb}[[[a]_{dt}[dime]_{nn}]_{np}[[in]_{in}[[the]_{dt} nn]_{np}]_{pp}]_{np}]_{vp}]_s$
	17	$[[[I]_{prp}]_{np}[[found]_{vb}[[[a]_{dt}[dime]_{nn}]_{np}[[in]_{in}[[the]_{dt} jj\ nn]_{np}]_{pp}]_{np}]_{vp}]_s$
wood	18	$[[[I]_{prp}]_{np}[[[found]_{vb}[[a]_{dt}[dime]_{nn}]_{np}]_{vp}[[in]_{in}[[the]_{dt}[wood]_{nn}]_{np}]_{pp}]_{vp}]_s$
	19	$[[[I]_{prp}]_{np}[[found]_{vb}[[[a]_{dt}[dime]_{nn}]_{np}[[in]_{in}[[the]_{dt}[wood]_{nn}]_{np}]_{pp}]_{np}]_{vp}]_s$

Example


I
found
a
dime
in
the
wood
#1
#2
#3
#4
#5
#6
#7
#8
#9
#10
#11
#12
#13
#14
#15
#16
#17
#18
#19
subsumption relation

Example



Parse Tree	Probability
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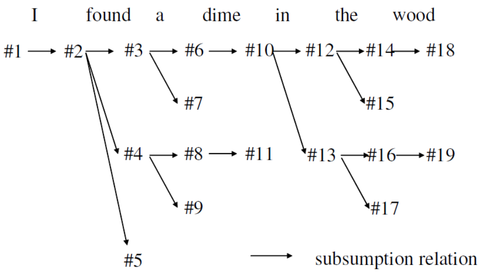

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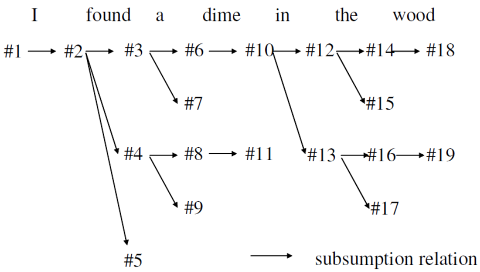

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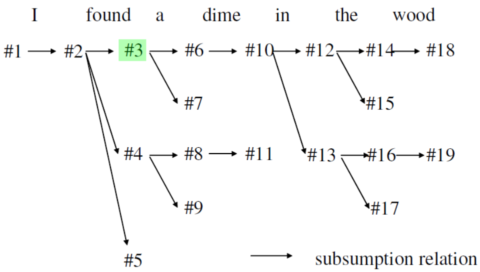

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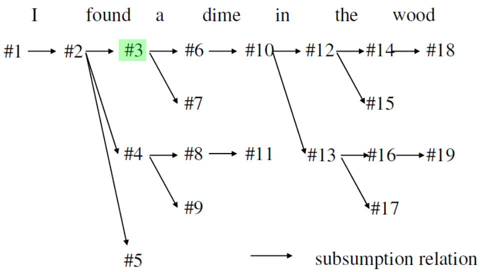
When will #3 (valid) be output?

Example



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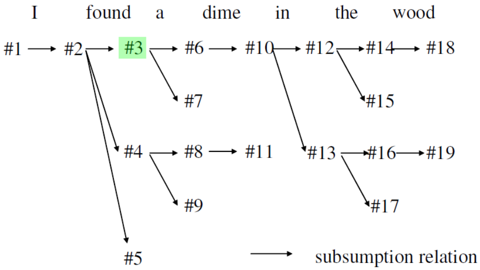

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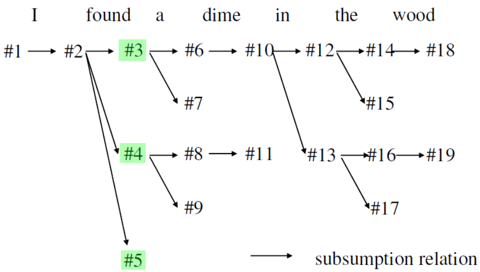

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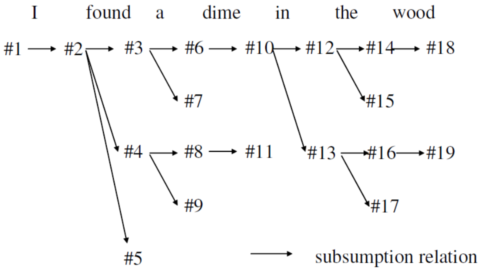

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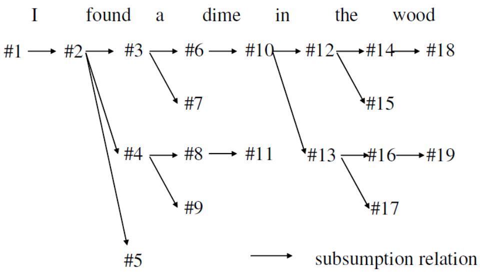

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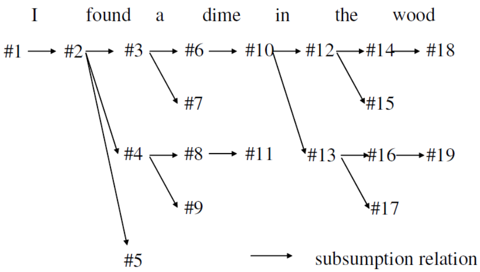

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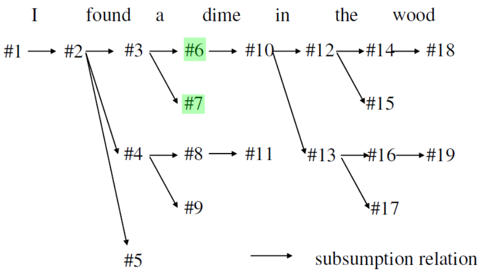

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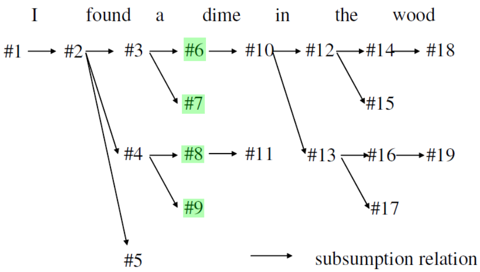

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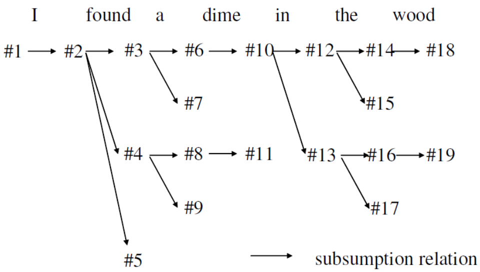

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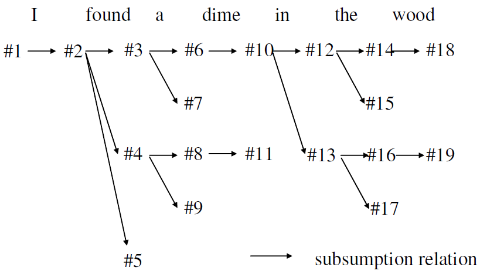

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Kato et. al

- ITAG: incremental-parsing-oriented tree adjoining grammar
- PITAG: probabilistic ITAG
- Validity of Partial Parse Trees
- Experimental Results and Conclusions

Experimental Setup

- parser implemented in Lisp
- input: POS-Sequences
- elementary trees extracted from Penn Treebank
- only used correctly parsed sentences

Measures

Degree of delay at j-th word

$D(j, s) = j - |\text{output parse tree at } w_j|$

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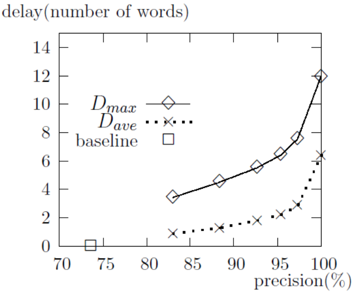
Precision

percentage of valid partial parse trees in the output

Results and Conclusions



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$\theta = 1.0$	100.0	11.9	6.4
$\theta = 0.9$	97.3	7.5	2.9
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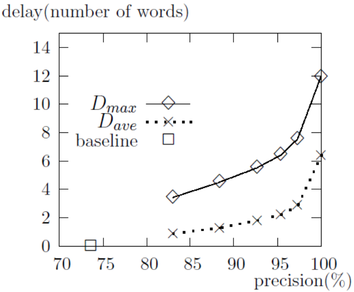

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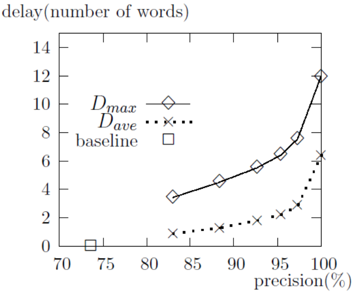
higher threshold

Results and Conclusions



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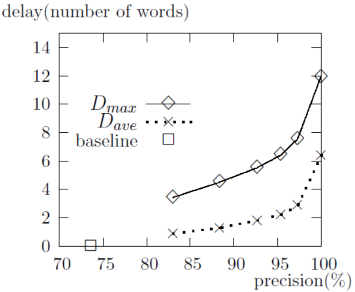

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higher threshold
$\Rightarrow$ higher precision, greater delays
$\Rightarrow$ trade-off between precision and delay

Summary

Baumann et. al

use right context and message smoothing to reduce/avoid wrong hypotheses in incremental ASR

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delay of output

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delay of output
$\Rightarrow$ **Trade-off between incrementality/speed and output quality (revisions)**

Thank you!

Thanks for your attention!

References

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Yoshihide Kato, Shigeki Matsubara, and Yasuyoshi Inagaki.
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