Tree Transformations for Parsing

2 Case Studies

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Overview

Outline for section 1

Introduction

- Common methodology - different motivation
- NLP engineering:
  Verb groups in UD parsing (de Lhoneux and Nivre, 2016)
- Linguistics (and NLP engineering):
  MWEs in CCG parsing (de Lhoneux, 2014)

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Outline for section 2

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- problem: UD suboptimal for parsing (de Marneffe et al., 2014)
- solution: Create a parsing representation (de Marneffe et al., 2014)
- focus of the study: verb groups

Auxiliary as heads of verb groups (Nilsson et al., 2006, 2007; Schwartz et al., 2012)

Figure : MS

Figure : UD

Verb Groups in UD parsing

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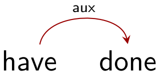

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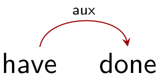

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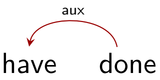
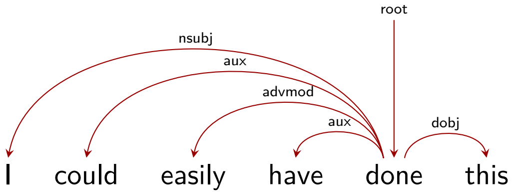


Figure : UD

Transformation Algorithm:
Modified from Nilsson et al. (2006)

Transformation Algorithm



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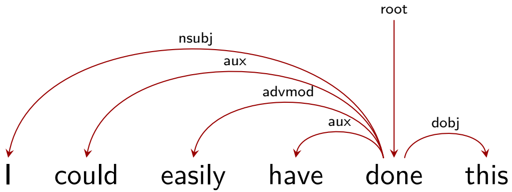

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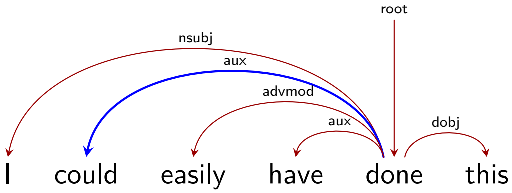
Transformation Algorithm



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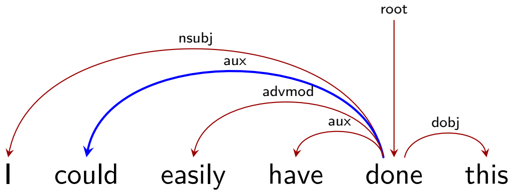
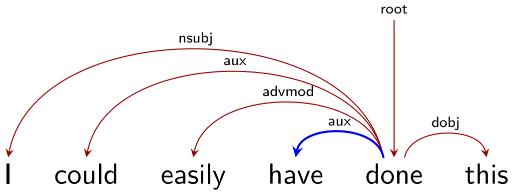


V = [V_i: main verb=done; aux = [could]]

Transformation Algorithm



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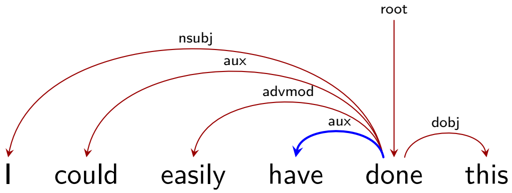

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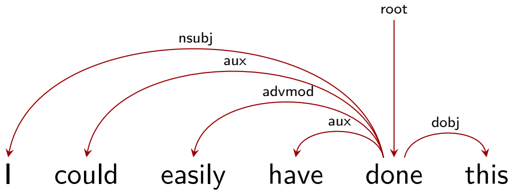

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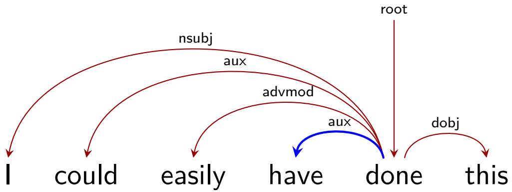

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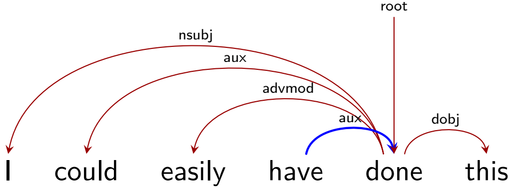

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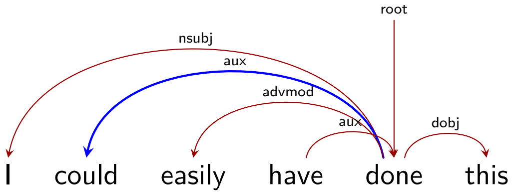

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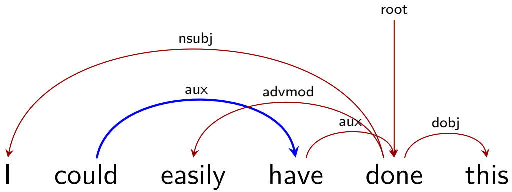

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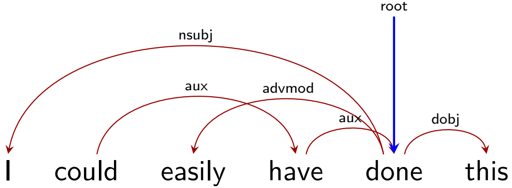

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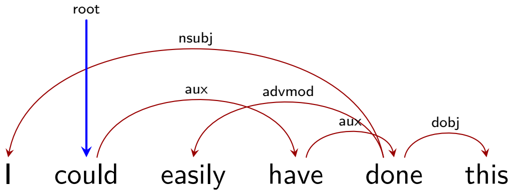

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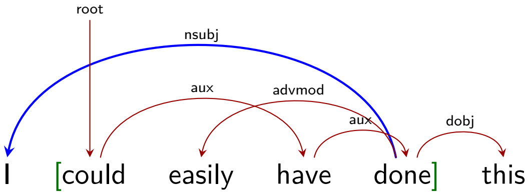

left dependents

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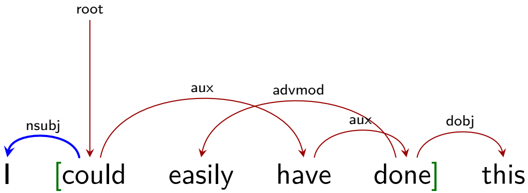

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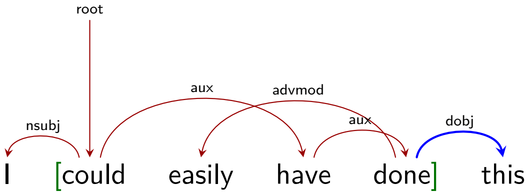
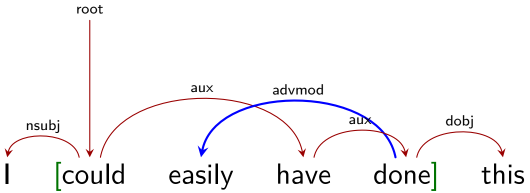


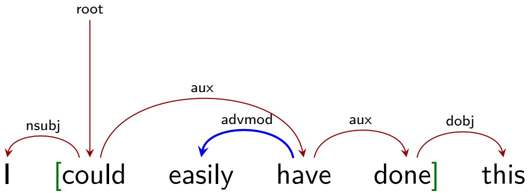
right dependents

Transformation Algorithm



middle dependents

Transformation Algorithm



middle dependents

Back Transformation Algorithm
Modified from Nilsson et al. (2006)

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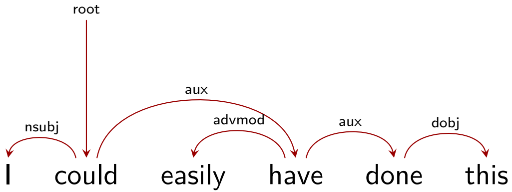

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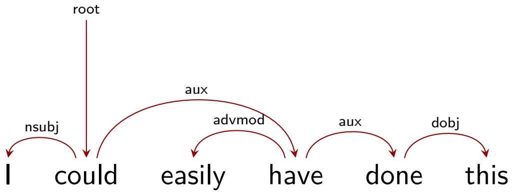

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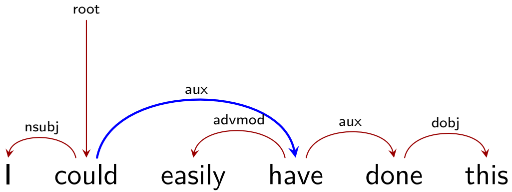

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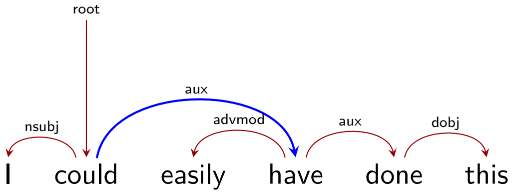

V = [V_i: aux=[could]]

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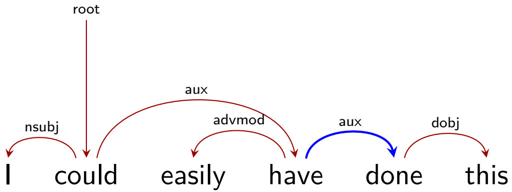

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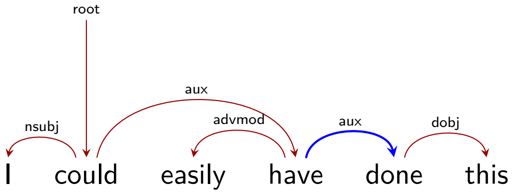

V = [V_i: aux=[could,have];main verb=done]

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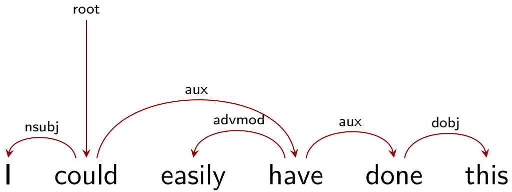

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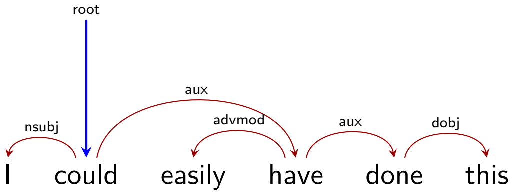

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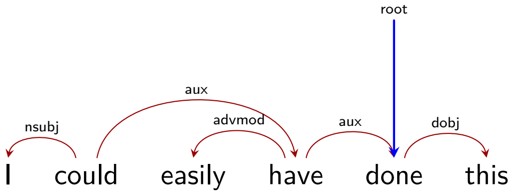

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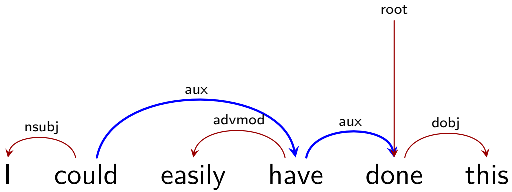

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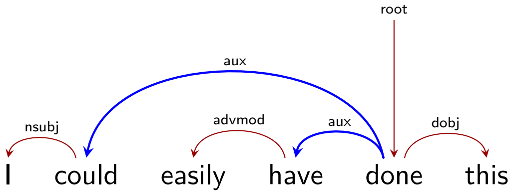

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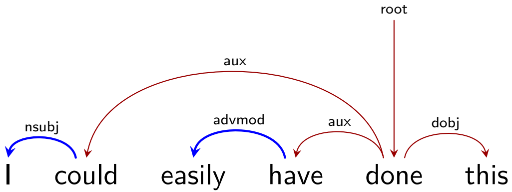

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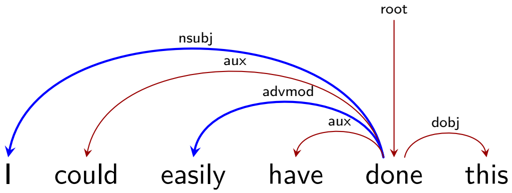

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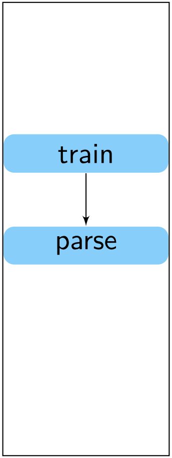

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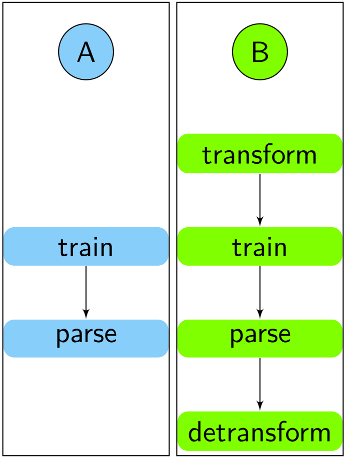

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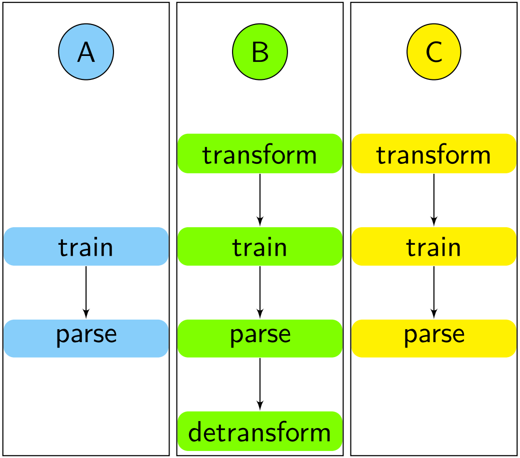
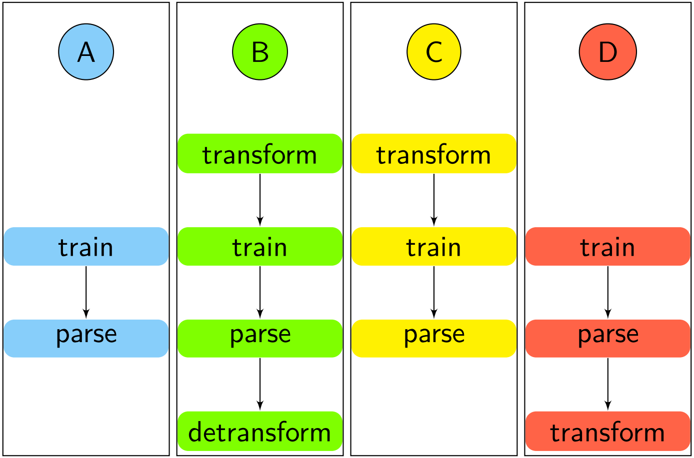

A
train
parse
B
transform
train
parse
detransform
C
transform
train
parse

Pipeline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parse
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train
parse
transform

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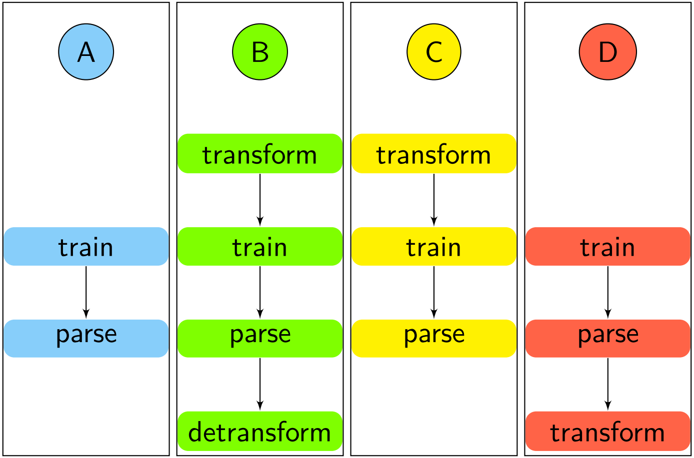

Model/Gold	UD	MS
UD	A	B
MS	D	C

Hypotheses

Model/Gold	UD	MS
UD	A	B
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MS is better than UD for parsing

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B > A

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B > A

MS is easier to learn than UD

Hypotheses

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MS	D	C

MS is better than UD for parsing — B > A

MS is easier to learn than UD — C > A

Hypotheses

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MS is better than UD for parsing B > A

MS is easier to learn than UD C > A

Symmetry in differences

Hypotheses

Model/Gold	UD	MS
UD	A	B
MS	D	C

MS is better than UD for parsing $B > A$

MS is easier to learn than UD $C > A$

Symmetry in differences $A - B = C - D$

Resources

- Parser: MaltParser (Nivre et al., 2006)
  - settings: default
  - POS tag used: UD coarse POS tag
- Data: 25 UD treebanks (version 1.2) + SDT and PDT

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Effect of VG transformation on UD

UD lang.	A	B
Basque	**64.4**	63.8**
Bulgarian	**83.4**	83.2*
Croatian	**75.9**	74.6**
Czech	**80.0**	76.5**
Danish	**75.9**	75.2**
English	**81.7**	80.4**
Estonian	77.1	**77.8**
Finnish	**66.9**	66.4*
Finnish-FTB	**71.3**	70.4**
French	**82.1**	81.6**
German	**76.6**	76.0**
Greek	75.2	**75.3**
Hebrew	**78.4**	77.9**
Hindi	**85.4**	84.2**
Italian	**83.8**	83.6
Norwegian	**84.5**	82.0**
Old_Church_Slavonic	**68.8**	68.7
Persian	**81.1**	79.8**
Polish	**79.4**	79.1
Portuguese	81.3	**81.5**
Romanian	**64.2**	62.5*
Slovenian	**80.8**	79.7**
Spanish	**81.5**	81.2**
Swedish	**76.8**	75.7**
Tamil	**67.2**	67.1

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MS is better than UD for parsing B > A

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MS is better than UD for parsing B > A ✗

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German	**76.6**	76.0	75.4
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Hebrew	**78.4**	77.9	77.9
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Polish	**79.4**	79.1	79.0
Portuguese	81.3	81.5	**81.6**
Romanian	**64.2**	62.5	64.0
Slovenian	**80.8**	79.7	79.8
Spanish	**81.5**	81.2	81.2
Swedish	**76.8**	75.7	75.6
Tamil	67.2	67.1	**67.4**

MS is better than UD for parsing   B > A   ✗

Results

UD language	A	B	C
Basque	**64.4**	63.8	64.0
Bulgarian	**83.4**	83.2	82.5
Croatian	**75.9**	74.6	73.7
Czech	**80.0**	76.5	76.4
Danish	**75.9**	75.2	74.8
English	**81.7**	80.4	80.2
Estonian	77.1	77.8	**77.6**
Finnish	**66.9**	66.4	65.9
Finnish-FTB	71.3	70.4	**72.1**
French	**82.1**	81.6	81.3
German	**76.6**	76.0	75.4
Greek	**75.2**	75.3	75.1
Hebrew	**78.4**	77.9	77.9
Hindi	**85.4**	84.2	84.9
Italian	**83.8**	83.6	83.3
Norwegian	**84.5**	82.0	81.7
OC_Slavonic	**68.8**	68.7	68.7
Persian	**81.1**	79.8	79.8
Polish	**79.4**	79.1	79.0
Portuguese	81.3	81.5	**81.6**
Romanian	**64.2**	62.5	64.0
Slovenian	**80.8**	79.7	79.8
Spanish	**81.5**	81.2	81.2
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MS is better than UD for parsing — B > A ✗

MS is easier to learn than UD — C > A

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Basque	**64.4**	63.8	64.0
Bulgarian	**83.4**	83.2	82.5
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OC_Slavonic	**68.8**	68.7	68.7
Persian	**81.1**	79.8	79.8
Polish	**79.4**	79.1	79.0
Portuguese	81.3	81.5	**81.6**
Romanian	**64.2**	62.5	64.0
Slovenian	**80.8**	79.7	79.8
Spanish	**81.5**	81.2	81.2
Swedish	**76.8**	75.7	75.6
Tamil	67.2	67.1	**67.4**

MS is better than UD for parsing — B > A ✗

MS is easier to learn than UD — C > A ✗

Results

UD language	A	B	C	D
Basque	**64.4**	63.8	64.0	**64.4**
Bulgarian	**83.4**	83.2	82.5	**82.9**
Croatian	**75.9**	74.6	73.7	**75.9**
Czech	**80.0**	76.5	76.4	**79.9**
Danish	**75.9**	75.2	74.8	**75.8**
English	**81.7**	80.4	80.2	**81.5**
Estonian	77.1	**77.8**	**77.6**	77.0
Finnish	**66.9**	66.4	65.9	**66.4**
Finnish-FTB	**71.3**	70.4	72.1	**72.5**
French	**82.1**	81.6	81.3	**81.8**
German	**76.6**	76.0	75.4	**76.1**
Greek	75.2	**75.3**	75.1	**75.2**
Hebrew	**78.4**	77.9	77.9	**78.5**
Hindi	**85.4**	84.2	84.9	**85.2**
Italian	**83.8**	83.6	83.3	**83.6**
Norwegian	**84.5**	82.0	81.7	**84.5**
OC_Slavonic	**68.8**	68.7	68.7	**68.9**
Persian	**81.1**	79.8	79.8	**81.1**
Polish	**79.4**	79.1	79.0	**79.3**
Portuguese	81.3	**81.5**	**81.6**	81.3
Romanian	**64.2**	62.5	64.0	**64.6**
Slovenian	**80.8**	79.7	79.8	**80.8**
Spanish	**81.5**	81.2	81.2	**81.4**
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Tamil	67.2	67.1	67.4	**67.5**

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MS is easier to learn than UD C > A ✗

Results

UD language	A	B	C	D
Basque	**64.4**	63.8	64.0	**64.4**
Bulgarian	**83.4**	83.2	82.5	**82.9**
Croatian	**75.9**	74.6	73.7	**75.9**
Czech	**80.0**	76.5	76.4	**79.9**
Danish	**75.9**	75.2	74.8	**75.8**
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Estonian	77.1	**77.8**	**77.6**	77.0
Finnish	**66.9**	66.4	65.9	**66.4**
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German	**76.6**	76.0	75.4	**76.1**
Greek	75.2	**75.3**	75.1	**75.2**
Hebrew	**78.4**	77.9	77.9	**78.5**
Hindi	**85.4**	84.2	84.9	**85.2**
Italian	**83.8**	83.6	83.3	**83.6**
Norwegian	**84.5**	82.0	81.7	**84.5**
OC_Slavonic	**68.8**	68.7	68.7	**68.9**
Persian	**81.1**	79.8	79.8	**81.1**
Polish	**79.4**	79.1	79.0	**79.3**
Portuguese	81.3	**81.5**	**81.6**	81.3
Romanian	**64.2**	62.5	64.0	**64.6**
Slovenian	**80.8**	79.7	79.8	**80.8**
Spanish	**81.5**	81.2	81.2	**81.4**
Swedish	**76.8**	75.7	75.6	**76.7**
Tamil	67.2	67.1	67.4	**67.5**

MS is better than UD for parsing — B > A ✗

MS is easier to learn than UD — C > A ✗

Symmetry in differences — A - B = C - D

Results

UD language	A	B	C	D
Basque	**64.4**	63.8	64.0	**64.4**
Bulgarian	**83.4**	83.2	82.5	**82.9**
Croatian	**75.9**	74.6	73.7	**75.9**
Czech	**80.0**	76.5	76.4	**79.9**
Danish	**75.9**	75.2	74.8	**75.8**
English	**81.7**	80.4	80.2	**81.5**
Estonian	77.1	**77.8**	**77.6**	77.0
Finnish	**66.9**	66.4	65.9	**66.4**
Finnish-FTB	**71.3**	70.4	72.1	**72.5**
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German	**76.6**	76.0	75.4	**76.1**
Greek	75.2	**75.3**	75.1	**75.2**
Hebrew	**78.4**	77.9	77.9	**78.5**
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Persian	**81.1**	79.8	79.8	**81.1**
Polish	**79.4**	79.1	79.0	**79.3**
Portuguese	81.3	**81.5**	**81.6**	81.3
Romanian	**64.2**	62.5	64.0	**64.6**
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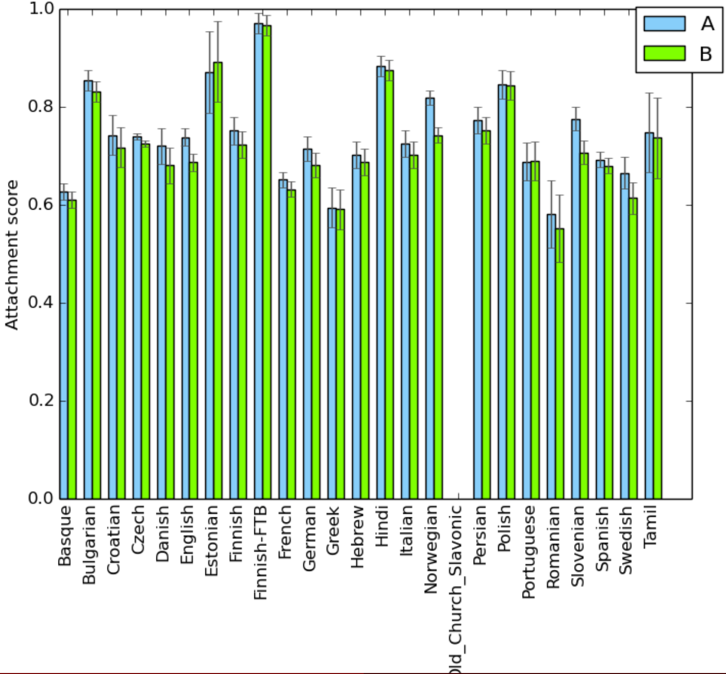
MS is better than UD for parsing B > A ✗

MS is easier to learn than UD C > A ✗

Symmetry in differences A - B = C - D ✗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0.6
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0.2
0.0
Attachment score
A
B
Basque
Bulgarian
Croatian
Czech
Danish
English
Estonian
Finnish
Finnish-FTB
French
German
Greek
Hebrew
Hindi
Italian
Norwegian
Old_Church_Slavonic
Persian
Polish
Portuguese
Romanian
Slovenian
Spanish
Swedish
Tamil

Comparison with SDT and PDT

	Orig	**Transf**
UD_Czech	**80.0**	76.5**
PDT	68.5	**68.8****
UD_Slovenian	**80.5**	79.1**
SDT	65.7	**66.2**

Table : LAS with the original and transformed treebanks.

Ambiguity of POS tags in SDT

POS	main verb	aux
Verb-main	72.81	0.22
Verb-copula	22.30	95.95

Were improvements in SDT/PDT the result of disambiguation?

Create different versions of the treebanks:

- Ambiguous: all verbal POS tags are the same (VERB)
- Disambiguated: main verb POS tag is Verb-main and auxiliary is AUX

Compare impact of VG transformation on:

- τ_o : original treebank
- τ_d : disambiguated treebank
- τ_a : ambiguous treebank

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Results of the ambiguous experiment

	A	B	Δ
SDT τ_d	**67.8**	67.4	-0.4
SDT τ_o	65.7	**66.2**	0.5
SDT τ_a	64.2	**65.4***	1.2
PDT τ_d	69.2	69.2	0.0
PDT τ_o	68.5	**68.8****	0.3
PDT τ_a	68.2	**68.4***	0.2

Table : LAS on A and B with different levels of POS tag ambiguity.

Δ = B - A

Predicted vs gold POS tags

Can UD benefit from the transformation when using predicted POS tags?

✗ It seems not.

POS tag	A	B	Δ
gold	76.8	75.7**	-1.1
predicted	76.4	75.6**	-0.8

Table : LAS on UD_Swedish. Δ = B - A

Conclusion and Future Work

Conclusions

- Keep verb groups as is in UD
- Benefits of error analysis
- Previous results were obtained through POS tag disambiguation

Future Work

- More in-depth error analysis
- Other representations (e.g. PPs)
- Other parsing models

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Outline for section 3

Multiword Expressions and Syntactic Parsing

MWE: A group of multiple lexemes which have some level of idiomaticity or irregularity.

Motivation

- Linguistics research: Construction Grammar (Hoffmann and Trousdale, 2013)
- MWE identification and syntactic parsing benefit from one another (Nivre and Nilsson, 2004; Korkontzelos and Manandhar, 2010)

Simple approach: representing MWEs as words-with-spaces

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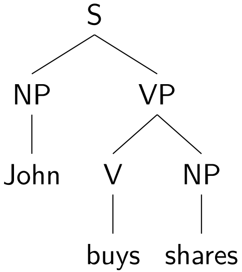
CCG: a strongly lexicalized formalism



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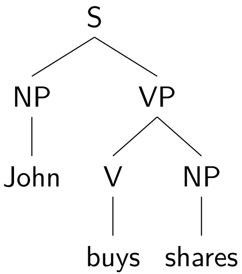

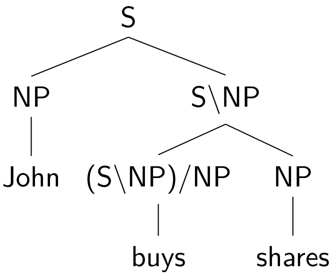

Research Questions

- Can CCG parsing benefit from MWE information?

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1 and 2

- Can we obtain a *training effect*?
- Can we obtain a *parsing effect*?

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1 and 2

- Can we obtain a *training effect*?
- Can we obtain a *parsing effect*?

An example

It gives part of speech and lemma information.
It gives part+of+speech and lemma information.

MWE Recognition

Library jMWE (Finlayson and Kulkarni, 2011)

- Input: sentence.
  e.g: *Mr. Spoon said the plan is not an attempt to shore up a decline in ad pages in the first nine months of 1989 ; Newsweek 's ad pages totaled 1,620 , a drop of 3.2 % from last year , according to Publishers Information Bureau .*

- Output: list of multiword expressions from left to right.

  mr._spoon, shore_up, according_to, publishers_information_bureau

MWE Recognition (2)

3 components: detector, filter, resolver

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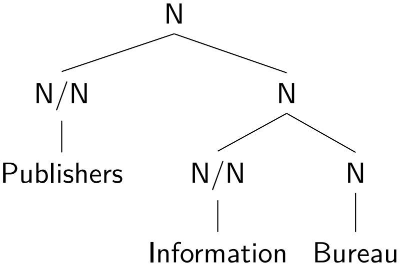
detector	**filter**	**resolver**
Exhaustive	MoreFrequentAsMWE	Longest
Exhaustive	MoreFrequentAsMWE	Leftmost
Proper Nouns	no filter	Longest
Exhaustive	ConstrainLength	Leftmost
Stop words	no filter	Longest

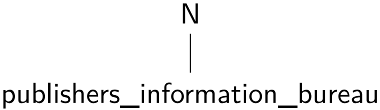
Transformation

MWEs with units that are siblings.

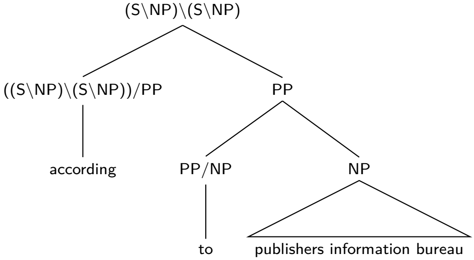
Input:



Output:



MWEs with units that are not sibling: less straightforward



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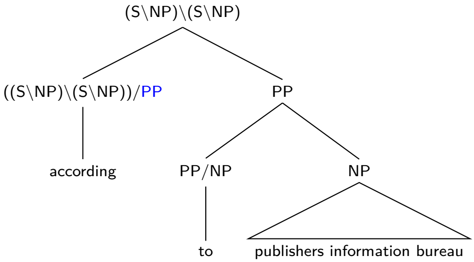

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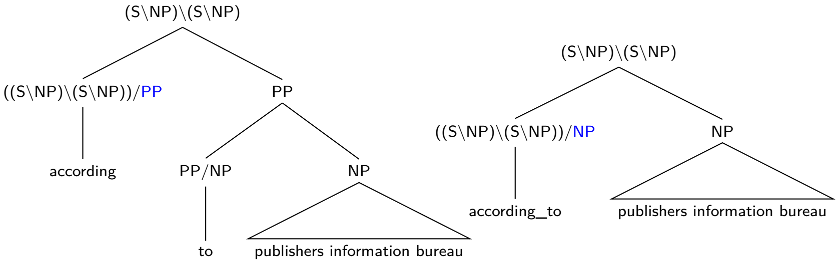
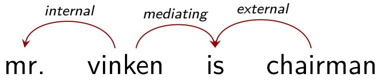
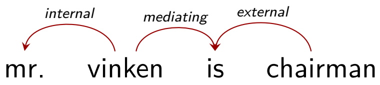


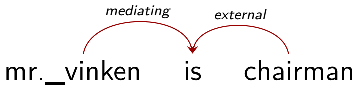
detector	**filter**	**resolver**	**MWE count**	**Sibling %**
Exhaustive	MoreFrequentAsMWE	Longest	53,208	79.51
Exhaustive	MoreFrequentAsMWE	Leftmost	51,543	41.85
Proper Nouns	no filter	Longest	32,583	86.14
Exhaustive	ConstrainLength	Leftmost	49,587	40.30
Stop words	no filter	Longest	13,623	2.09

Transformation (2)

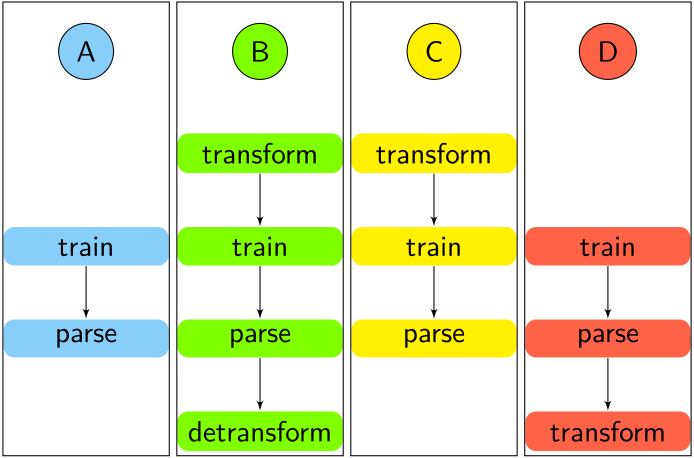


Transformation (2)



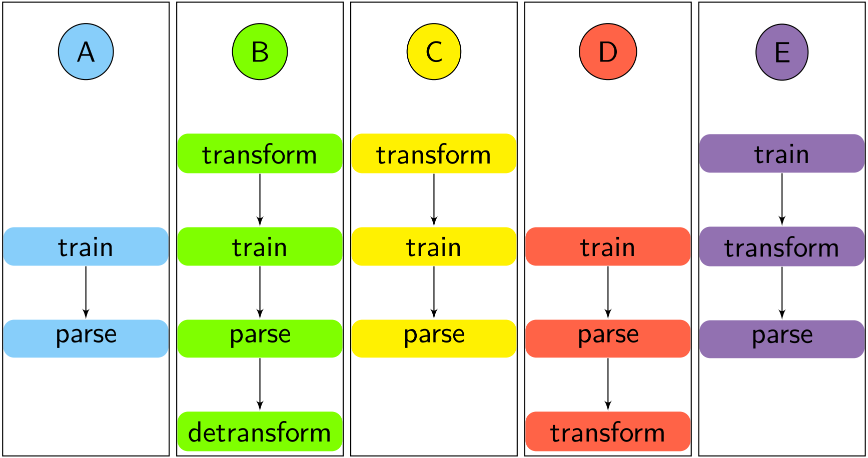


Pipeline



A
train
parse
B
transform
train
parse
detransform
C
transform
train
parse
D
train
parse
transform

Pipeline


A
train
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D
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E
train
transform
parse

Research Questions

Research Questions

Is there a training effect?

Research Questions

Is there a training effect? C > E

Research Questions

Is there a training effect? C > E

Is there a parsing effect?

Research Questions

Is there a training effect? C > E

Is there a parsing effect? E > D

Research Questions

Is there a training effect? C > E

Is there a parsing effect? E > D

Can we improve results on the original gold standard?

Research Questions

Is there a training effect?	C > E
Is there a parsing effect?	E > D
Can we improve results on the original gold standard?	B > A

Research Questions

Is there a training effect? C > E

Is there a parsing effect? E > D

Can we improve results on the original gold standard? B > A

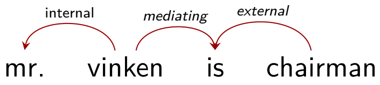
Can we obtain improvements on different types of MWEs?

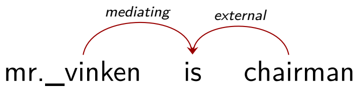
Research Questions

Is there a training effect?	C > E
Is there a parsing effect?	E > D
Can we improve results on the original gold standard?	B > A
Can we obtain improvements on different types of MWEs?	repeat and compare B

How to detransform?

How to detransform?

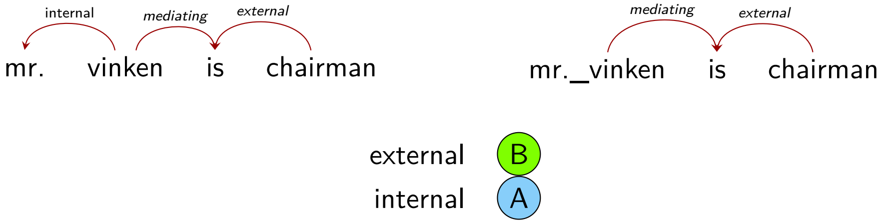




How to detransform?

external B

How to detransform?



How to detransform?

external B
internal A
mediating A

Results

Results

	E	C
only sibling MWEs	84.64	**84.88**
all MWEs	72.77	**72.92**

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Is there a training effect? C > E

Results

	E	C
only sibling MWEs	84.64	**84.88**
all MWEs	72.77	**72.92**

Is there a training effect? C > E ✓

Results

	D	E
only sibling MWEs	79.17	**84.06**
all MWEs	79.49	**79.69**

Is there a training effect? C > E ✓

Results

	D	E
only sibling MWEs	79.17	**84.06**
all MWEs	79.49	**79.69**

Is there a training effect? C > E ✓

Is there a parsing effect? E > D

Results

	D	E
only sibling MWEs	79.17	**84.06**
all MWEs	79.49	**79.69**

Is there a training effect? C > E ✓

Is there a parsing effect? E > D ✓

Results

A	B
85.15	**85.28**

Is there a training effect?	C > E	✓
Is there a parsing effect?	E > D	✓

Results

A	B
85.15	**85.28**

Is there a training effect?	C > E	✓
Is there a parsing effect?	E > D	✓
Can we improve results on the original gold standard?	B > A	

Results

A B

85.15 **85.28**

Is there a training effect?	C > E	✓
Is there a parsing effect?	E > D	✓
Can we improve results on the original gold standard?	B > A	✓

Results

model	detector type	resolver type	F_1
A			85.15
B_1	exhaustive	longest	85.18
B_2	exhaustive	leftmost	85.02
B_3	Proper Nouns	longest	**85.28**
B_4	Length 2	leftmost	85.07
B_5	Stop words	longest	85.19

Is there a training effect?	C > E	✓
Is there a parsing effect?	E > D	✓
Can we improve results on the original gold standard?	B > A	✓

Results

model	detector type	resolver type	F_1
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B_5	Stop words	longest	85.19

Is there a training effect?	C > E	✓
Is there a parsing effect?	E > D	✓
Can we improve results on the original gold standard?	B > A	✓
Can we obtain improvements on different types of MWEs?	repeat and compare B	

Results

model	detector type	resolver type	F_1
A			85.15
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B_5	Stop words	longest	85.19

Is there a training effect?	C > E	✓
Is there a parsing effect?	E > D	✓
Can we improve results on the original gold standard?	B > A	✓
Can we obtain improvements on different types of MWEs?	repeat and compare B	✓

Conclusion

Contributions

- Improvements on CCG parsing with automatic MWE recognition
- Significant results despite limited settings
- Techniques for distinguishing training from parsing effects
- Empirical support that there is both training and parsing effects
- Differences in results when using different recognizers

Conclusion

Future Work

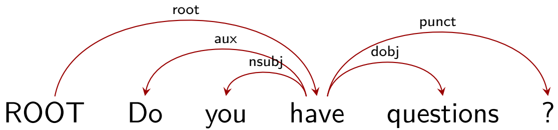
- Extending the transformation algorithm to the non-sibling case
- Testing more MWE recognition methods
- Conducting error analysis

Outline for section 4

General Conclusion

Principled methods for studying the interaction between syntactic representations and parsing accuracy.

Thanks!



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