# Subcategorial considerations in statistical categorial parsing

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Aditya Bhargava

# Syntactic structure in NLP

# Meaning is what we want

When was the dog-wolf genetic split?

between 27,000 and 40,000 years ago

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“Text Bob, ‘How to recognize speech?’”

“Texting Bob, ‘How to wreck a nice beach’”

---

I would like eight pizzas, please

मुझे दो पिज्जा चाहिए

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# How can syntax help?

# Syntax: a vehicle for semantics

Book a train from Toronto to Montréal

vs.

Book a train from Montréal to Toronto

# Categorial grammars (CGs)

- CG categories can “be thought of as a shorthand for the semantics” (Ades and Steedman, 1982)
- Rules have semantic correspondences as well
  - E.g., CCG composition: $\mathbf{B}{=}\lambda abc.a(bc)$
- CG derivations carry semantics

# CG lexical categories vs. parts of speech

N
N/N
$NP_{nb}$/N
(NP\NP)/NP
((S\NP)\(S\NP))/NP
Conj
NP
PP/NP
(S\NP)\(S\NP)
((S\NP)\(S\NP))/((S\NP)\(S\NP))
(((S\NP)\(S\NP))\((S\NP)\(S\NP)))/NP
...

CC
CD
DT
EX
FW
IN
JJ
JJR
JJS
LS
MD
NN
NNS
NNP
NNPS
PDT
POS
PRP

PRP$
RB
RBR
RBS
RP
SYM
TO
UH
VB
VBD
VBG
VBN
VBP
VBZ
WDT
WP
WP$
WRB

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…

CC
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WDT
WP
WP$
WRB

# Statistical LCG & CCG parsing

- LCG parsing: non-statistical only
  - No corpus until LCGbank (Fowler, 2016)
  - Relevance of category structure in proof nets (Roorda, 1991; Penn, 2004; Fowler, 2010)
- CCG parsing: lacking in consideration of category structure
  - Early work in the context of statistical methods for other formalisms (e.g., Hockenmaier, 2001; Clark, 2002)
  - Still-influential statistical CCG parser (Clark and Curran, 2007)

# Thesis

Subcategorial information in CG lexical categories is useful for statistical parsing

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1. Supertagging with CCG primitives

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2. Proof net structure for neural LCG parsing

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2. Proof net structure for neural LCG parsing
3. Decomposed scoring of CCG dependencies

# Contributions

- Subcategorial supertagging improves:
  - Supertagging accuracy
  - Parser $F_1$
  - Parser coverage
- Subcategories allow for more effective use of prediction history
- Enables OOV category prediction

1. Supertagging with CCG primitives
2. Proof net structure for neural LCG parsing
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# Category internals are useful for supertagging

| | |
|---|---|
| ... | ... |
| law | N |
| that | $(NP\backslash NP)/(S_{dcl}\backslash NP)$ |
| makes | $(((S_{dcl}\backslash NP)/(S_{to}\backslash NP))/NP)/NP_{expl}$ |
| it | $NP_{expl}$ |
| a | $NP_{nb}/N$ |
| crime | N |
| to | $(S_{to}\backslash NP)/(S_{b}\backslash NP)$ |
| ... | ... |

# Category internals are useful for supertagging

| | |
|---|---|
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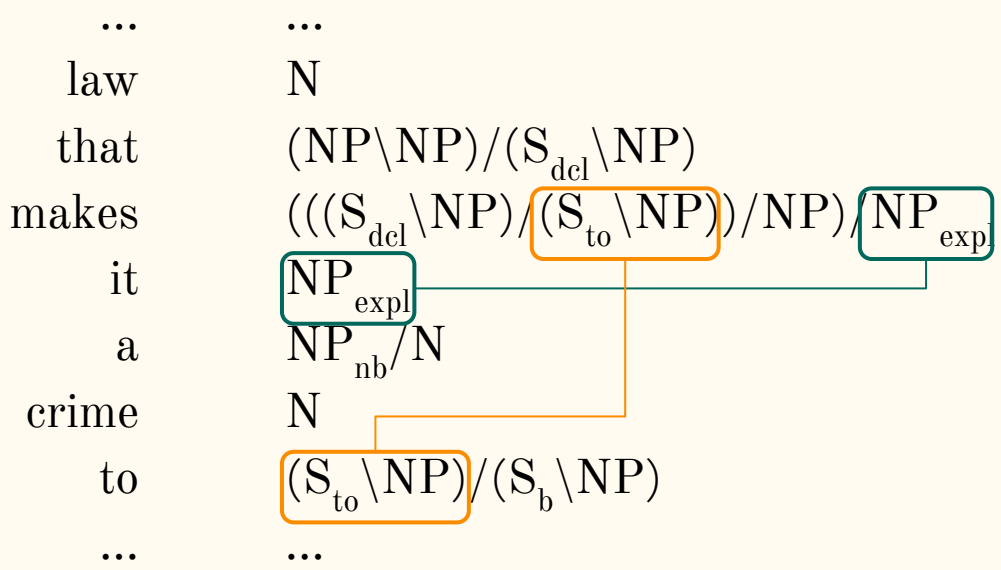
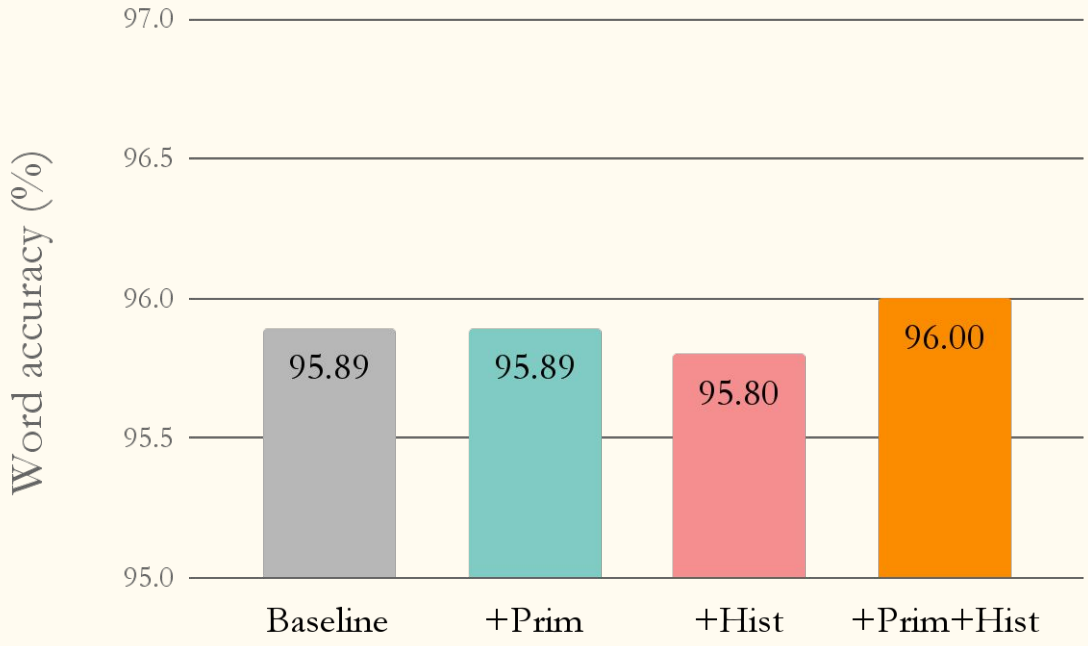
| ... | ... |

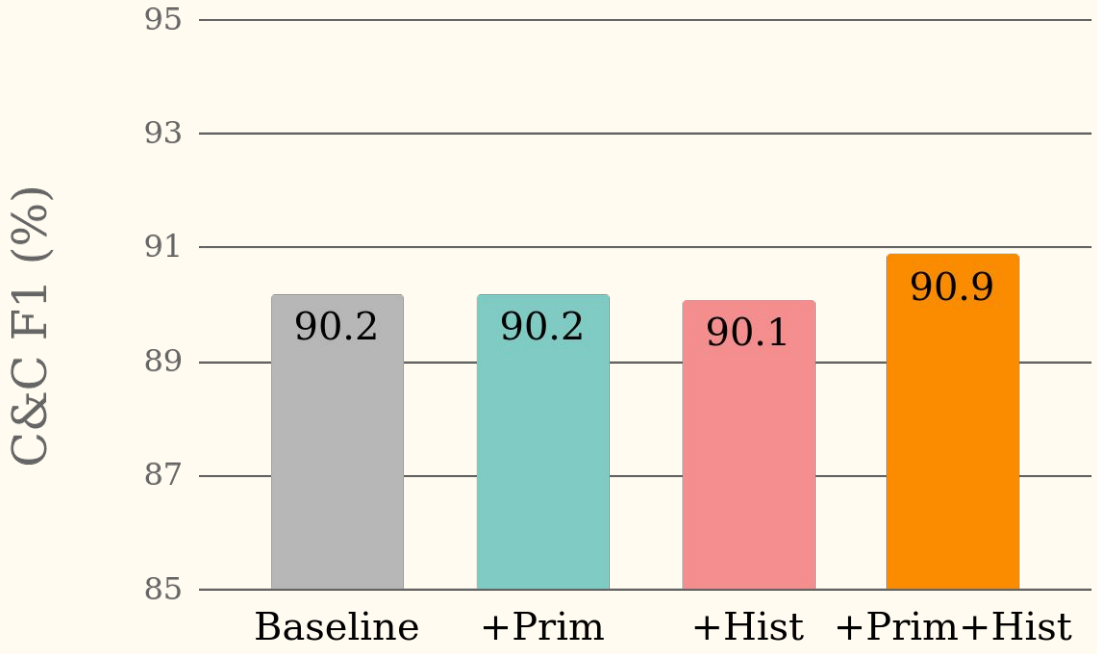
# Category internals are useful for supertagging



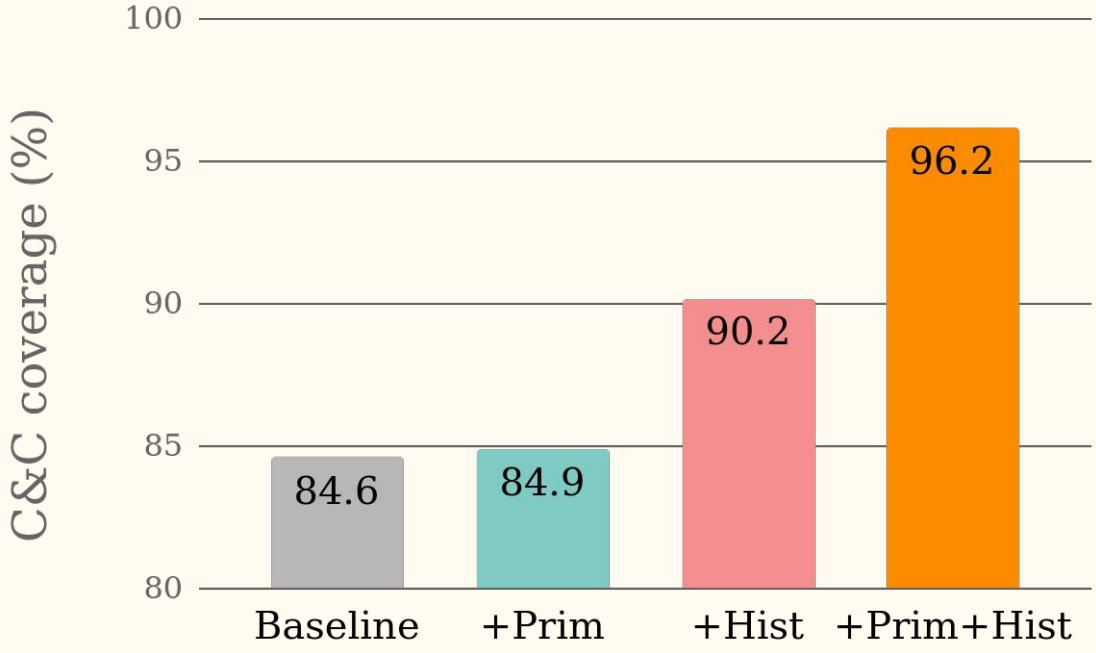
# Supertagging word accuracy



# C&C parser $F_1$


C&C F1 (%)
95
93
91
89
87
85
90.2
90.2
90.1
90.9
Baseline
+Prim
+Hist
+Prim+Hist

# C&C parser coverage

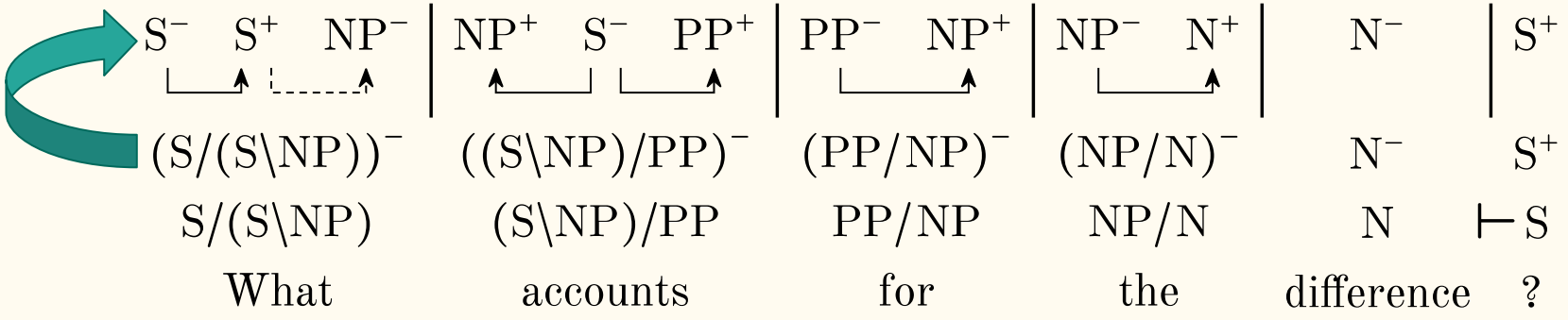


# Contributions

- First statistical LCG parser
- Proof net parsing with lexical decomposition
- Novel loss functions and structural constraints
  - Increase parser performance
  - Enable training without ground truth

1. Supertagging with CCG primitives
2. Proof net structure for neural LCG parsing
3. Decomposed scoring of CCG dependencies

# LCG proof nets

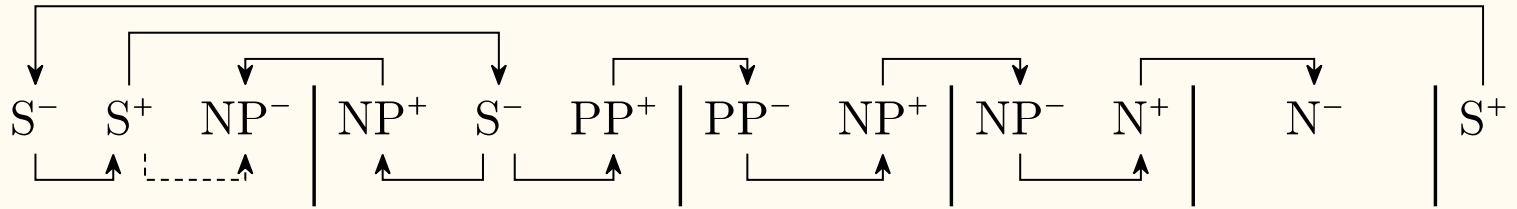


# LCG parsing with proof nets: validity conditions

T1. Linkage must be half-planar
- No crossing edges in half-plane above vertices

T2. No regular cycles (solid edges)

T3. Each Lambek edge must have regular path between its vertices (dashed edges)



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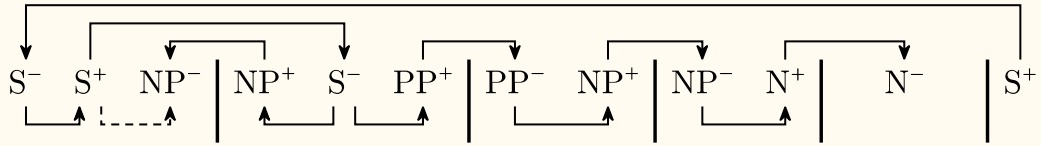


Each condition can be expressed as a differentiable function of the *graph*—no ground truth linkages needed

# Parsing performance

| Condition | Link Acc | Sent Acc | Coverage |
|---|---|---|---|
| Base | 97.7 | 86.2 | 97.3 |
| Enhanced model | 97.9 | 87.4 | 98.4 |
| Enhanced model + losses | 97.9 | 87.2 | 98.7 |

# Training without ground truth

| Condition | Link Acc |
|---|---|
| Enhanced model + losses | 91.2 |
| —T1 loss | 84.5 |
| —T2 loss | 72.9 |
| —T3 loss | 70.6 |
| —Link filter | 73.9 |
| —planar attention — T1 loss | 19.2 |

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All planarity information removed

# Contributions

- Decomposed scoring fixes cases of error amplification
- Systematic human validation of statistical parsing scoring method
  - Expert judges find in favour of decomposed scoring (overall)
  - Raises questions about the validity of aggregated parser scores

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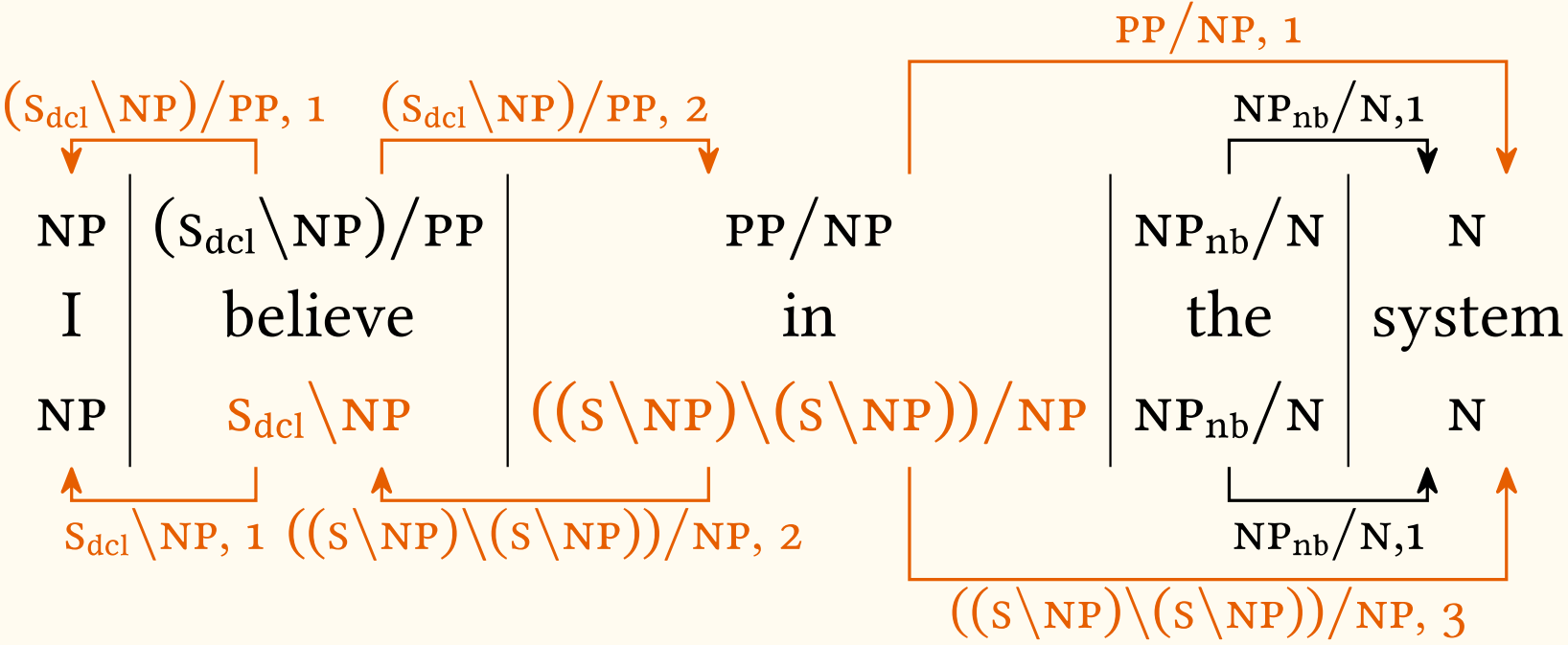
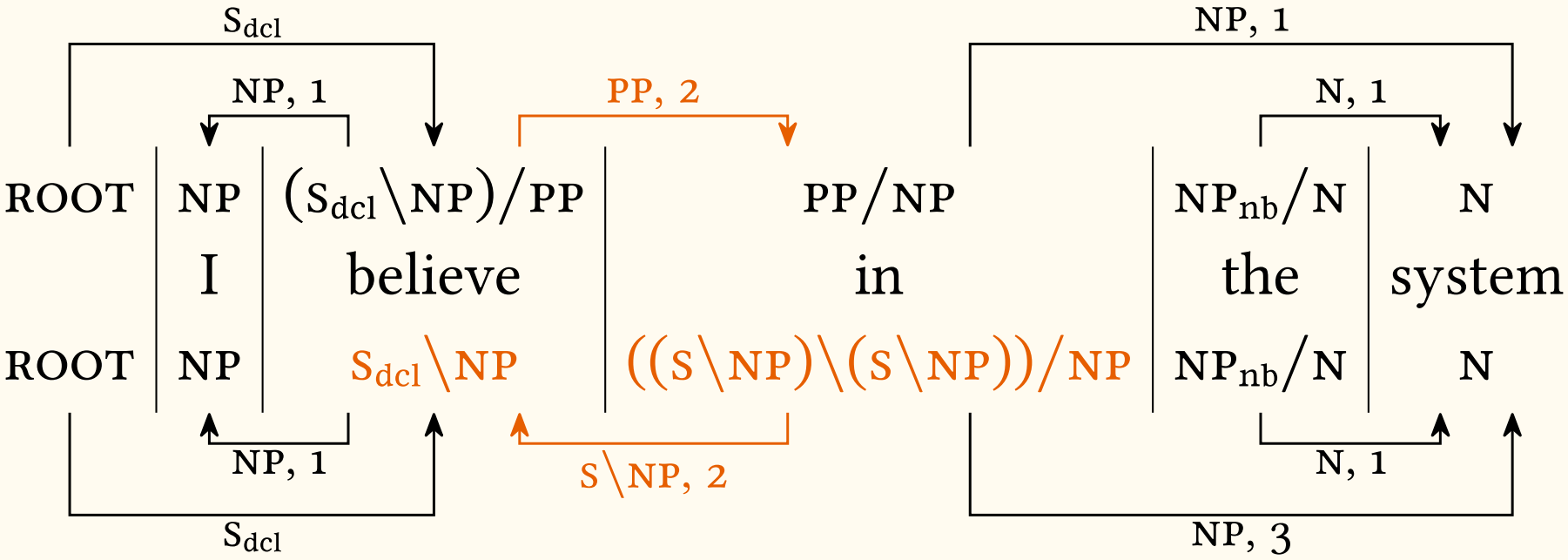
# CCG dependency evaluation



# Decomposed scoring



# Expert judgements

- Intrinsic task: direct comparison of scoring methods
  - Strong agreement among judges in favour of decomposed scoring
- Extrinsic task: pairwise rank inversions
  - Overall agreement among judges in favour of decomposed scoring, but...
  - High disagreement: 50% ties in pilot study; 24% ties in main study

# Future directions

# End-to-end categorial parsing

- End-to-end systems pass training signals from output back to original input
  - Would be helpful for parsing errors to propagate back to supertagging decisions
- Recent “end-to-end” parsers aren’t truly end-to-end (Kasai et al., 2018; Kogkalidis et al., 2020)
  - Better described as “joint” or “multi-task”
- Tighter coupling between subcategorial supertagger and parser

# Mildly context-sensitive proof nets

- LCG is weakly CF-equivalent
- Phenomena in some languages are known to be trans-CF (Bresnan et al., 1982; Huybregts, 1984; Shieber, 1985)
- Development of proof nets for CCG (Buch, 2009)
- Encoding of proof net conditions for MCS extension of LCG (Komatsu, 2021)

# Low-data/unsupervised categorial parsing

- Recent unsupervised parsers have relatively *ad hoc* structure (Drozdov et al., 2019)
  - Advantages of formalism-driven structure unexplored
- Novel loss functions suggest a path to structured learning from unlabelled data
  - Structural constraints may help lower data requirements

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