

Selective-Sharing for Multilingual Dependency Parsing

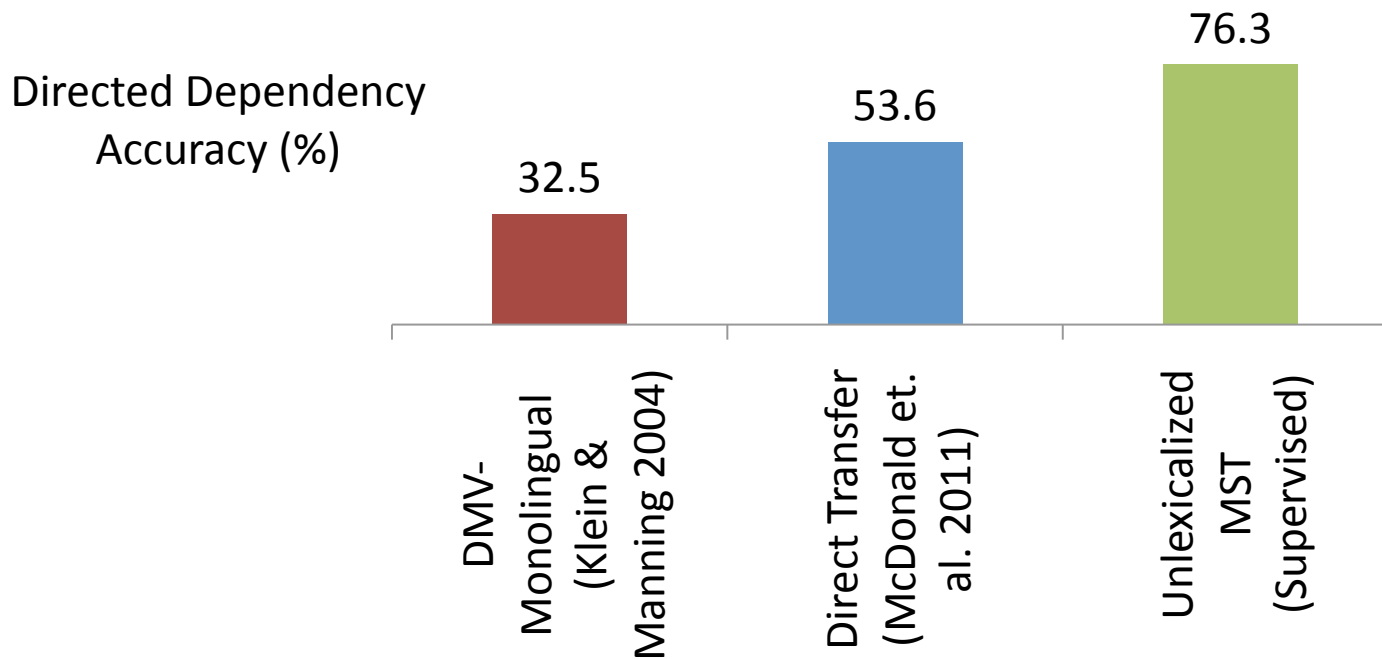
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MIT, CSAIL¹

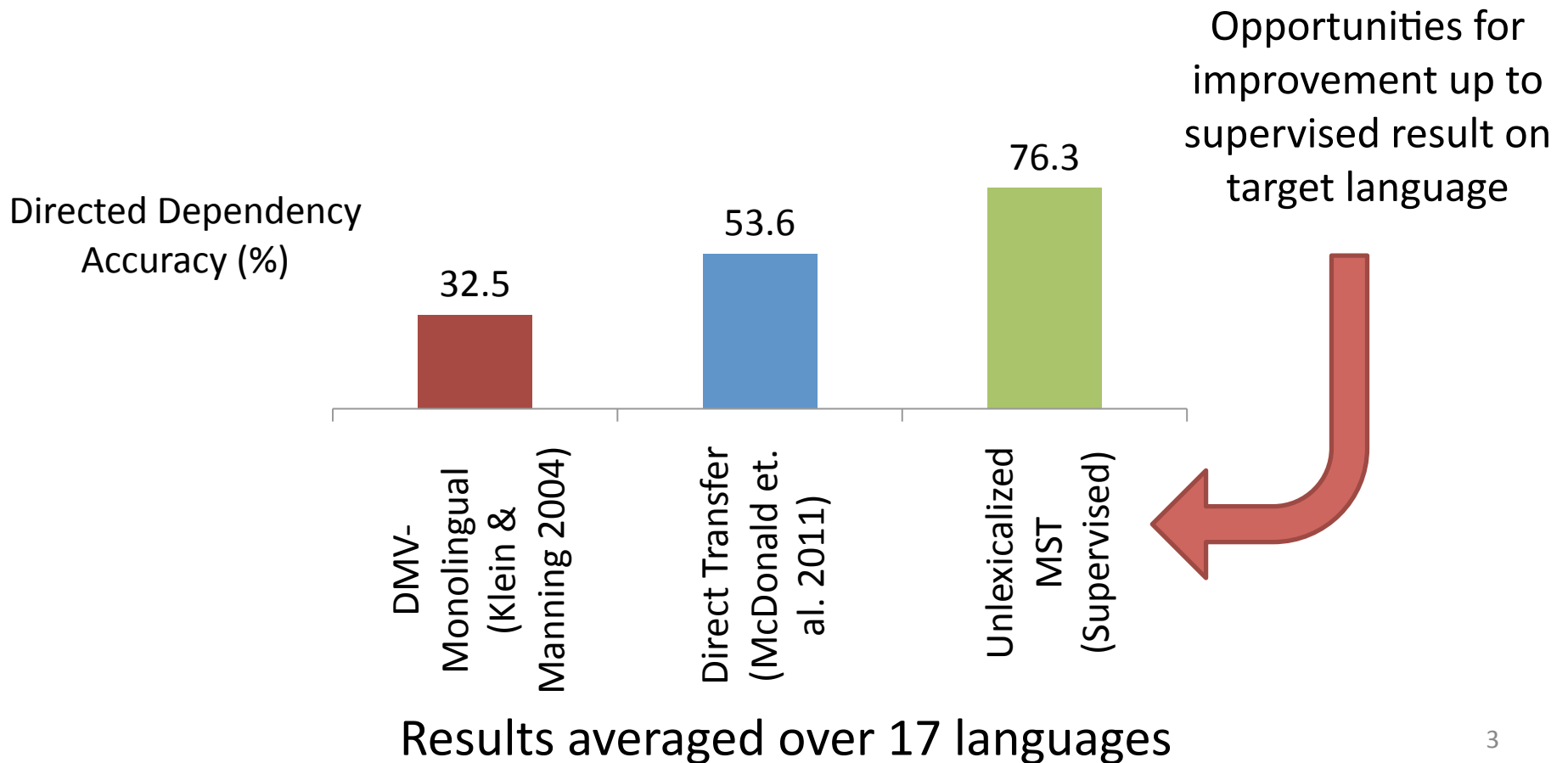
Hebrew University²

- Multilingual parsing is essential for text analysis in resource-poor languages (e.g. tree-to-tree MT systems)
- Existing methods do not capture linguistic similarities and differences



Results averaged over 17 languages

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- Existing methods do not capture linguistic similarities and differences

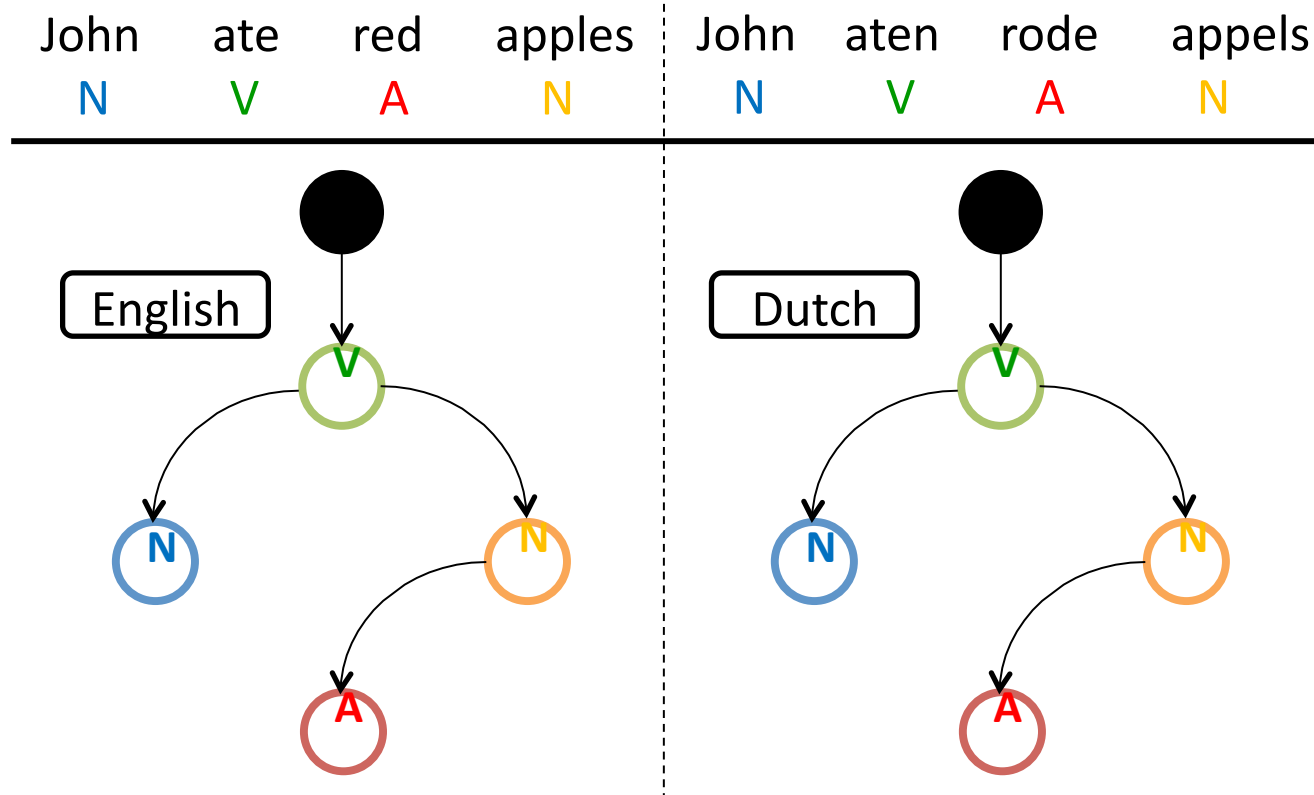


Crosslingual Parser Transfer

Motivated by Syntactic Similarities across Languages

Crosslingual Parser Transfer

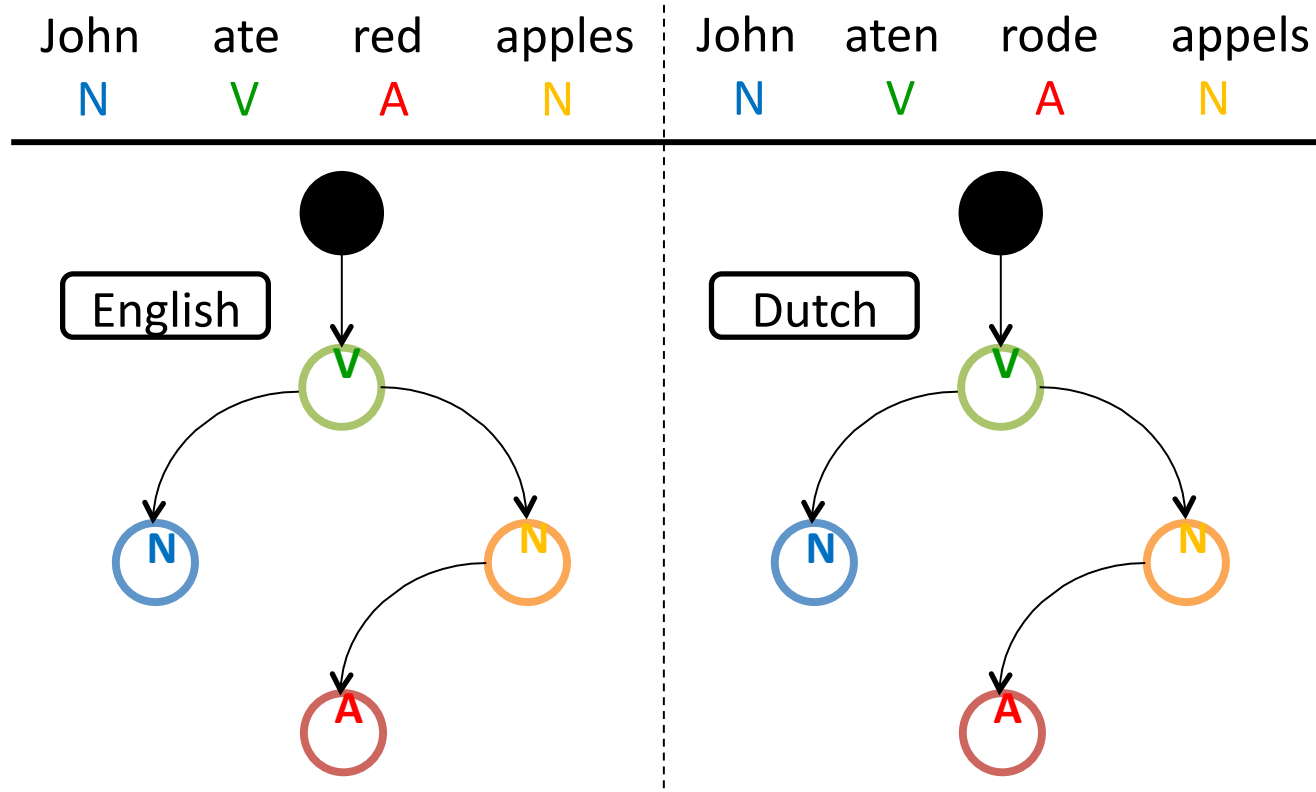
Motivated by Syntactic Similarities across Languages



Crosslingual Parser Transfer

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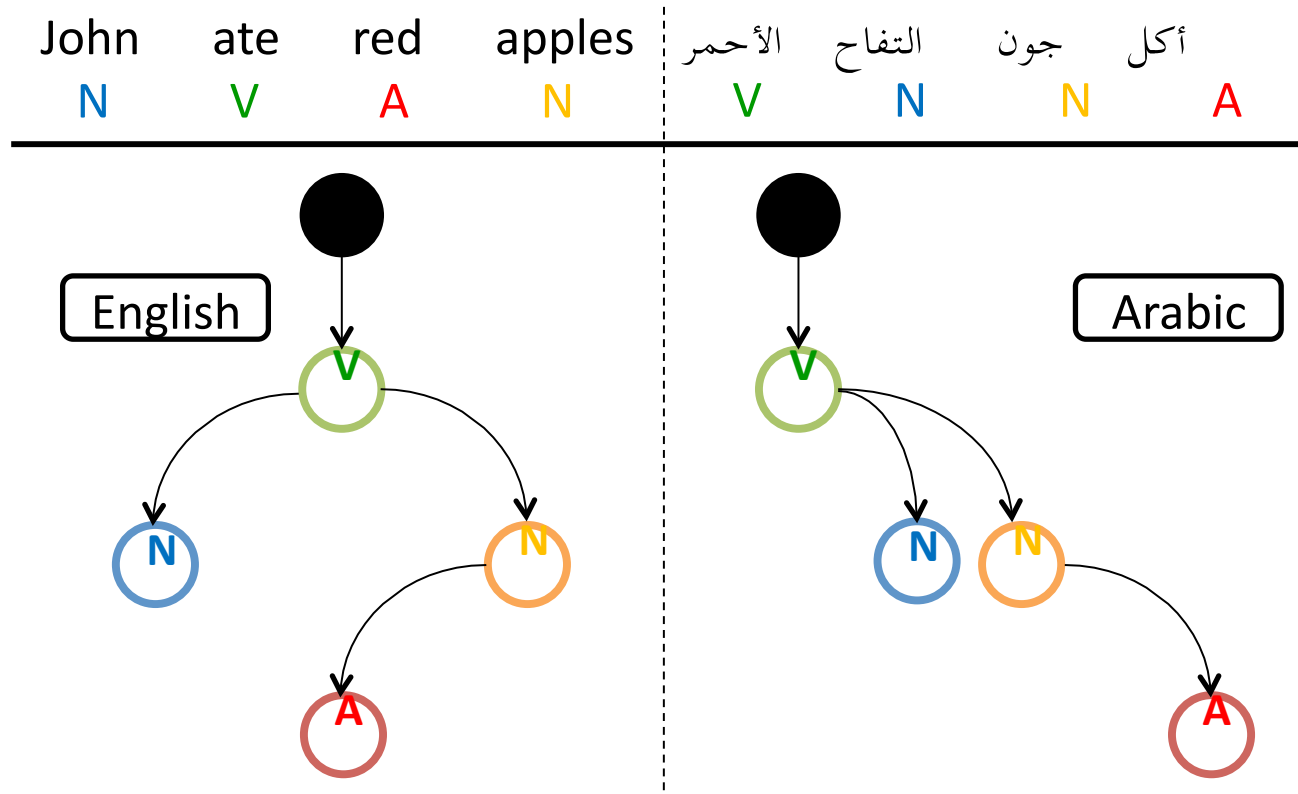
Q. What if the target language is very different?



Crosslingual Parser Transfer

Motivated by Syntactic Similarities across Languages

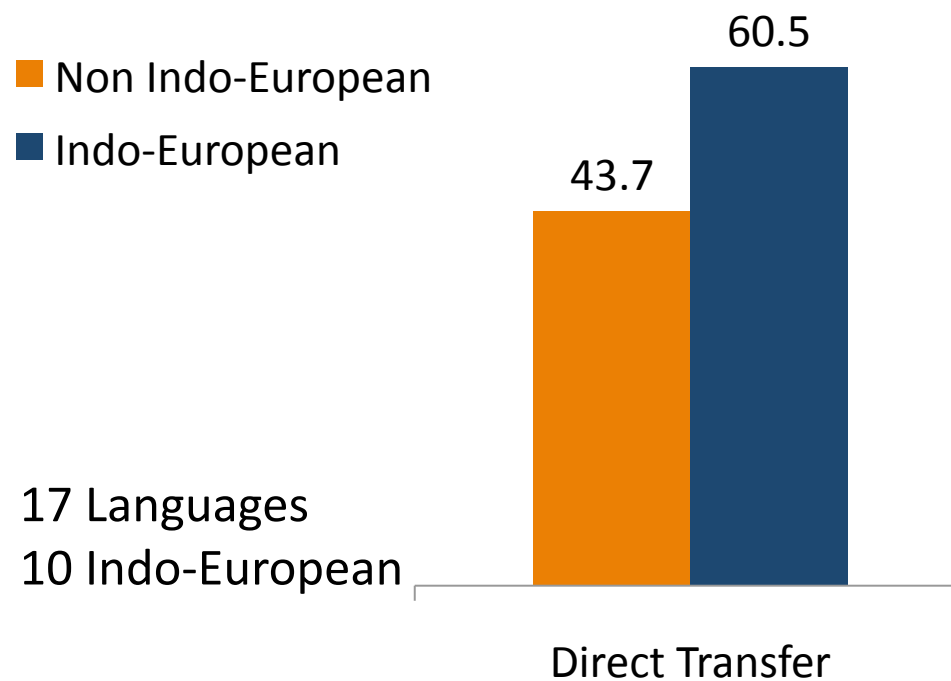
Q. What if the target language is very different?



Crosslingual Parser Transfer

Motivated by Syntactic Similarities across Languages

- Q.** What if the target language is very different?
A. Existing transfer approaches are not effective.



Crosslingual Parser Transfer

Motivated by Syntactic Similarities across Languages

Q. What if the target language is very different?

A. Existing transfer approaches are not effective.

Our approach: Selective Sharing

Accounts for both **Similarities** and **Differences**

Selective Sharing: Linguistic Basis

- **Linguistic theories:** a unified view of syntax that encodes crosslingual **similarities**
 - The definition of POS tags (Nouns, Verbs etc.) is the same across languages
 - All languages are analyzed into NP's, VP's, PP's etc.
- **Linguistic typology:** systematic study of crosslingual **differences**
 - Prefixing vs. Postfixing languages
 - Preposition vs. Postposition

John ate red apples

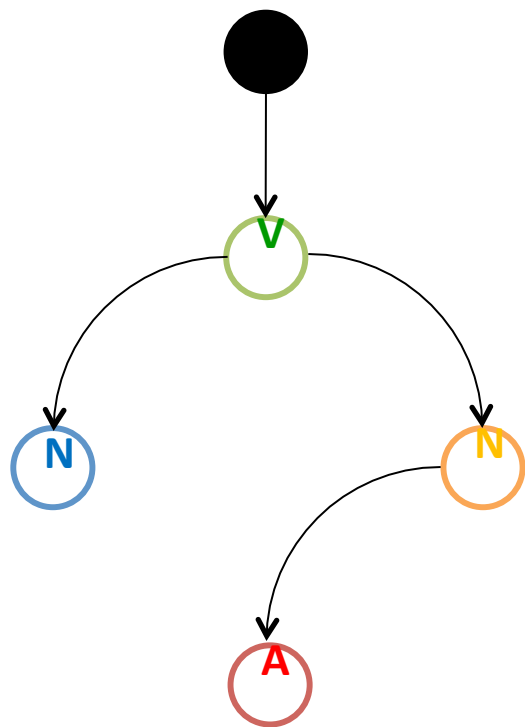
N V A N

João comeu maçãs vermelhas

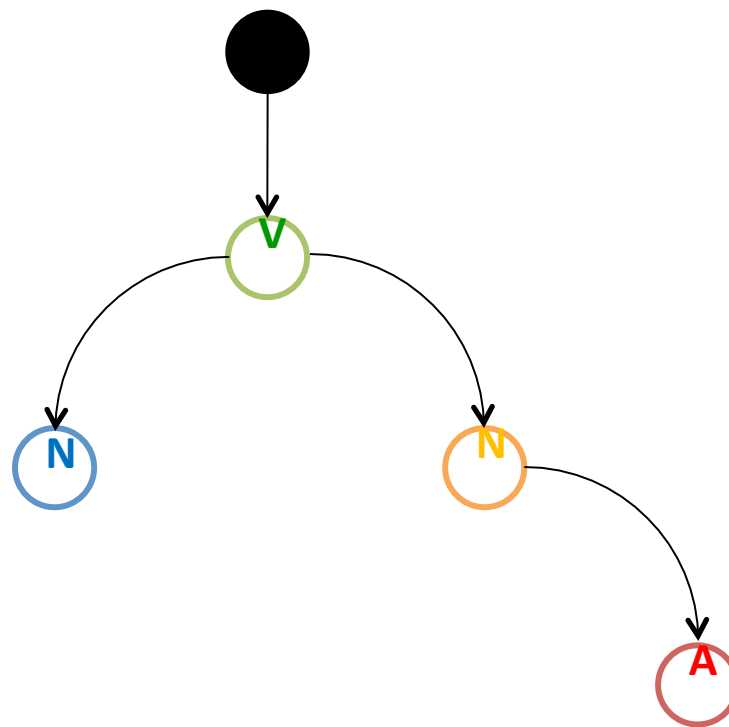
N V N A

أكلت جون التفاح الأحمر

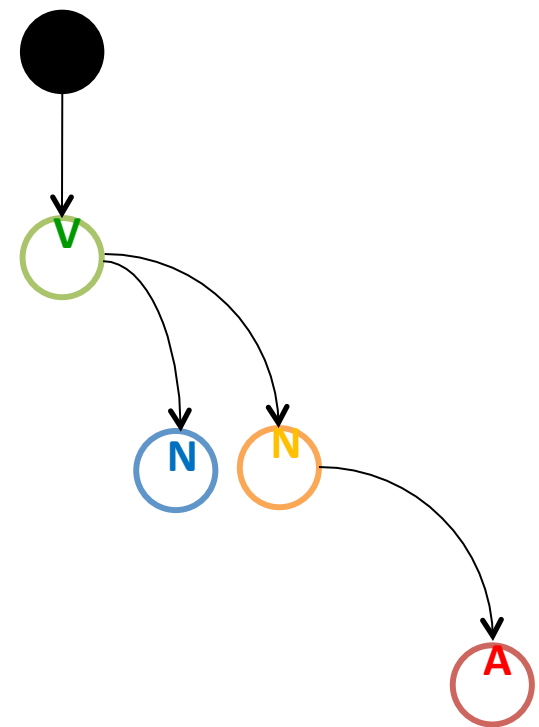
V N N A



English

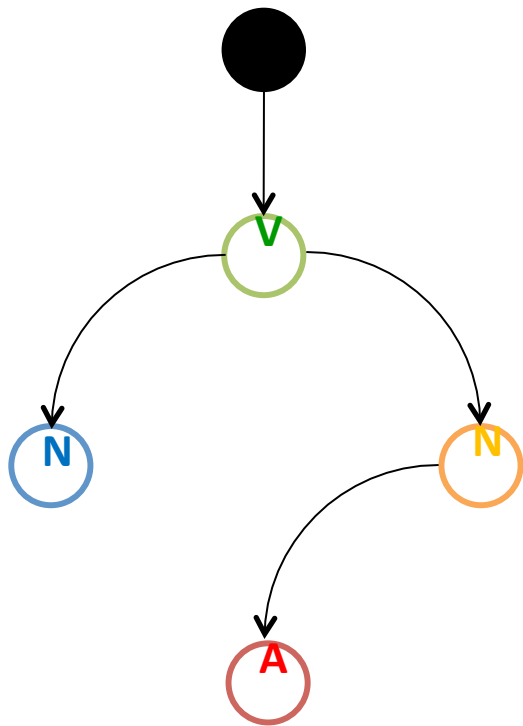


Portuguese

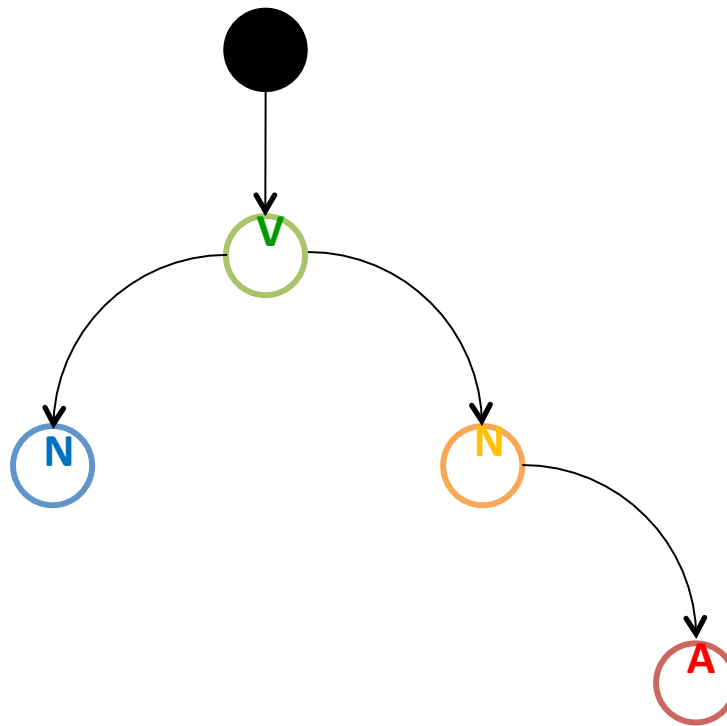


Arabic

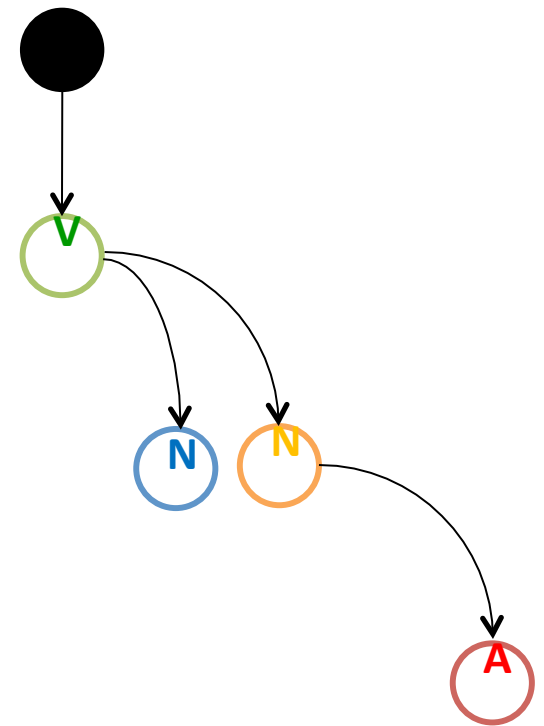
What is language-universal?



English

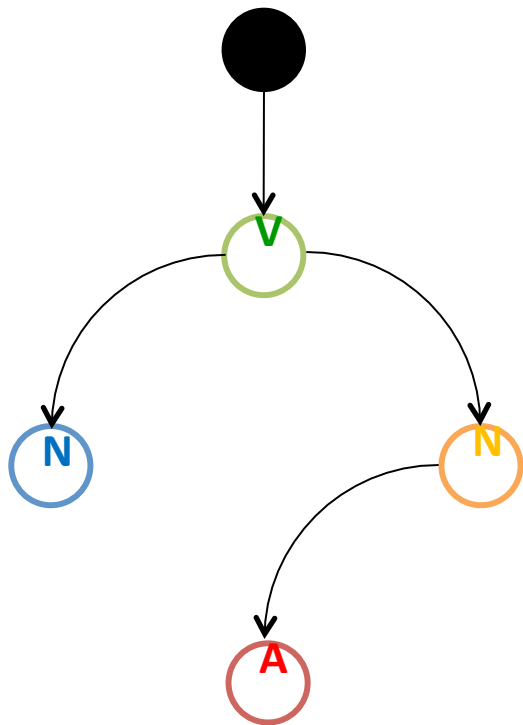
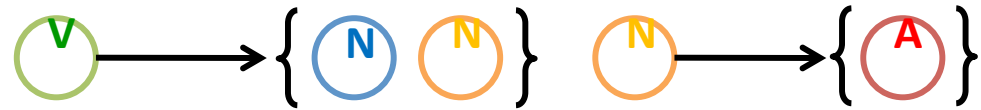


Portuguese

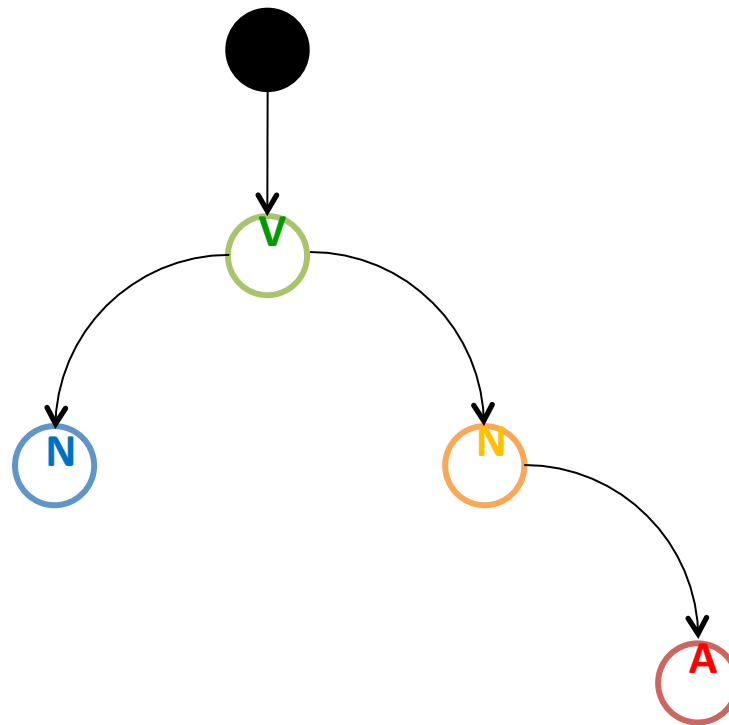


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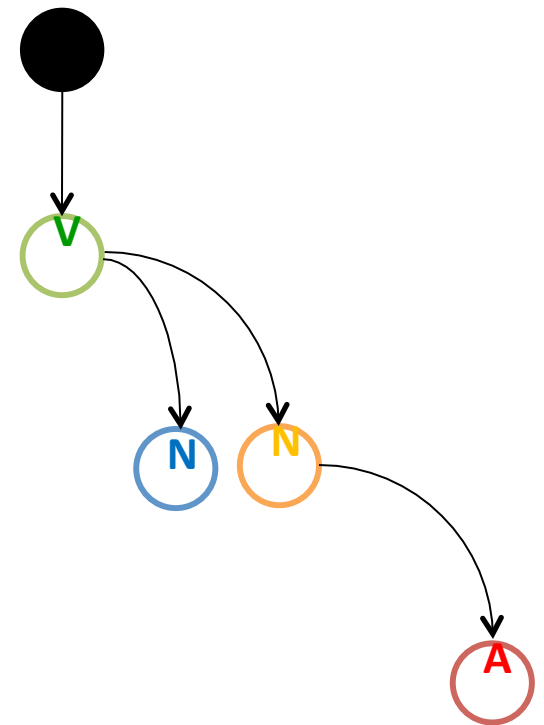
What is language-universal? dependent *“Selection”*



English

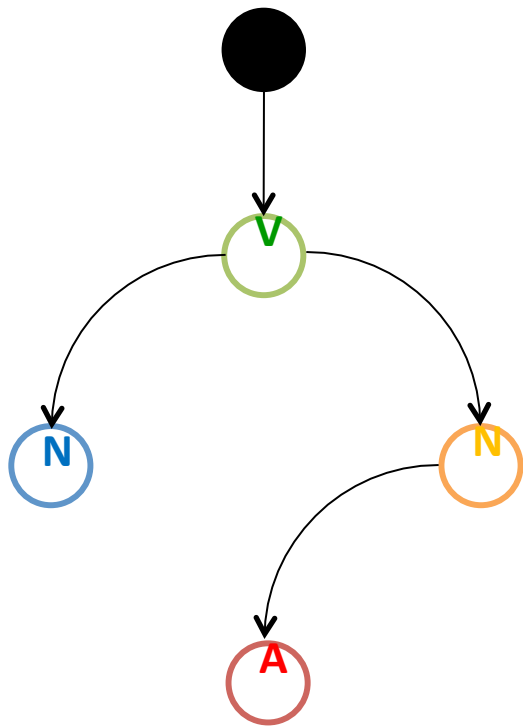


Portuguese

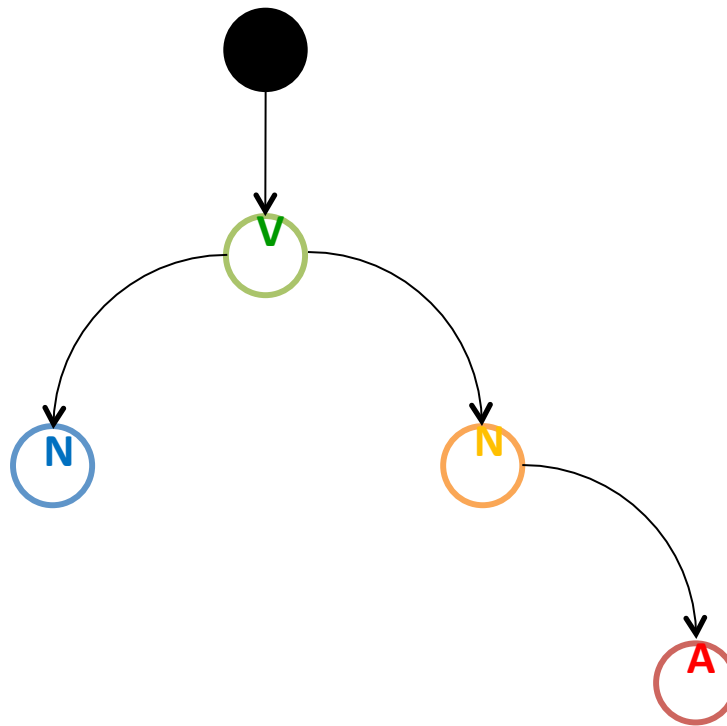


Arabic

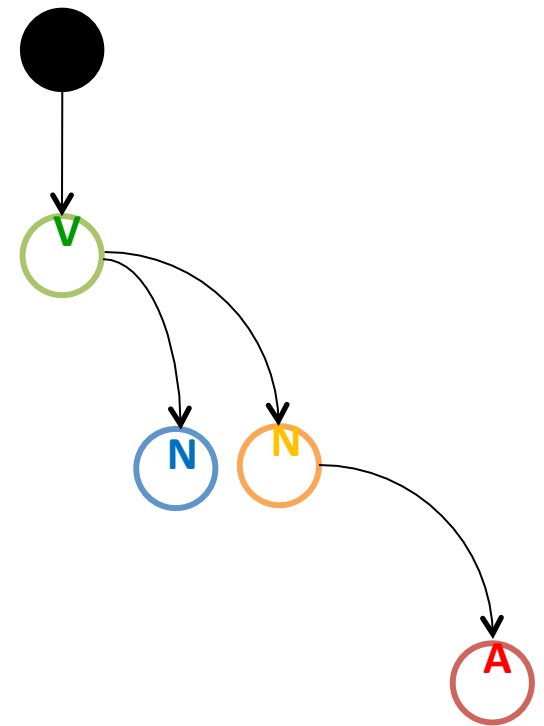
What is language-specific? ... ordering



English



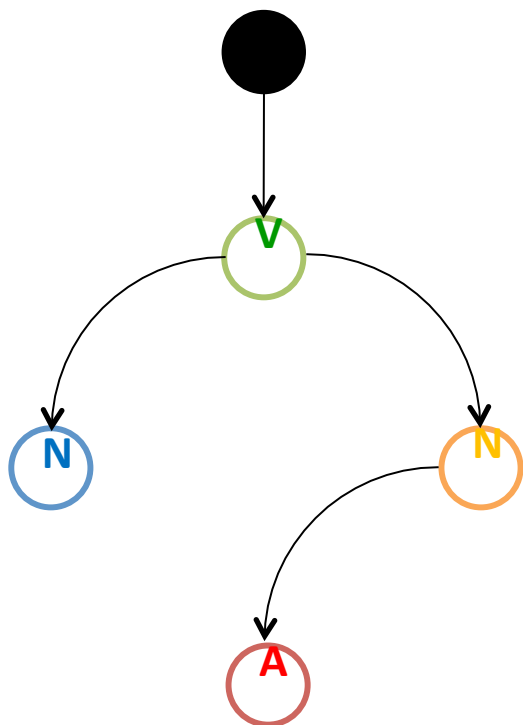
Portuguese



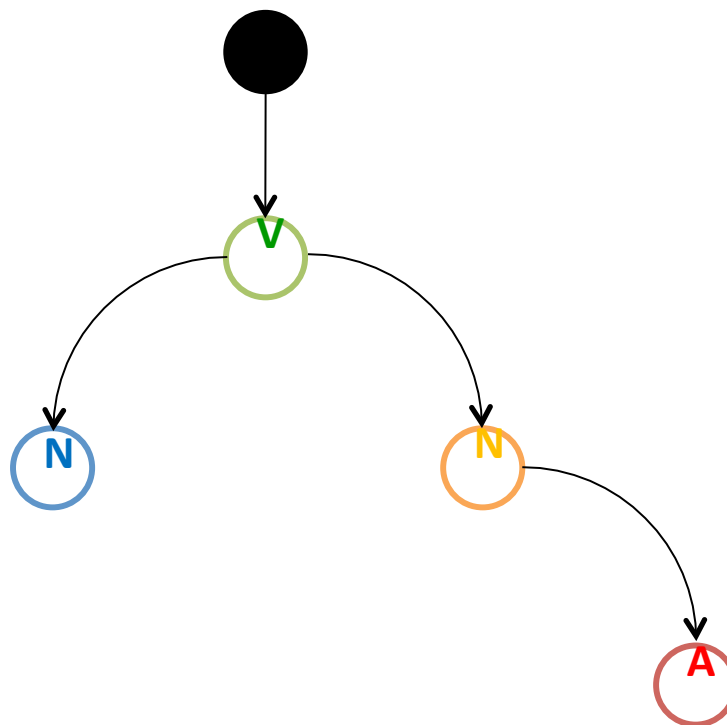
Arabic

“Ordering”

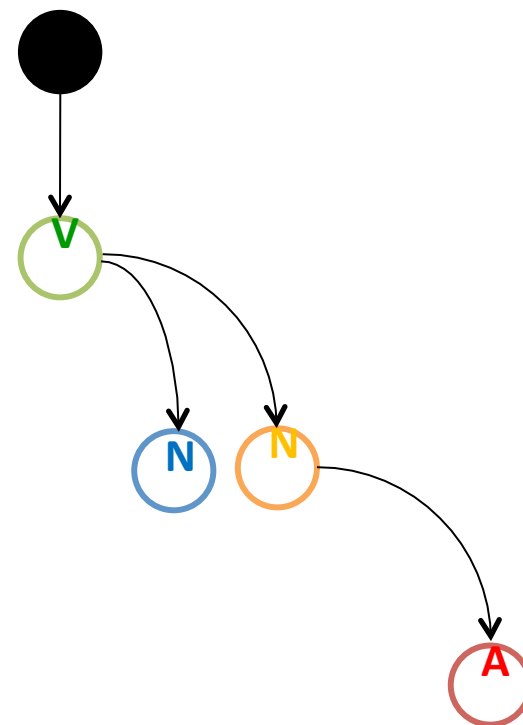
typological features can guide



English



Portuguese



Arabic

Model

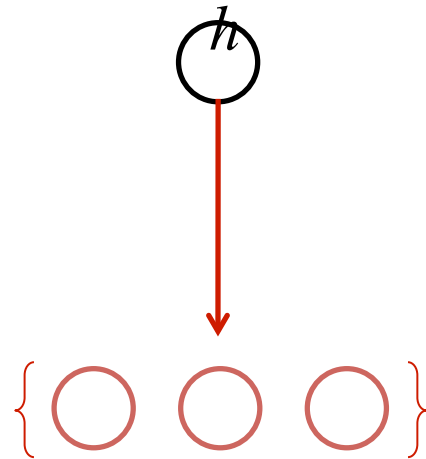
- Separate “*Selection*” from “*Ordering*”
 - *Selection* is fully shared across all languages
 - *Ordering* is selectively shared across languages
(sharing is guided by typology)

Generative Process



Generative Process: Selection

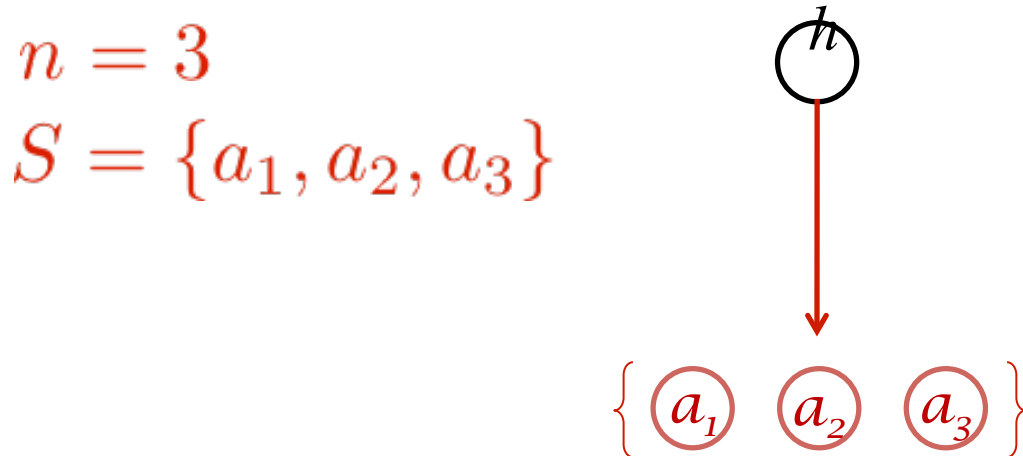
$n = 3$



Select the number n of arguments

$$P(n|h) = \theta(n|h)$$

Generative Process: Selection



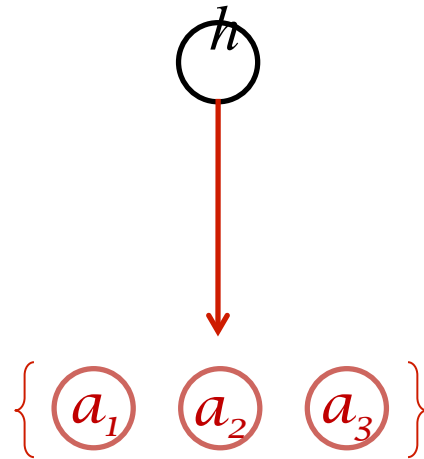
Select the set S of arguments

$$P(S|h, n) = \frac{e^{\mathbf{w}_{sel} \cdot \mathbf{f}(S, h, n)}}{Z_{h, n}}$$

Generative Process: Selection

$$n = 3$$

$$S = \{a_1, a_2, a_3\}$$

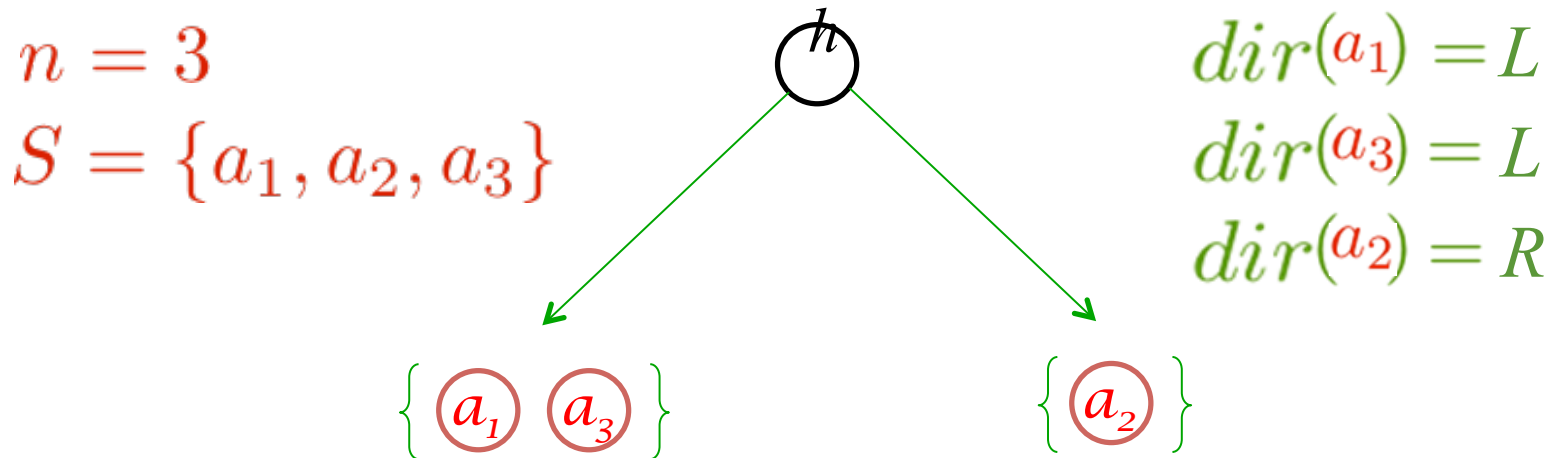


Only pair-wise
parent-child
features

Select the set S of arguments

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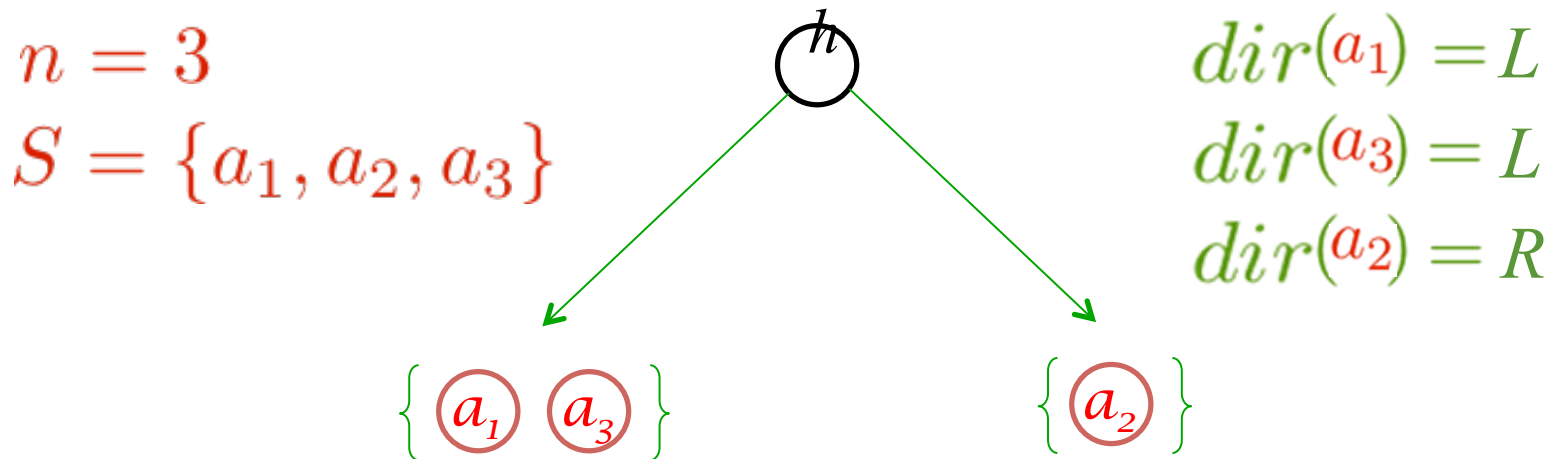
Generative Process: Ordering



for each argument select *dir* (right/left) w.r.t. head

$$P(dir|a, h, l) = \frac{e^{\mathbf{w}_{ord} \cdot \mathbf{f}(dir, a, h, \mathbf{v}_l)}}{Z_{a, h, l}}$$

Generative Process: Ordering



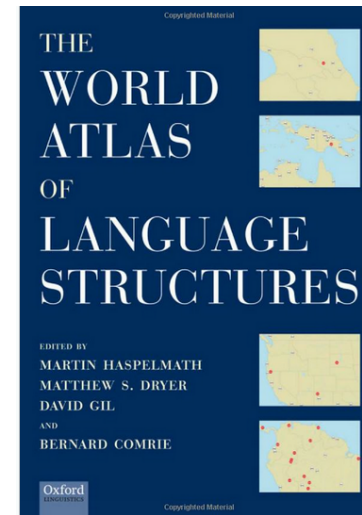
Ordering depends on language specific features

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Generative Process: Ordering Guided by Typology

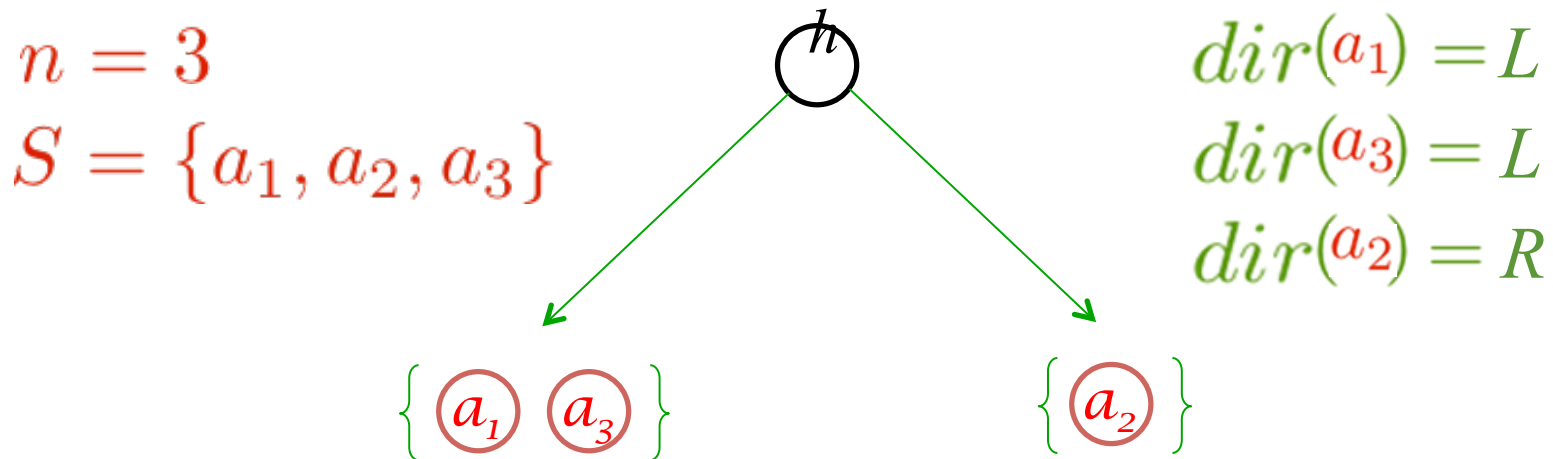
Typological Features

1. Order of Subject, Object and Verb
2. Order of Adposition and Noun
3. Order of Genitive and Noun
4. Order of Adjective and Noun
5. Order of Demonstrative and Noun
6. Order of Numeral and Noun



- Correspondence between the features and the parameters is learned automatically.
- These features do not cover all ordering decisions.

Generative Process: Ordering



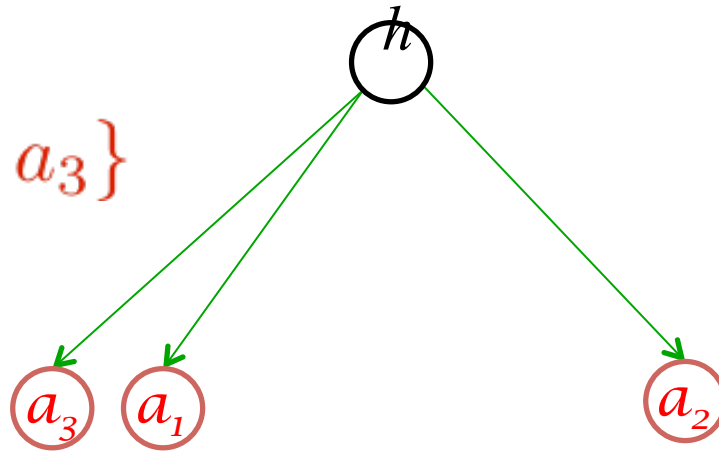
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Generative Process: Ordering

$$n = 3$$

$$S = \{a_1, a_2, a_3\}$$



$$dir(a_1) = L$$

$$dir(a_3) = L$$

$$dir(a_2) = R$$

Select the **internal order** of right/left arguments
Uniformly from among all possible orderings

Model Parameters

- Distribution over number of arguments given the parent tag $\theta(n|h)$
- Weights for selection features, shared across all set sizes

$$P(S|h, n) = \frac{e^{\mathbf{w}_{sel} \cdot \mathbf{f}(S, h, n)}}{Z_{h, n}}$$

- Weights for ordering features

$$P(dir|a, h, l) = \frac{e^{\mathbf{w}_{ord} \cdot \mathbf{f}(dir, a, h, \mathbf{v}_l)}}{Z_{a, h, l}}$$

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All parameters are shared across languages

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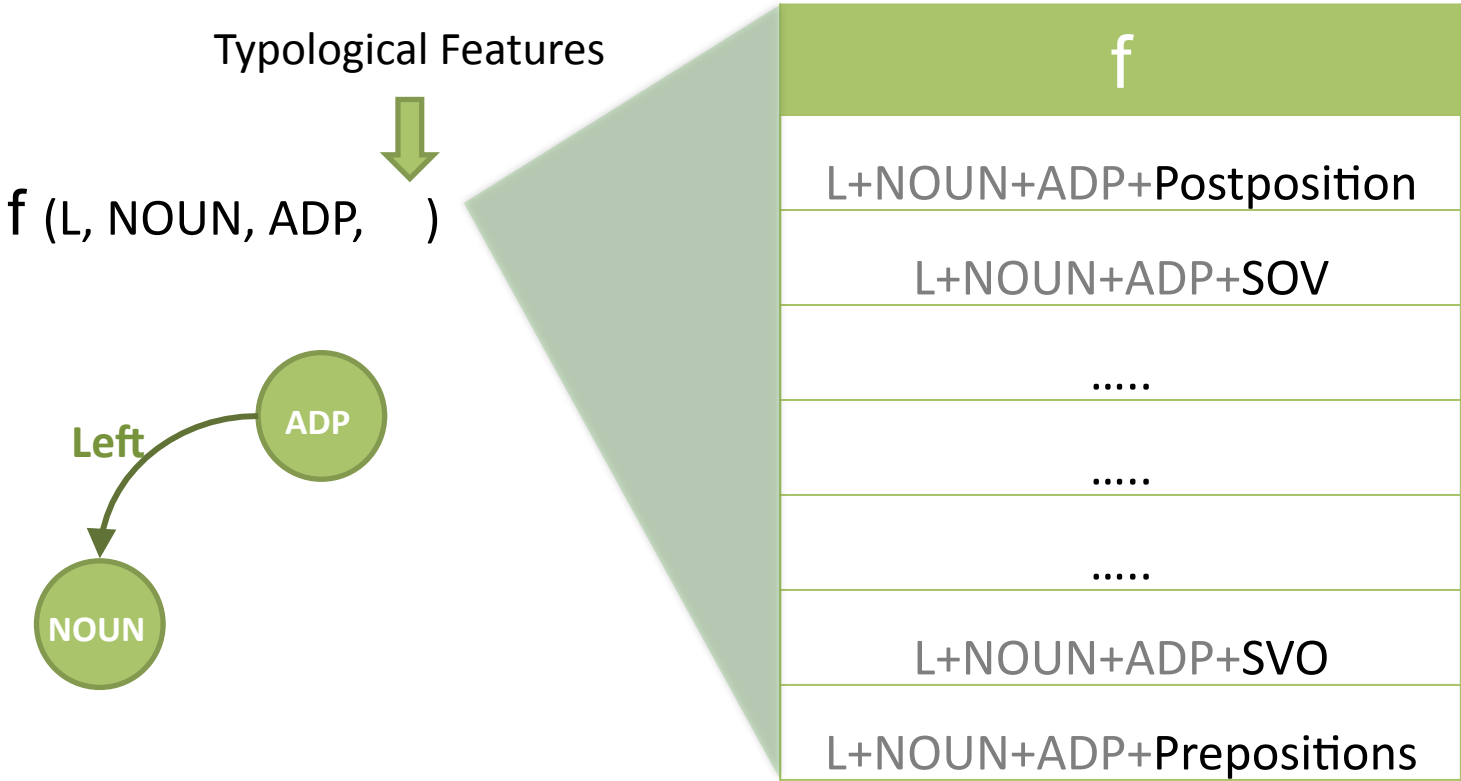
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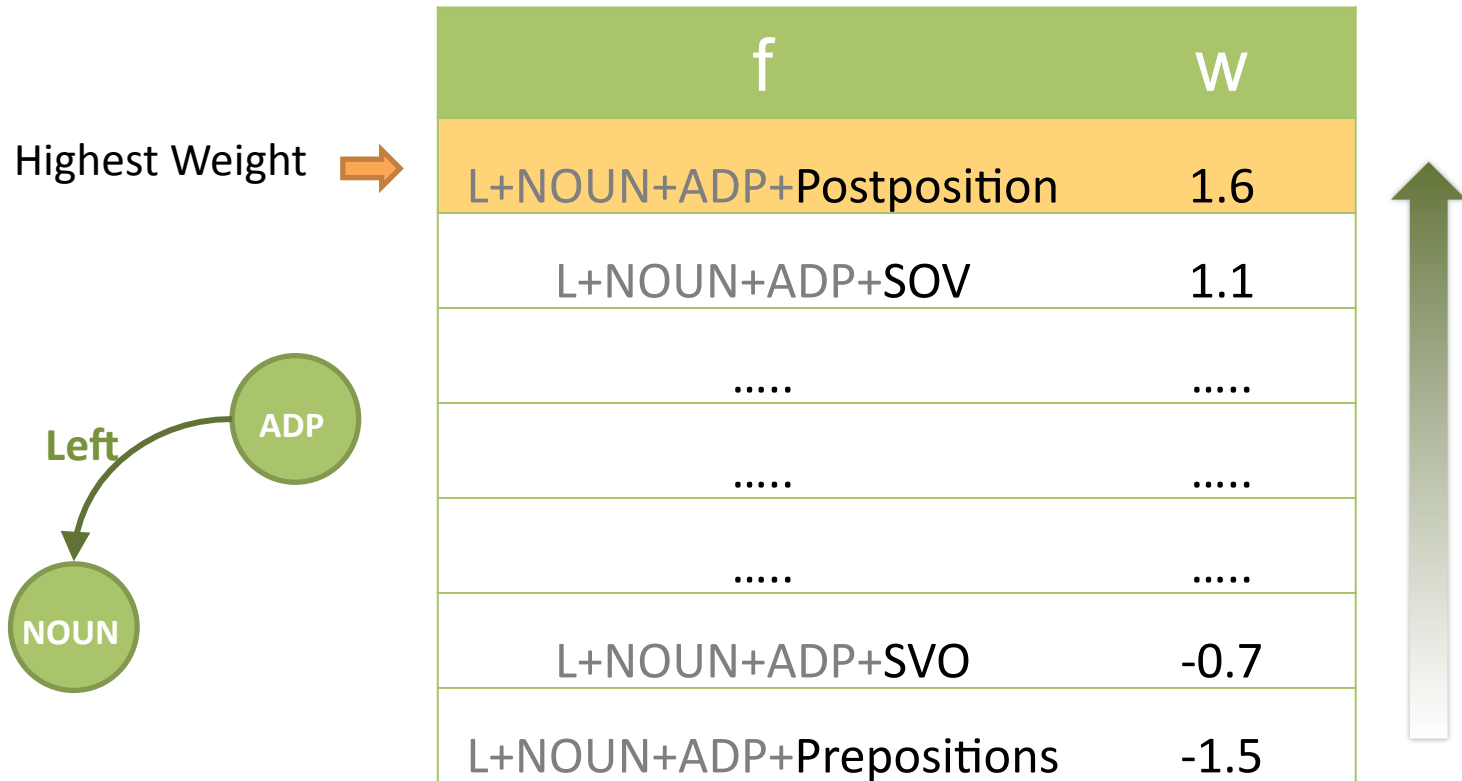
Setup

- For all languages:
 - Observed part-of-speech tags
 - Ordering features
 - **Either** observed typology for all languages
 - **Or** latent binary features for all languages
- For helper languages:
 - Observed dependency trees
- For unsupervised language:
 - Latent dependency trees

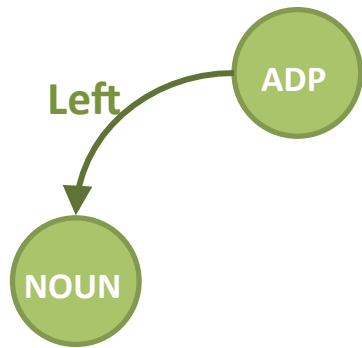
Analysis of Ordering Feature Weights



Analysis of Ordering Feature Weights



Analysis of Ordering Feature Weights



Lowest Weight →

f	W
L+NOUN+ADP+Postposition	1.6
L+NOUN+ADP+SOV	1.1
....
....
....
L+NOUN+ADP+SVO	-0.7
L+NOUN+ADP+Prepositions	-1.5



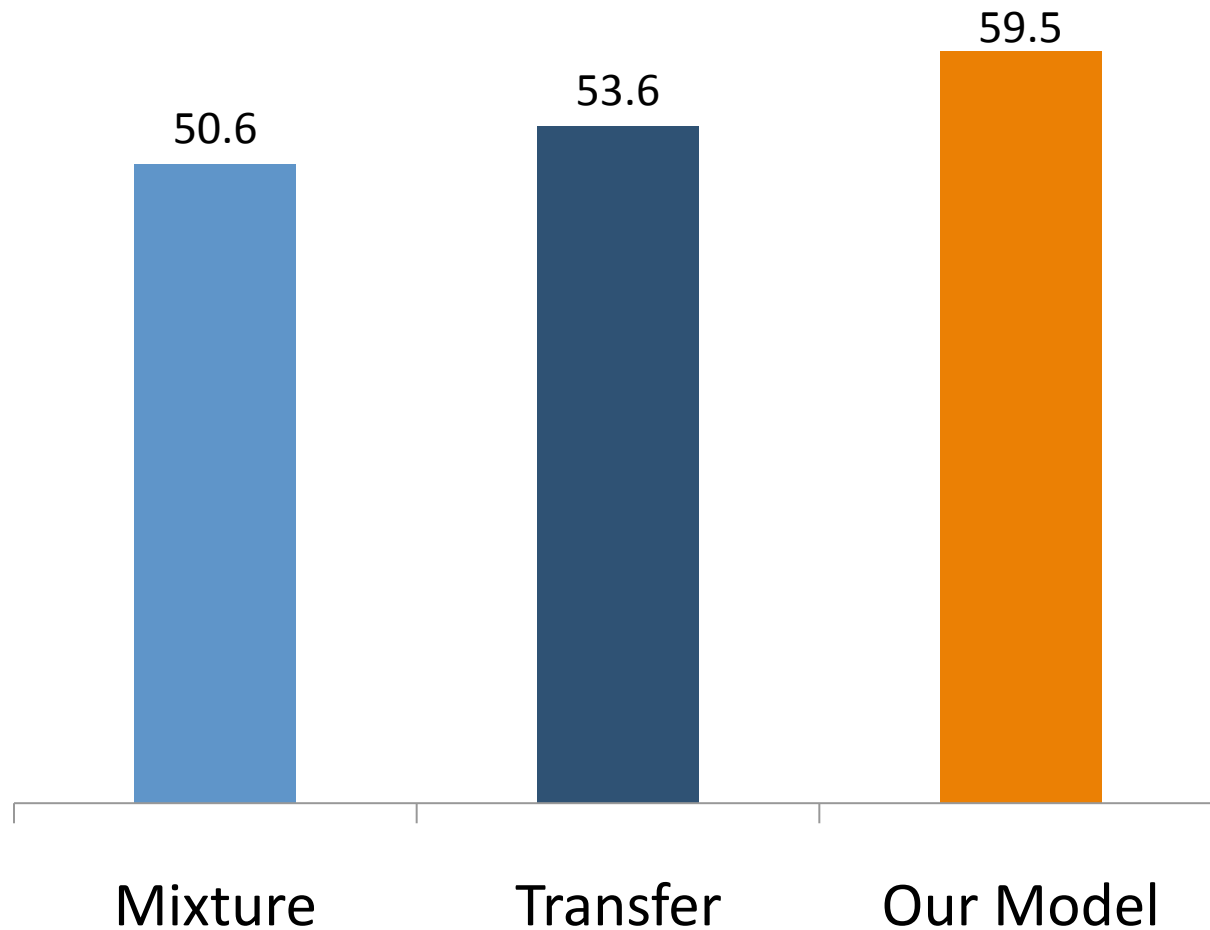
Learning

- Optimizes the log-likelihood of data
 - Standard Expectation Maximization
 - Marginalize over all latent variables
 - M-Step requires gradient search
 - Posterior Constraint on dependency length
(Graca et. al. 2008)

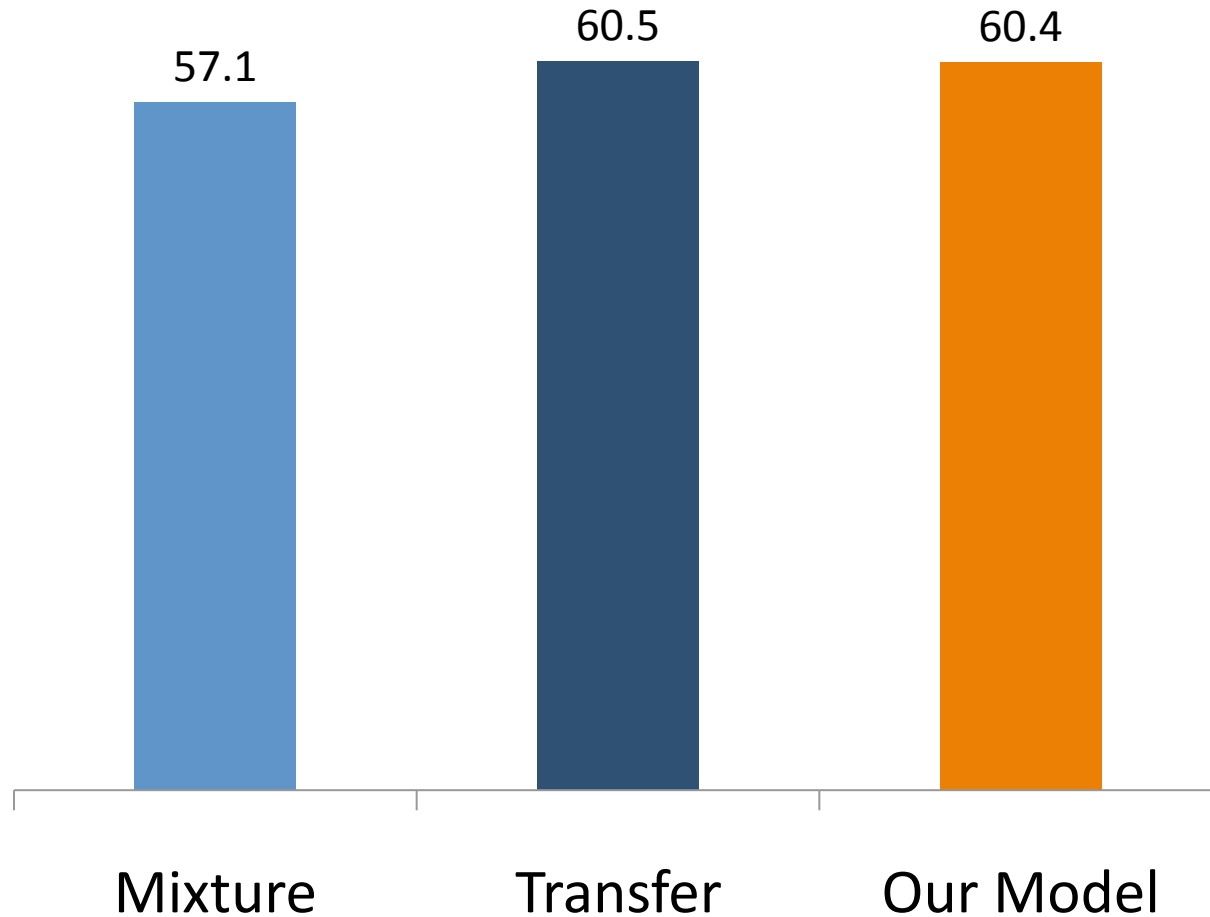
Experiments & Results

- **17** languages from **10** families:
Arabic, Basque, Bulgarian, Catalan, Chinese, Czech, Dutch, English, German, Greek, Hungarian, Italian, Japanese, Portuguese, Spanish, Swedish and Turkish
- CoNLL 2006 and 2007 datasets
- Sentences of length ≤ 50
- Baselines:
 - Transfer (McDonald et al., 2011)
 - Mixture (Cohen et al., 2011)

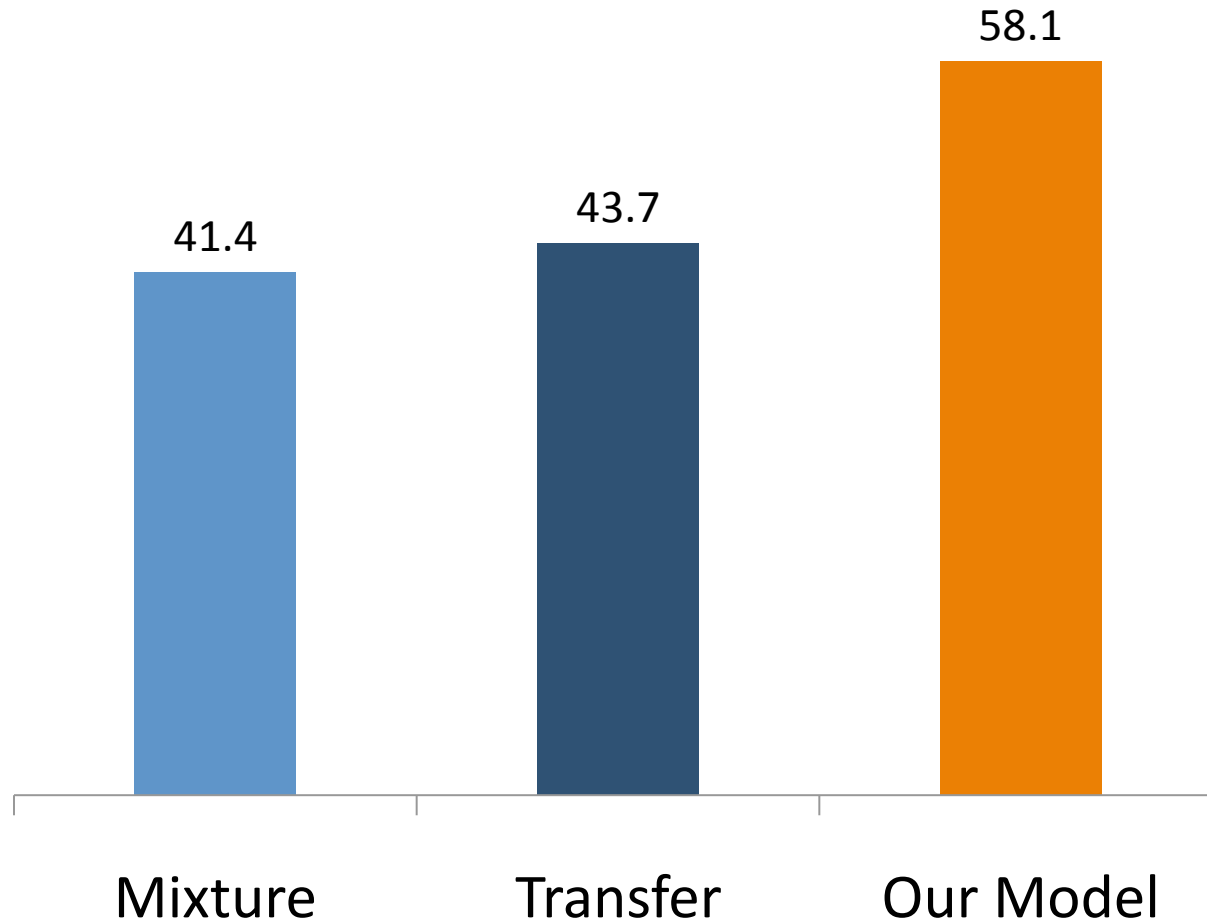
Comparison with the Baselines



Indo-European Languages



Non Indo-European Languages



Contributions

- Developed a novel generative model for multilingual parsing to incorporate linguistic knowledge
- Separated selection from ordering in the generative model in order to enable more effective parser transfer
- Designed a selective sharing mechanism for ordering parameters
- **Better dependency parsers that work across a variety of language families are crucial to robust text analysis and tree-to-tree MT systems**

Next Steps

- Lexicalization – incorporation of lexical selection parameters into the model
 - Unsupervised learning on target language
 - Transfer of lexical selection parameters from helper languages through bilingual lexicons
- Development of algorithms for learning typological features of resource-poor languages
- Testing and evaluation on focus languages