Inspecting the Structural Biases of Dependency Parsing Algorithms

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CoNLL 2010, Sweden

There are many ways to parse a sentence

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Transition Based Parsers
- Covington
- Multiple Passes
- Arc-Eager
- Arc-Standard
- With Swap Operator
- First-Best Parser
- DAG Parsing
- With a Beam
- With Dynamic Programming
- With Tree Revision
- Left-to-right
- Right-to-left

Easy-First Parsing (check out our naacl 2010 paper)

Graph Based Parsers
- First Order
- Second Order (two children / with grandparent)
- Third Order
- MST Algorithm / Matrix Tree Theorem
- Eisner Algorithm
- Belief Propagation
- With global constraints (ILP / gibbs sampling)

Combinations
- Voted Ensembles (Sagae's way, Attardi's way)
- Stacked Learning

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Parser combinations work

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$\Rightarrow$ every parser has its strong points

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Different parsers behave differently

Open questions

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WHY do they behave as they do?

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WHAT are the differences between them?

More open questions

Which linguistic phenomena are hard for parser X?

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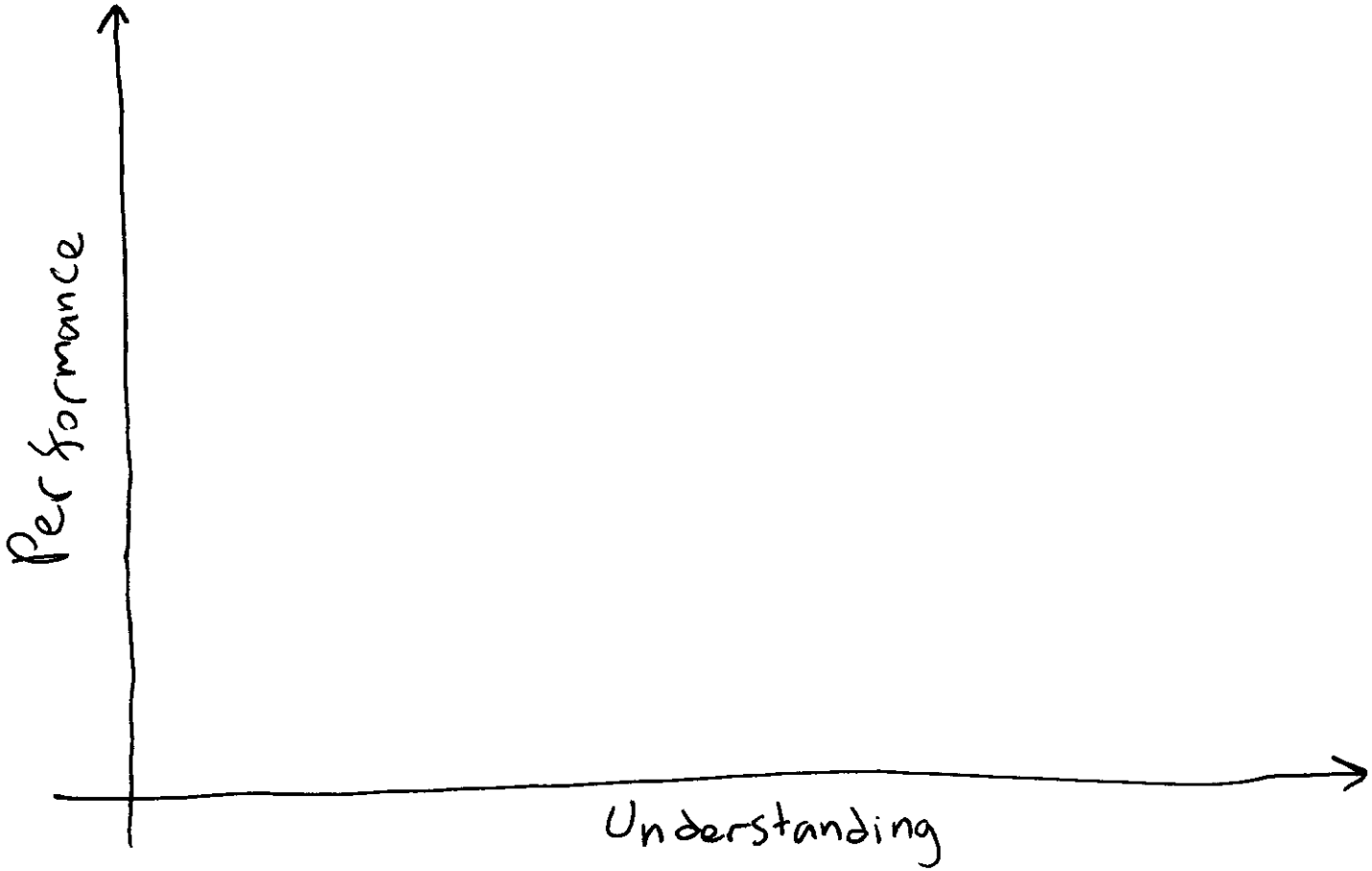
What kinds of errors are common for parser Y?

More open questions

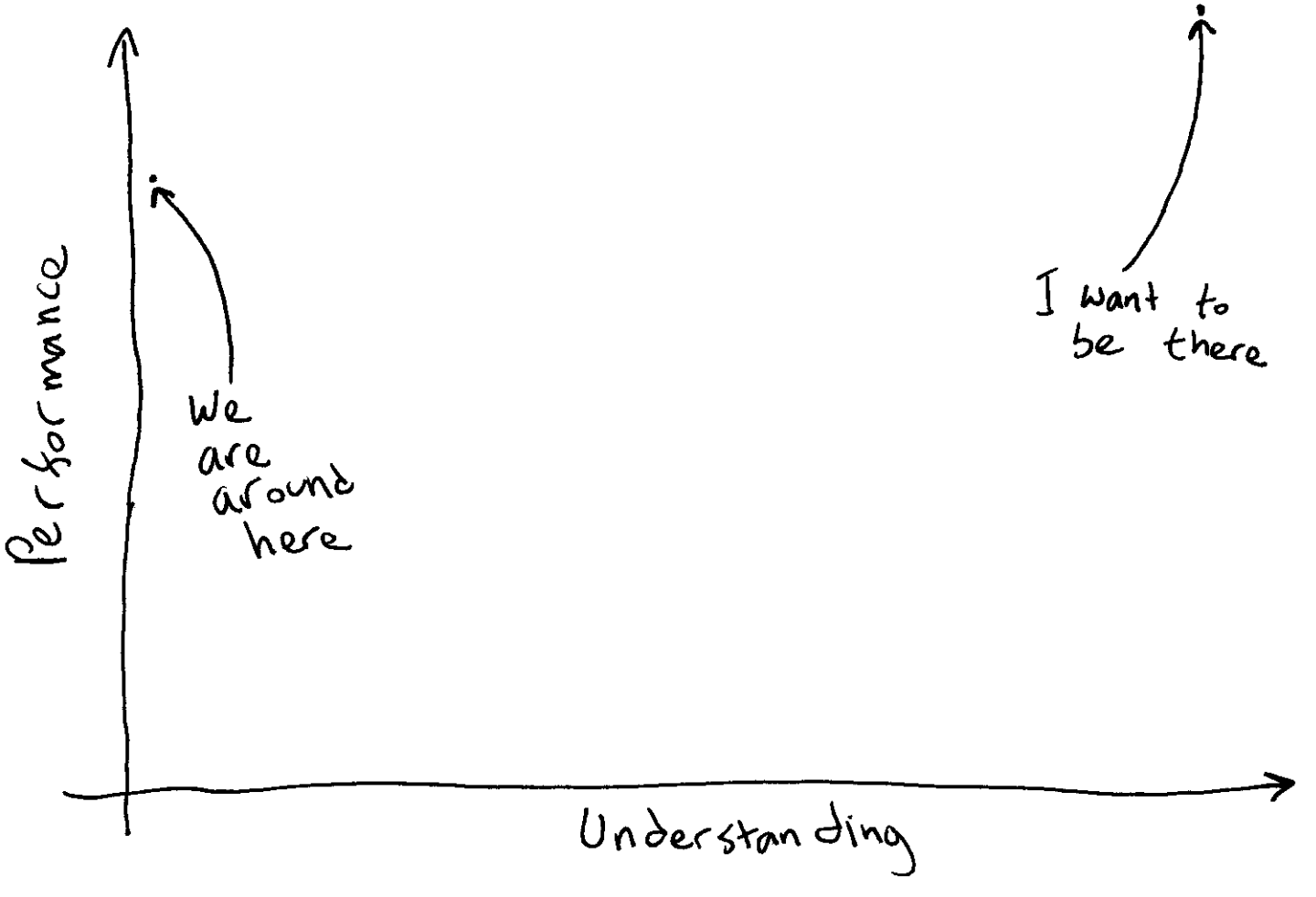
Which linguistic phenomena are hard for parser X?

What kinds of errors are common for parser Y?

Which parsing approach is most suitable for language Z?


Performance
Understanding


Performance
we are around here
Understanding


Performance
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I want to be there
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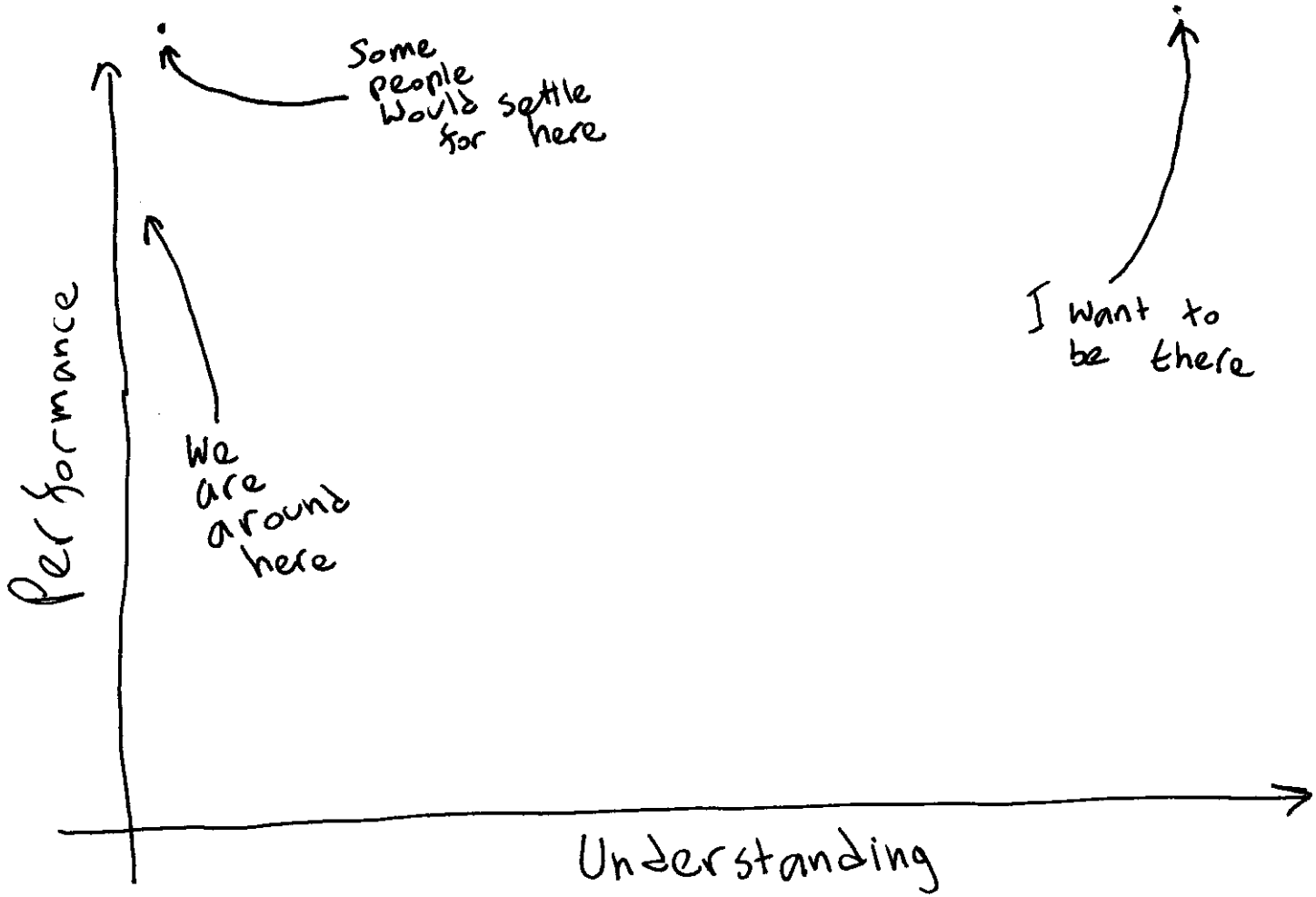
Some people would settle for here
I want to be there
We are around here
Performance
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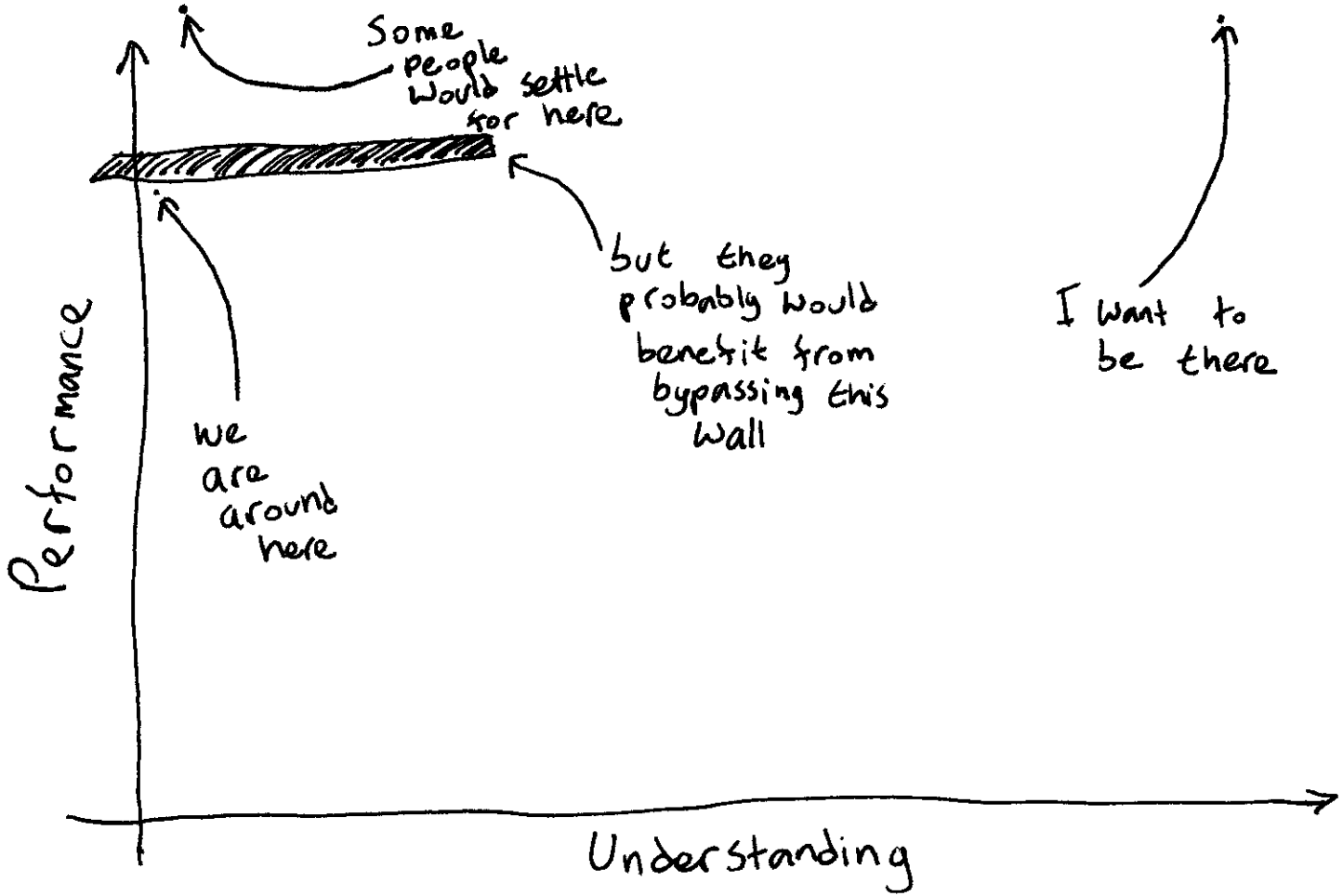
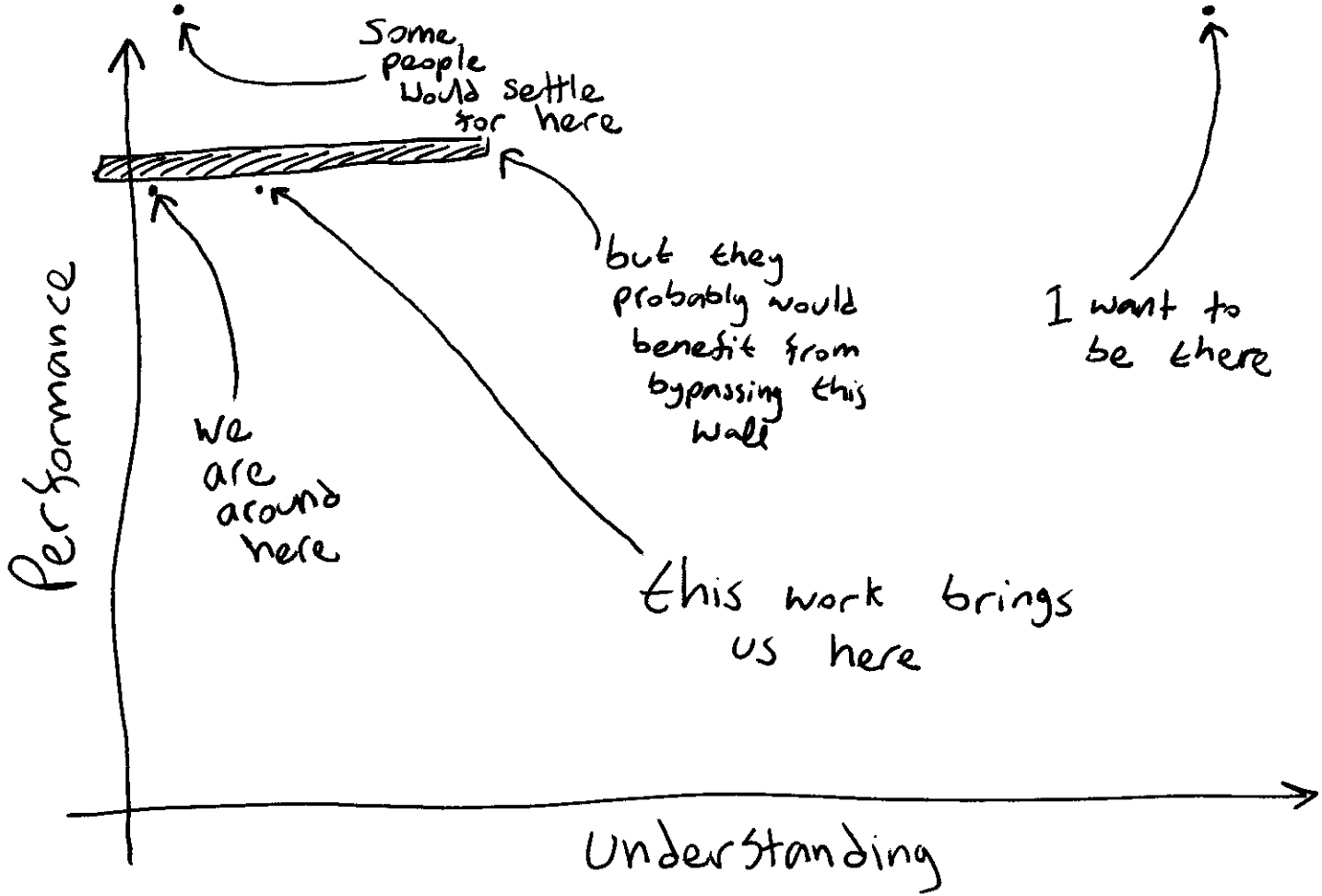

Some people would settle for here
but they probably would benefit from bypassing this wall
I want to be there
we are around here
Performance
Understanding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I want to be there
We are around here
this work brings us here
Performance
Understanding

Previously

McDonald and Nivre 2007:

"Characterize the Errors of Data-Driven Dependency Parsing Models"

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  - MST better near root, MALT better away from root
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- ...but all these differences are very small

we do something a bit different

Assumptions

- Parsers fail in predictable ways
- those can be analyzed
- analysis should be done by inspecting **trends** rather than individual decisions

Note: We do not do error analysis

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we are aiming at more global trends

Structural Preferences

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for a given language+syntactic theory

- Some structures are more common than others
  - (think Right Branching for English)

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for a given language+syntactic theory

- Some structures are more common than others
  - (think Right Branching for English)
- Some structures are very rare
  - (think non-projectivity, OSV constituent order)

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parsers also exhibit structural preferences

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  - data
  - interactions
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These trends are interesting!

Structural Bias

Structural bias

“The difference between the structural preferences of two languages”

Structural bias

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For us:

Which structures tend to occur more in language than in parser?

Bias vs. Error

related, but not the same

Parser X makes many PP attachment errors

- claim about error pattern

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Parser X tends to attach PPs low, while language Y tends to attach them high

- claim about structural bias (and also about errors)

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related, but not the same

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Parser X tends to attach PPs low, while language Y tends to attach them high

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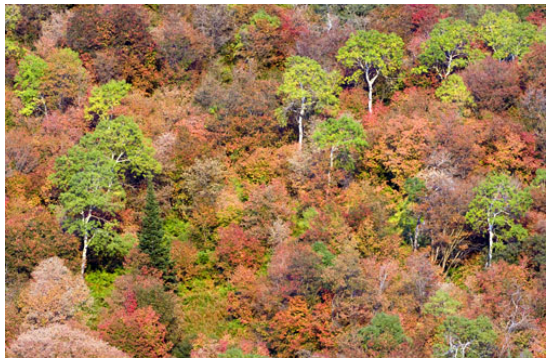
Parser X can never produce structure Y

- claim about structural bias

Formulating Structural Bias

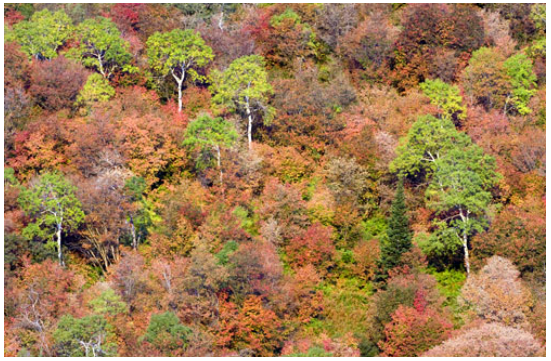
"given a tree, can we say where it came from?"

?



Formulating Structural Bias

"given two trees of the same sentence, can we tell which parser produced each parse?"



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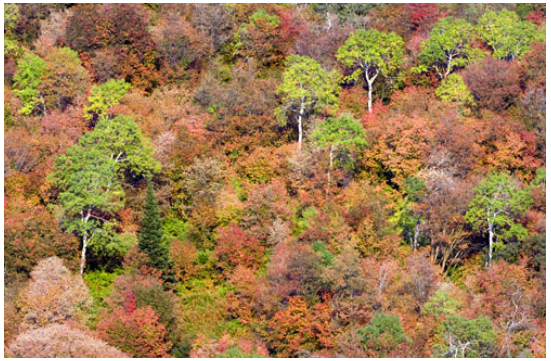

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"which parser produced which tree?"

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uncovering structural bias = searching for good predictors

Method

- start with two sets of parses for same set of sentences
- look for predictors that allow to distinguish between trees in each group

Our Predictors

- all possible subtrees

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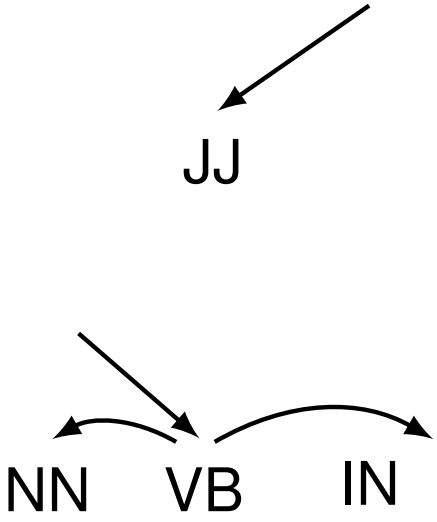
- always encode:
  - parts of speech
  - relations
  - direction



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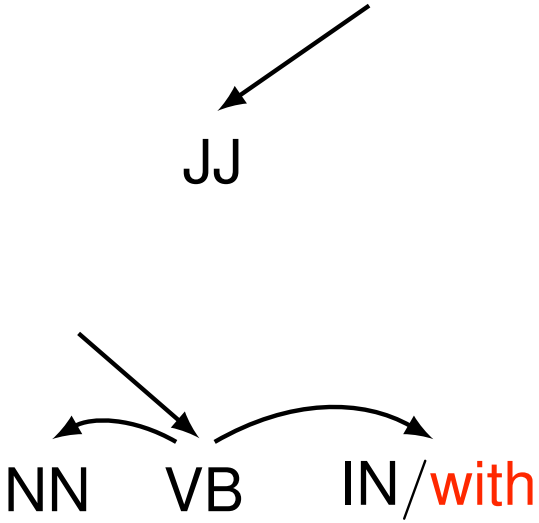

Our Predictors

- all possible subtrees
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- can encode also:
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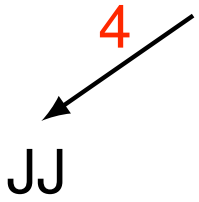

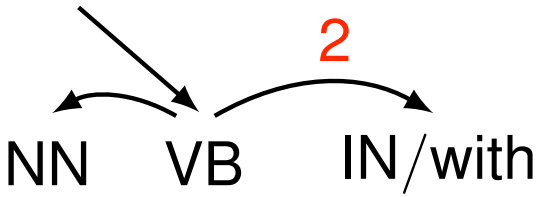

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boosting with subtree features

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very briefly:

- **input: two sets of constituency trees**
- while not done:
  - choose a subtree that classifies most trees correctly
  - re-weight trees based on errors
- **output: weighted subtrees (= linear classifier)**

Setup

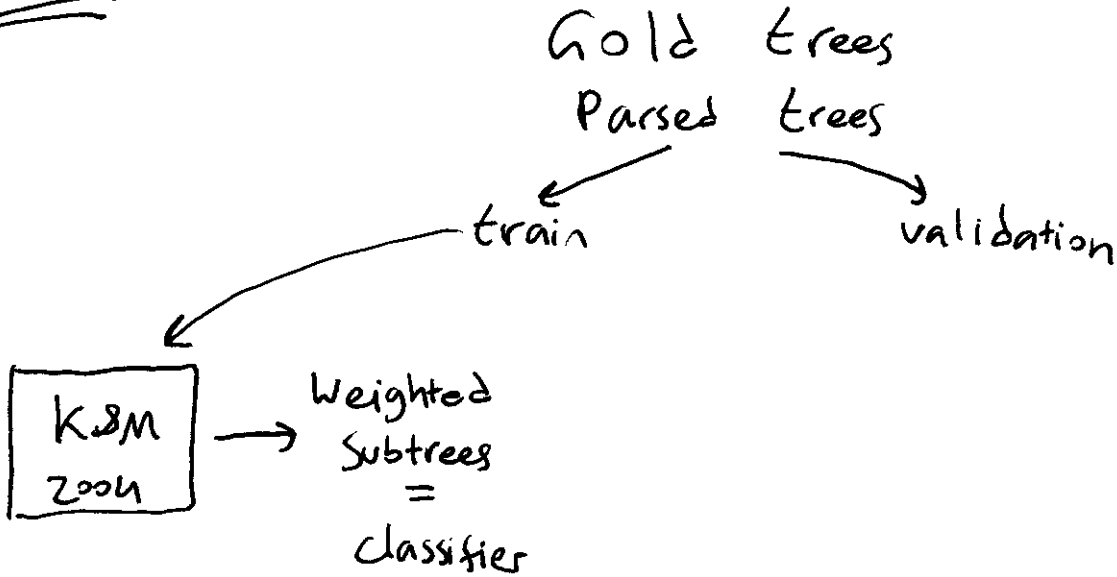
Gold trees

Parsed trees

train

Validation

Setup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validation
K&M 2004
Weighted Subtrees = classifier

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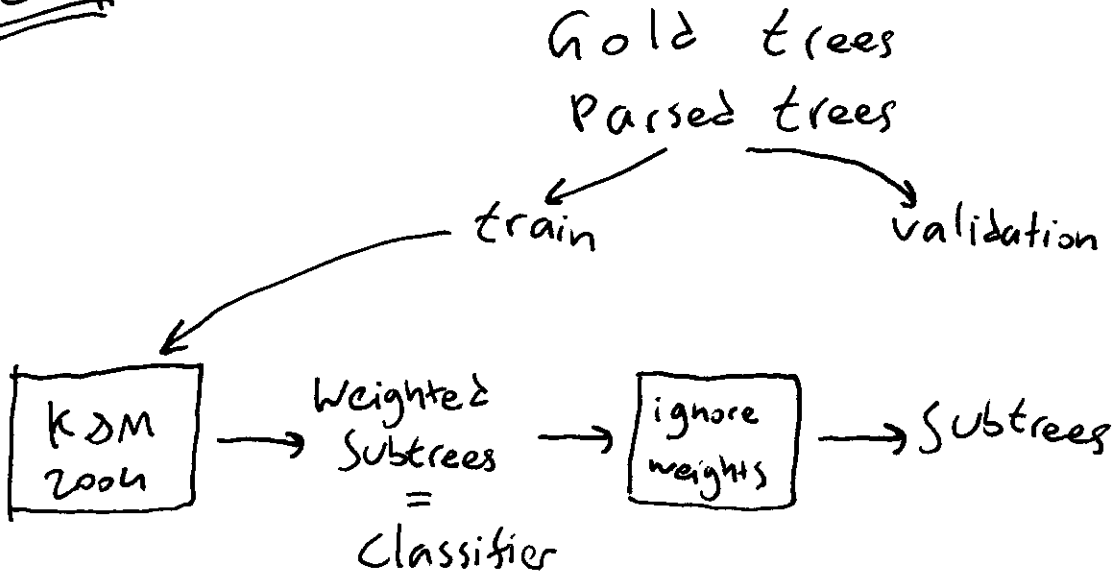
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ignore weights
Subtrees

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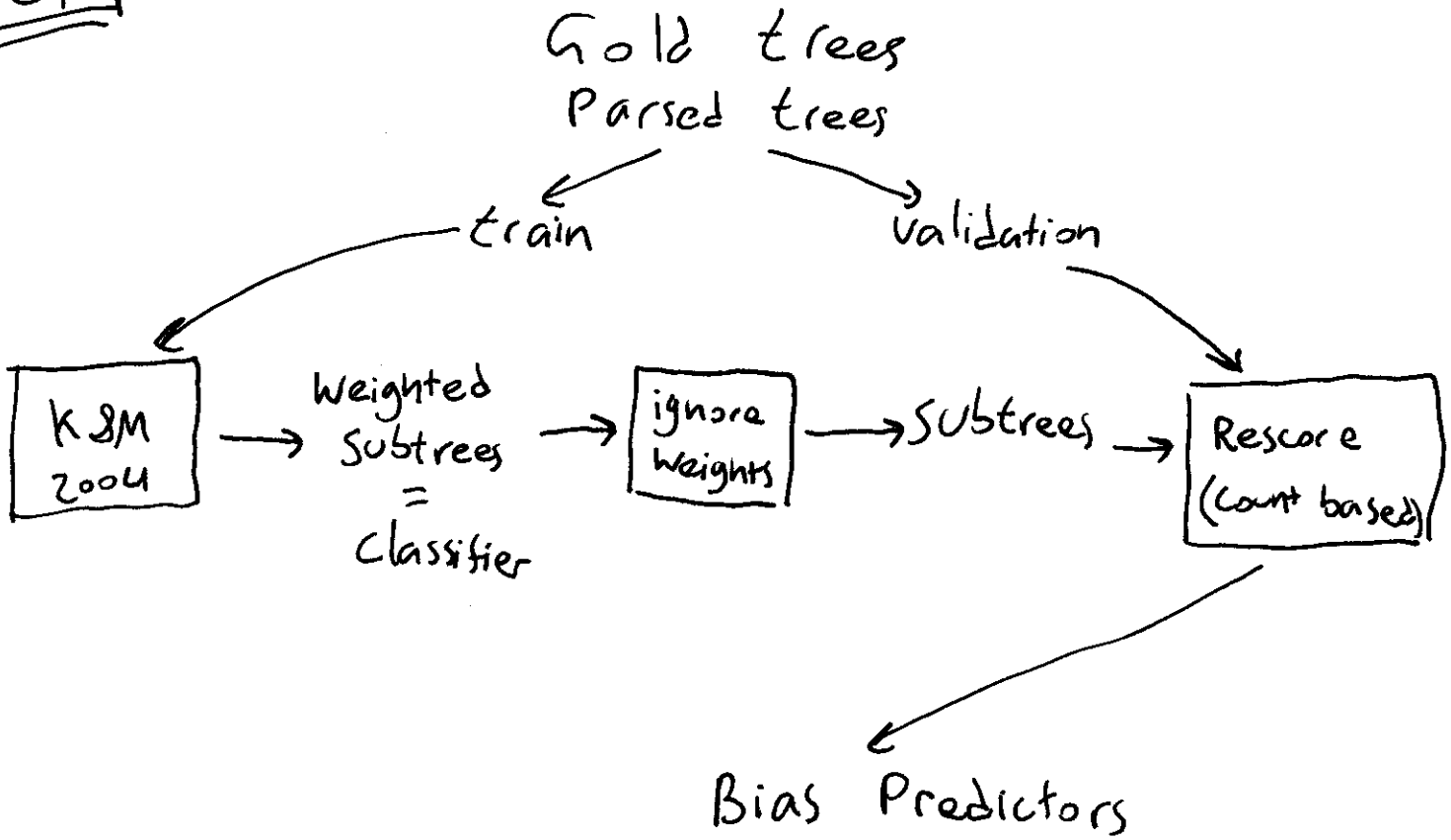
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Rescore (count based)
Bias Predictors

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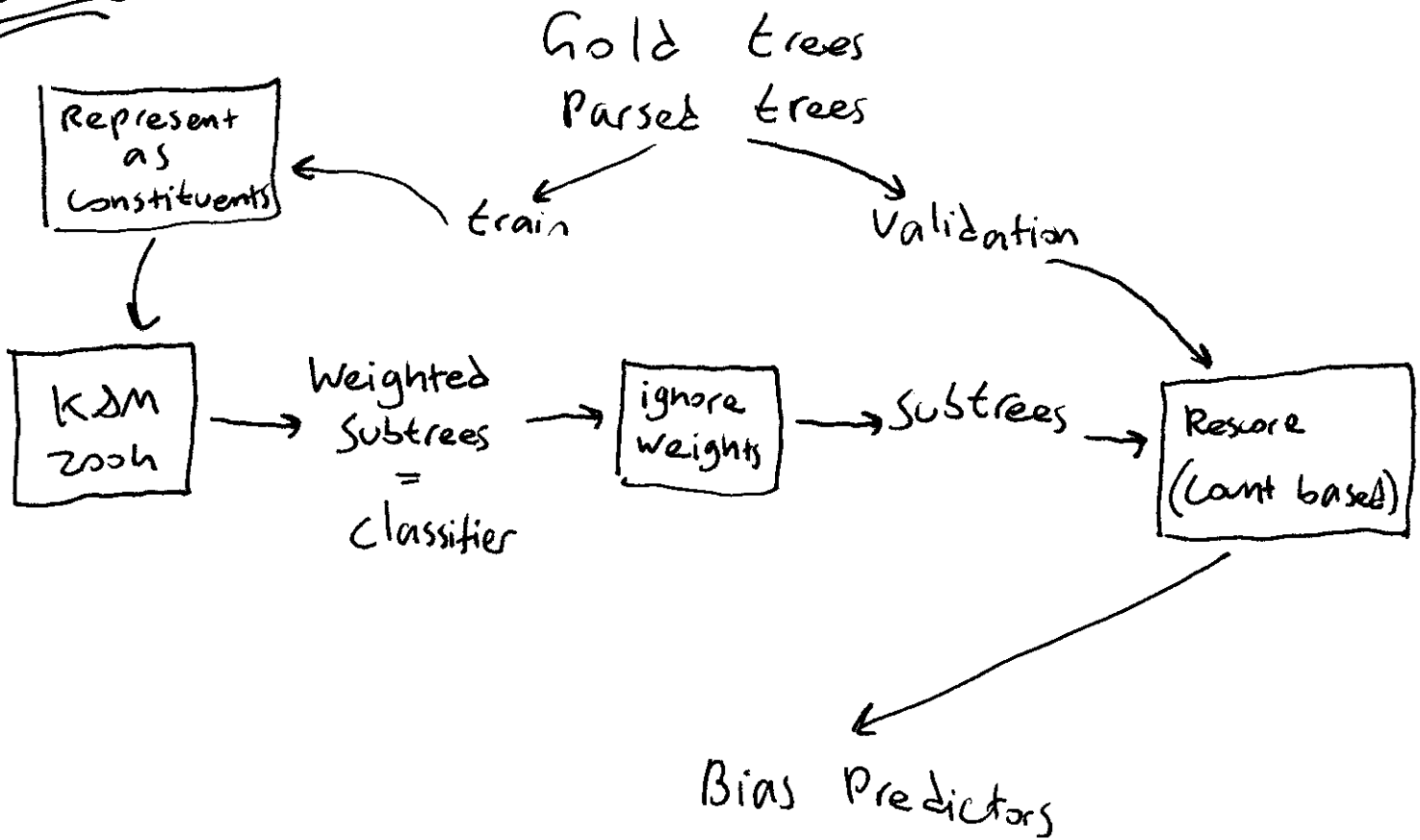
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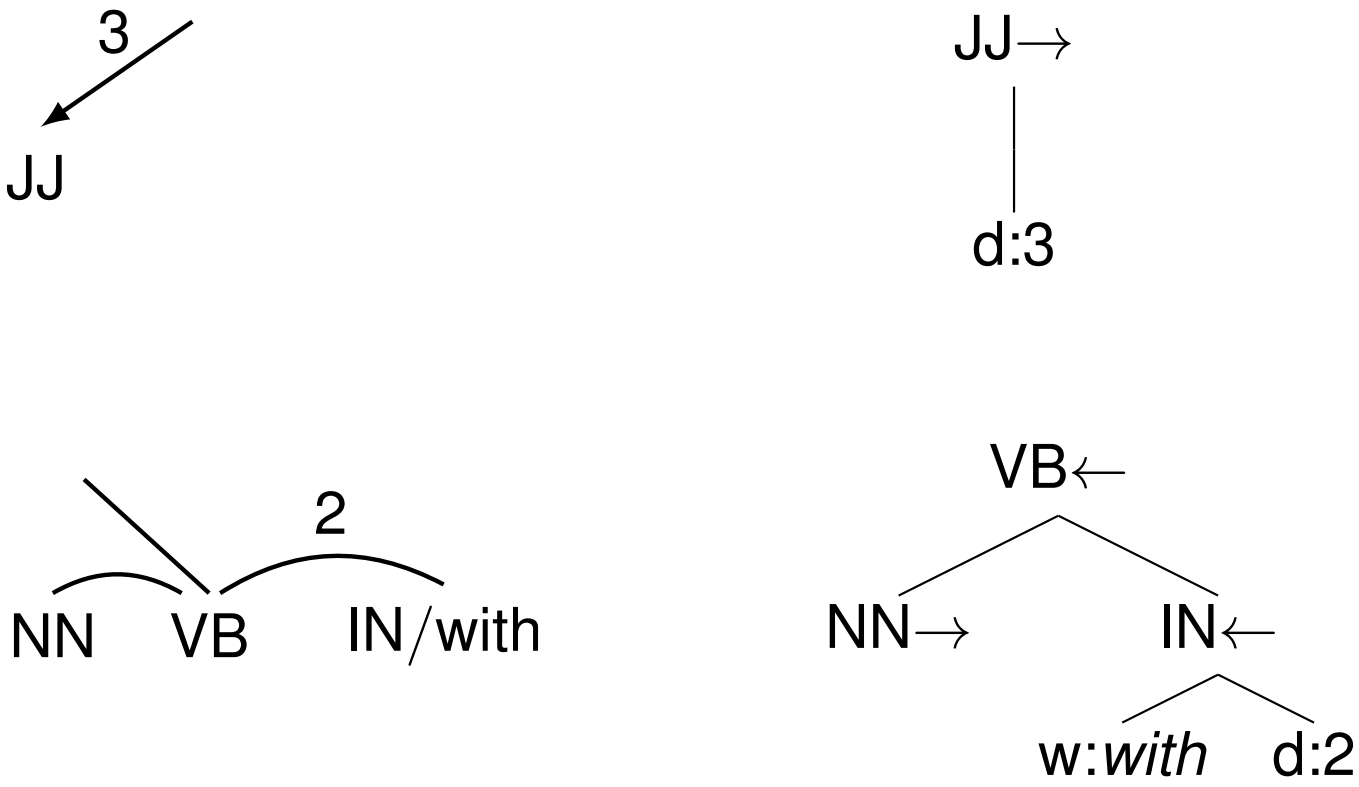
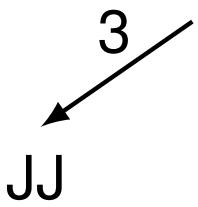
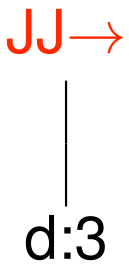
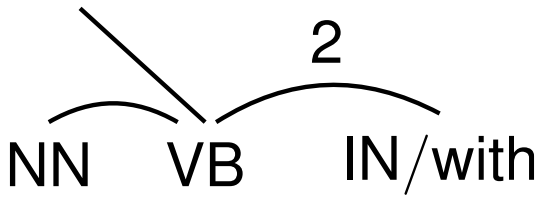


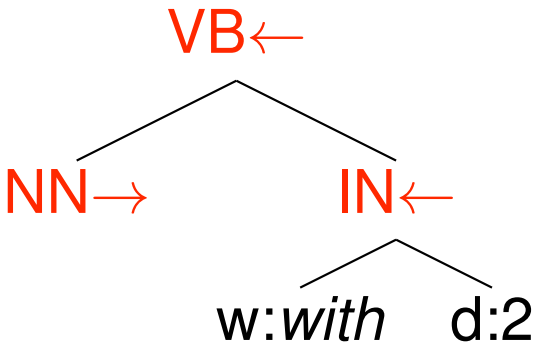
mandatory information at node label
optional information as leaves

conversion to constituency









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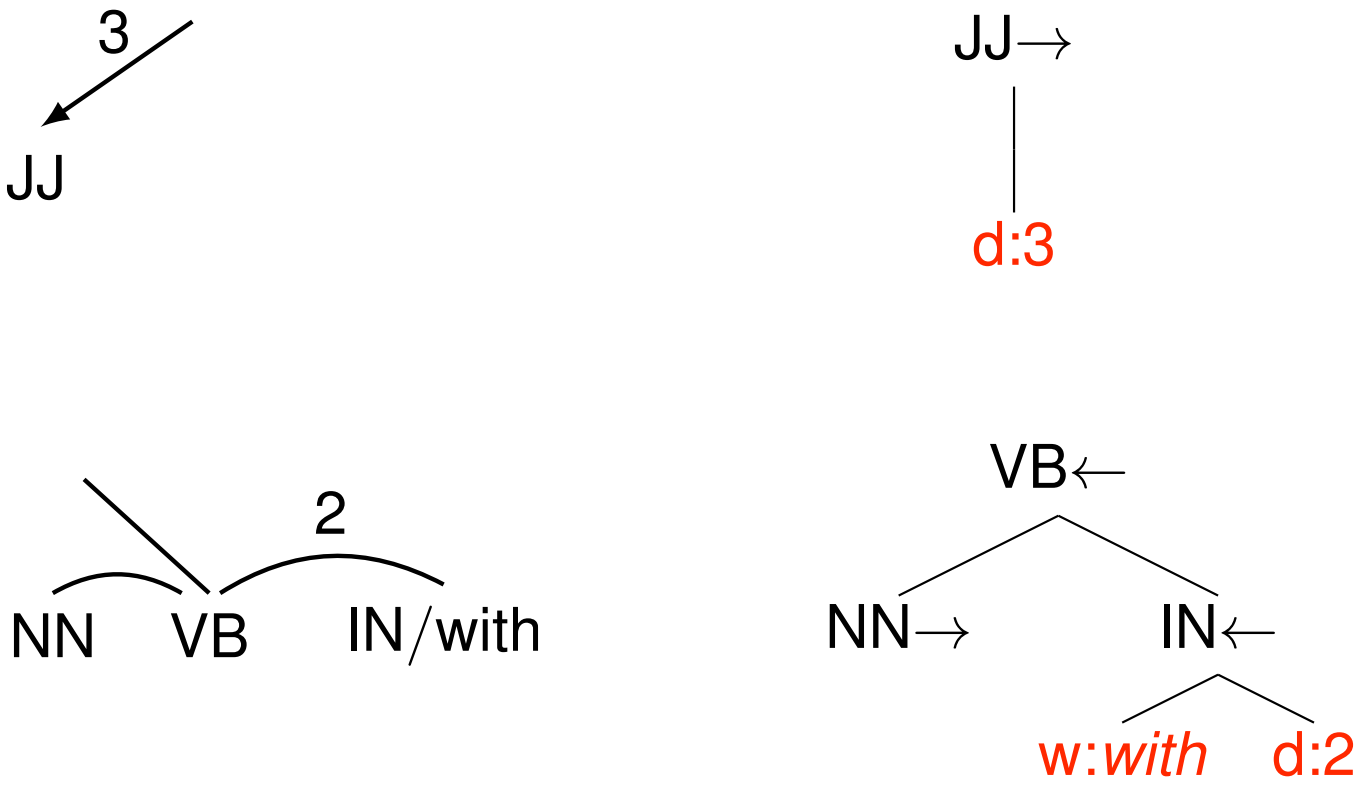

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Experiments

Analyzed Parsers

- Malt Eager
- Malt Standard
- Mst 1
- Mst 2

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Data

- WSJ (converted using Johansson and Nugues)
- splits: parse-train (15-18), boost-train (10-11), boost-val (4-7)
- gold pos-tags

Quantitative Results

Q: Are the parsers biased with respect to English?

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A: Yes

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Parser	Train Accuracy	Val Accuracy
MST1	65.4	57.8
MST2	62.8	56.6
MALTE	69.2	65.3
MALTS	65.1	60.1

Table: Distinguishing parser output from gold-trees based on structural information

Qualitative Results (teasers)

Over-produced by ArcEager:

Qualitative Results (teasers)

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ROOT→“ ROOT→DT ROOT→WP

(we knew it’s bad at root, now we know how!)

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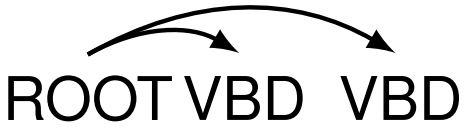

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Over-produced by ArcEager and ArcStandard

Qualitative Results (teasers)

Over-produced by ArcEager and ArcStandard

$$\rightarrow \text{VBD} \overset{\rightarrow}{{}_{9}{}_{+}} \text{VBD}$$

$$\rightarrow \text{VBD} \overset{\rightarrow}{{}_{5}{}_{-}{}_{7}} \text{VBD}$$

$$\text{ROOT} \rightarrow \text{VBZ} \rightarrow \text{VBZ}$$

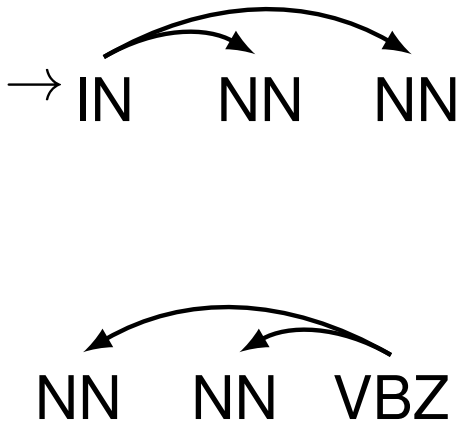
(prefer first verb above second one: because of left-to-right processing?)

Qualitative Results (teasers)

Over-produced by MST1

Qualitative Results (teasers)

Over-produced by MST1



(independence assumption failing)

Qualitative Results (teasers)

Under-produced by MST1 and MST2

Qualitative Results (teasers)

Under-produced by MST1 and MST2

(hard time in coordinating “heavy” NPs: due to *pos-in-between* feature?)

Qualitative Results (teasers)

More in paper

You should read it

Qualitative Results (teasers)

Software available

Try with your language / parser

To Conclude

- understanding HOW parsers behave and WHY is important
  - we should do more of that
- we defined structural bias as way of characterizing behaviour
- we presented an algorithm for uncovering structural bias
- applied to English with interesting results