Carnegie Mellon University

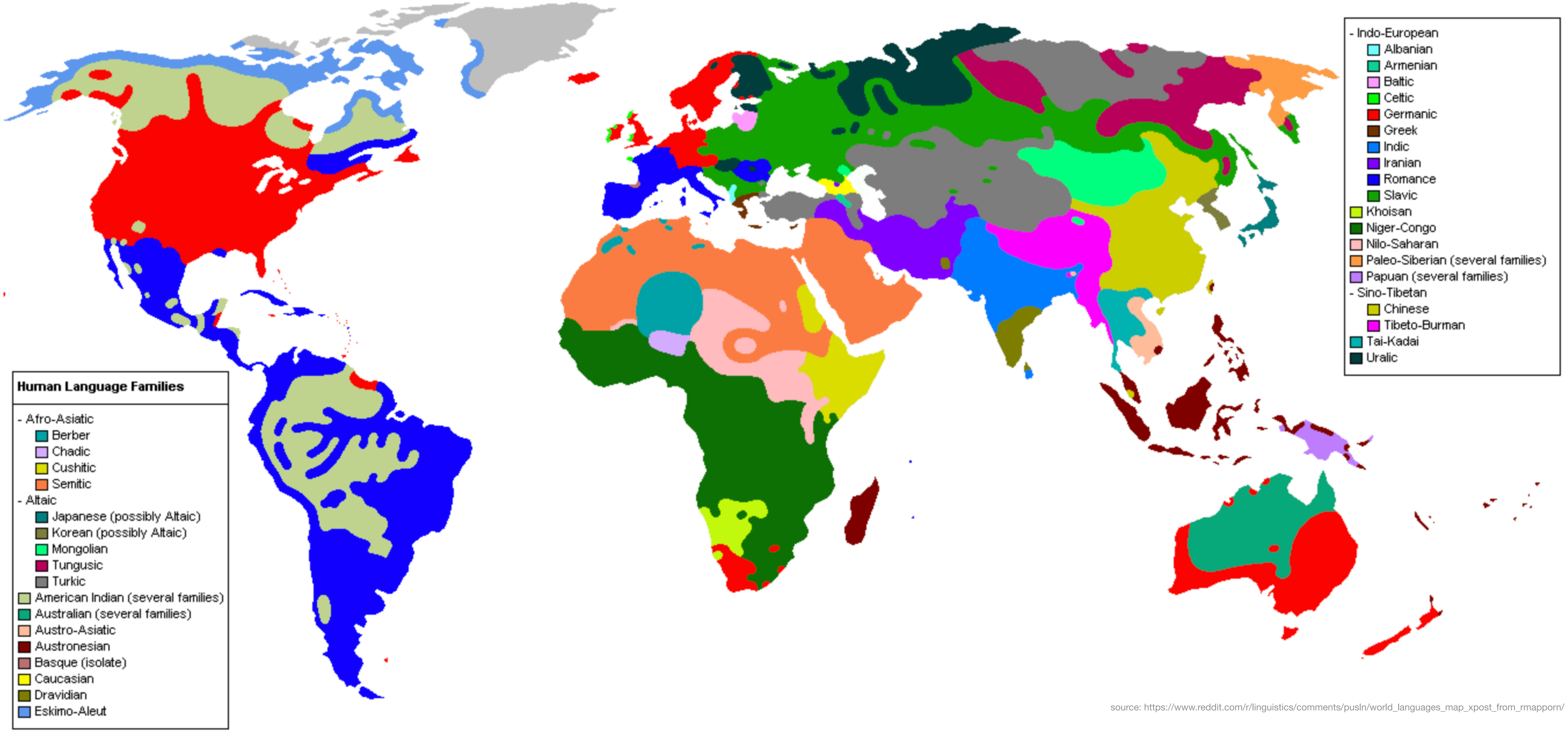
Can we Automatically Create Language-learning Textbooks?

https://www.autolex.co/

Graham Neubig

w/ Aditi Chaudhary

Antonios Anastasopoulos, David Mortensen, Zaid Sheikh, Arun Sampath, Ashwin Sheshadri, Adithya Pratapa, Yulia Tsvetkov, Kayo Yin



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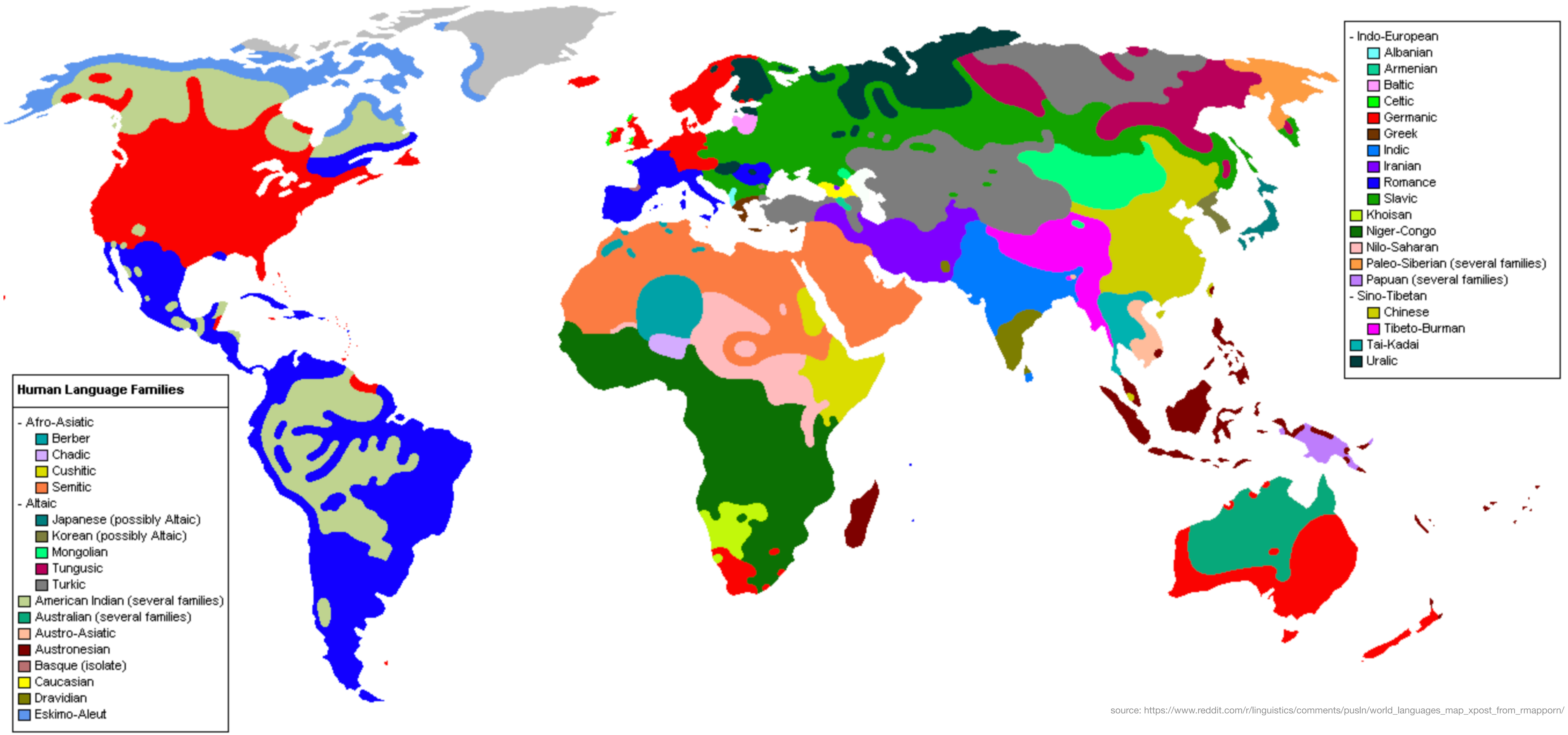

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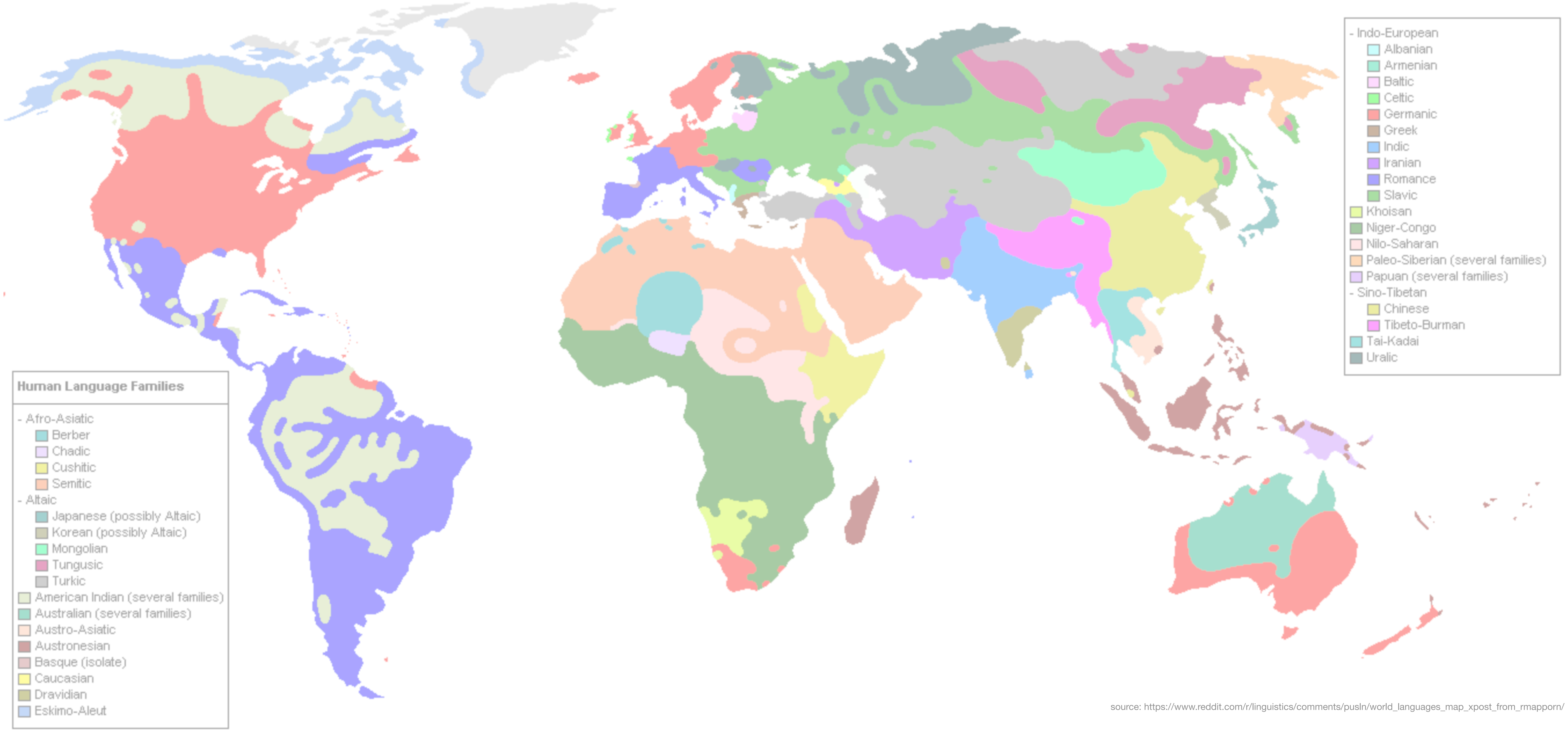
Remarkable language diversity!



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Remarkable language diversity!

Anna is eating an apple

आना सफरचंद खाते आहे

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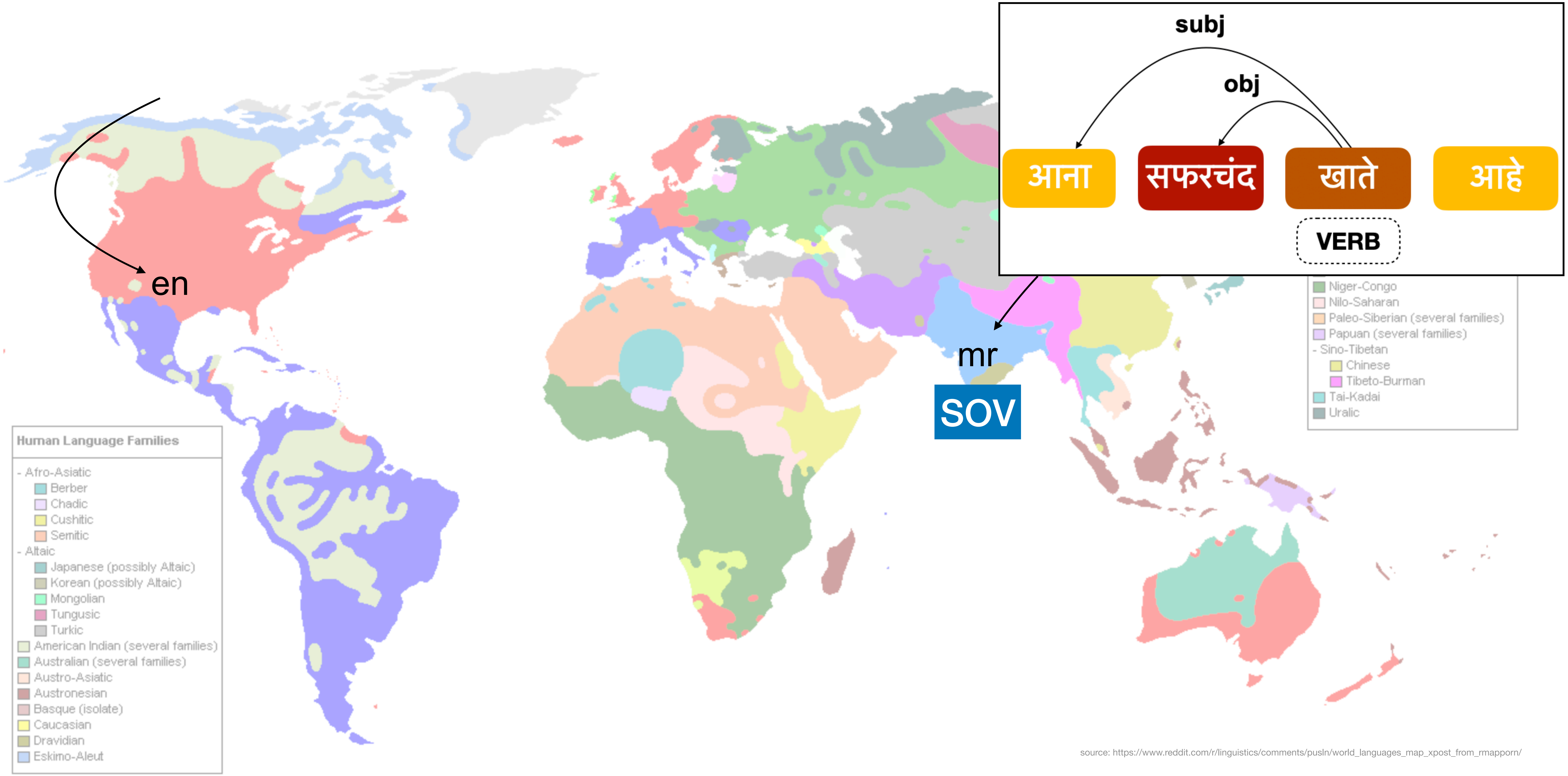

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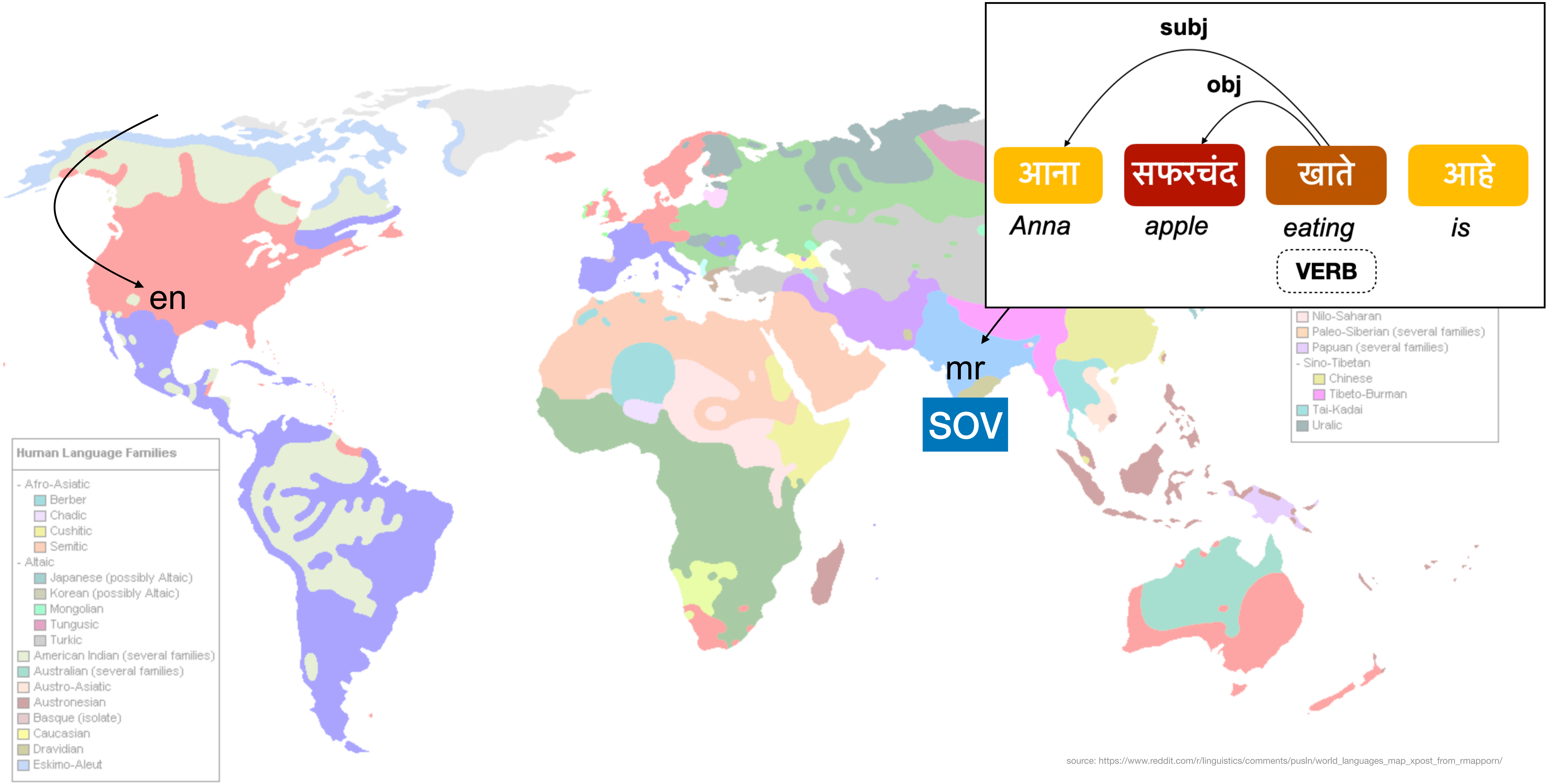

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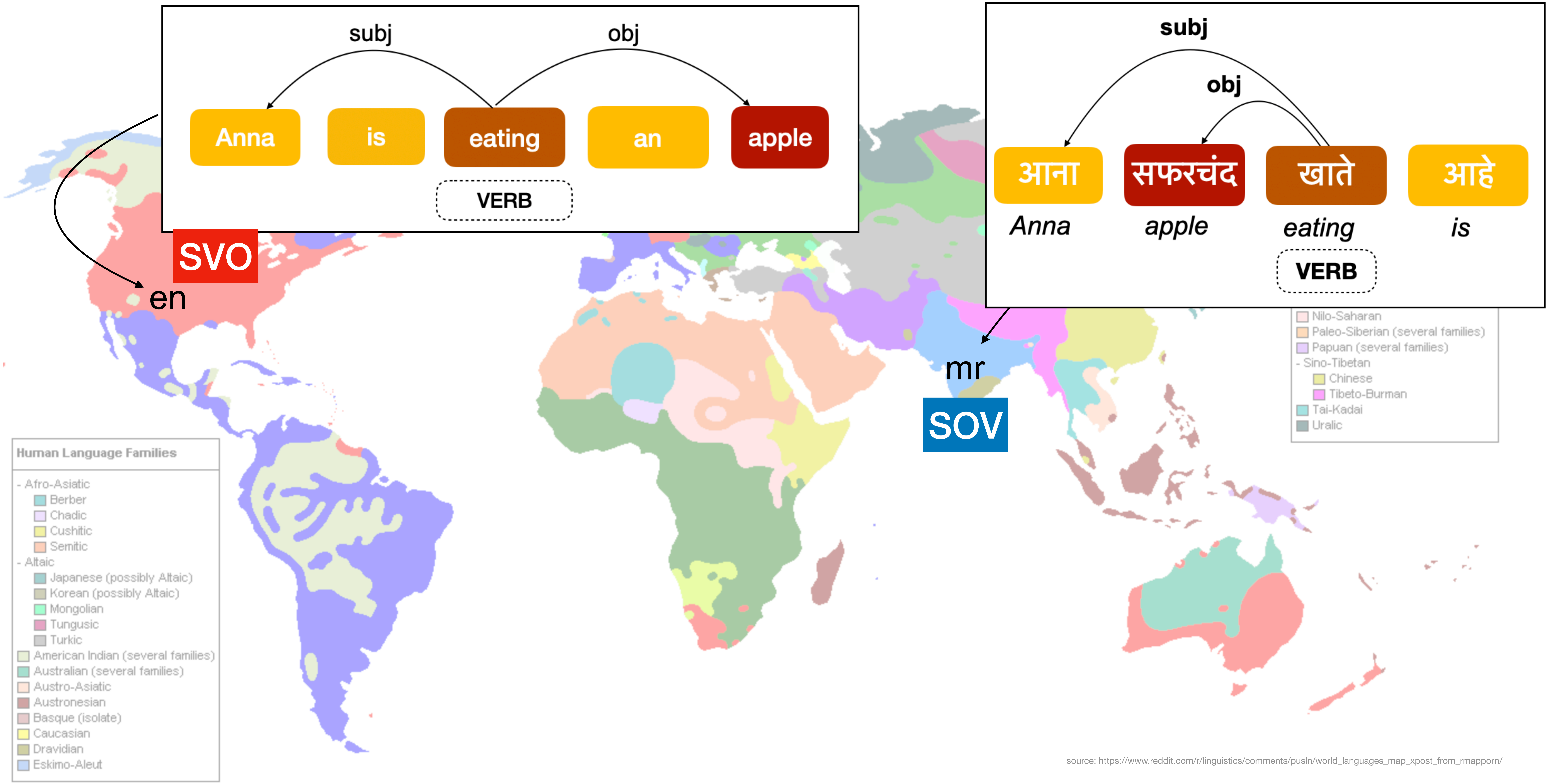

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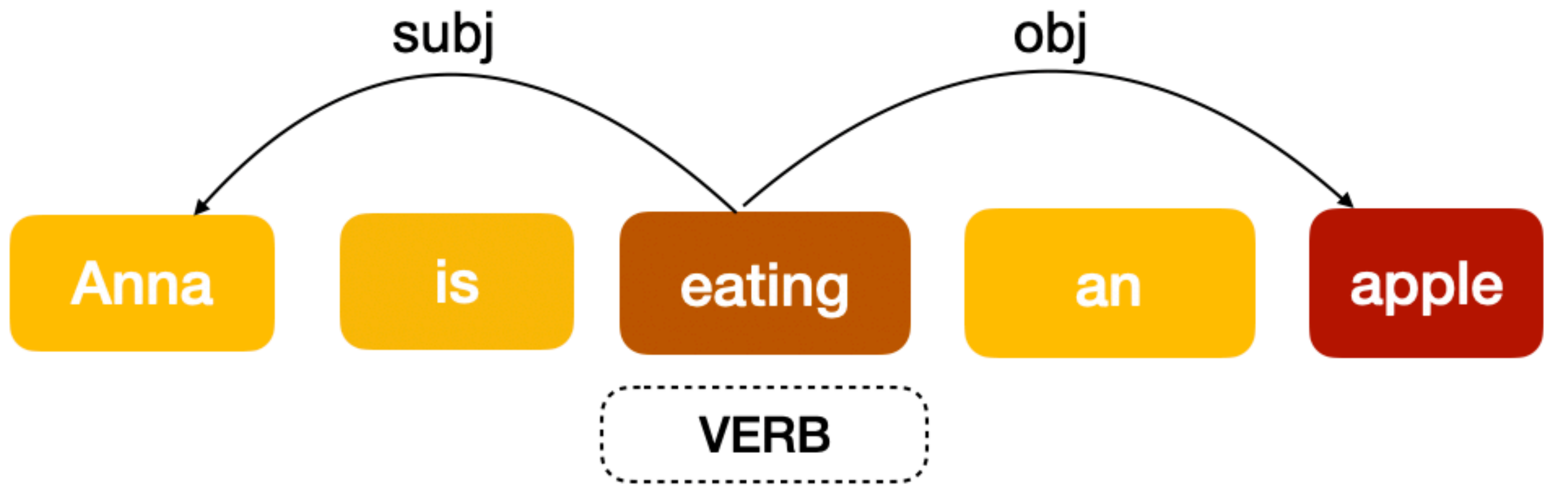
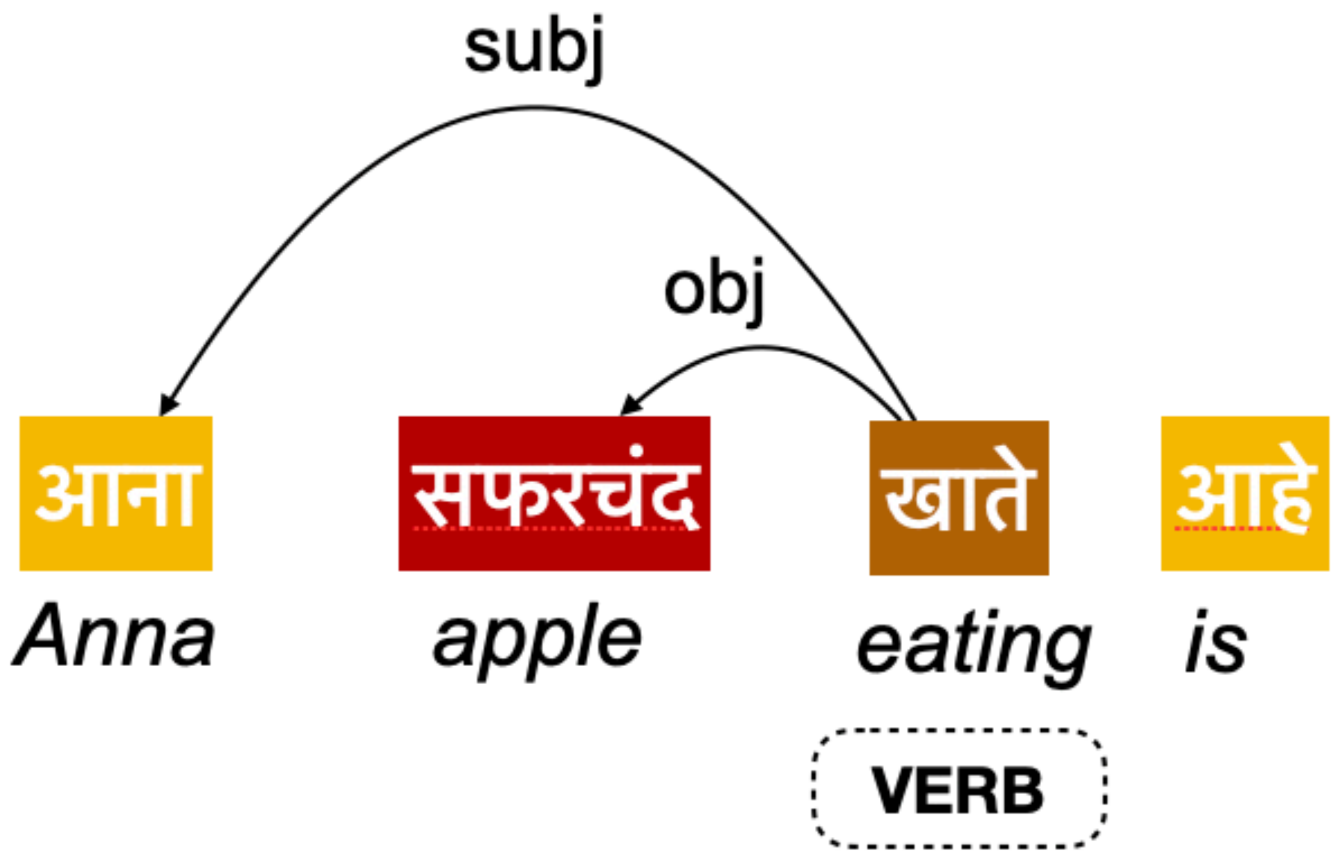
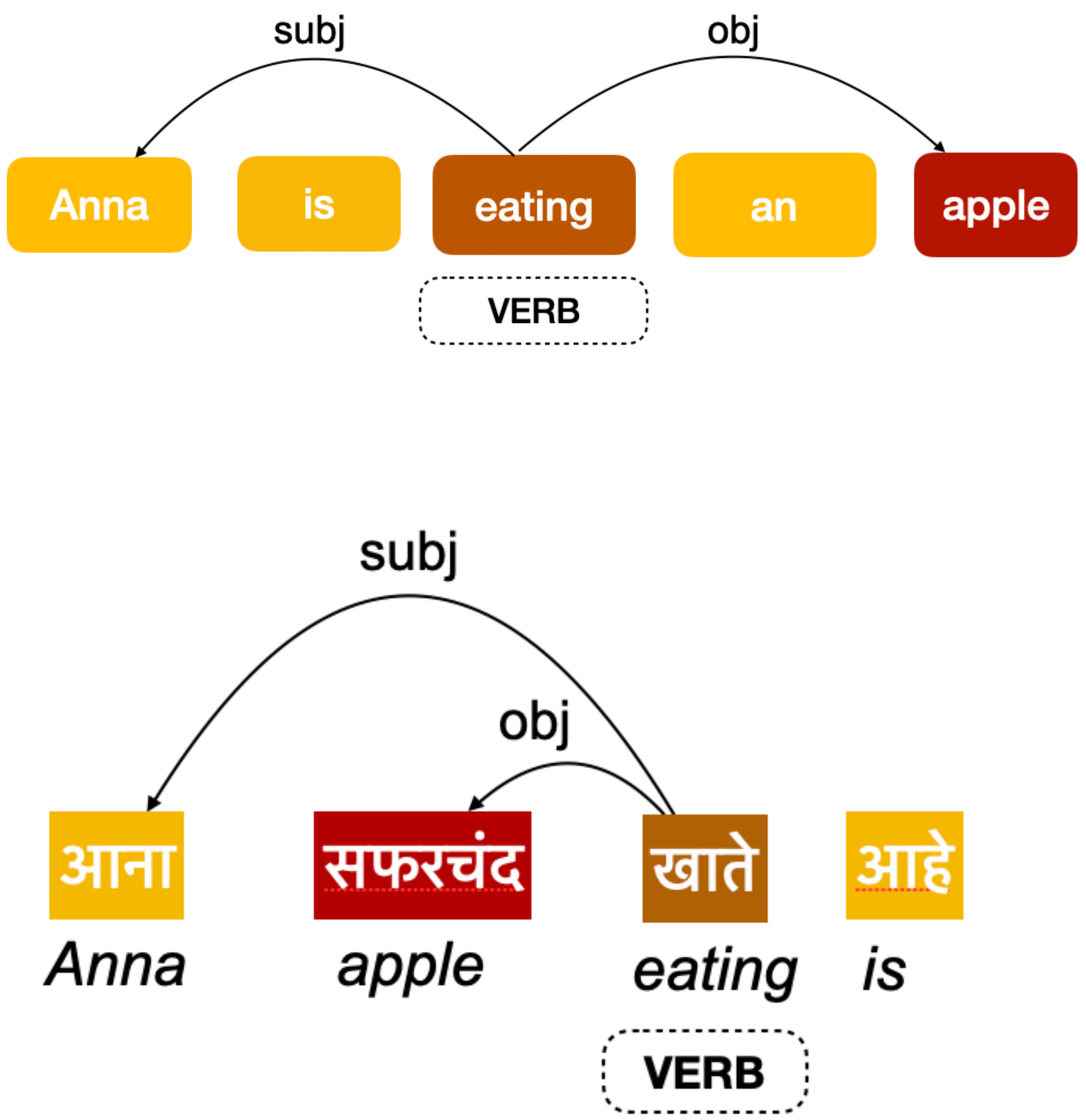
Different Systems Governing Language





Syntax

Different Systems Governing Language



subj obj

Anna is eating an apple

VERB

subj obj

आना सफरचंद खाते आहे

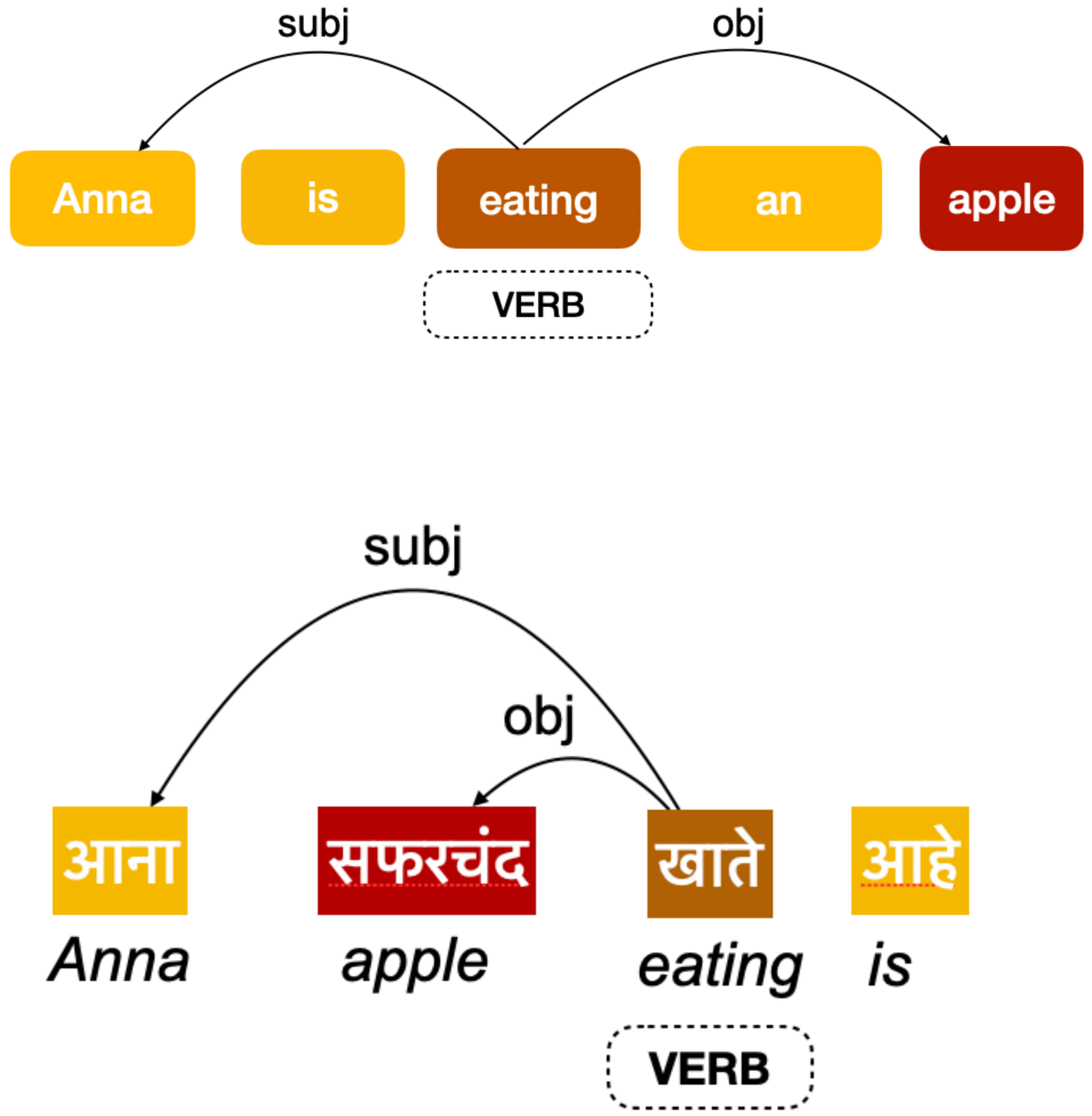
Anna apple eating is

VERB

Syntax

Morphology

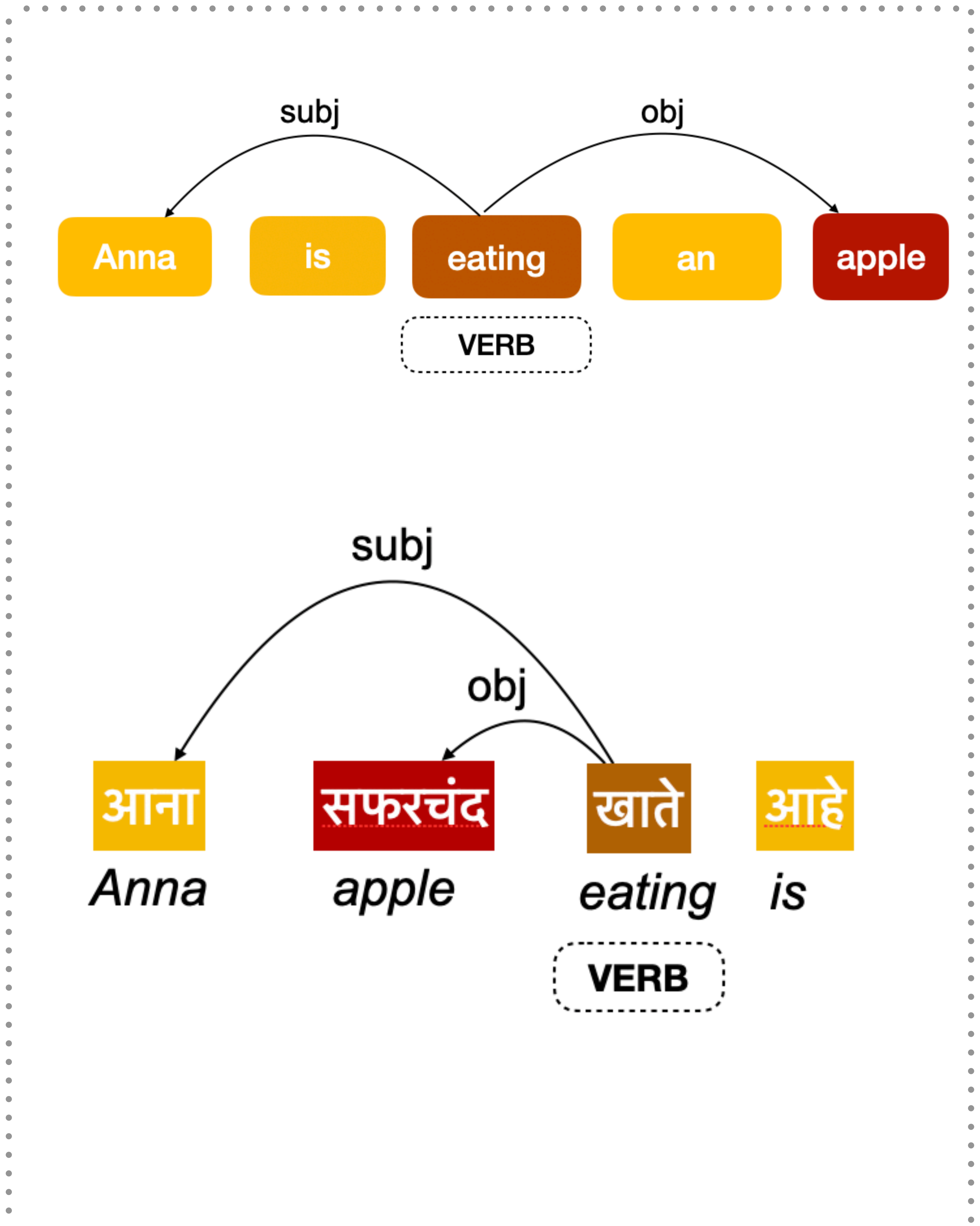
Different Systems Governing Language



Syntax

Morphology

Different Systems Governing Language



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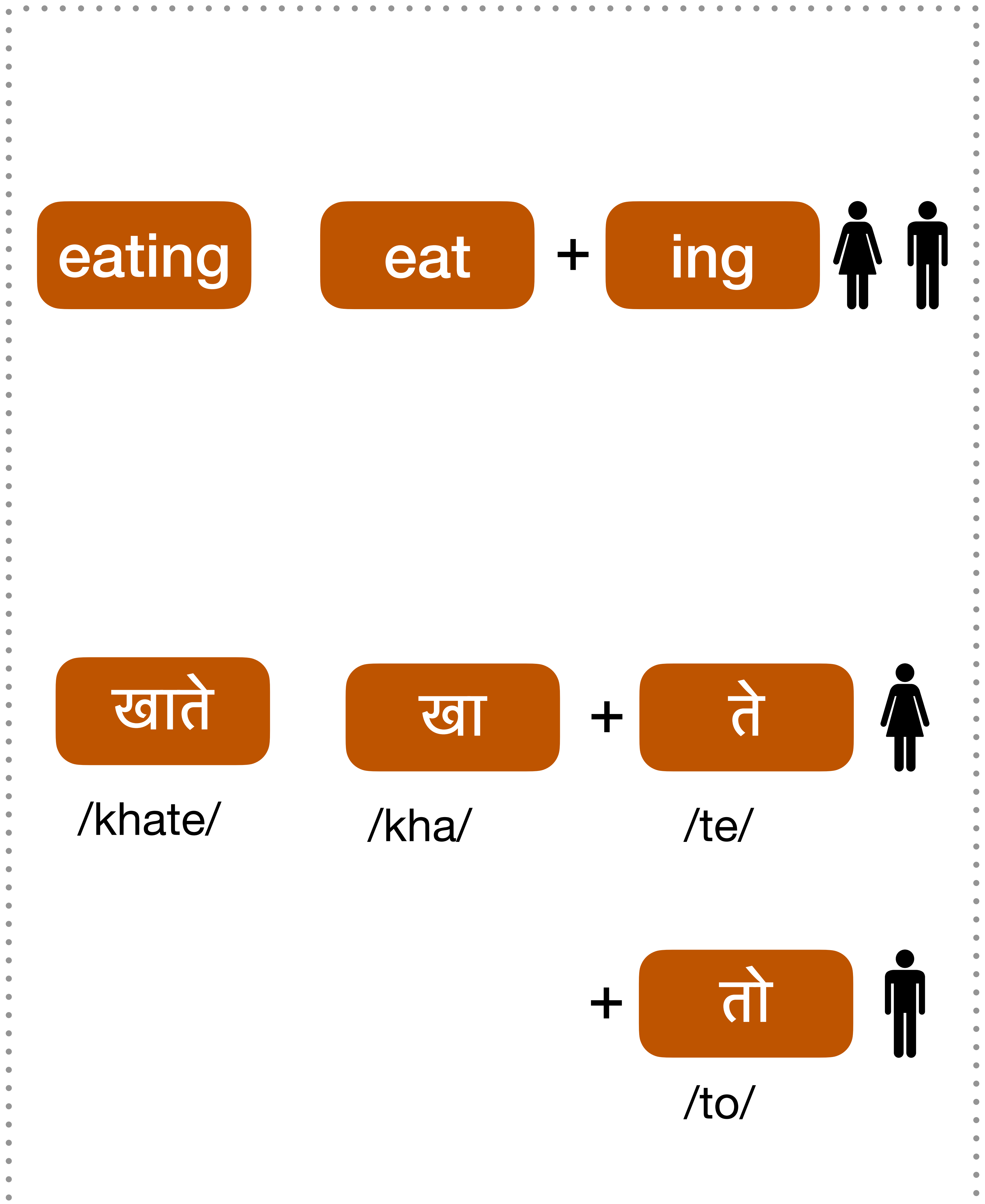

Morphology

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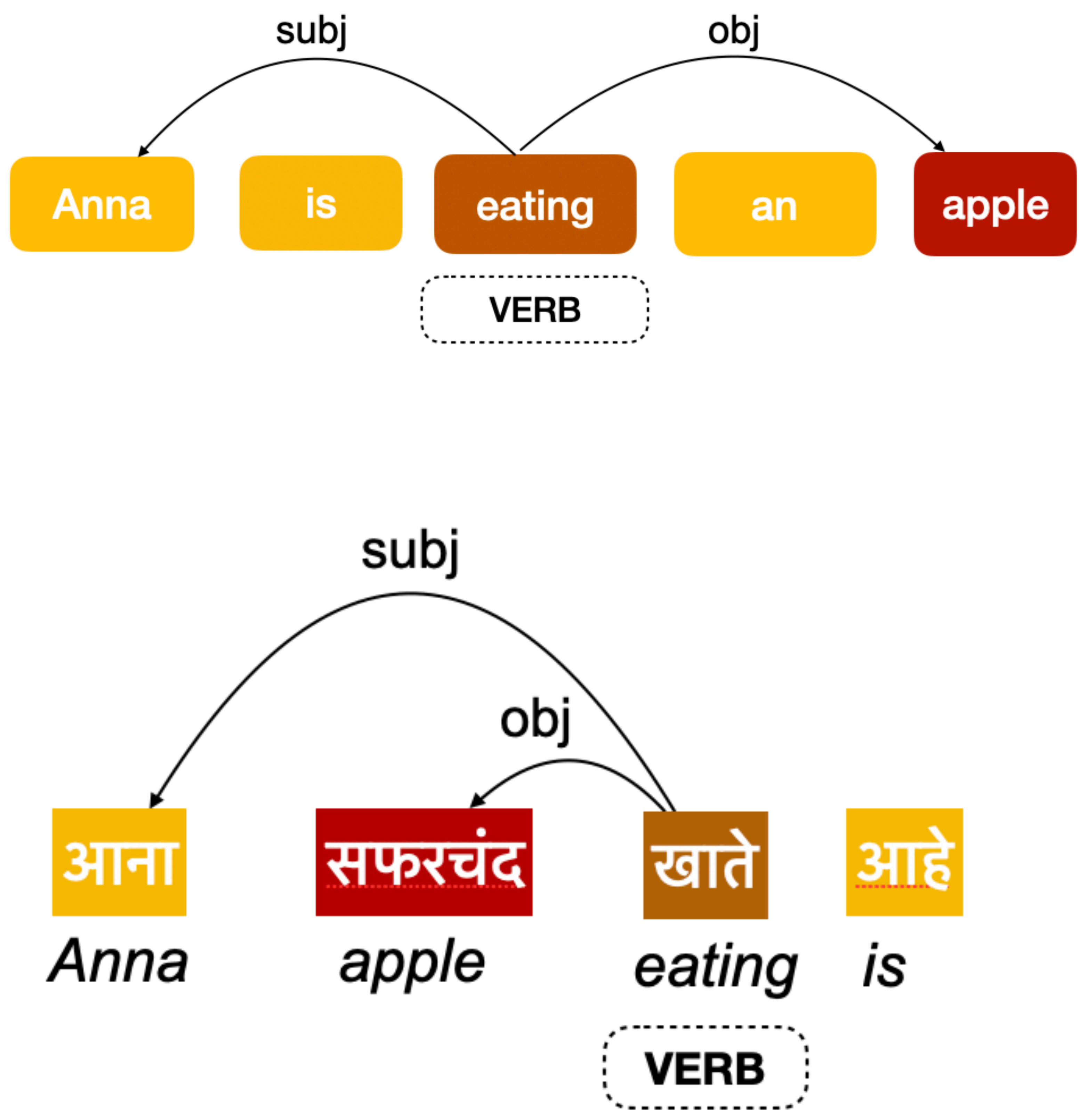

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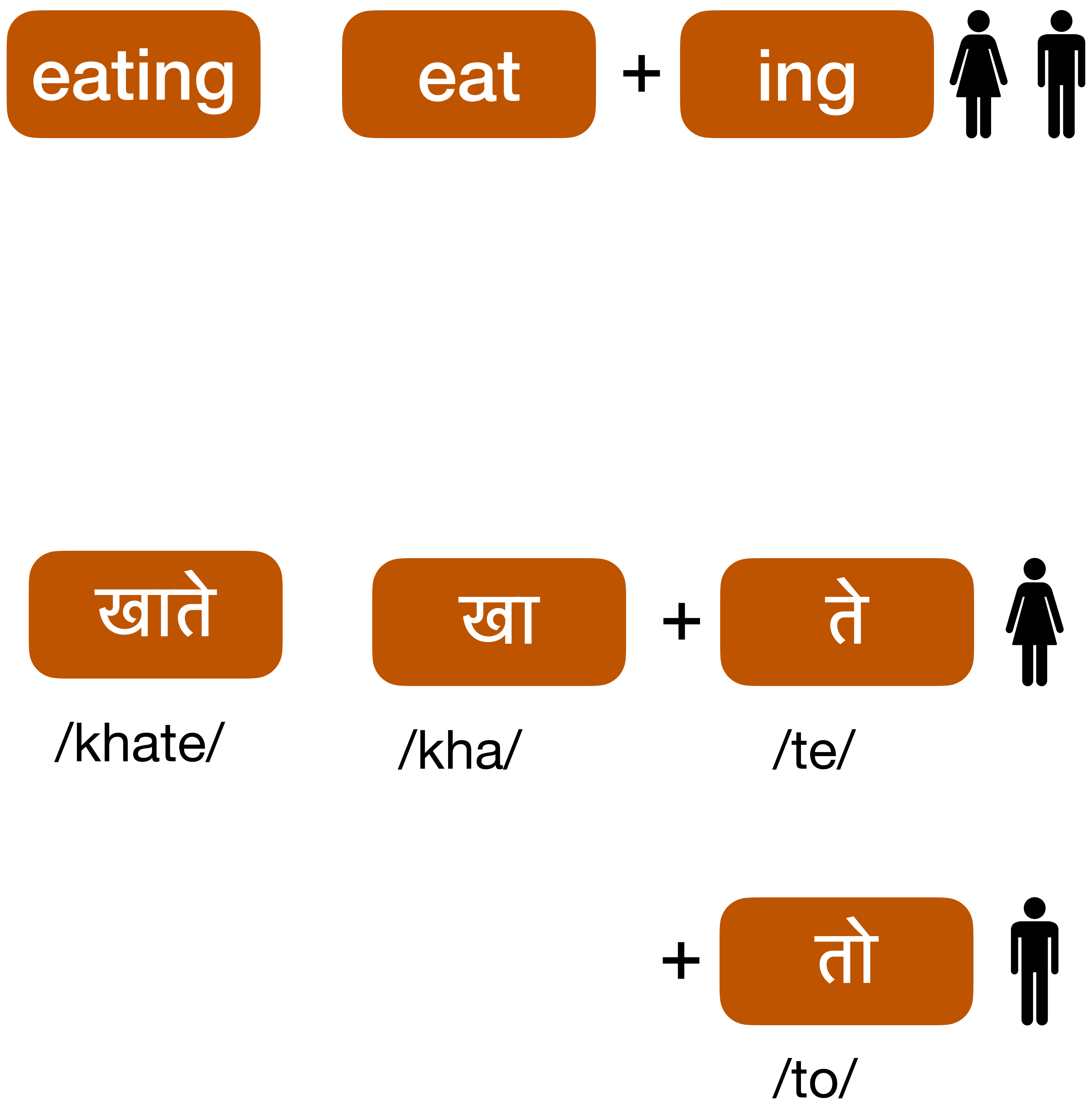
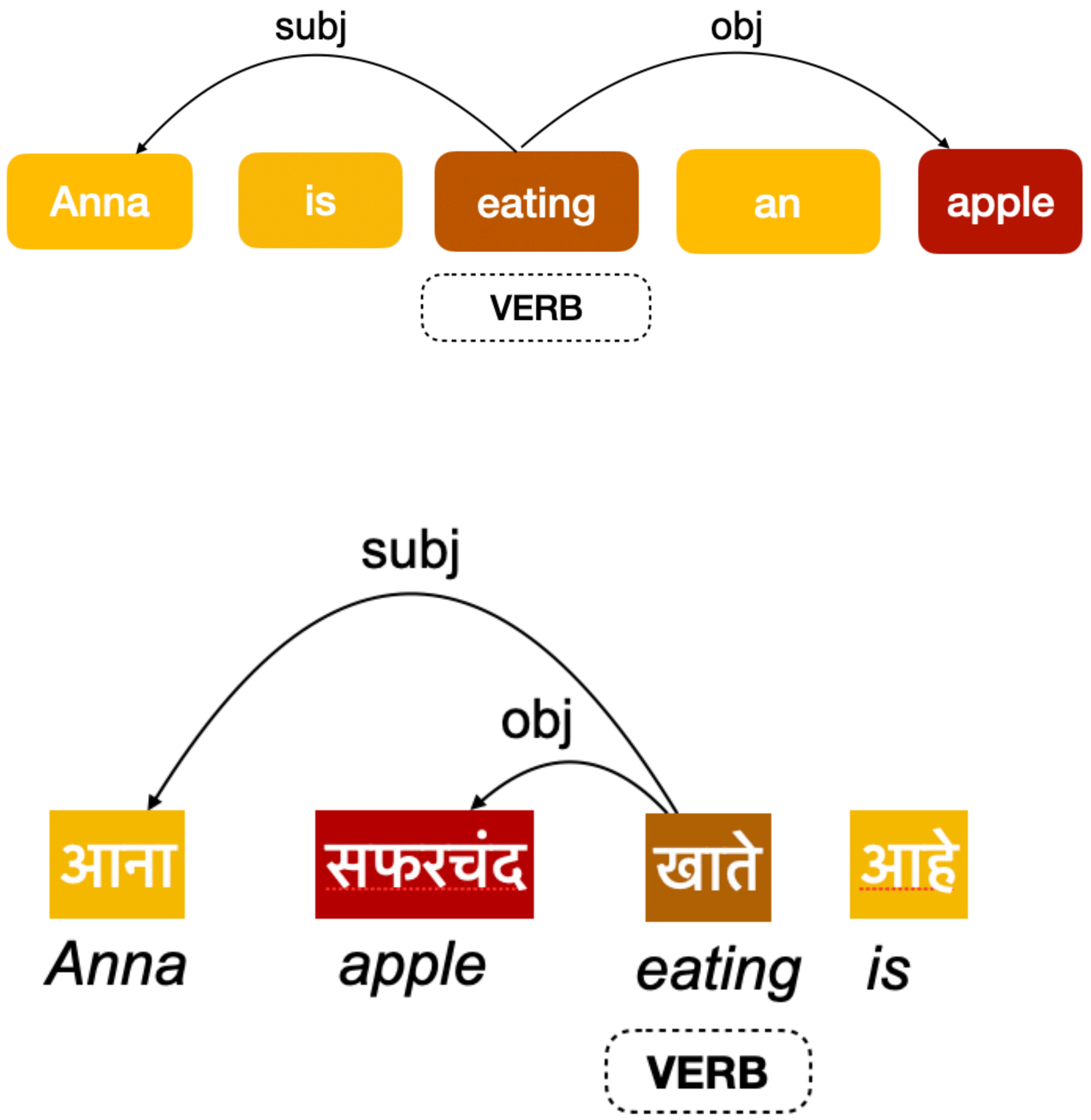


Morphology

Semantics

Different Systems Governing Language



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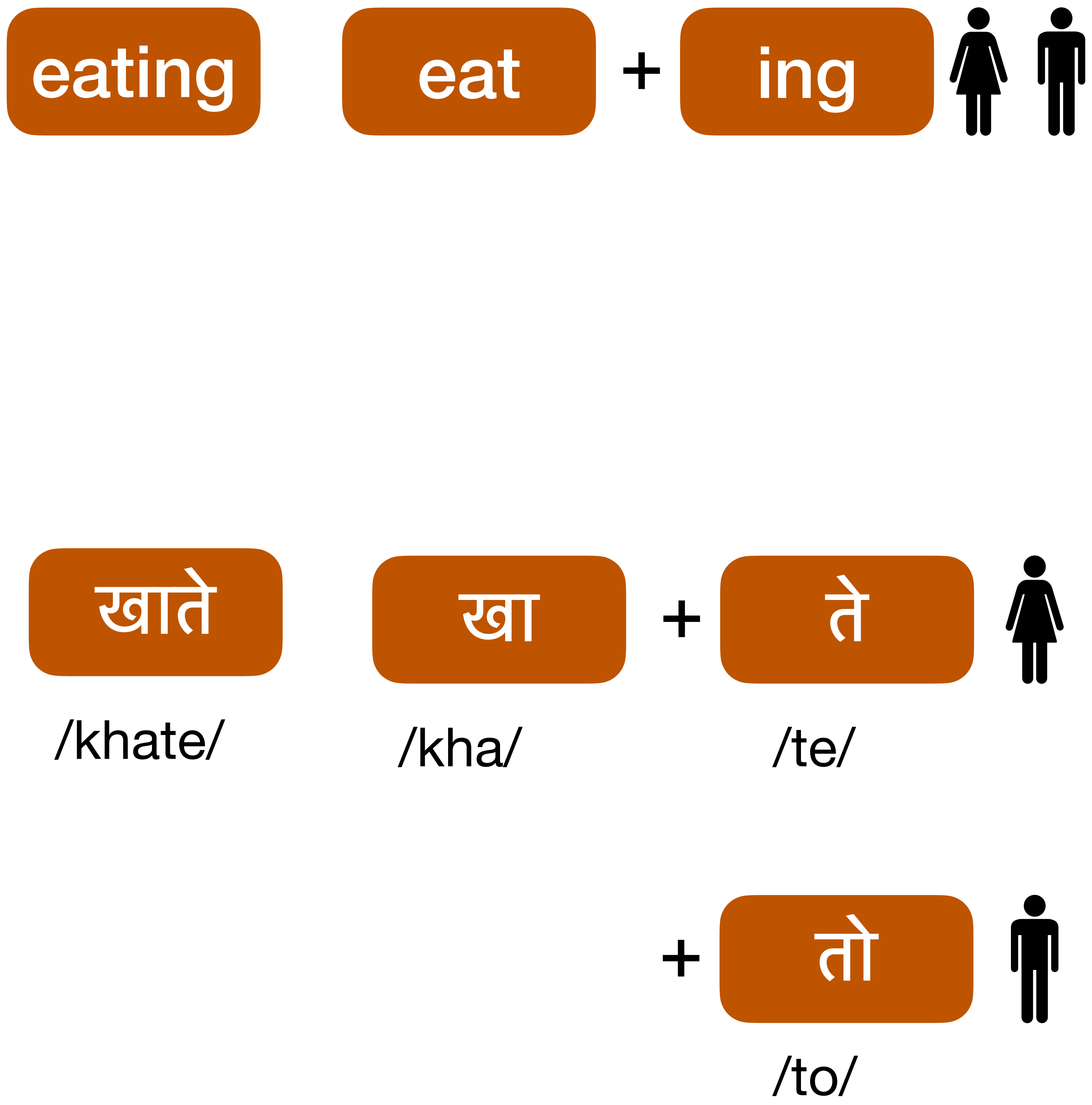

Morphology

Semantics

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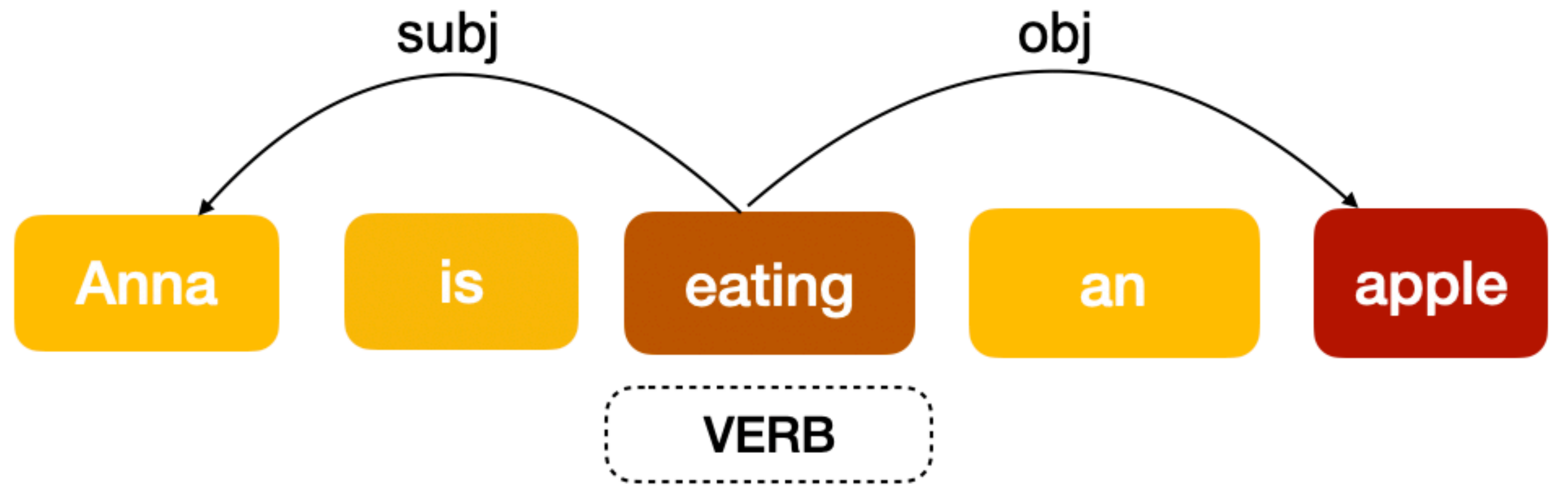

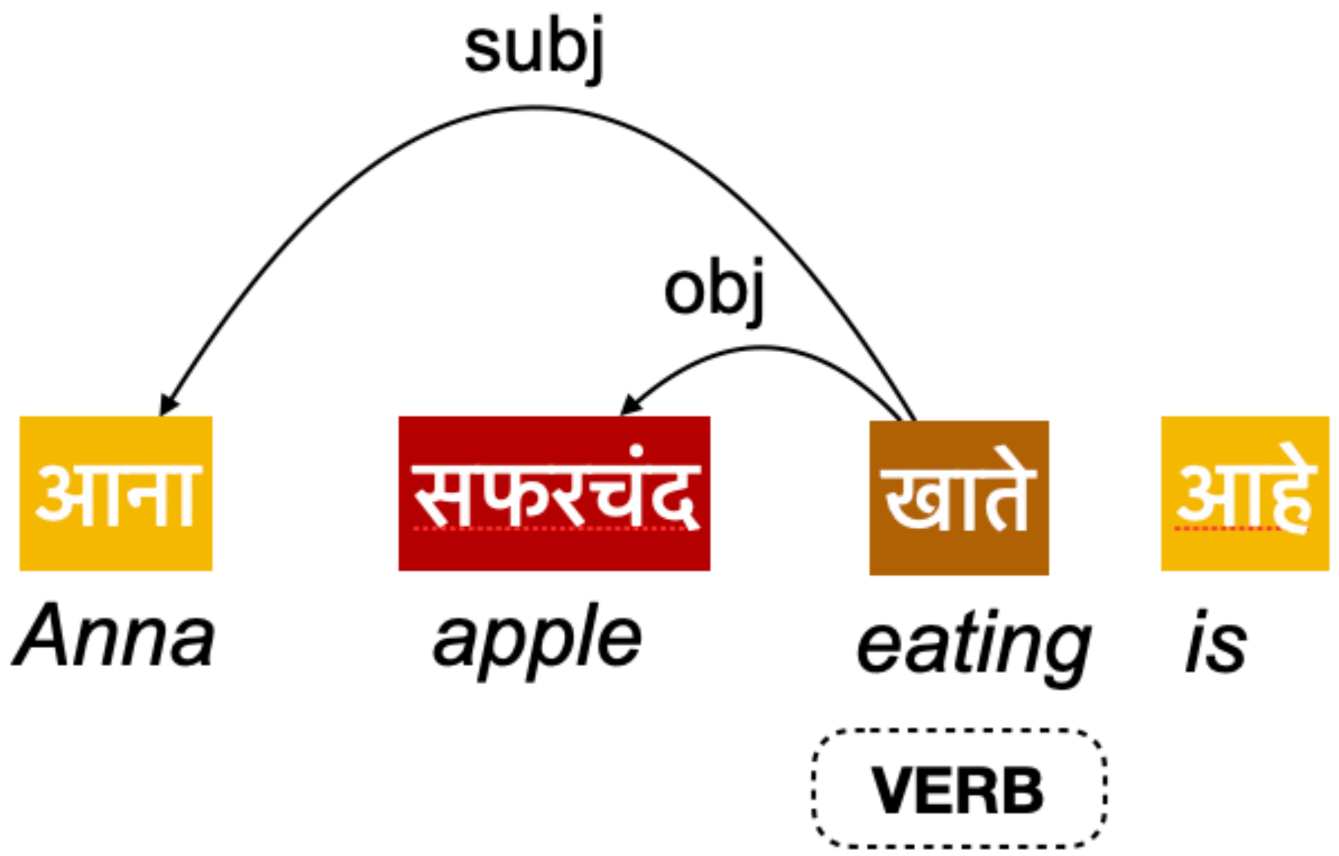

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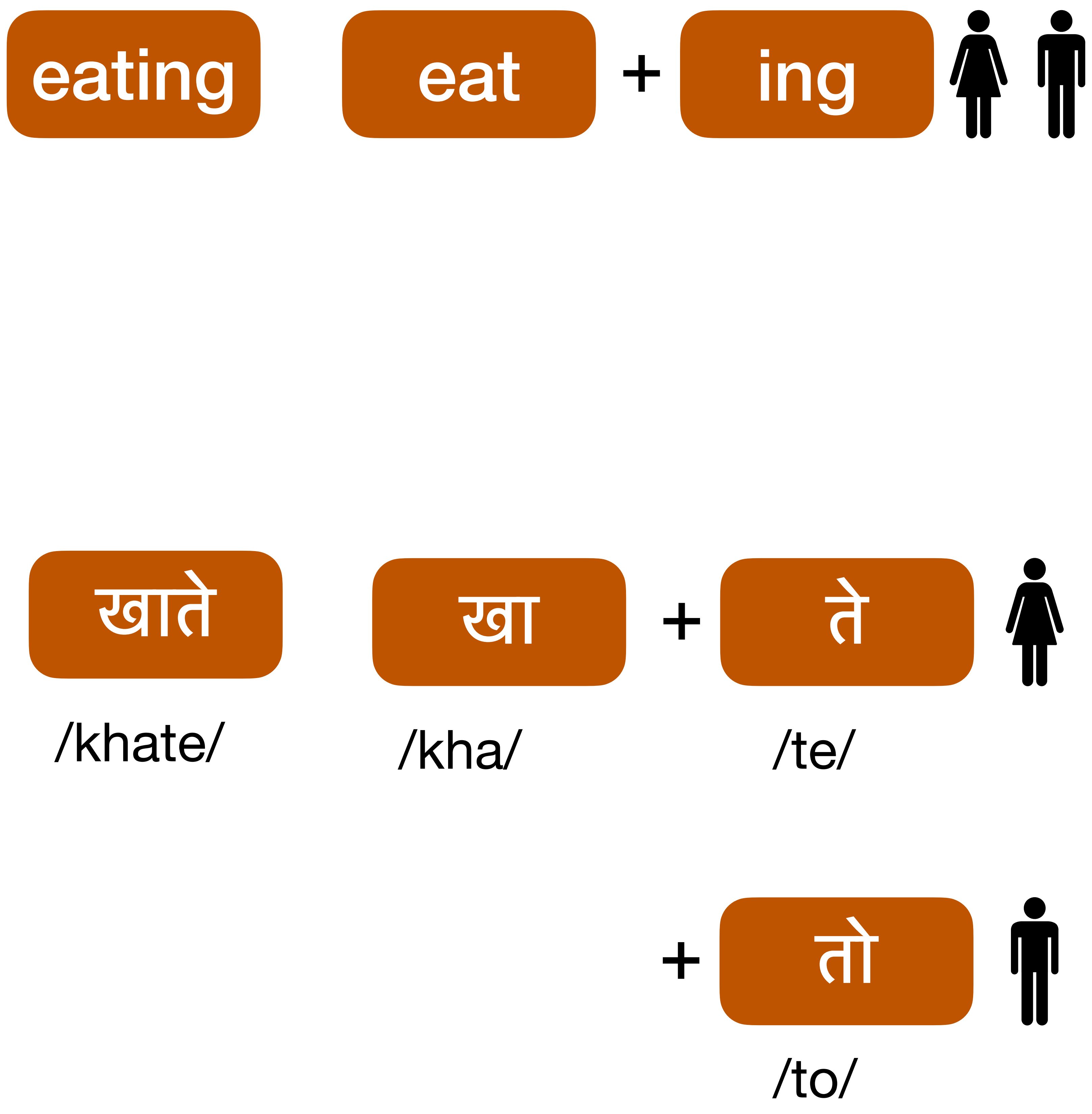


Morphology

तांदूळ
tandul
'raw rice'

भात
bhaat
'cooked rice'

Semantics

Describing Systems of Language

Describing Systems of Language

Describing Systems of Language

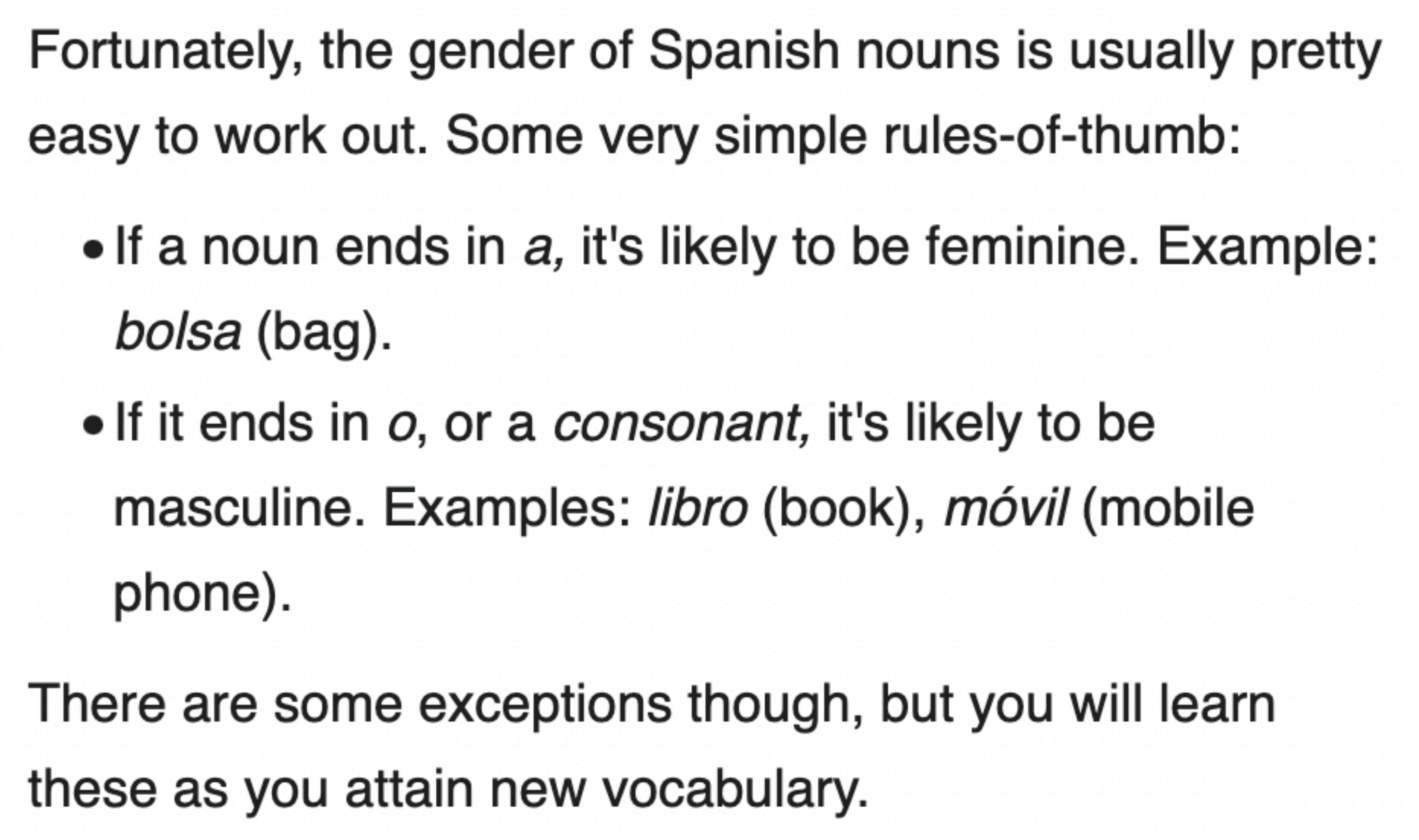
WIKIBOOKS
Open books for an open world

Main Page
Help

Book
Discussion

Spanish

Describing Systems of Language

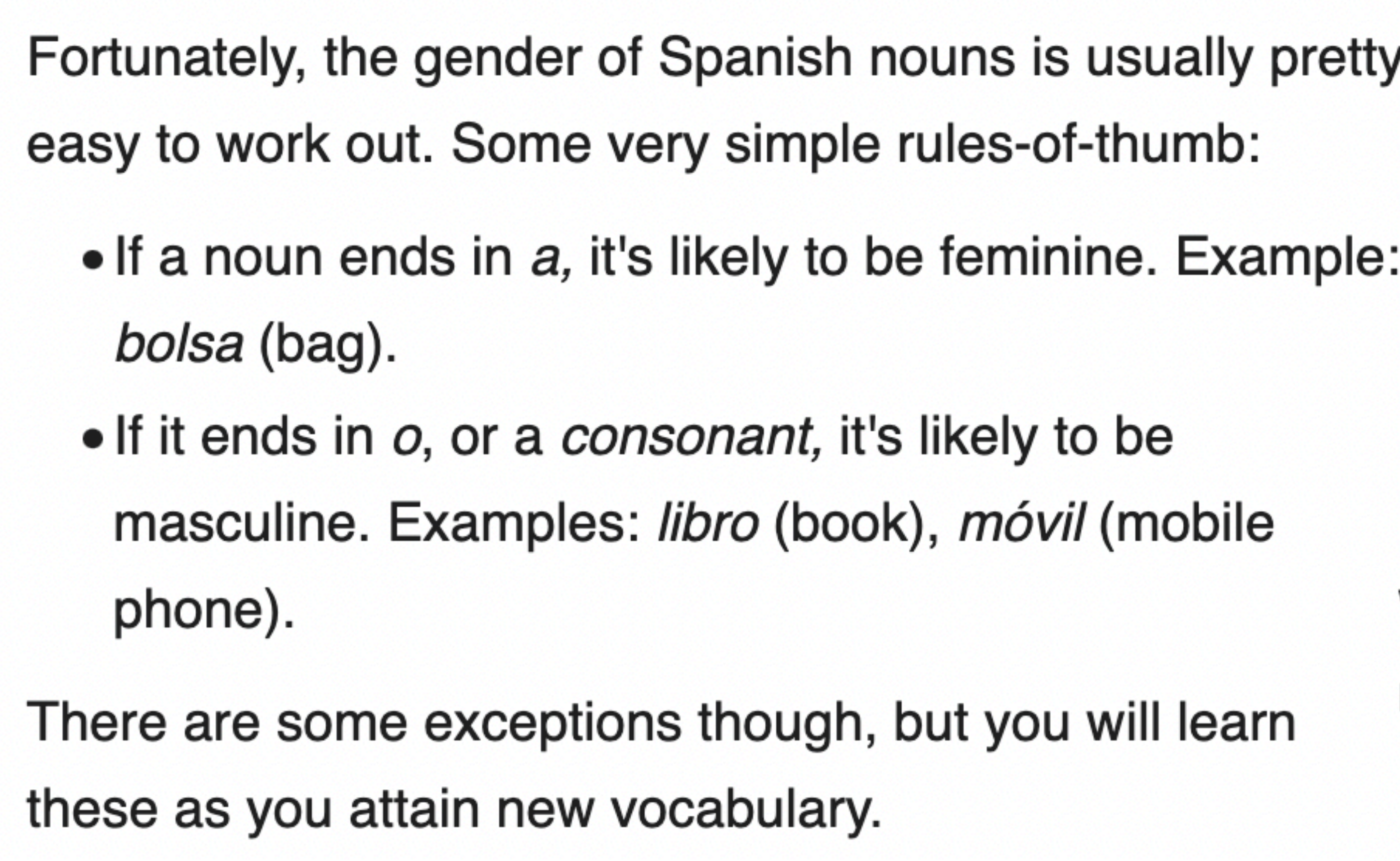


Fortunately, the gender of Spanish nouns is usually pretty easy to work out. Some very simple rules-of-thumb:

- If a noun ends in *a,* it's likely to be feminine. Example: *bolsa* (bag).
- If it ends in *o*, or a *consonant,* it's likely to be masculine. Examples: *libro* (book), *móvil* (mobile phone).

There are some exceptions though, but you will learn these as you attain new vocabulary.

Describing Systems of Language



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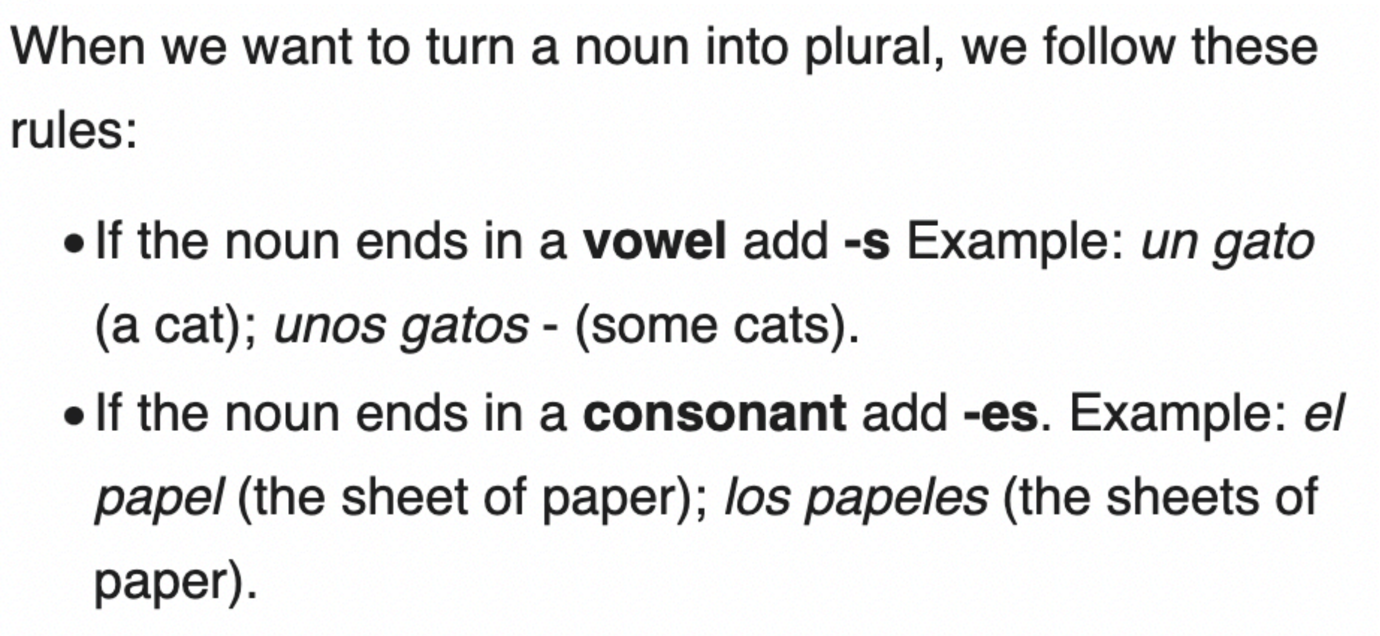
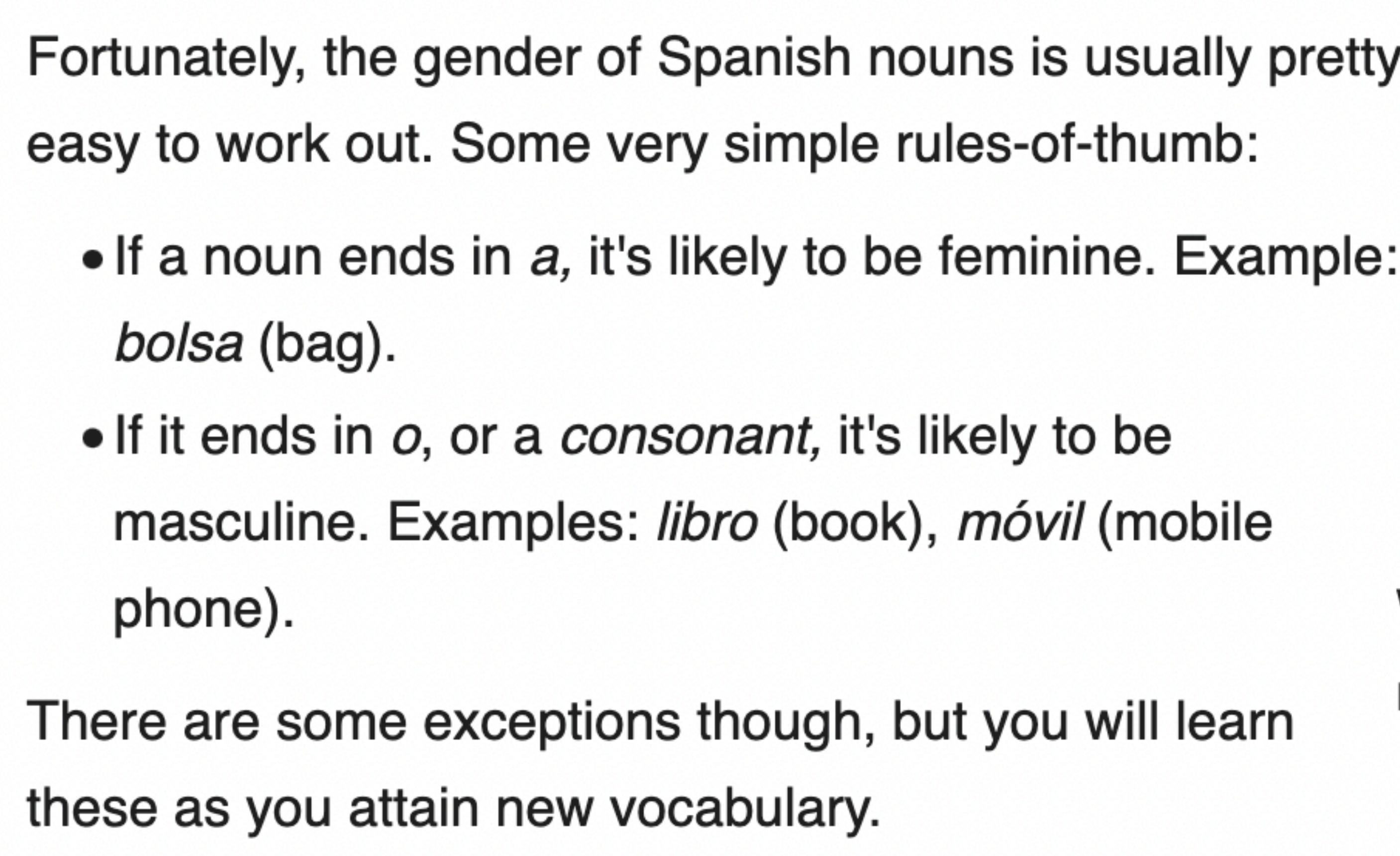


When we want to turn a noun into plural, we follow these rules:

- If the noun ends in a **vowel** add **-s** Example: *un gato* (a cat); *unos gatos* - (some cats).
- If the noun ends in a **consonant** add **-es**. Example: *el papel* (the sheet of paper); *los papeles* (the sheets of paper).

Describing Systems of Language



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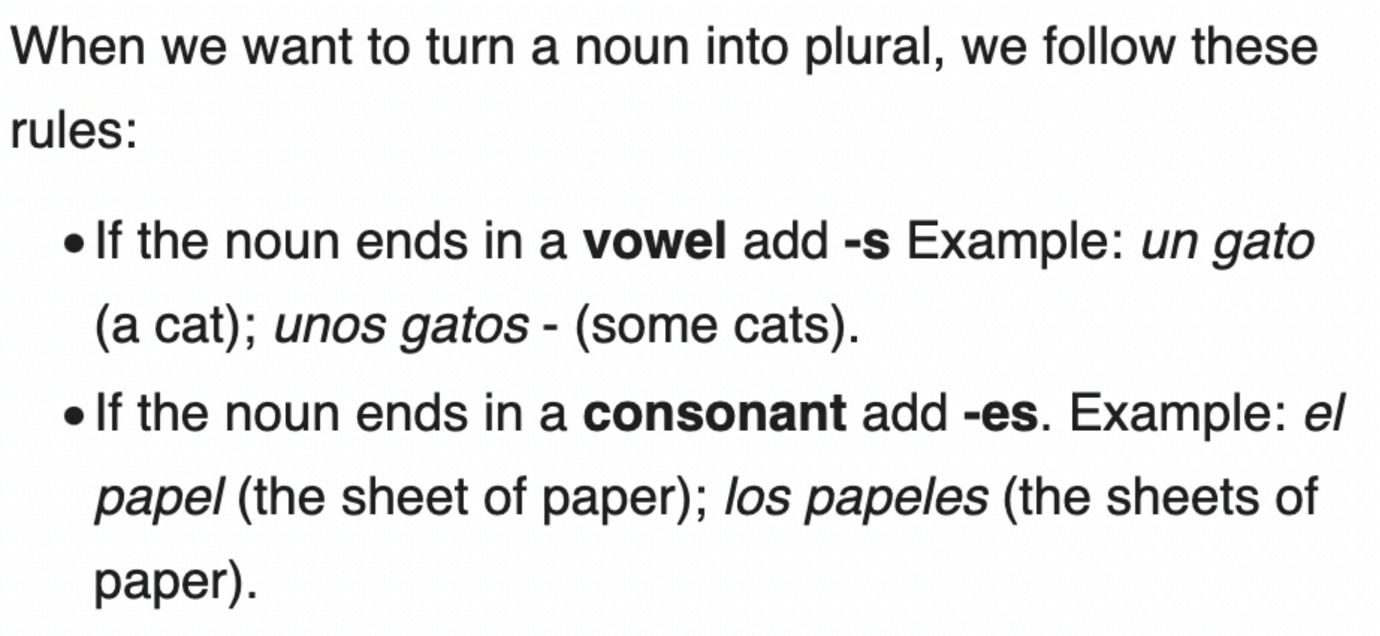

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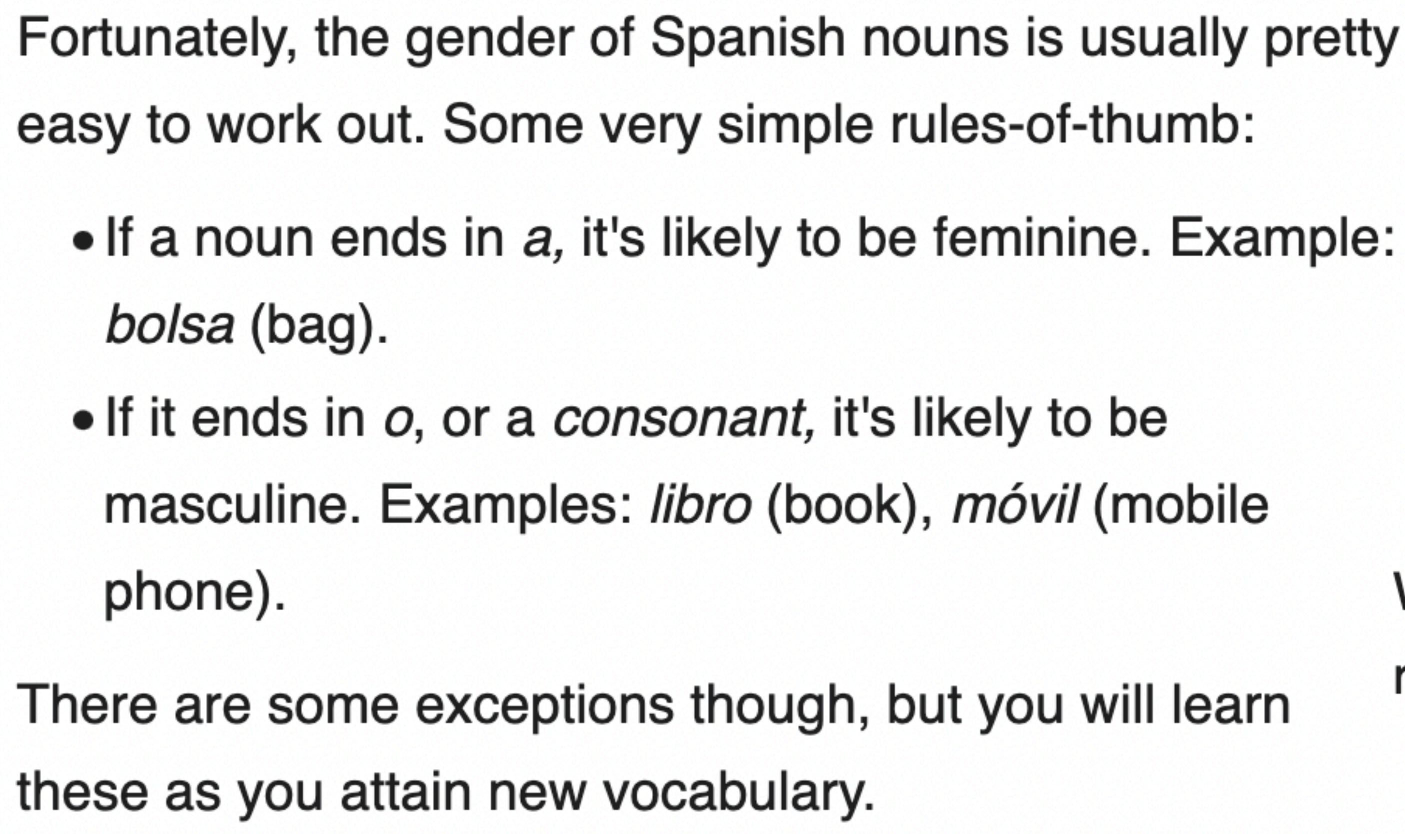
Language Learning

Language Documentation

Describing Systems of Language

Spanish



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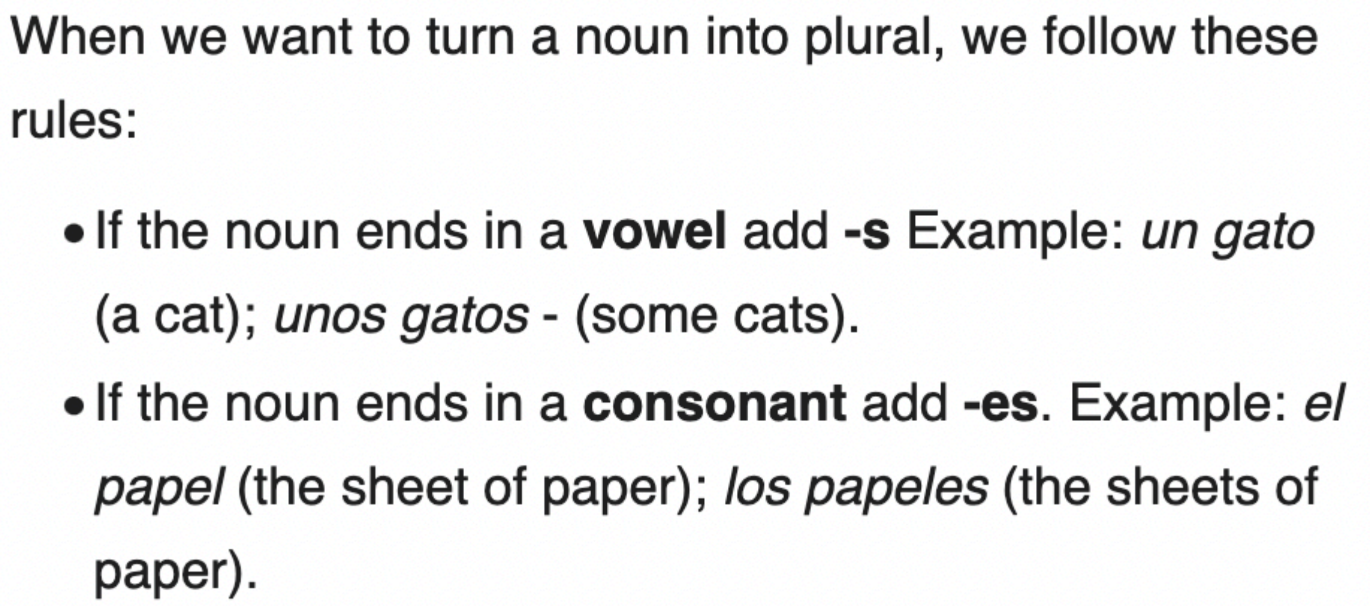

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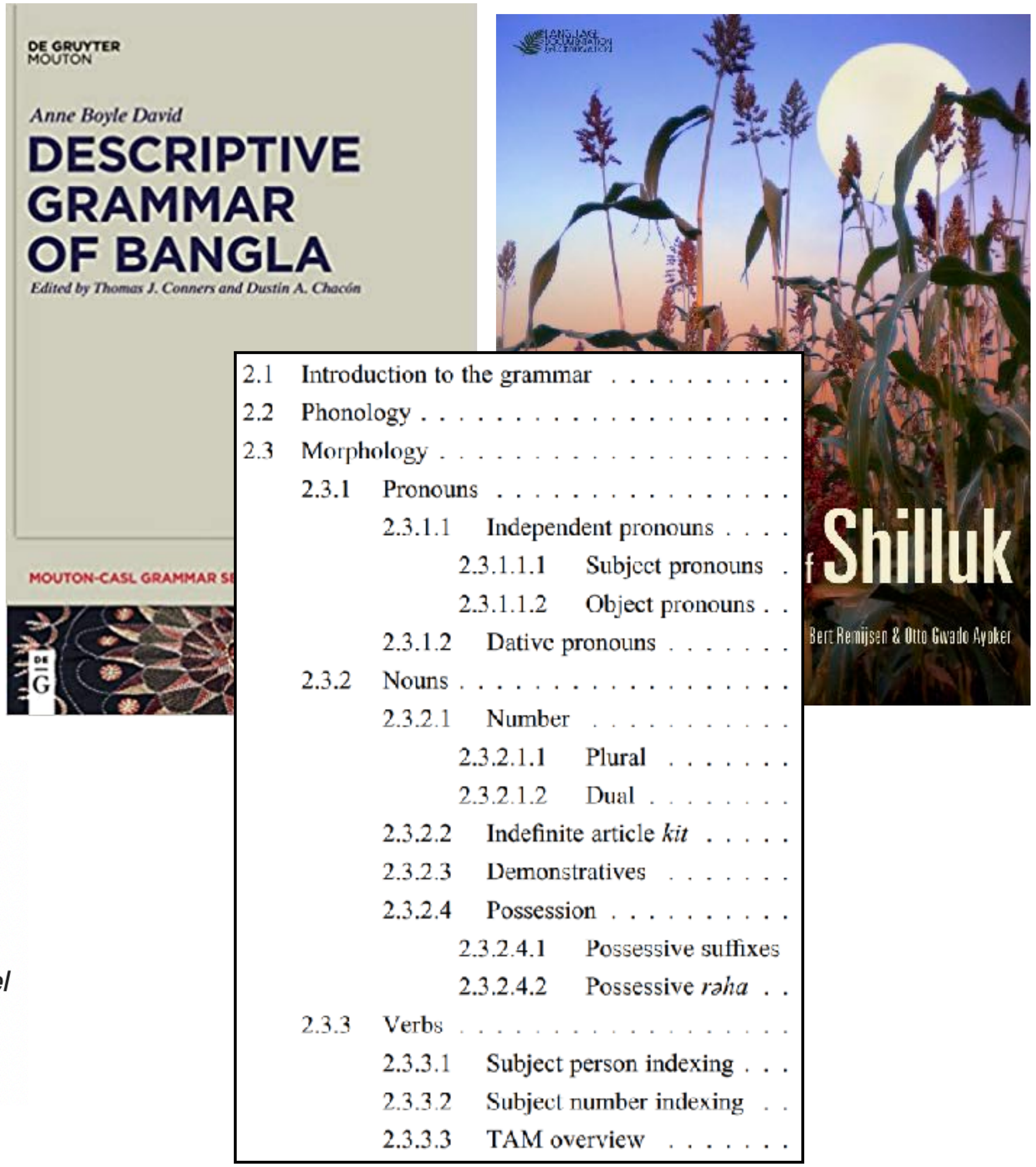
Language Learning



2.1 Introduction to the grammar
2.2 Phonology
2.3 Morphology
  2.3.1 Pronouns
    2.3.1.1 Independent pronouns
      2.3.1.1.1 Subject pronouns
      2.3.1.1.2 Object pronouns
    2.3.1.2 Dative pronouns
  2.3.2 Nouns
    2.3.2.1 Number
      2.3.2.1.1 Plural
      2.3.2.1.2 Dual
    2.3.2.2 Indefinite article *kìt*
    2.3.2.3 Demonstratives
    2.3.2.4 Possession
      2.3.2.4.1 Possessive suffixes
      2.3.2.4.2 Possessive *rəha*
  2.3.3 Verbs
    2.3.3.1 Subject person indexing
    2.3.3.2 Subject number indexing
    2.3.3.3 TAM overview

Language Documentation

What are Language Descriptions?

आना सफरचंद खाते आहे

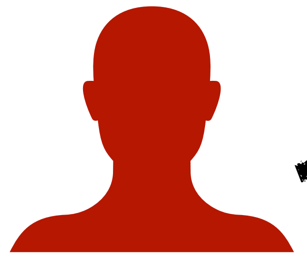
What are Language Descriptions?

आना	सफरचंद	खाते	आहे
Anna	*apple*	*eating*	*is*

How are subjects ordered wrt verbs in Marathi?

What are Language Descriptions?

आना	सफरचंद	खाते	आहे
Anna	*apple*	*eating*	*is*
PROPN	NOUN	**VERB**	AUX



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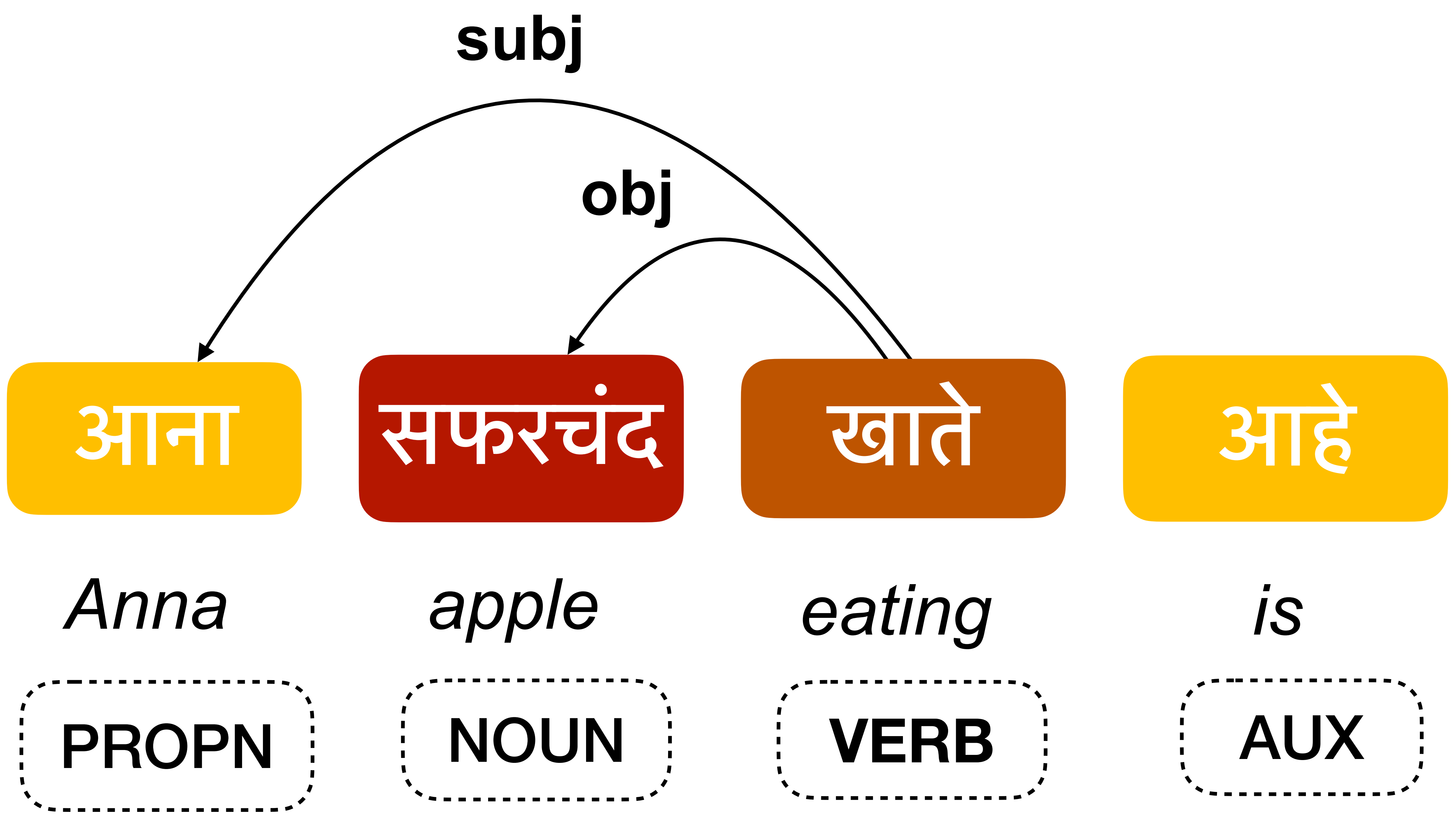

subj

obj

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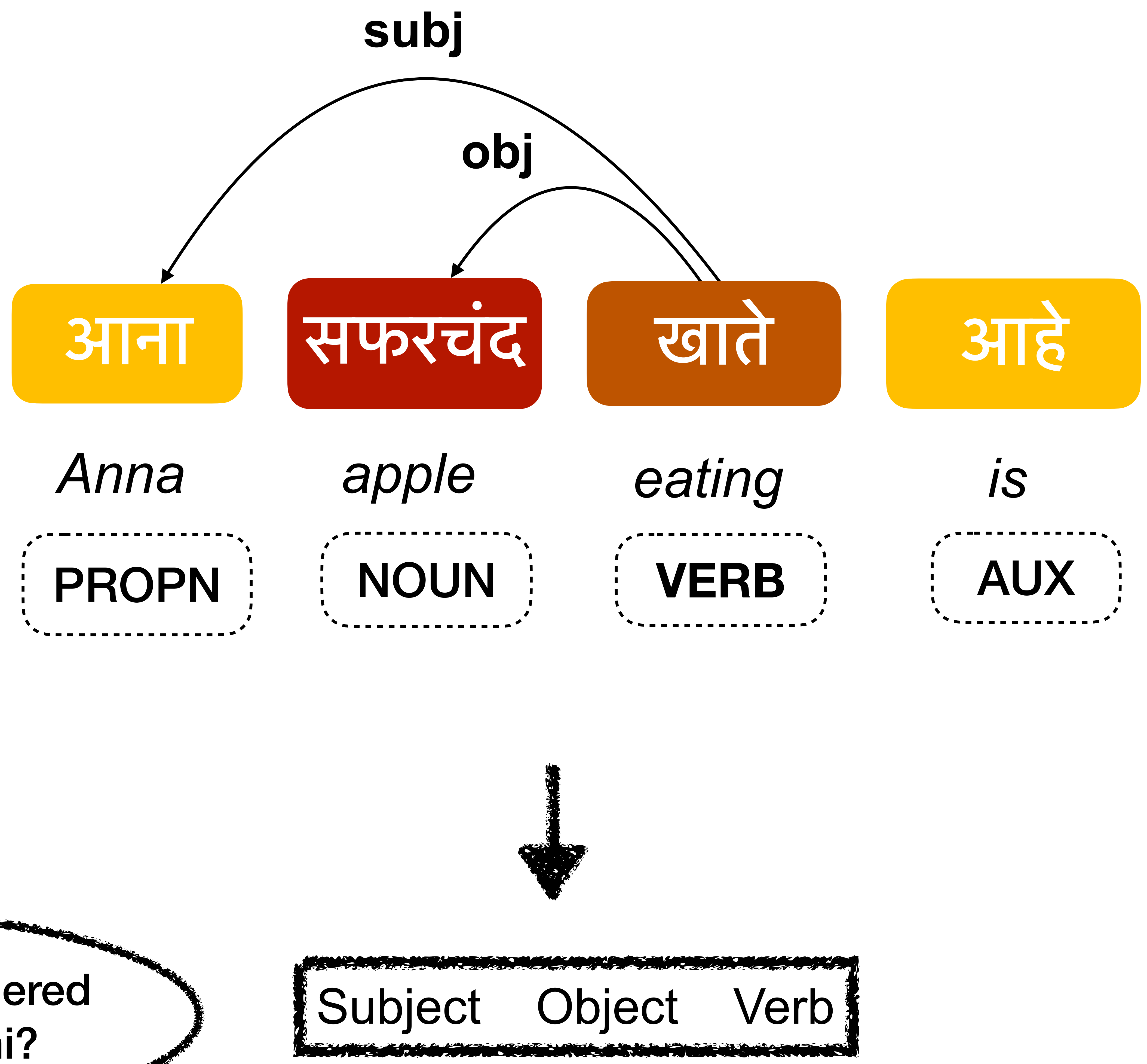
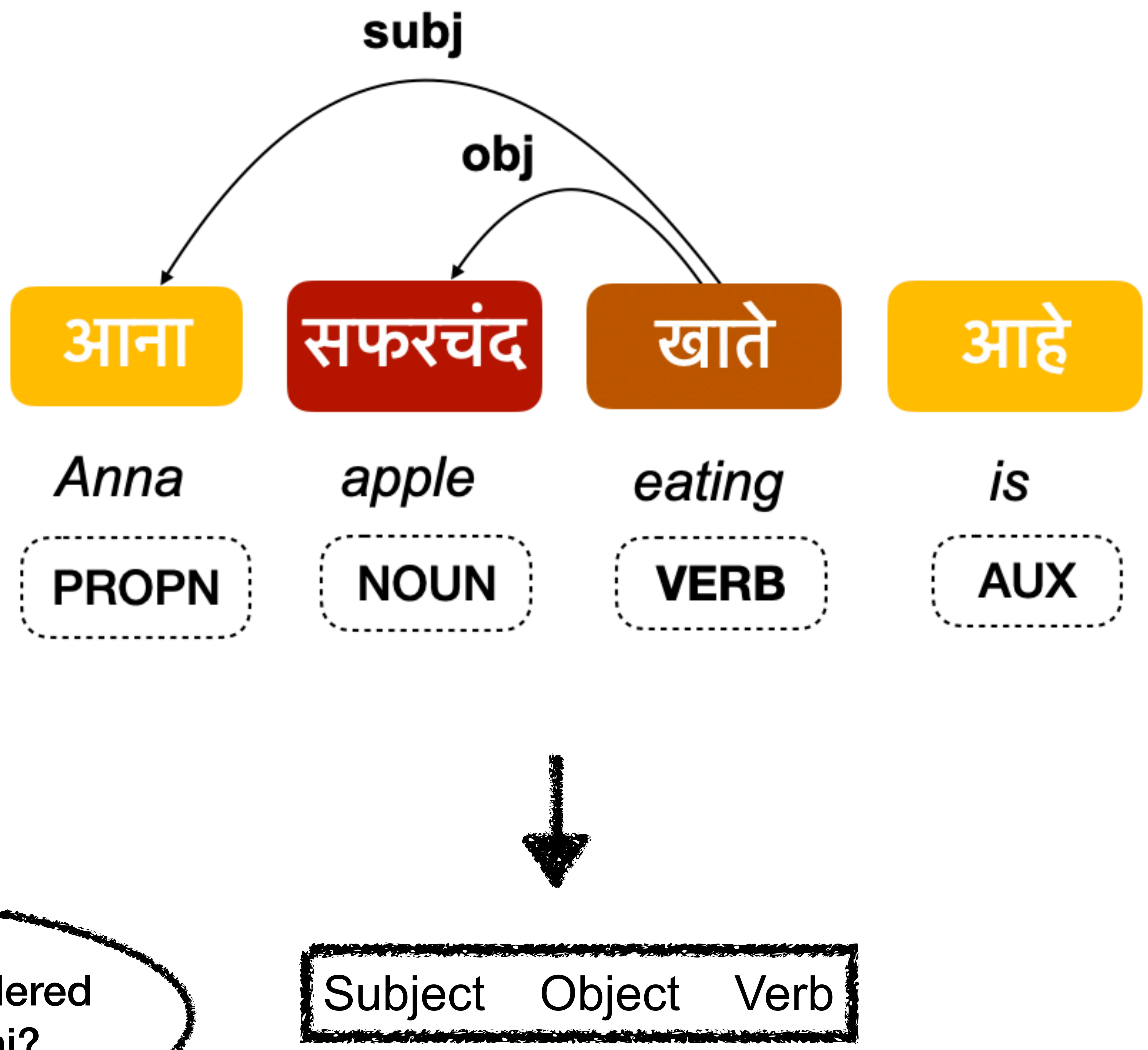


Subject Object Verb

How are subjects ordered wrt verbs in Marathi?

Why is this challenging?



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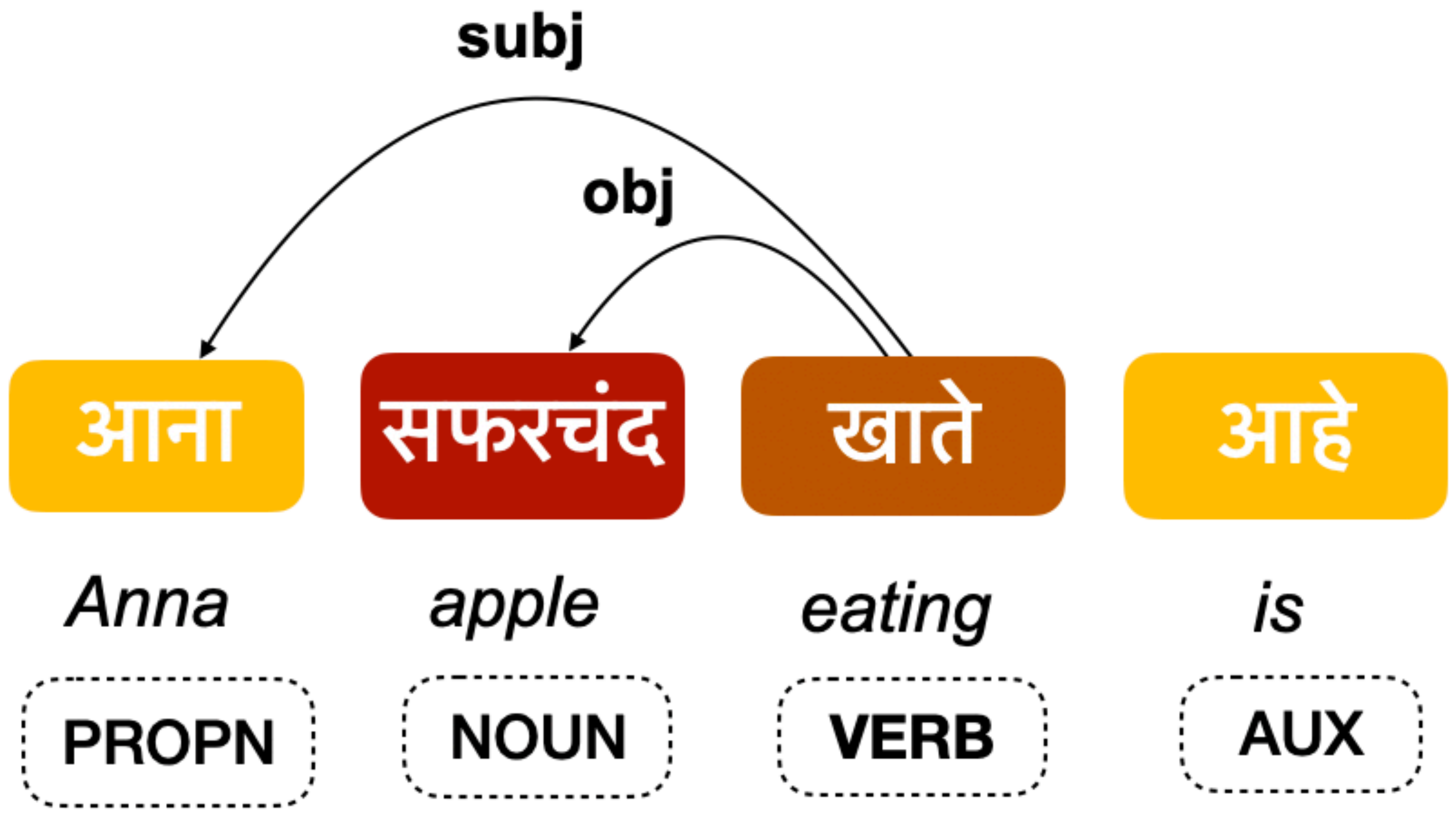

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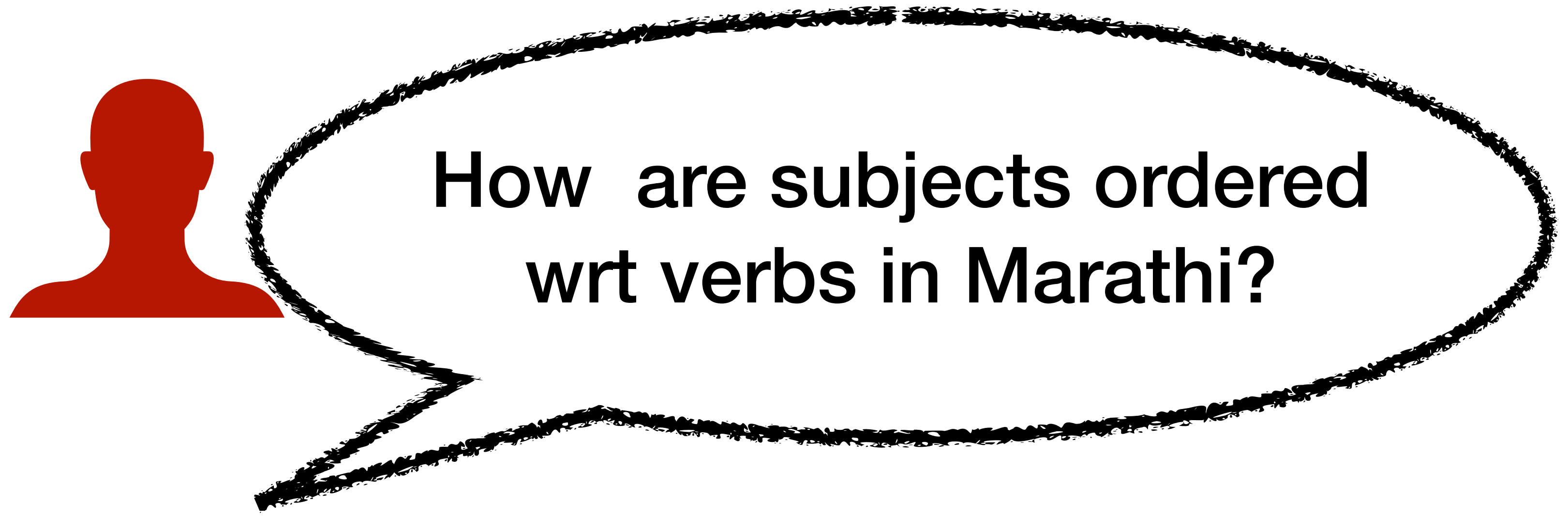

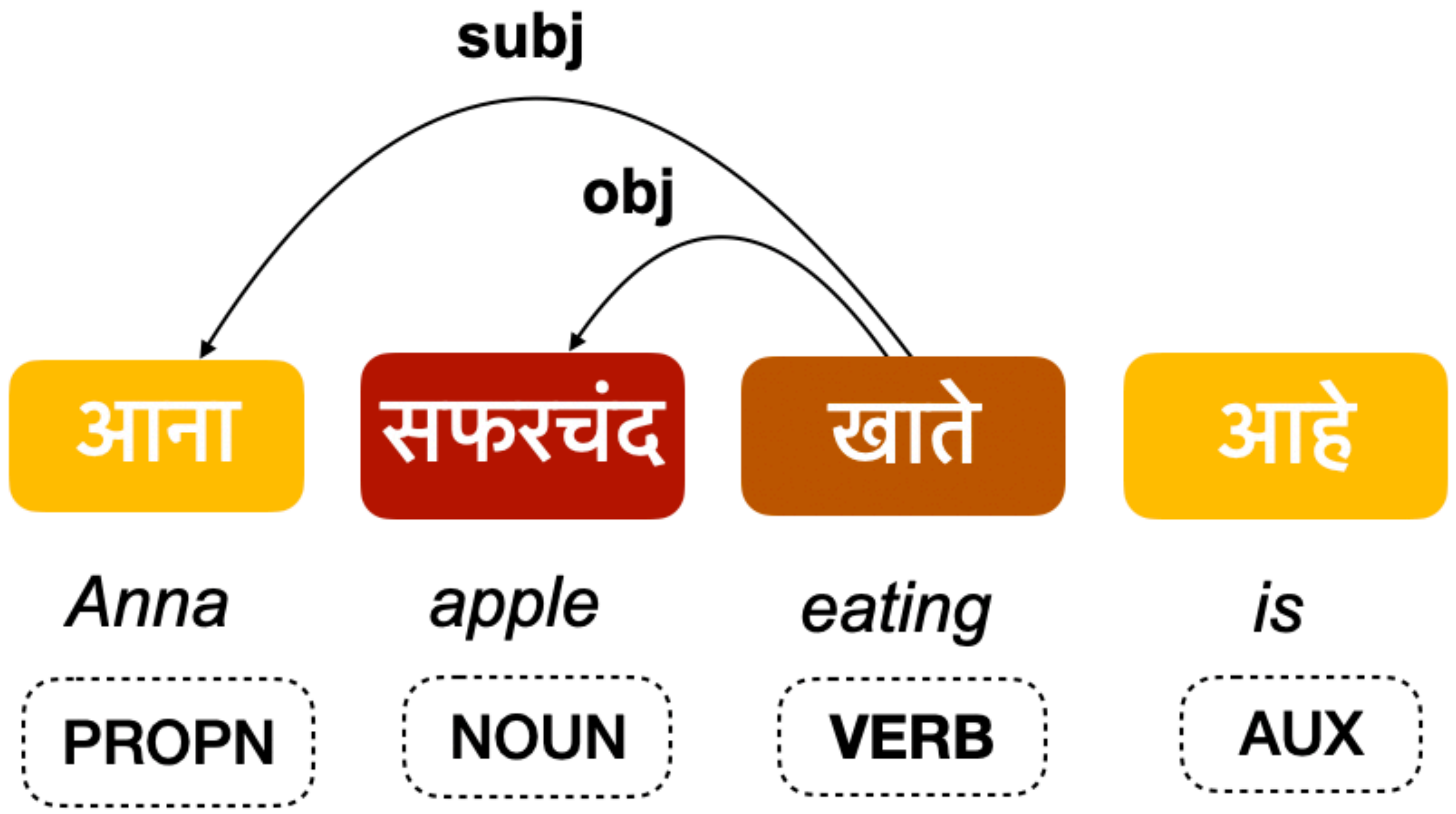

Subject Object Verb

Where Languages Are Dying

Languages classified as threatened/ endangered in 2022, by region

* Including the Caribbean
** Including the Caucasus
Source: Endangered Languages Project

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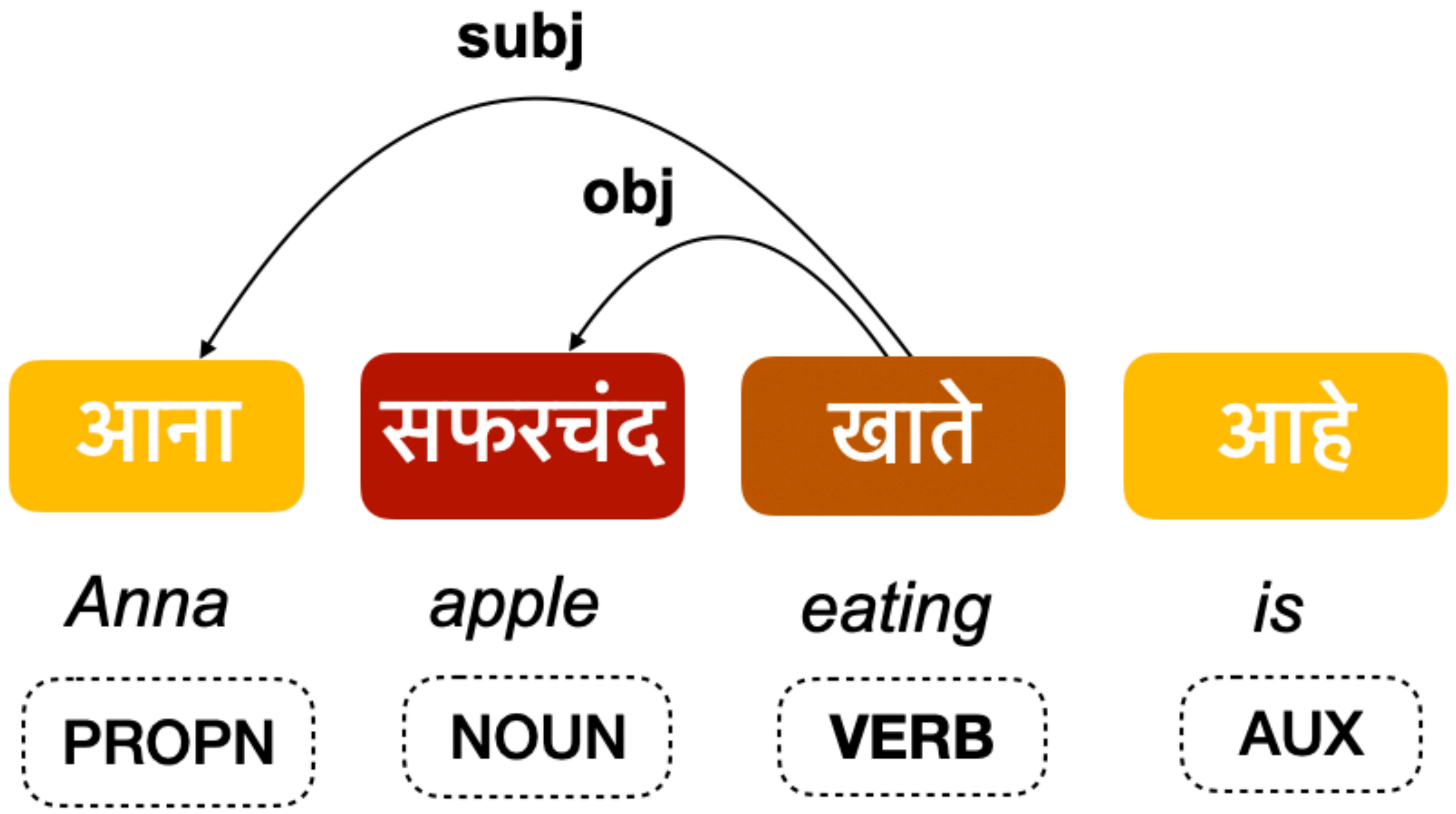

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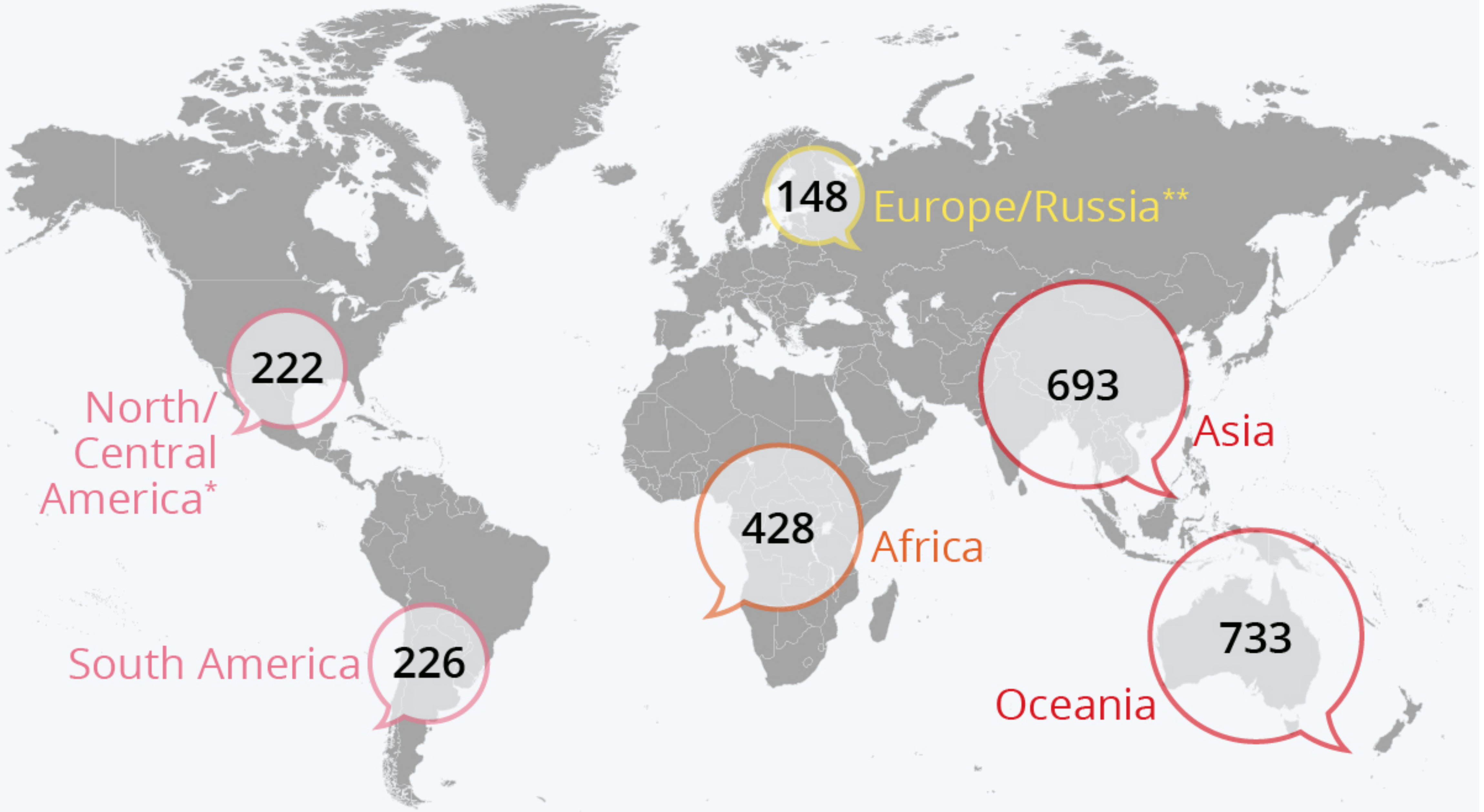

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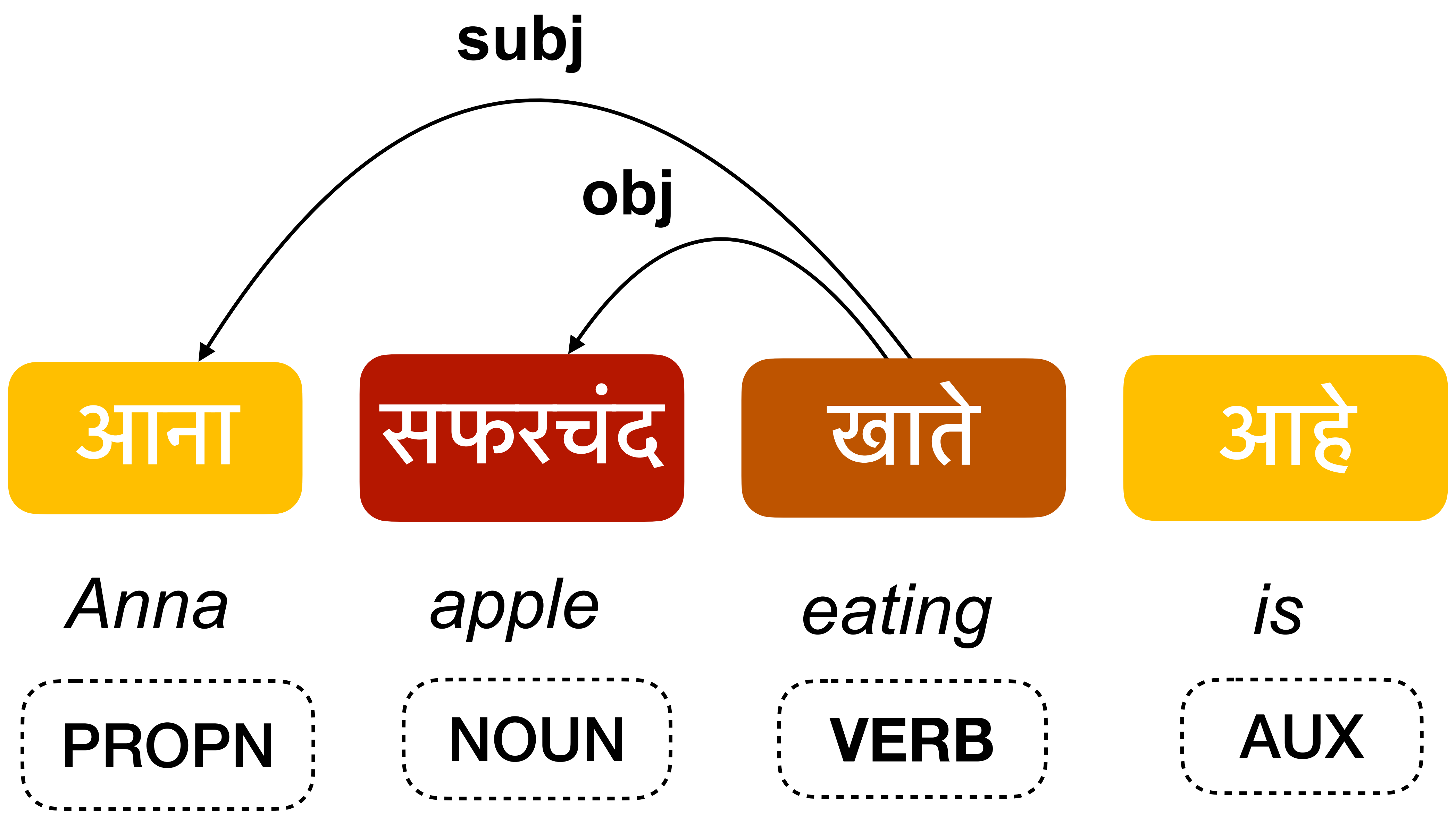
Subject Object Verb

Could we help in some way?

NLP already does some of this!



Subject Object Verb

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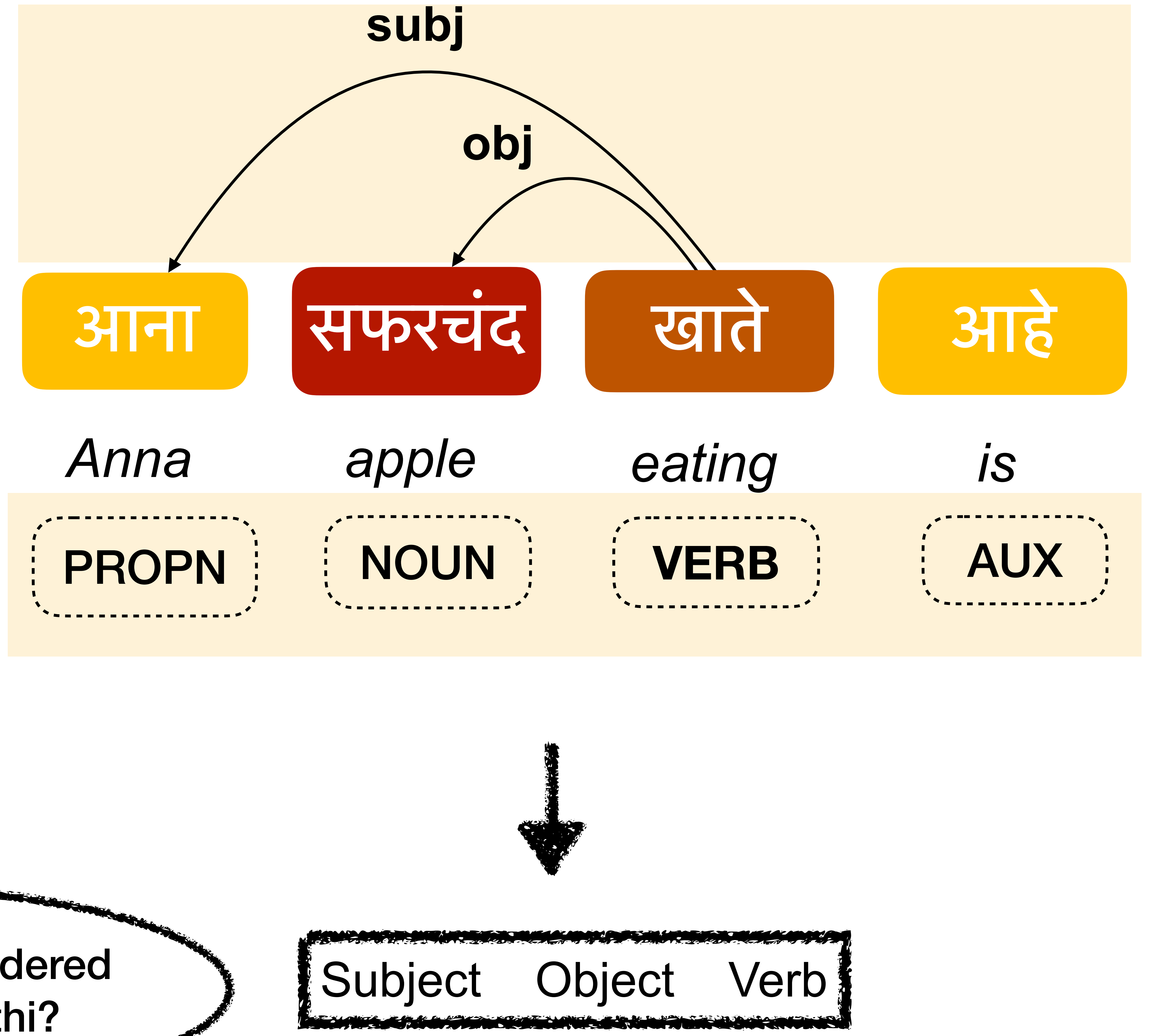

subj

obj

आना सफरचंद खाते आहे

Anna apple eating is

PROPN NOUN VERB AUX

Dependency Parsing

POS Tagging

Subject Object Verb

How are subjects ordered wrt verbs in Marathi?

Our Proposed Pipeline

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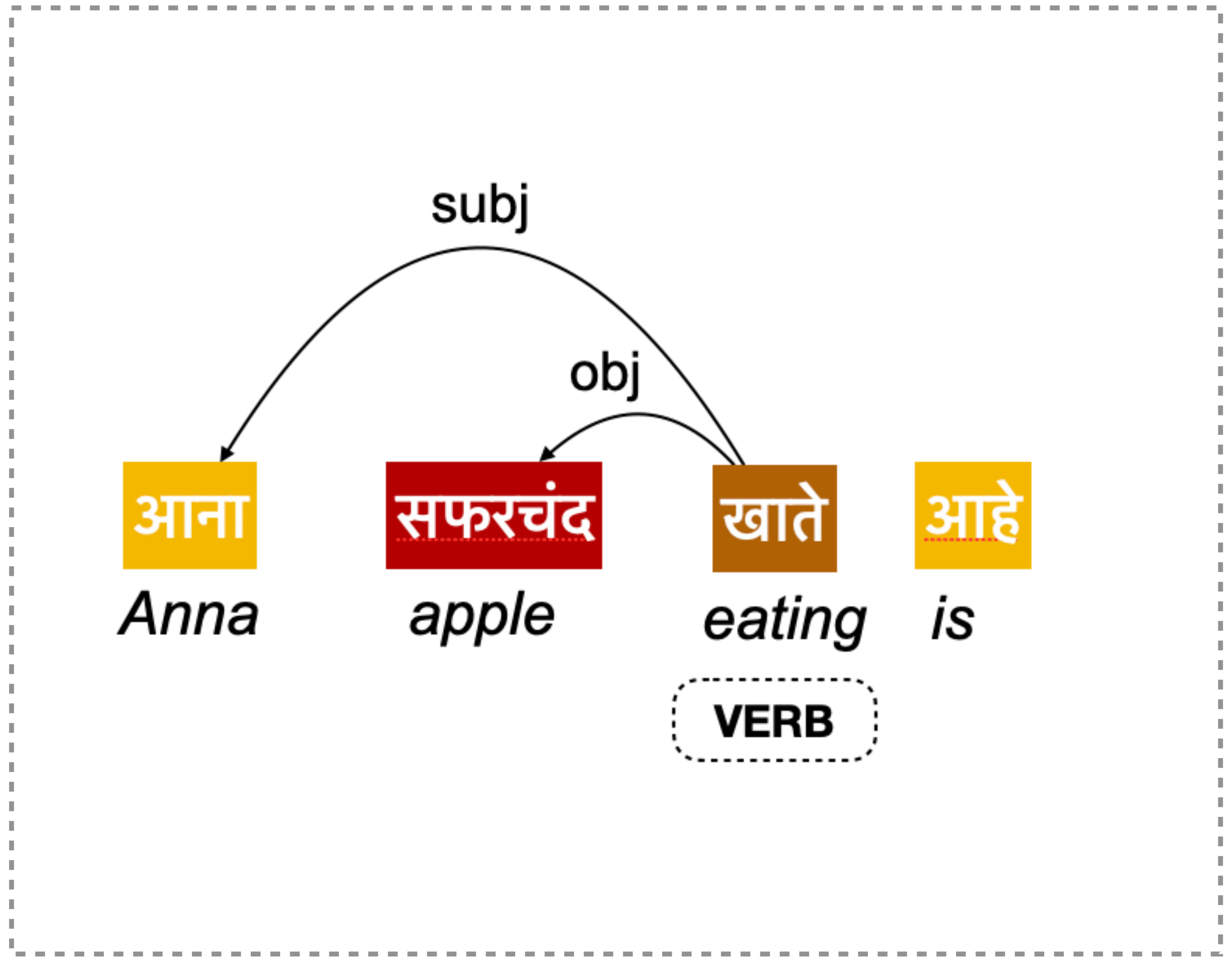
Our Proposed Pipeline

(Low-resource) Language Analysis



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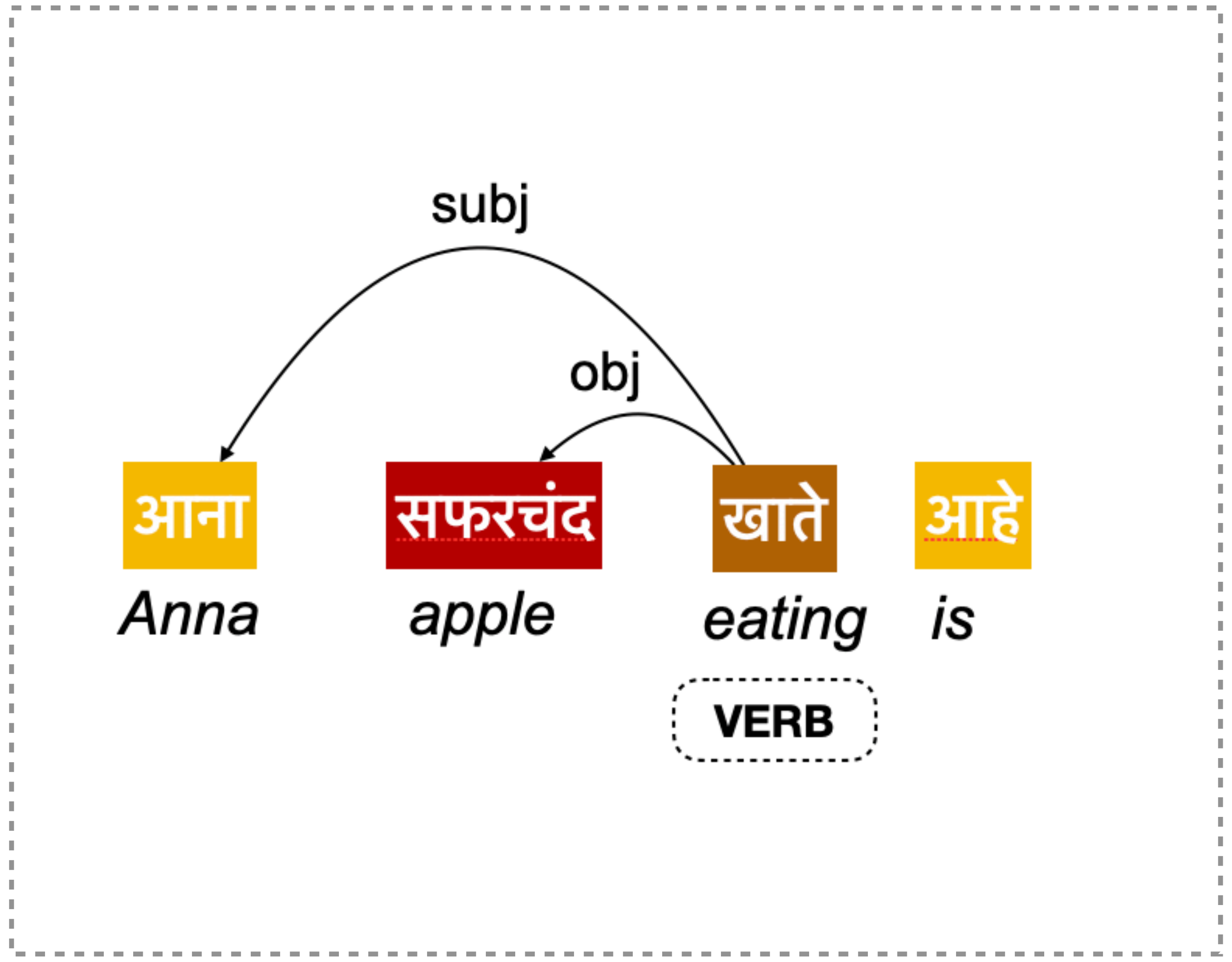

AutoLEX: Automatic Language Explorer

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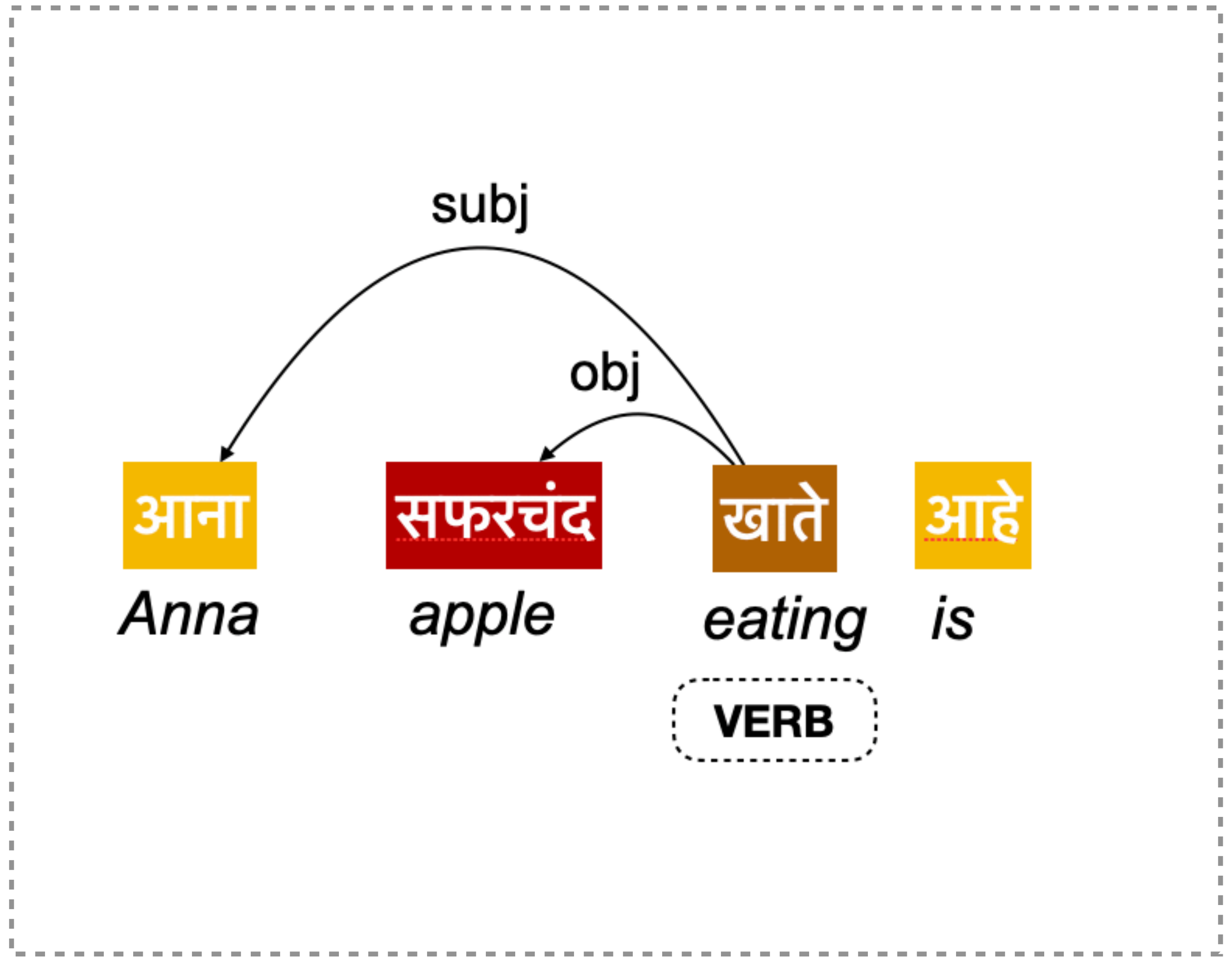

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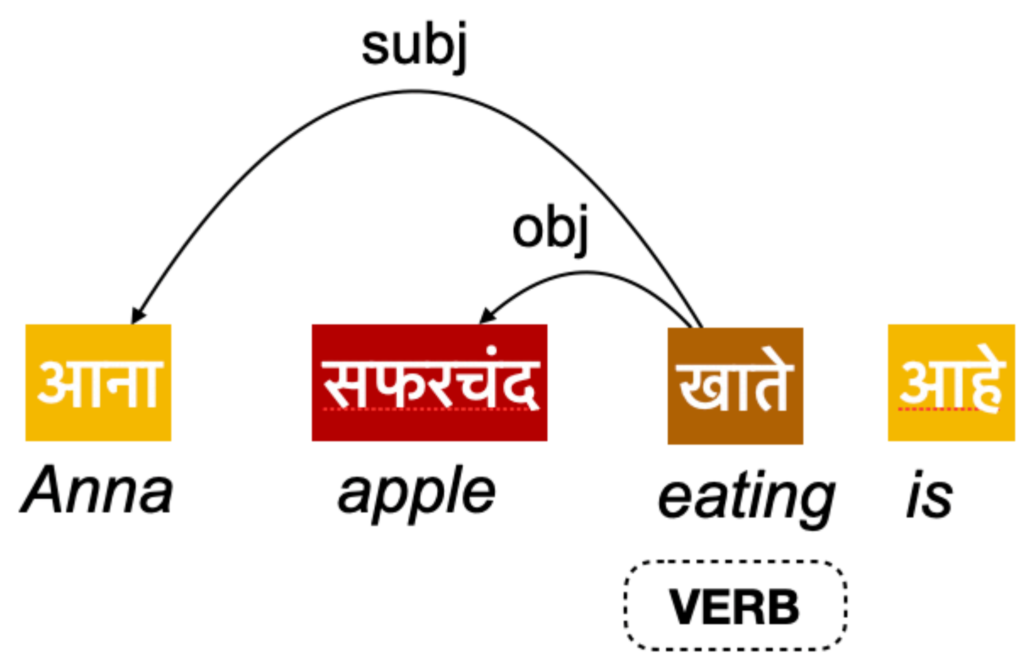

→

AutoLEX: Automatic Language Explorer

Subject Object Verb

तांदूळ
/tandul/
‘raw rice’

भात
/bhaat/
‘cooked rice’

→

Applications

Language Education and Documentation

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Extract and visualize answers to different linguistic questions in both human- and machine-readable formats

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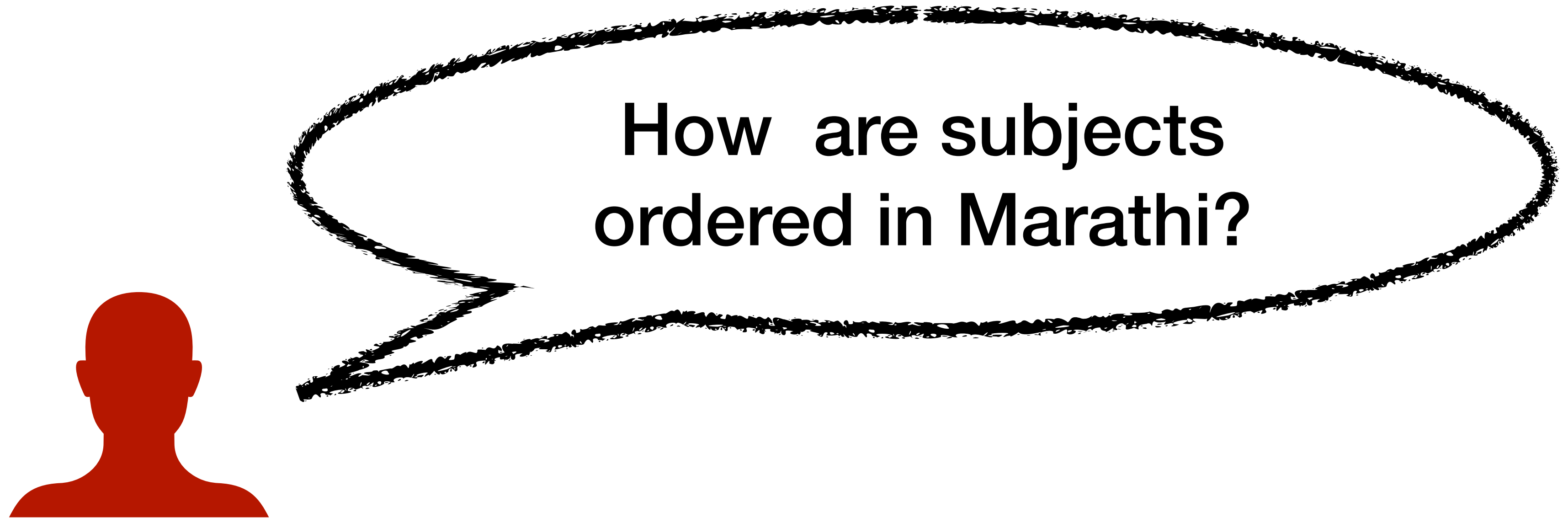
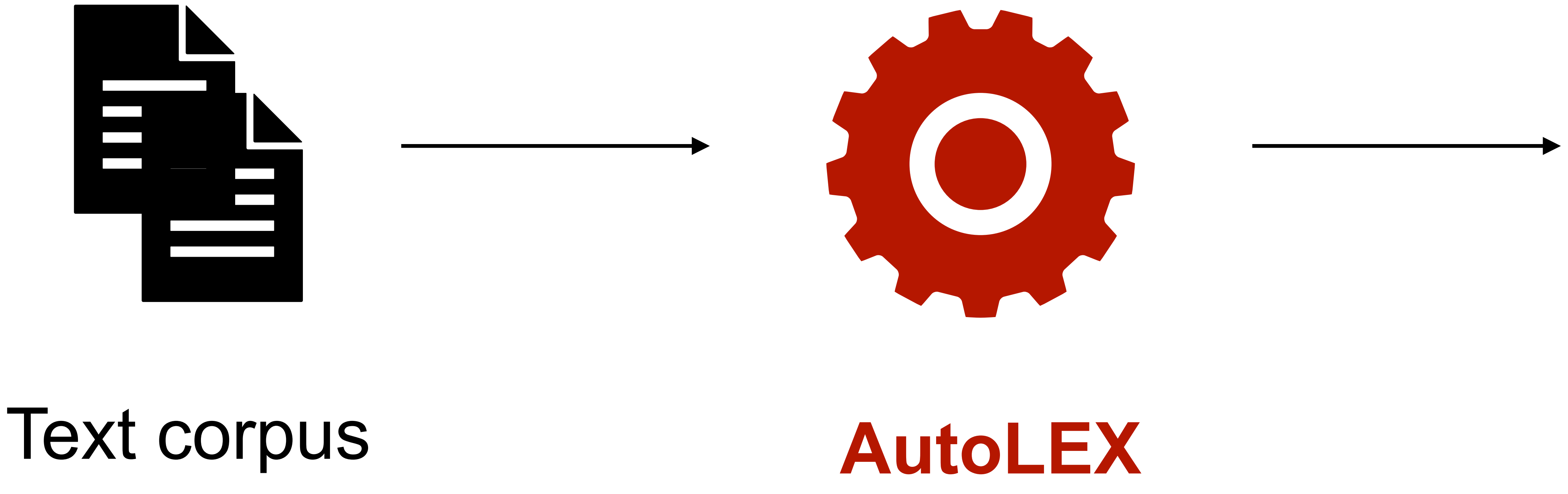
Text corpus

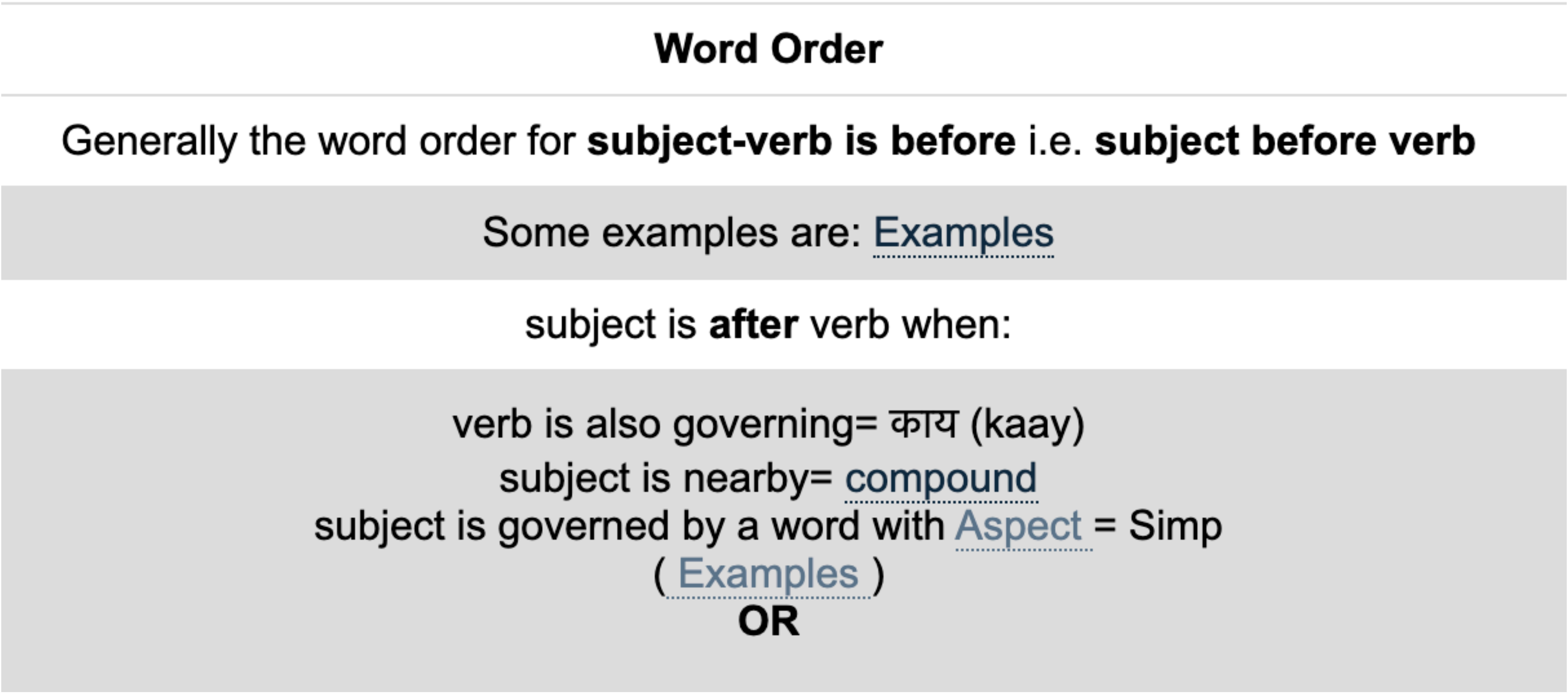
AutoLEX: Automatic Language Explorer

Extract and visualize answers to different linguistic questions in both human- and machine-readable formats




Text corpus

AutoLEX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(Examples)
OR

AutoLEX: Automatic Language Explorer

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How are subjects ordered in Marathi?

Formulate the linguistic question into a classification task

Extract Features and Construct Training Data

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Extract and Visualize Rules

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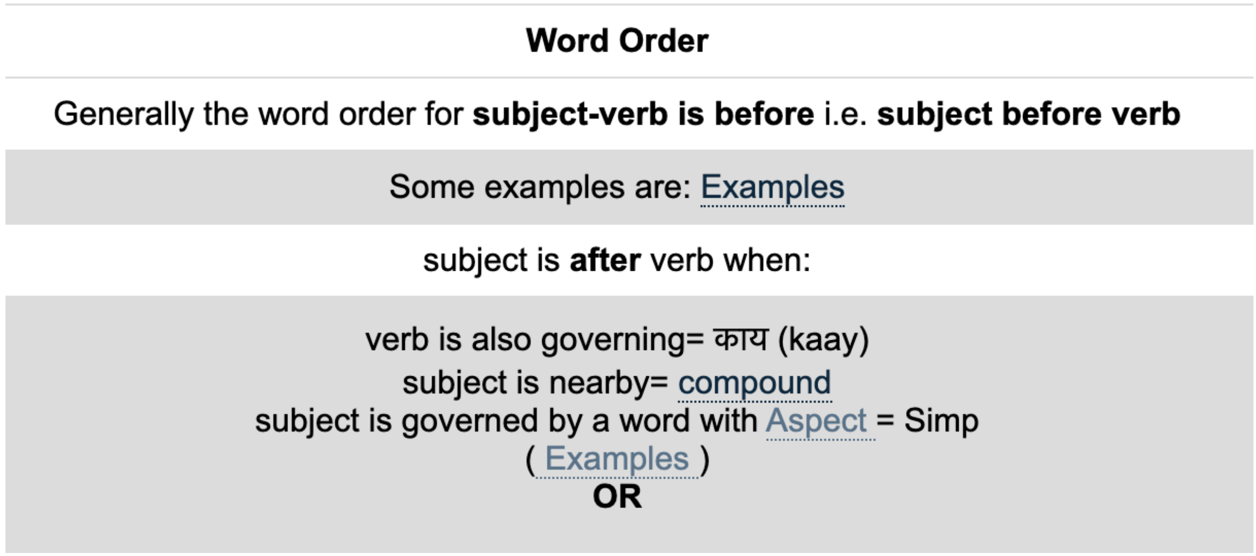

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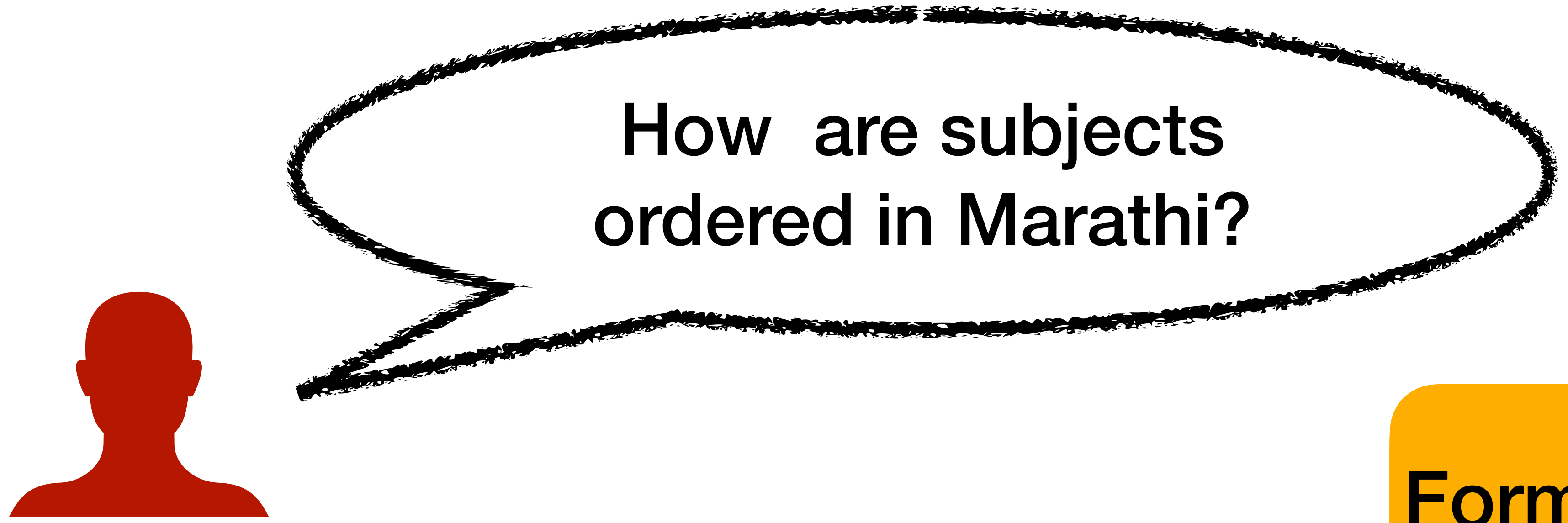
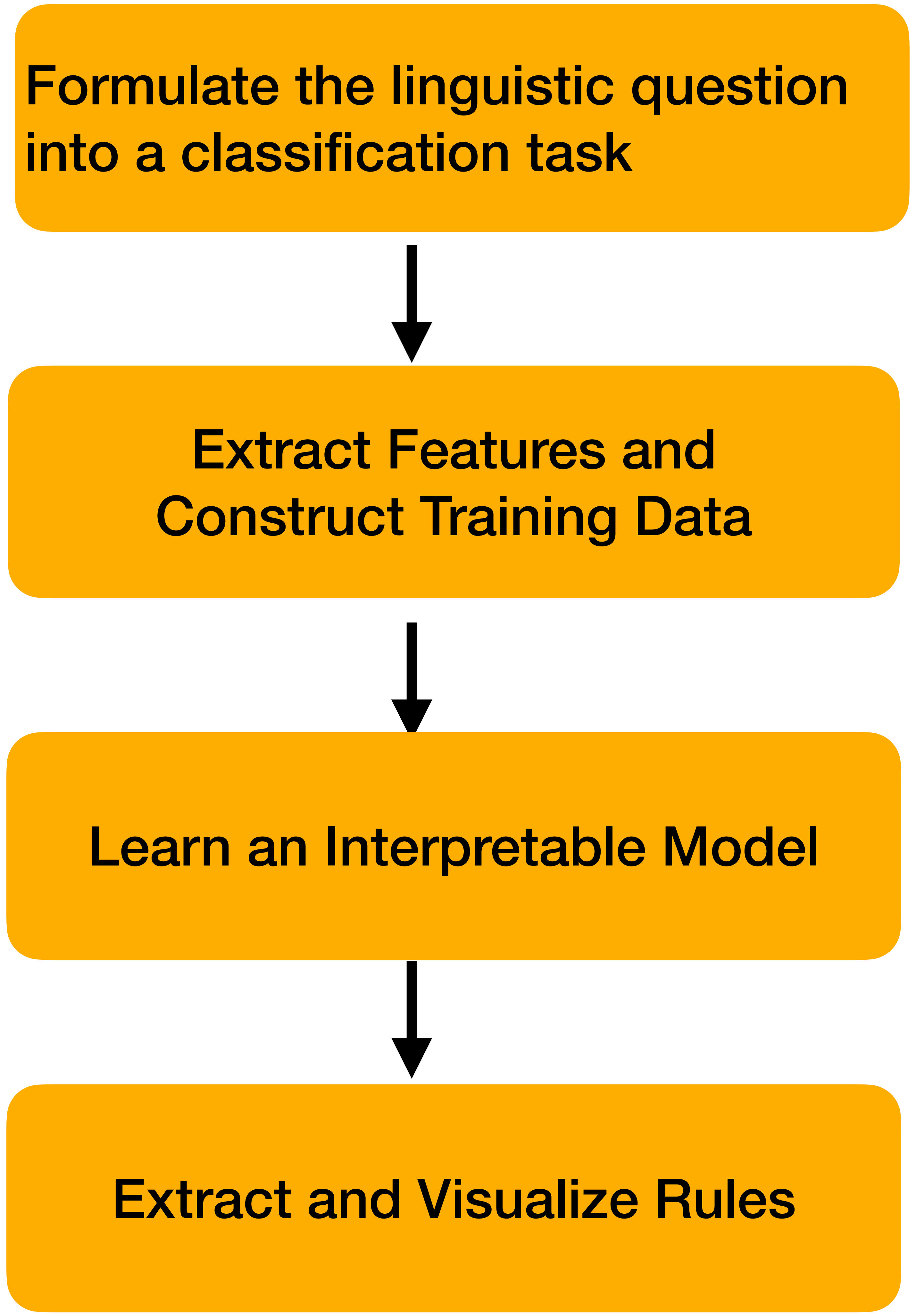


ext corpus



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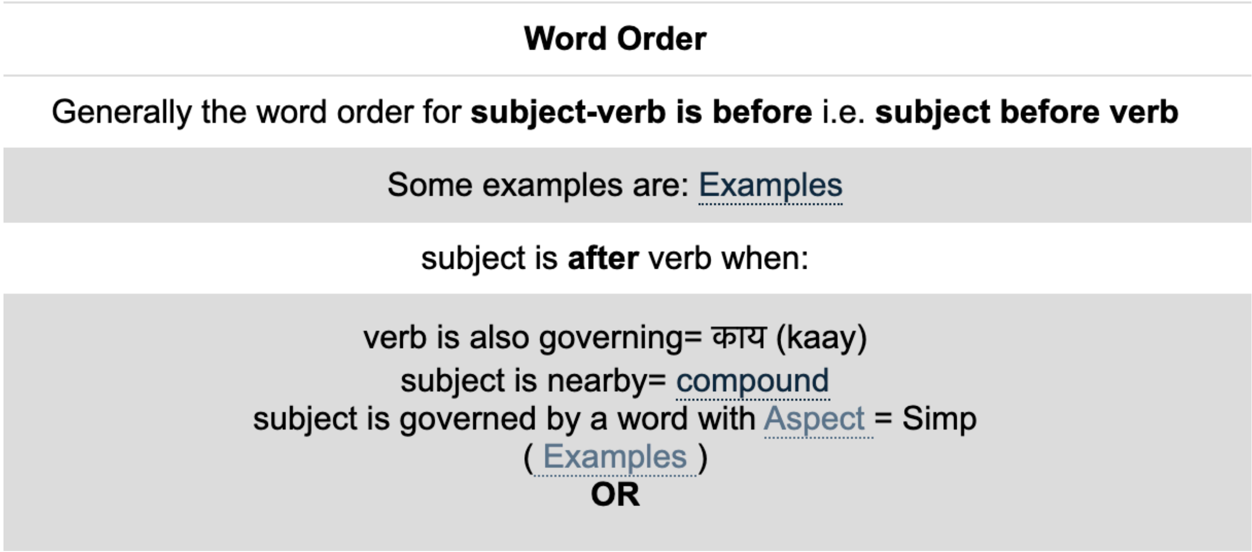

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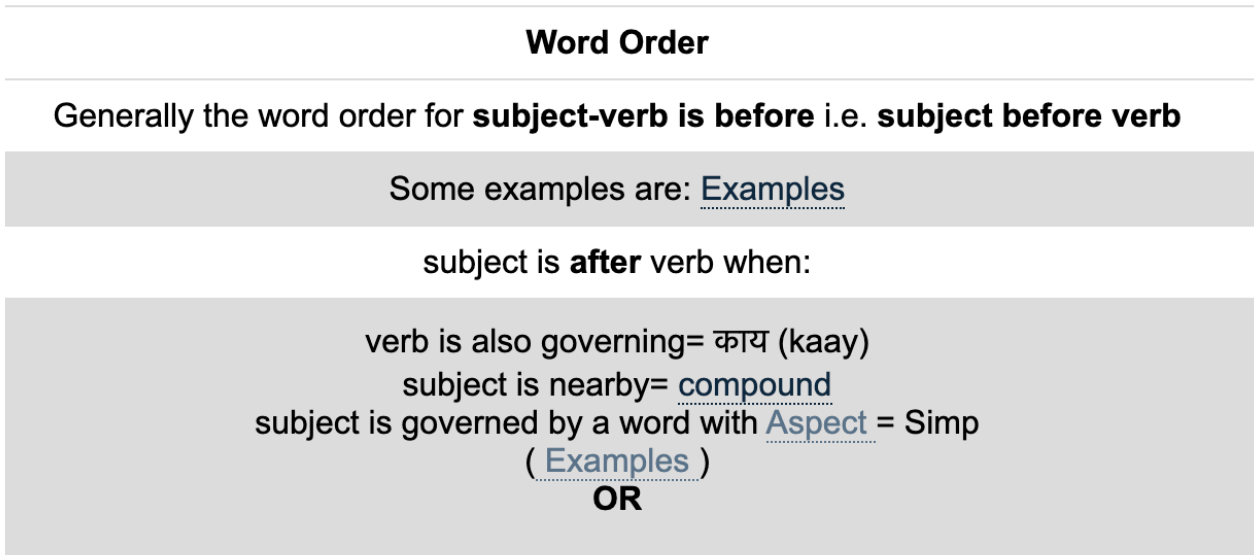

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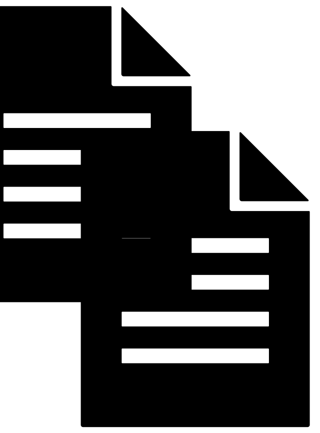

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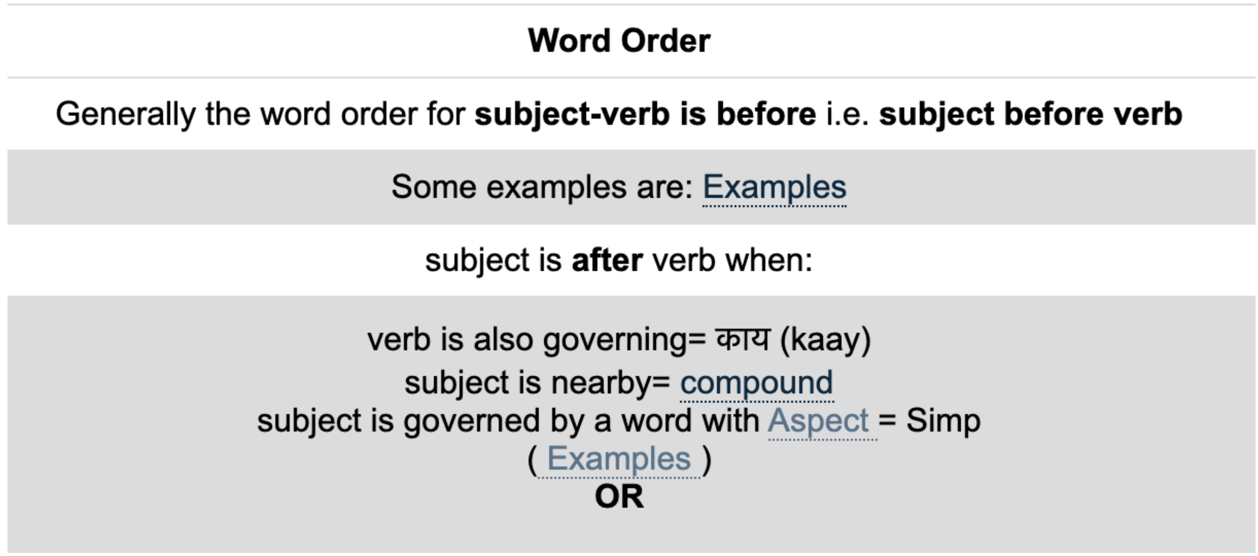

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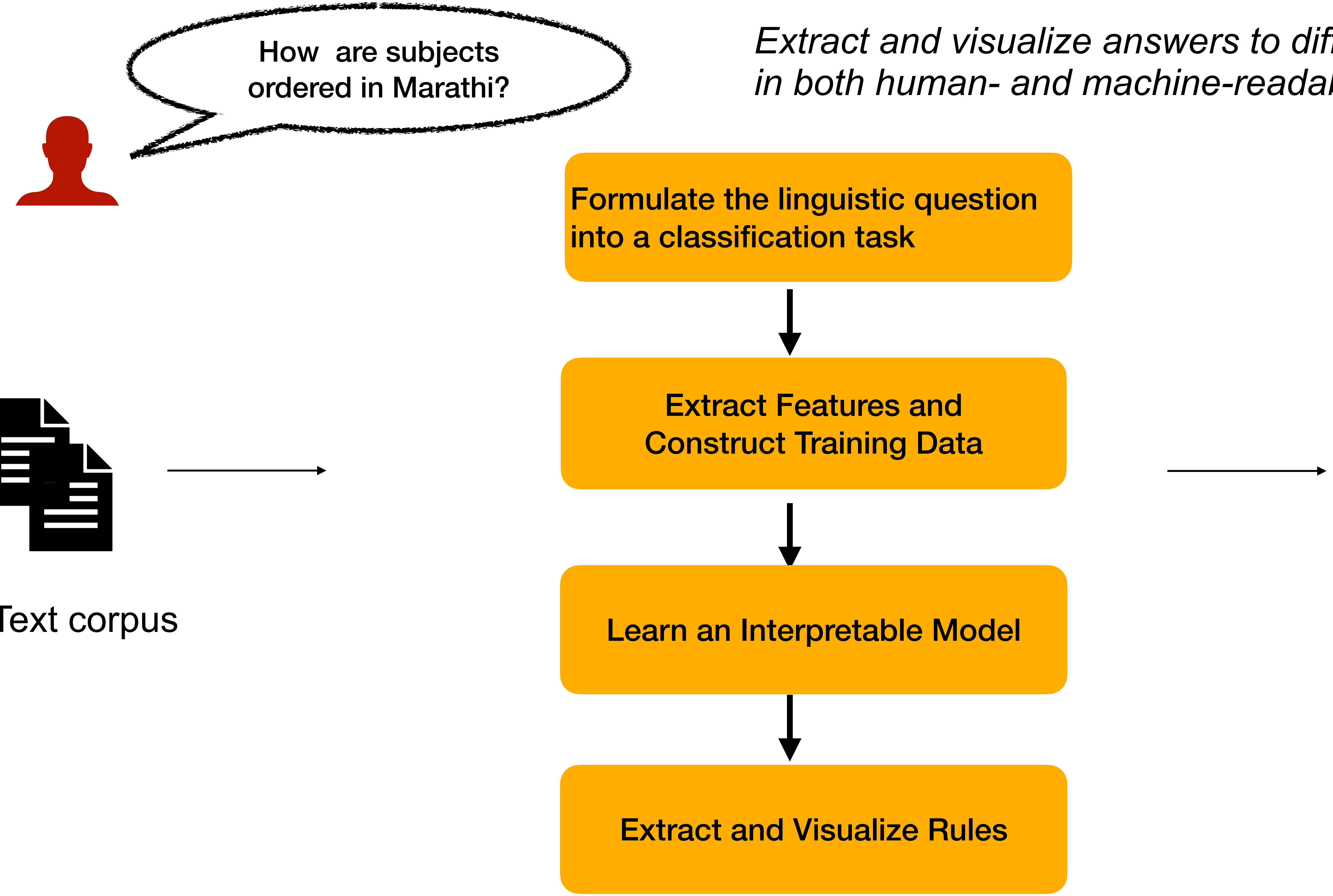

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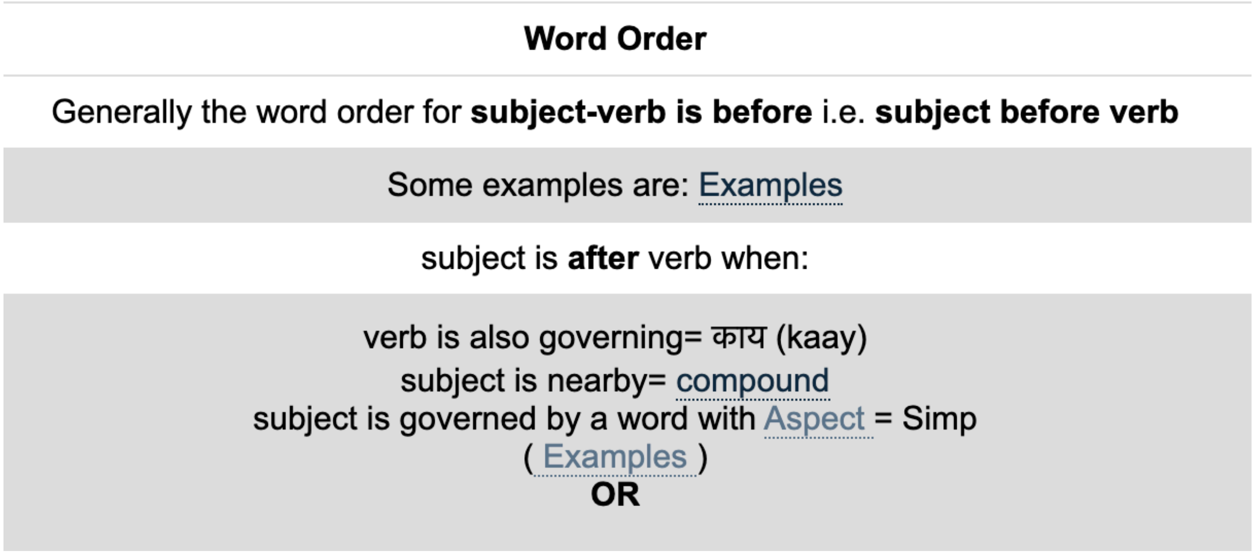

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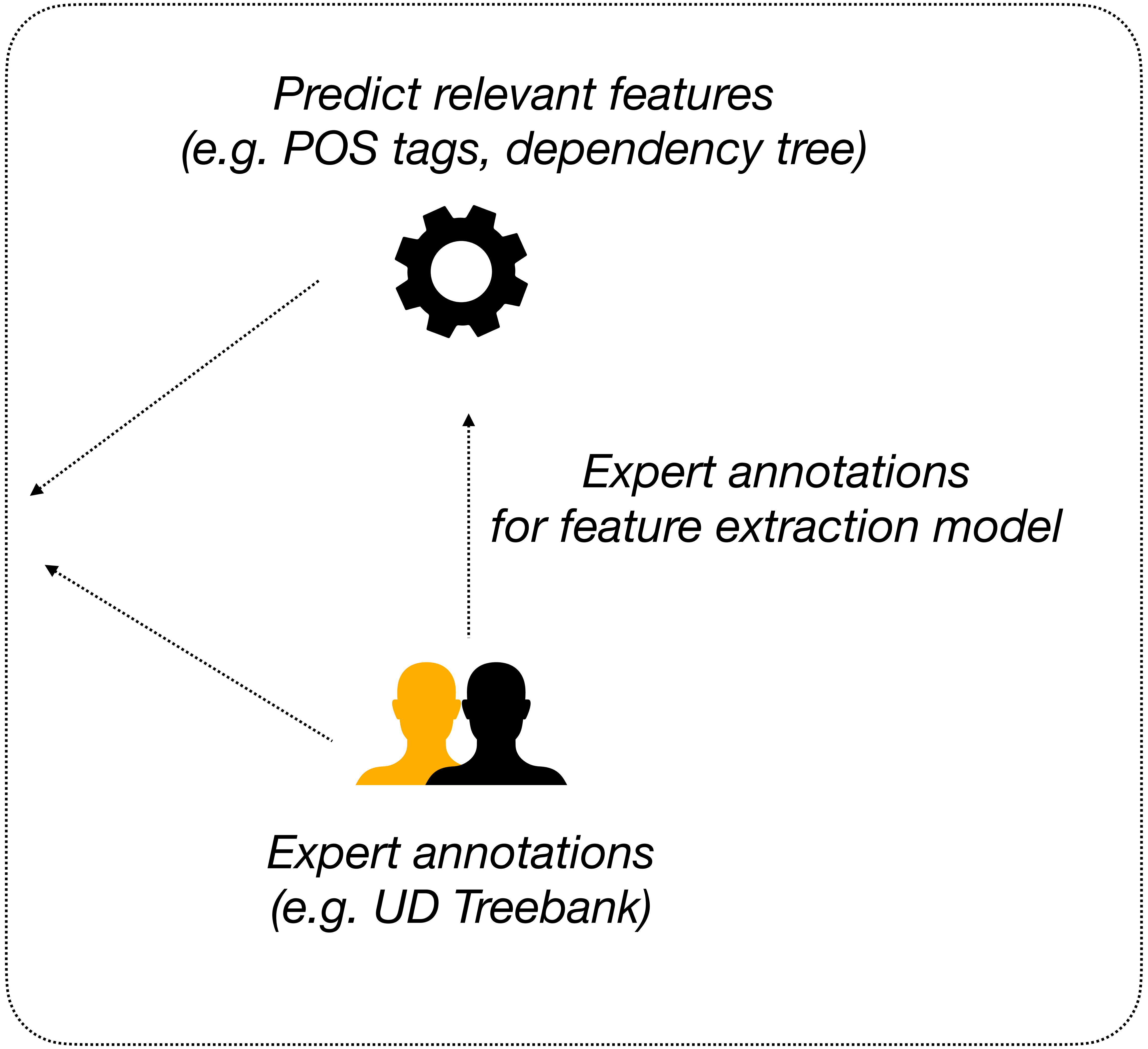

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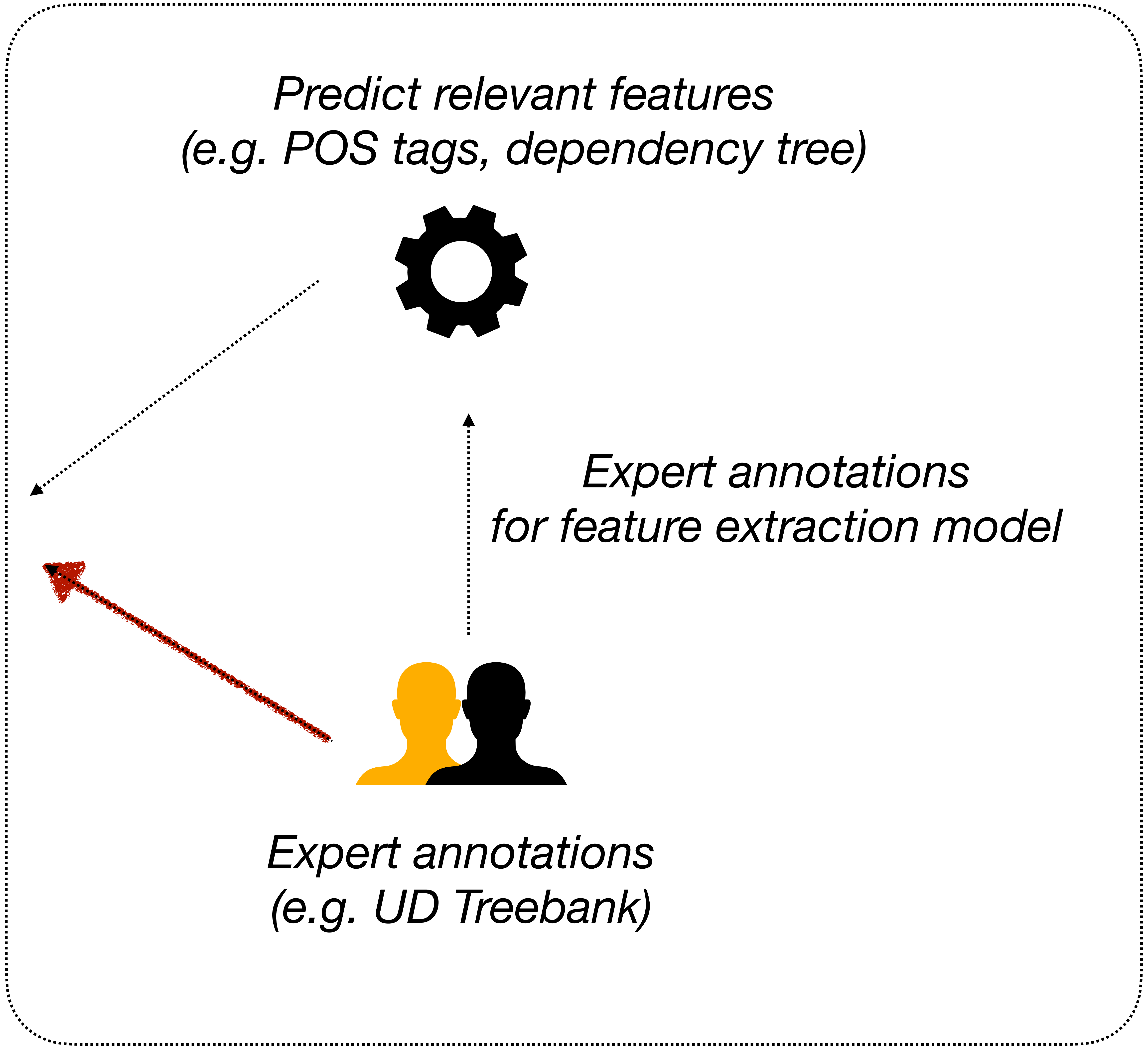

Predict relevant features (e.g. POS tags, dependency tree)

Expert annotations for feature extraction model

Expert annotations (e.g. UD Treebank)

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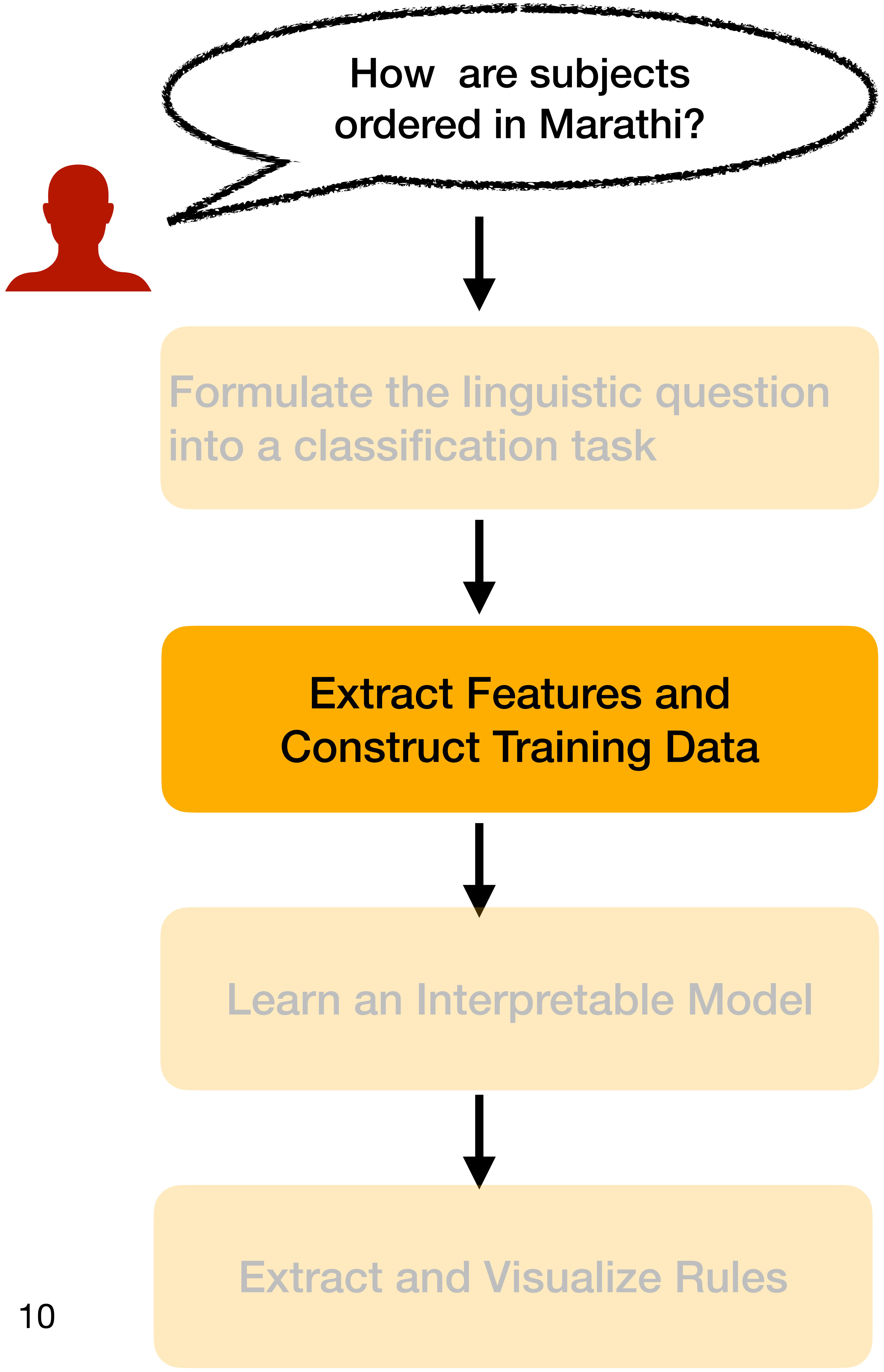

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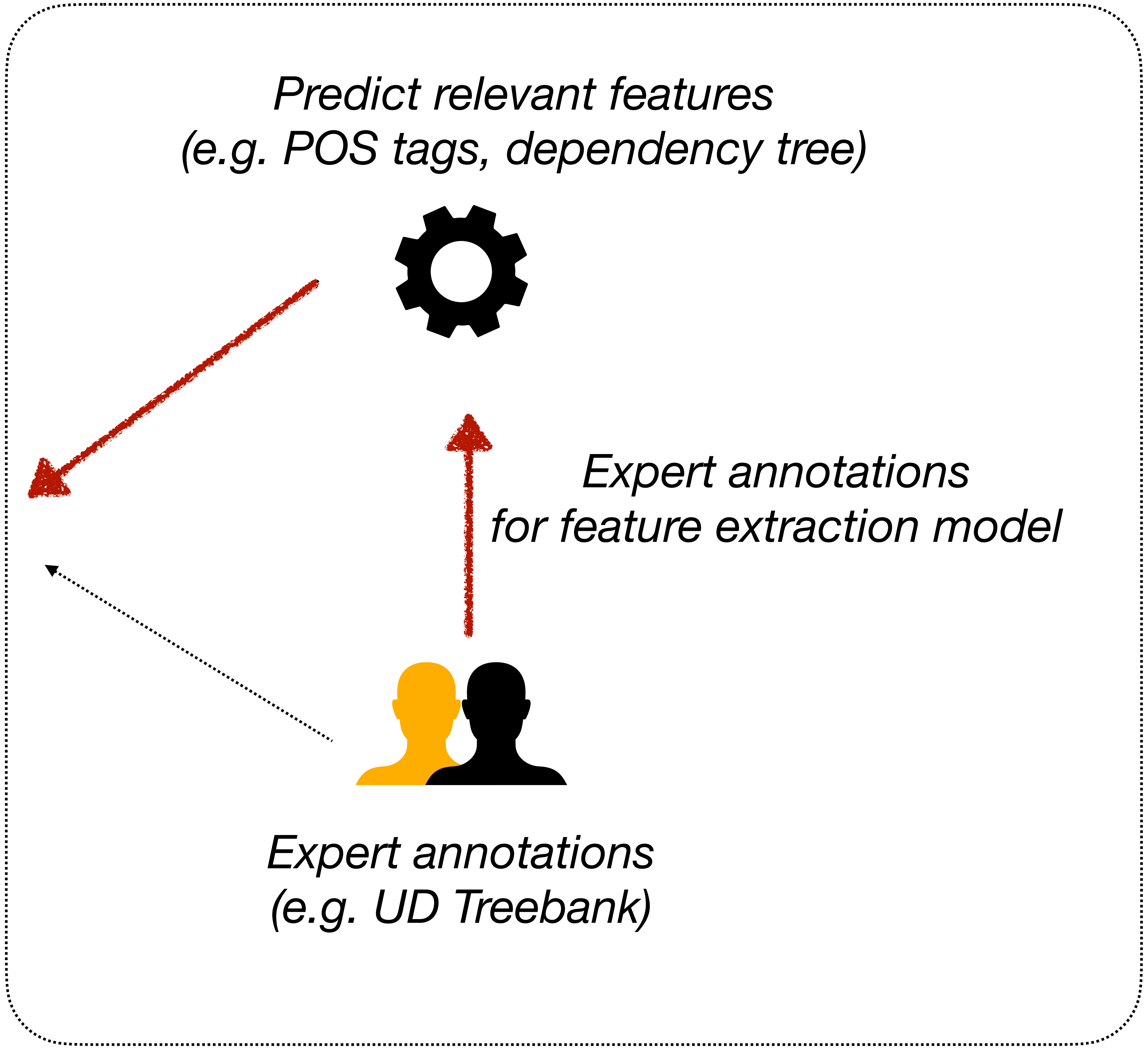

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Types of Grammar Aspects covered in AutoLEX

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Agreement

Types of Grammar Aspects covered in AutoLEX

Agreement

Word Order

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Affix Usage

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Types of Grammar Aspects covered in AutoLEX

Morpho-Syntax

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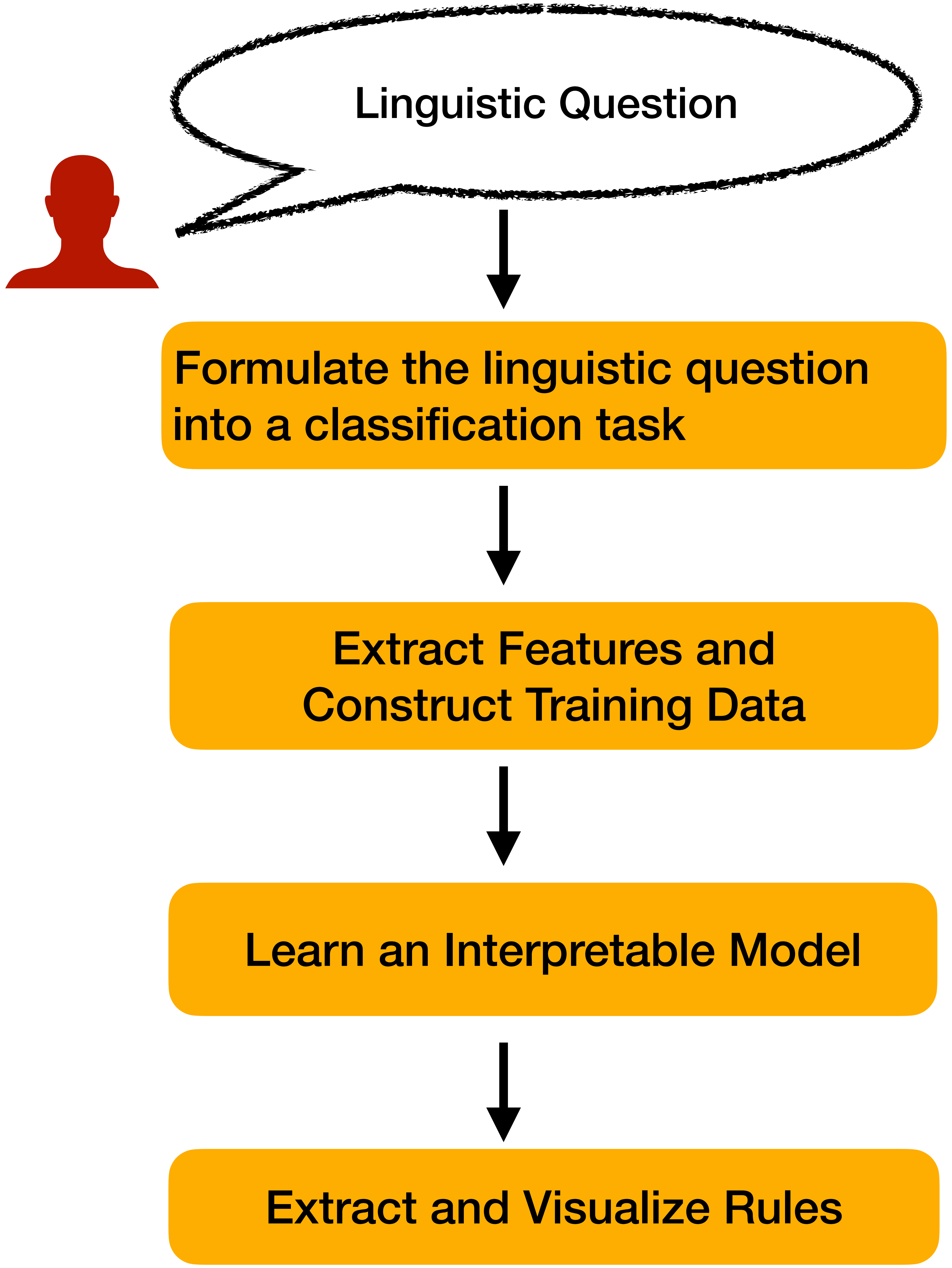


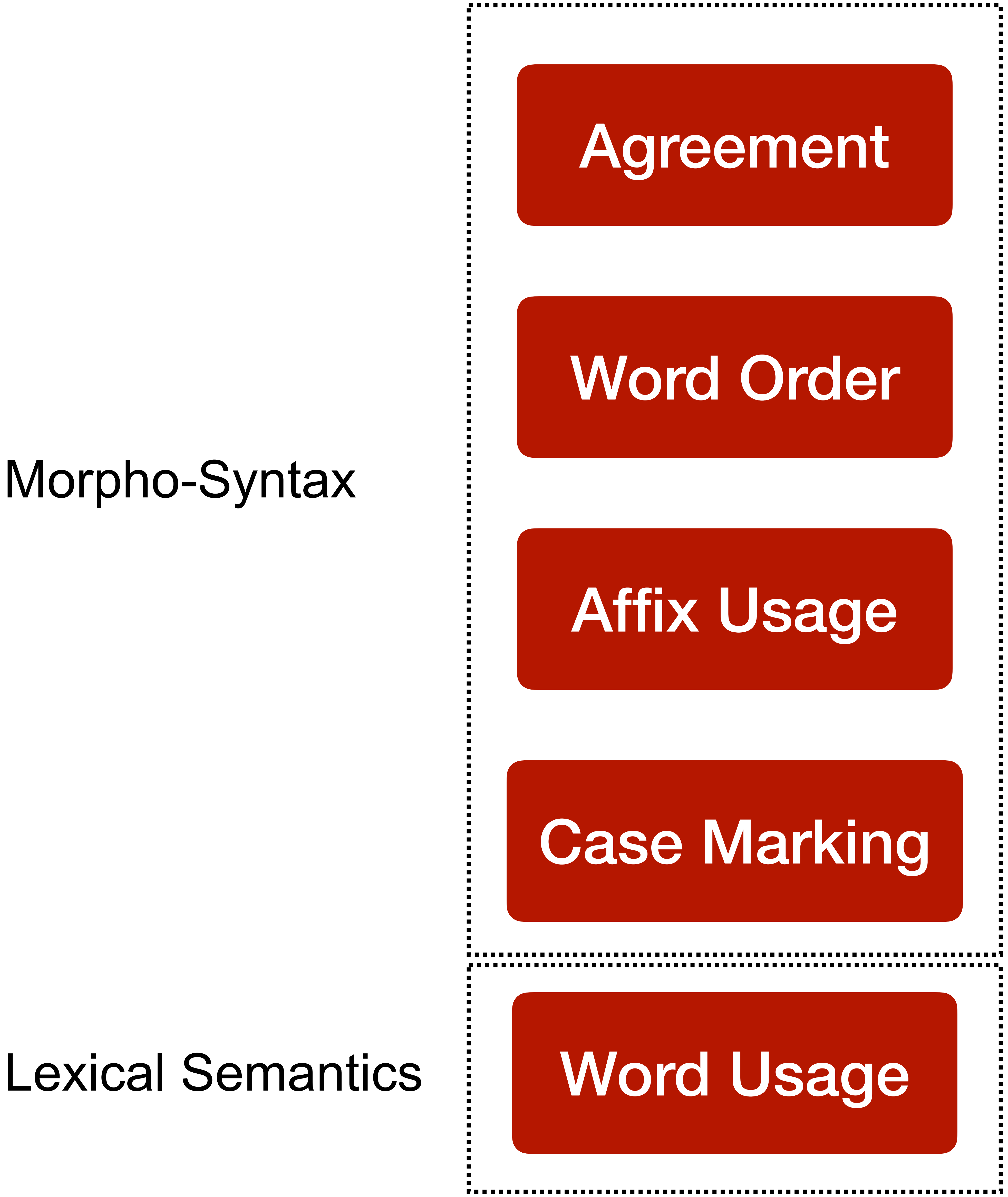
Linguistic Question

Formulate the linguistic question into a classification task

Extract Features and Construct Training Data

Learn an Interpretable Model

Extract and Visualize Rules



Morpho-Syntax

- Agreement
- Word Order
- Affix Usage
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Lexical Semantics

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Chaudhary**, Sheikh, Mortensen, Anastasopoulos, Neubig.* ***In Submission

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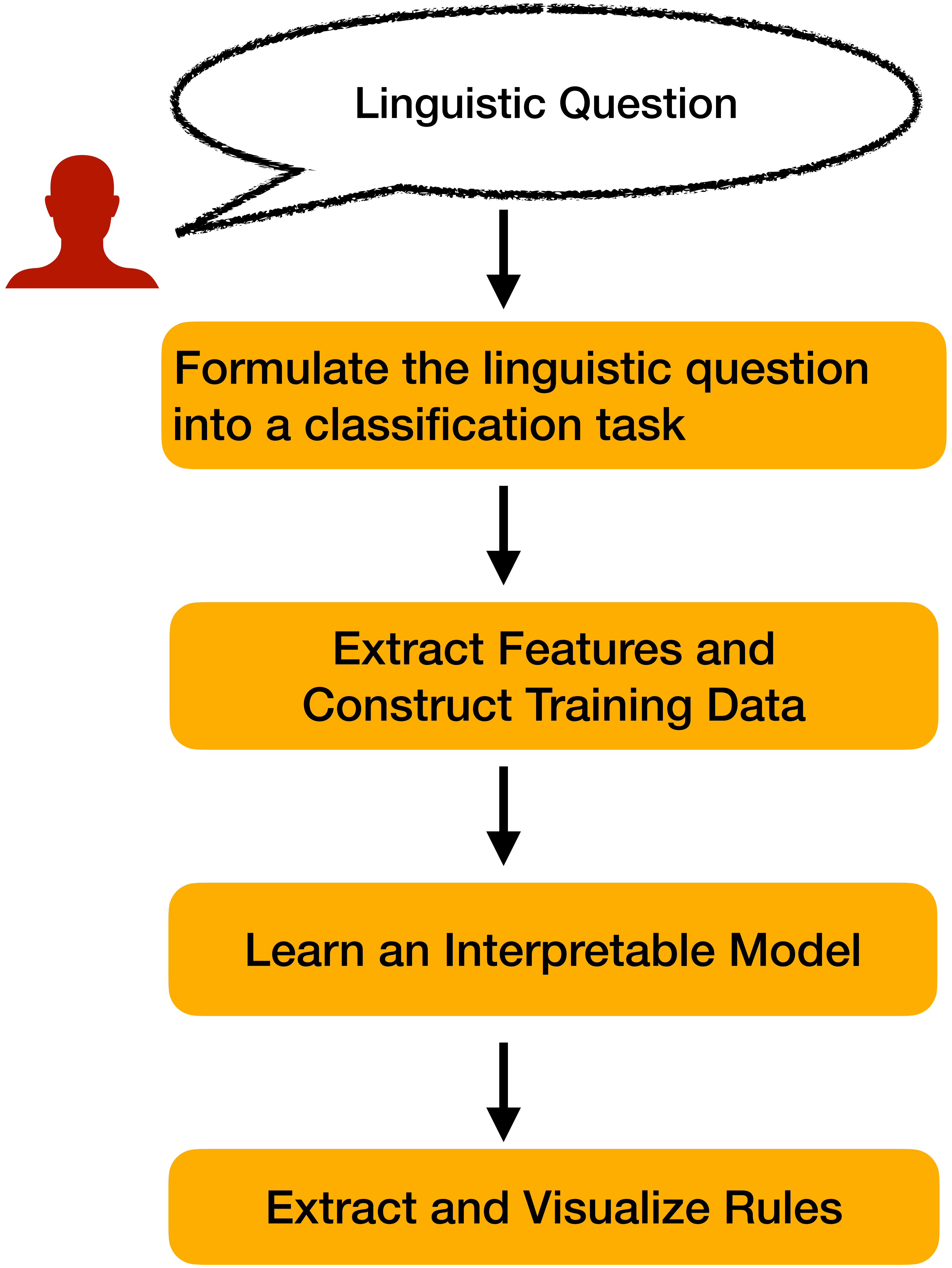

Linguistic Question

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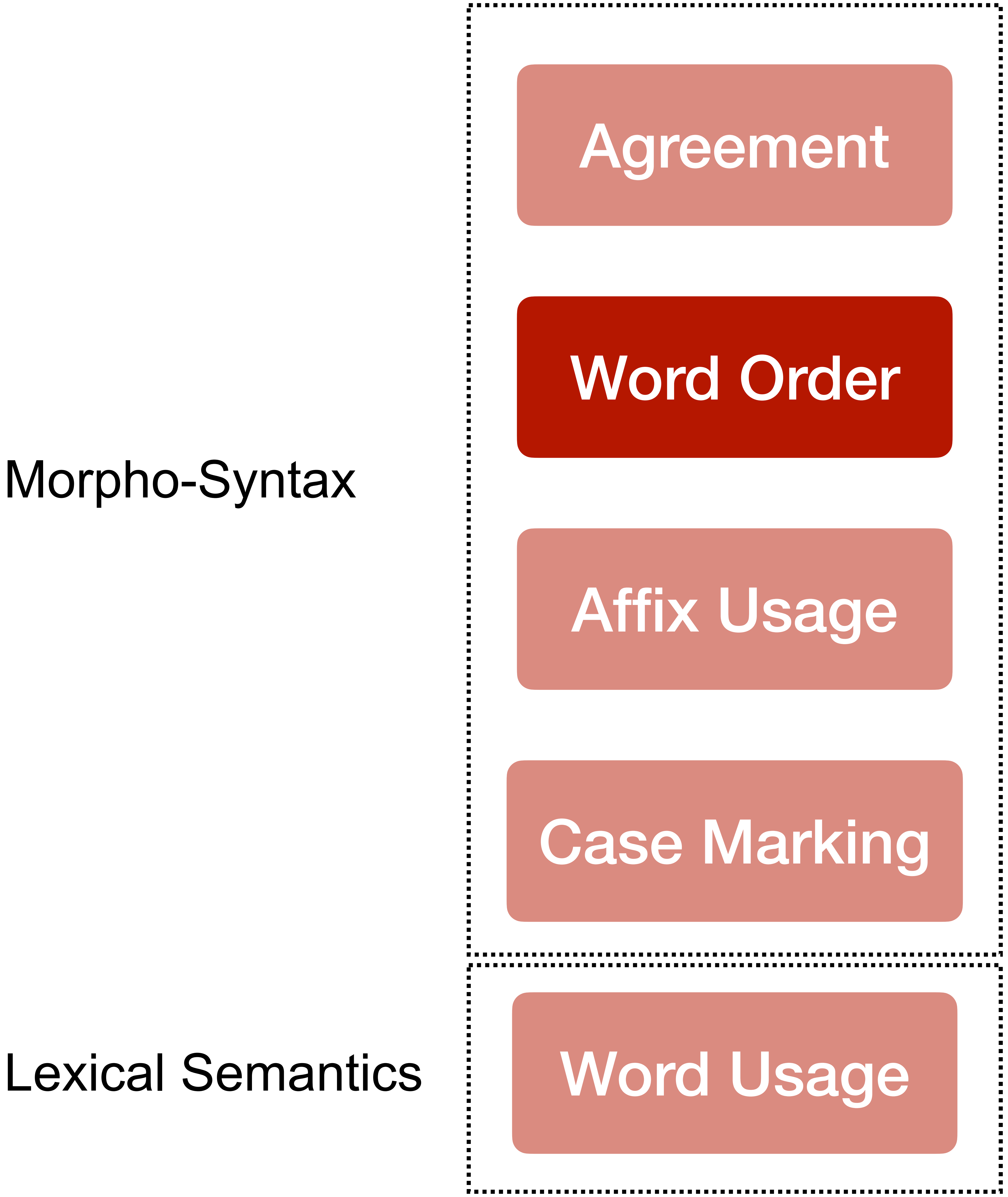

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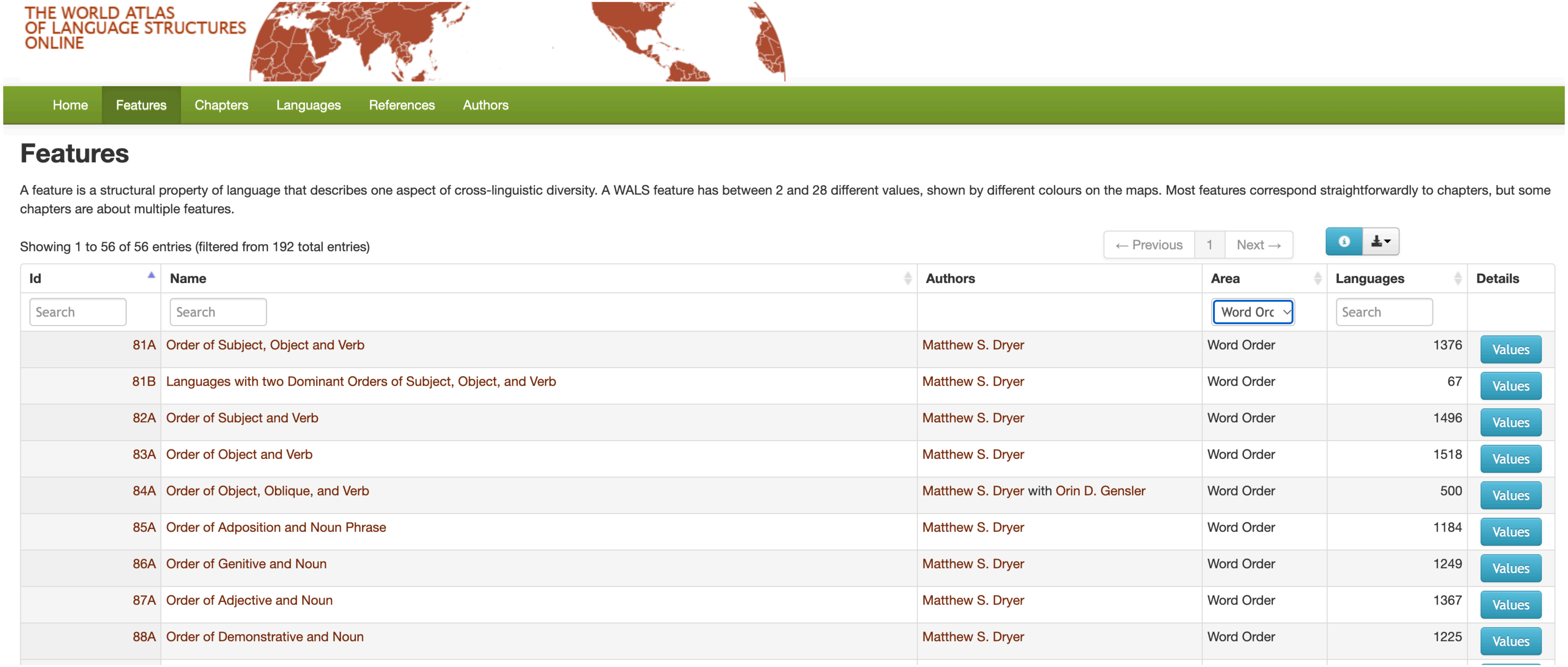
Word Order



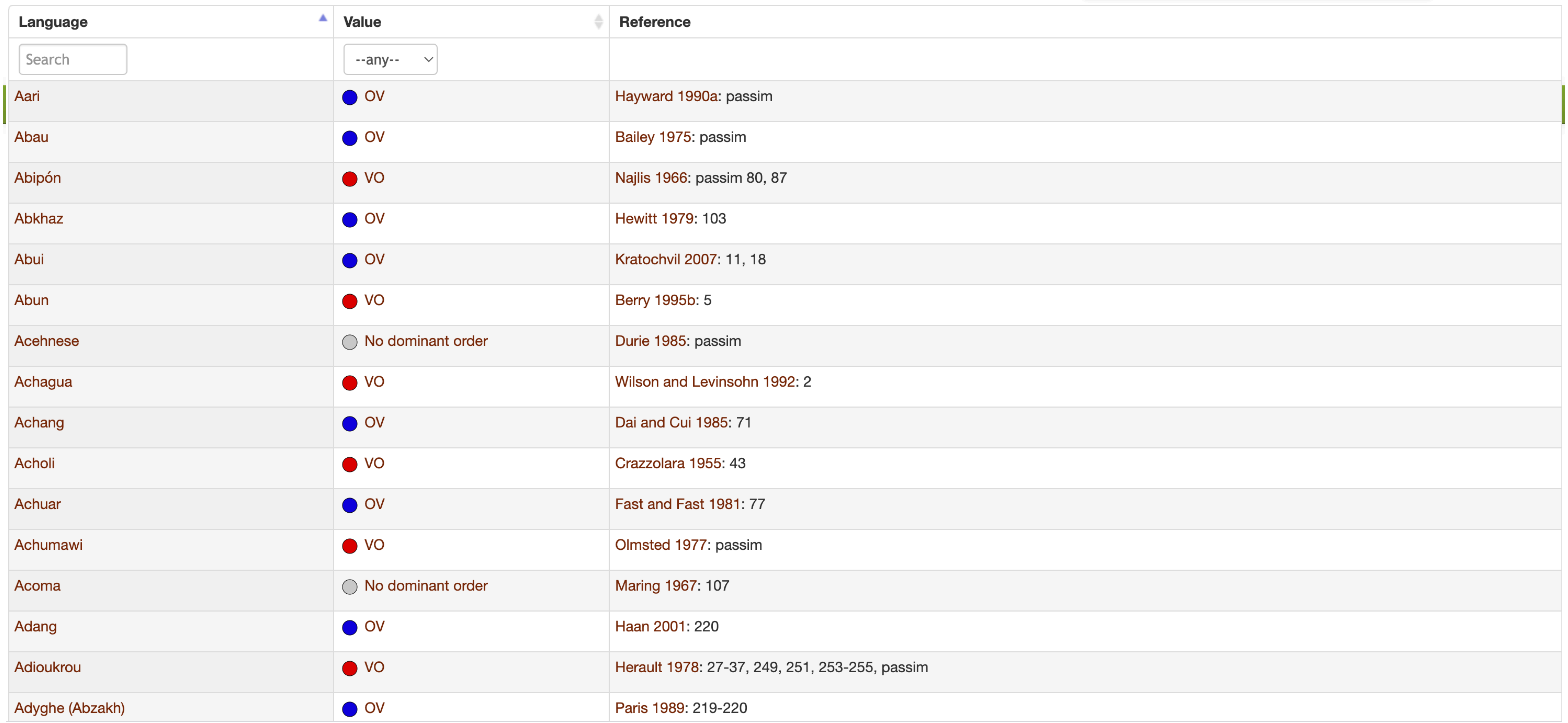
Features

A feature is a structural property of language that describes one aspect of cross-linguistic diversity. A WALS feature has between 2 and 28 different values, shown by different colours on the maps. Most features correspond straightforwardly to chapters, but some chapters are about multiple features.

Showing 1 to 56 of 56 entries (filtered from 192 total entries)

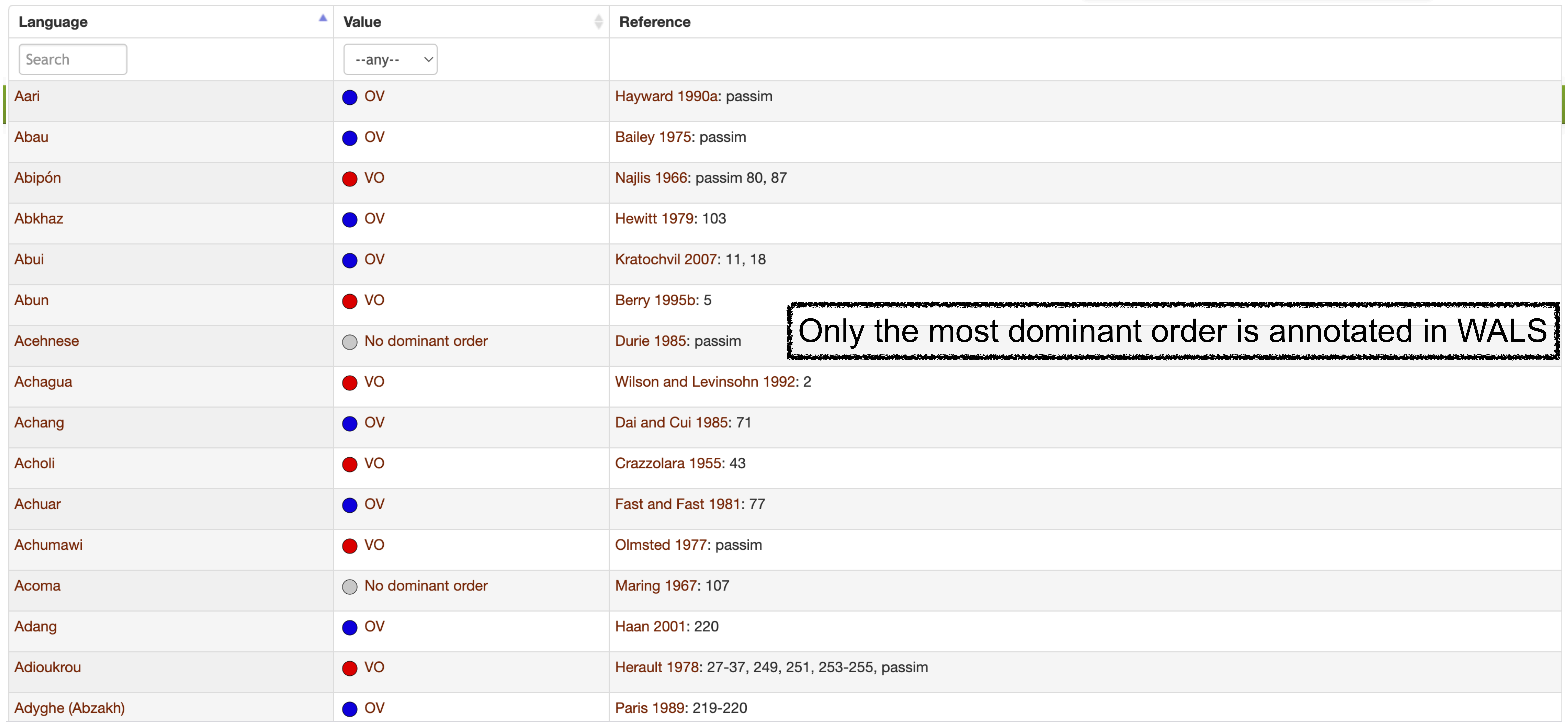
Id	Name	Authors	Area	Languages	Details
81A	Order of Subject, Object and Verb	Matthew S. Dryer	Word Order	1376	Values
81B	Languages with two Dominant Orders of Subject, Object, and Verb	Matthew S. Dryer	Word Order	67	Values
82A	Order of Subject and Verb	Matthew S. Dryer	Word Order	1496	Values
83A	Order of Object and Verb	Matthew S. Dryer	Word Order	1518	Values
84A	Order of Object, Oblique, and Verb	Matthew S. Dryer with Orin D. Gensler	Word Order	500	Values
85A	Order of Adposition and Noun Phrase	Matthew S. Dryer	Word Order	1184	Values
86A	Order of Genitive and Noun	Matthew S. Dryer	Word Order	1249	Values
87A	Order of Adjective and Noun	Matthew S. Dryer	Word Order	1367	Values
88A	Order of Demonstrative and Noun	Matthew S. Dryer	Word Order	1225	Values

Word Order



Language	Value	Reference
Search	--any--	
Aari	🔵 OV	Hayward 1990a: passim
Abau	🔵 OV	Bailey 1975: passim
Abipón	🔴 VO	Najlis 1966: passim 80, 87
Abkhaz	🔵 OV	Hewitt 1979: 103
Abui	🔵 OV	Kratochvil 2007: 11, 18
Abun	🔴 VO	Berry 1995b: 5
Acehnese	⚪ No dominant order	Durie 1985: passim
Achagua	🔴 VO	Wilson and Levinsohn 1992: 2
Achang	🔵 OV	Dai and Cui 1985: 71
Acholi	🔴 VO	Crazzolara 1955: 43
Achuar	🔵 OV	Fast and Fast 1981: 77
Achumawi	🔴 VO	Olmsted 1977: passim
Acoma	⚪ No dominant order	Maring 1967: 107
Adang	🔵 OV	Haan 2001: 220
Adioukrou	🔴 VO	Herault 1978: 27-37, 249, 251, 253-255, passim
Adyghe (Abzakh)	🔵 OV	Paris 1989: 219-220

Word Order



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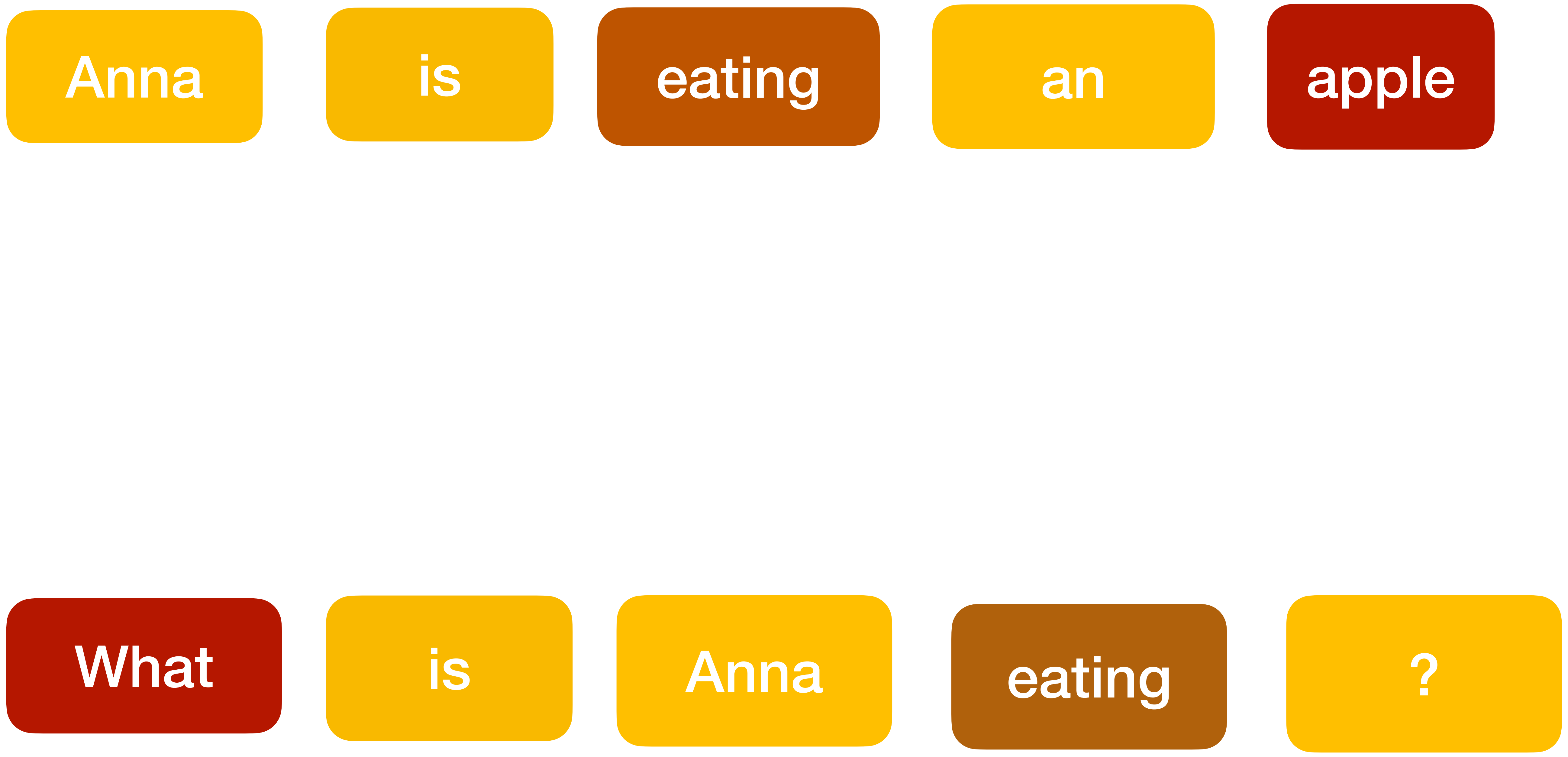
Only the most dominant order is annotated in WALS

Word Order

Word Order

Anna is eating an apple

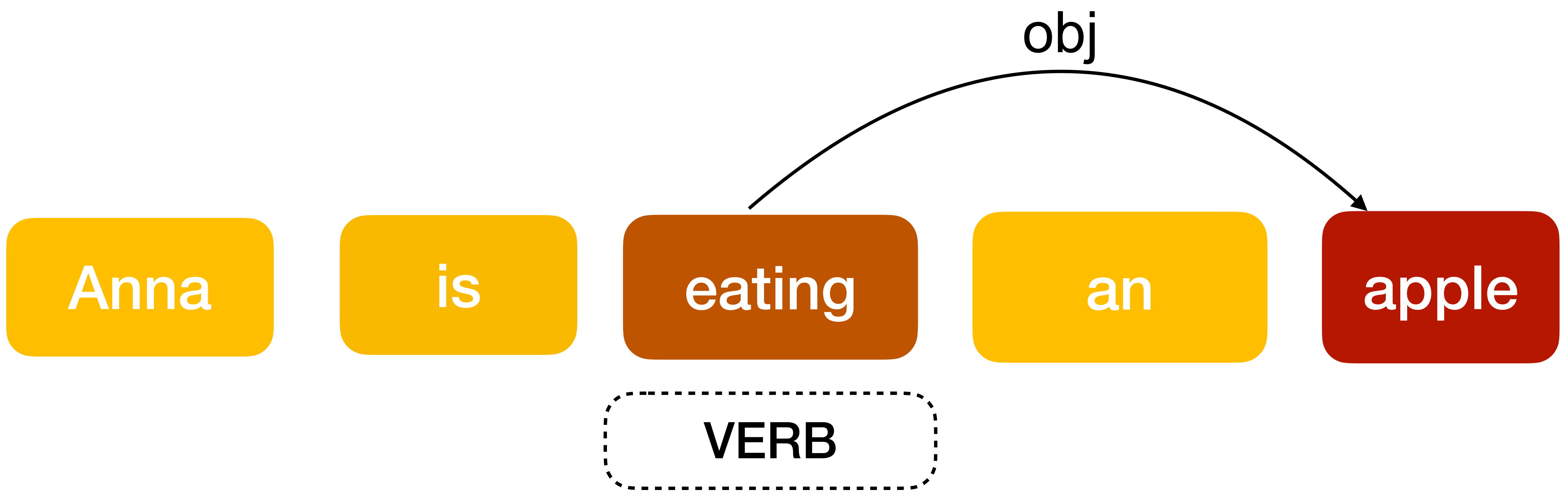
Word Order



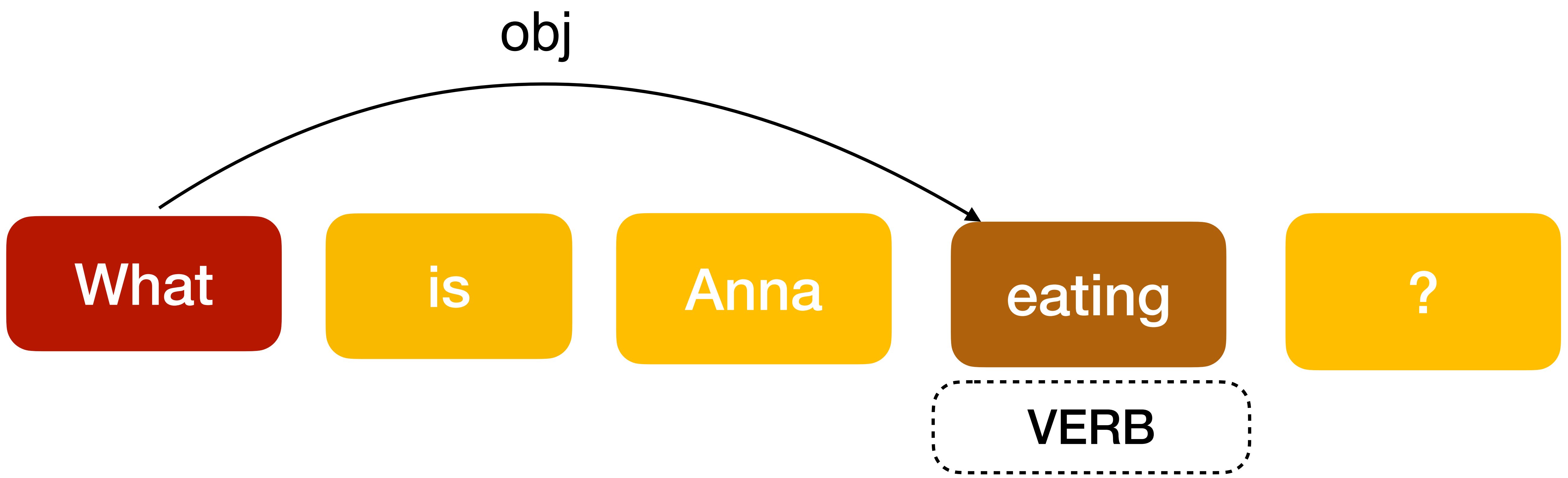
Anna is eating an apple

What is Anna eating ?

Word Order

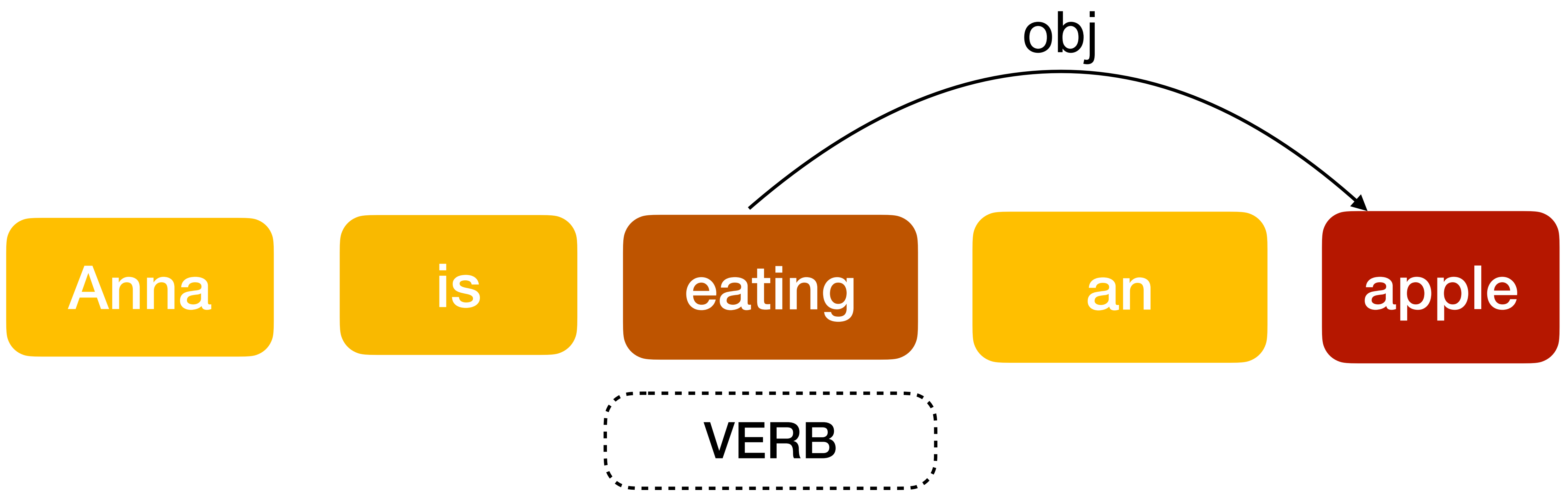


Verb-Object



Object-Verb

Word Order



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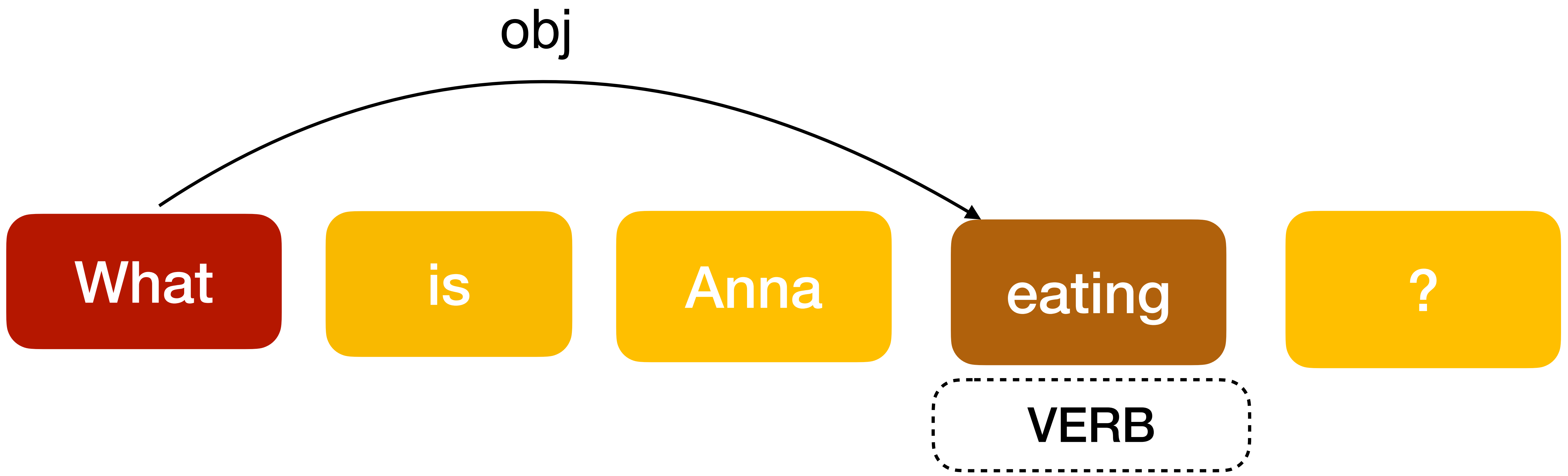

Object-Verb

When are **objects** before or after the **verbs**?

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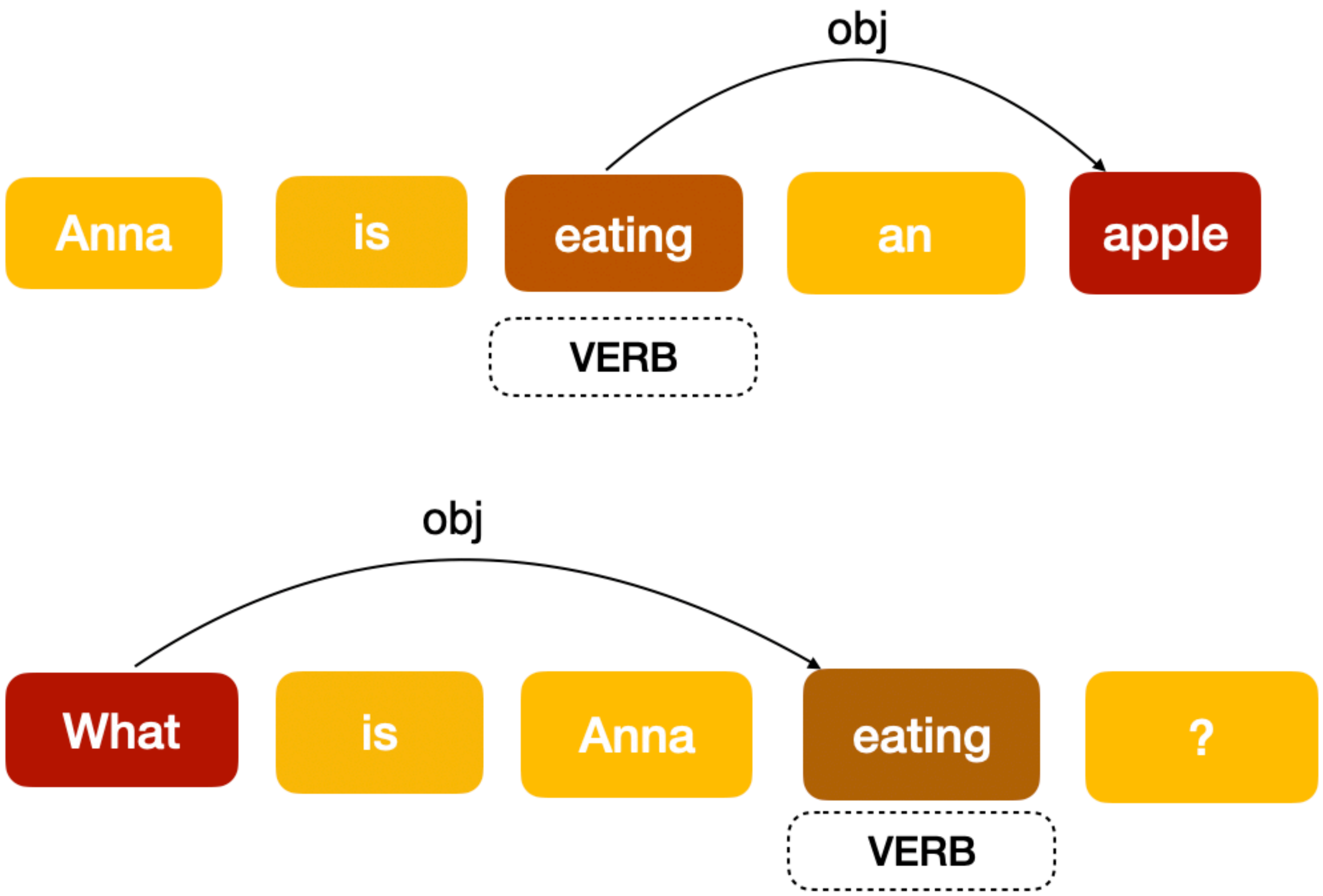
Chaudhary**, Sheikh, Mortensen, Anastasopoulos, Neubig.* ***In Submission

Word Order: Formulate Linguistic Question



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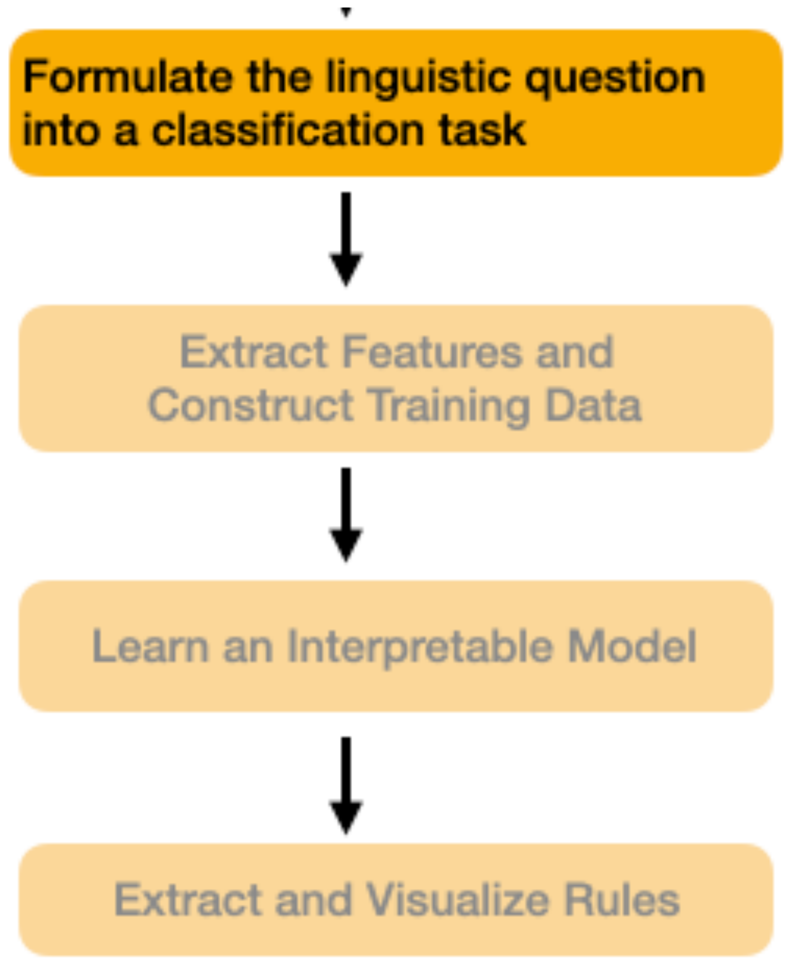
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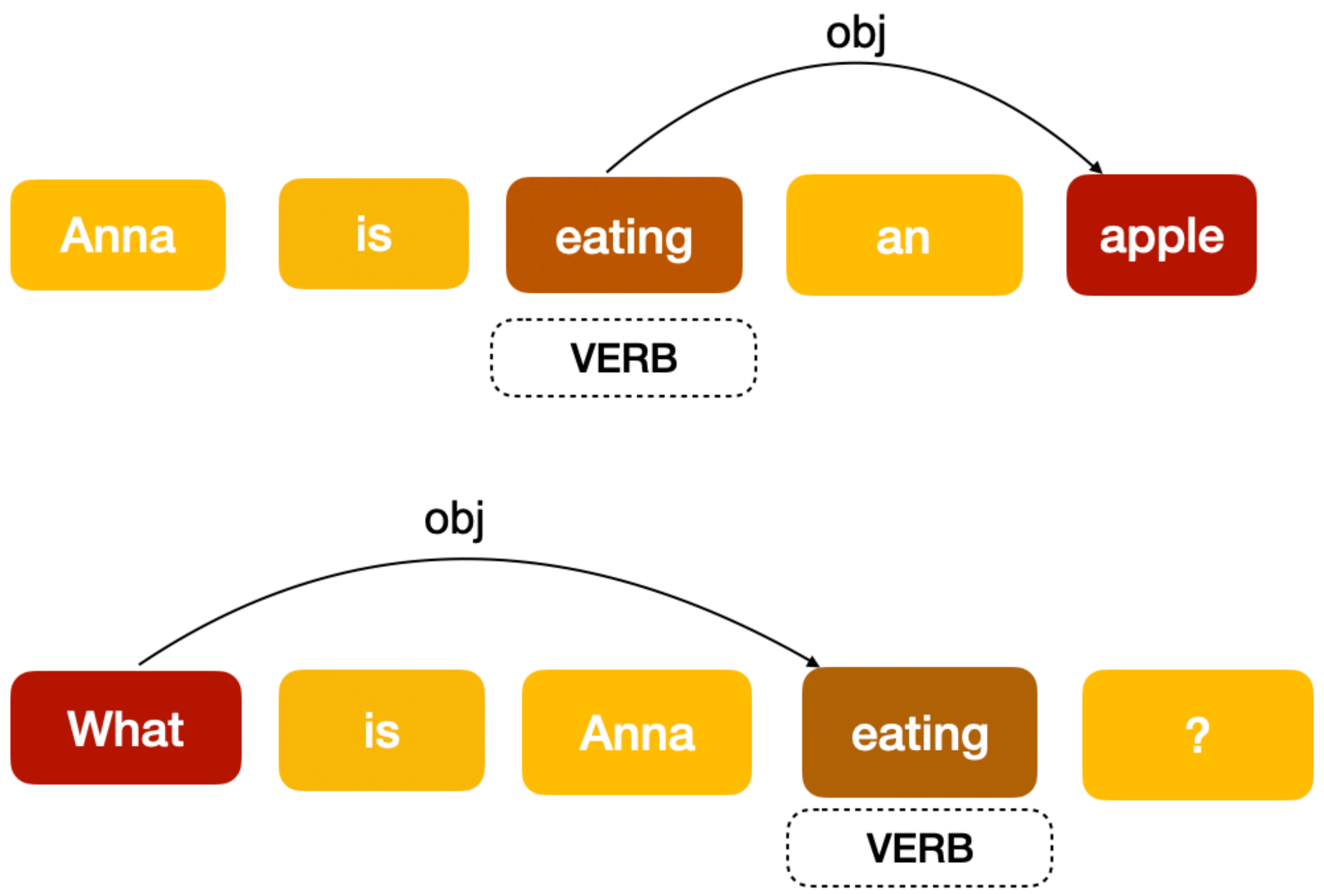

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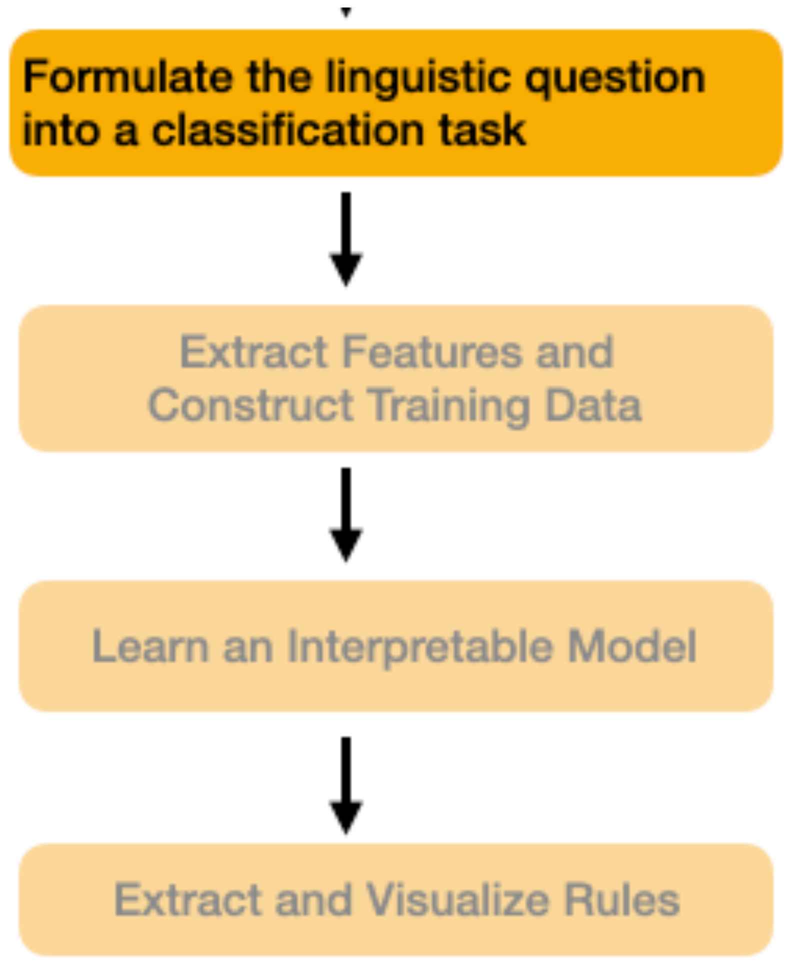
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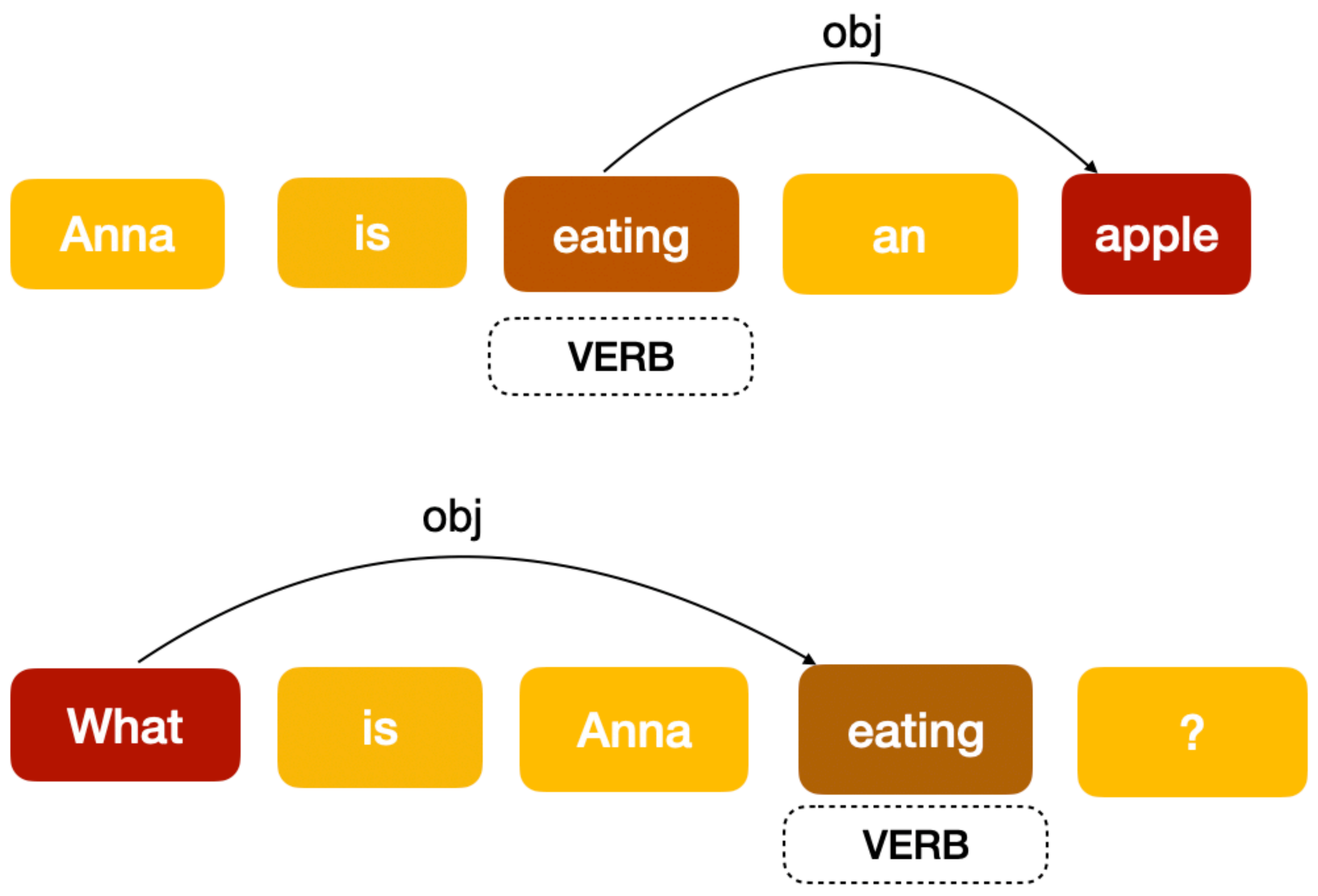

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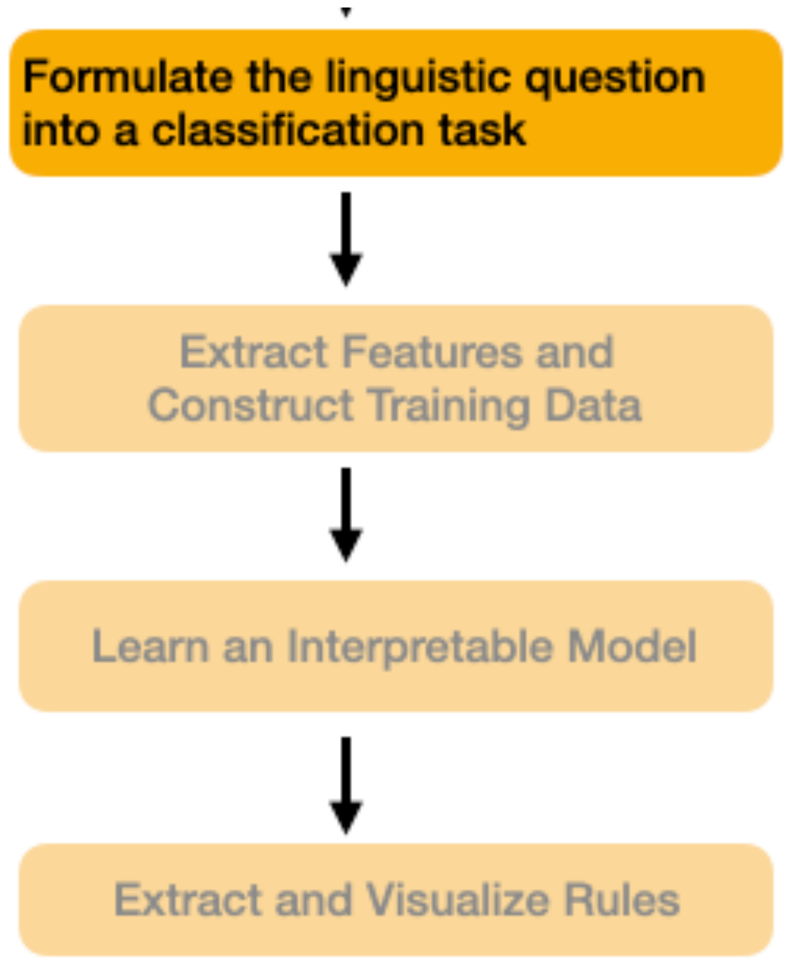

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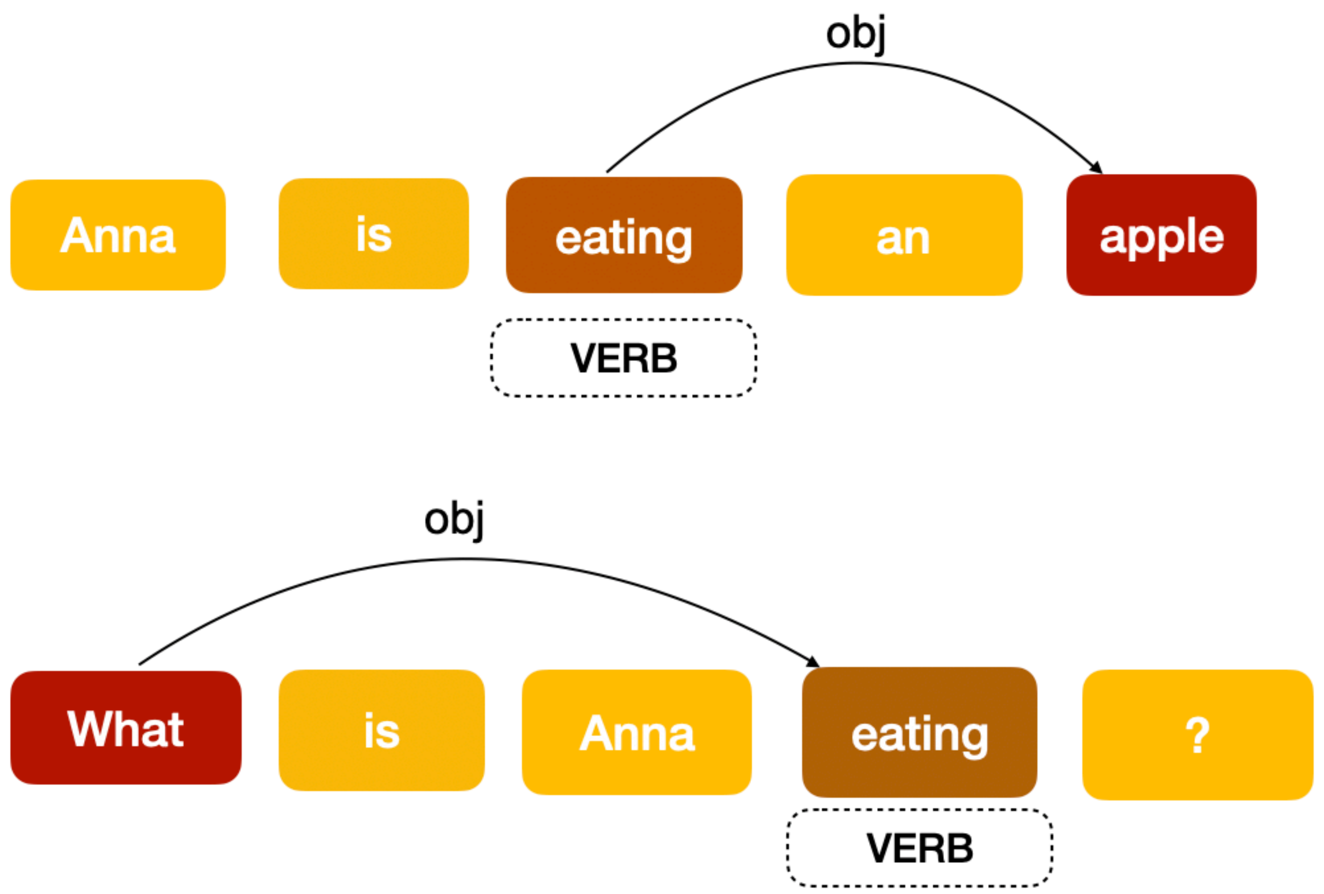

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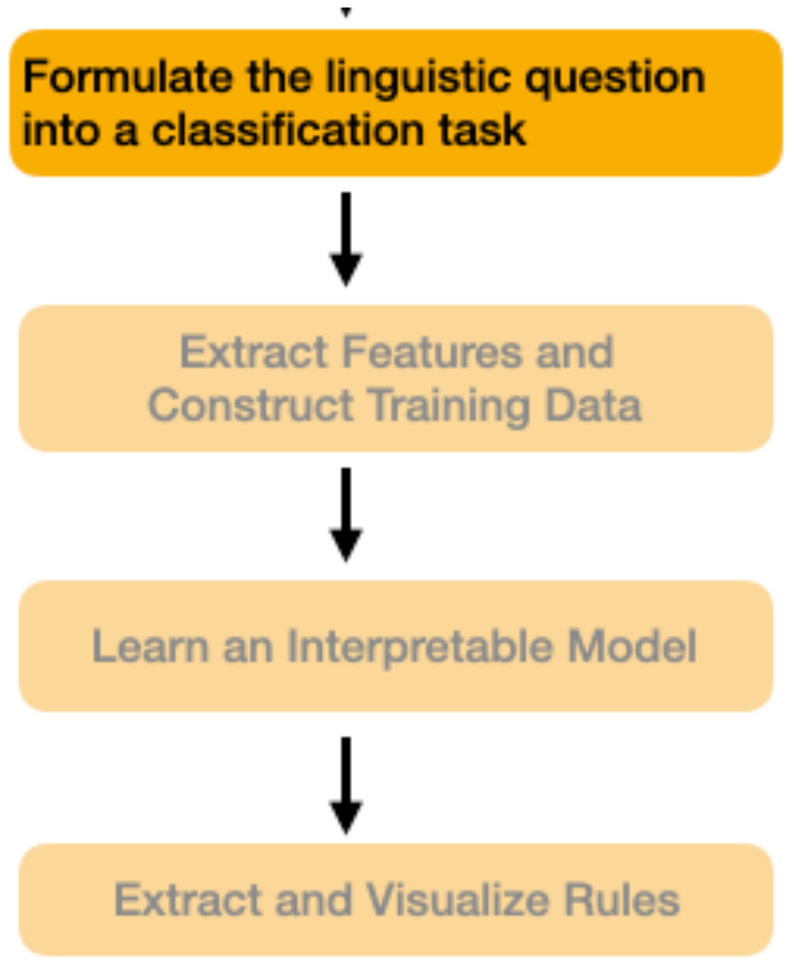
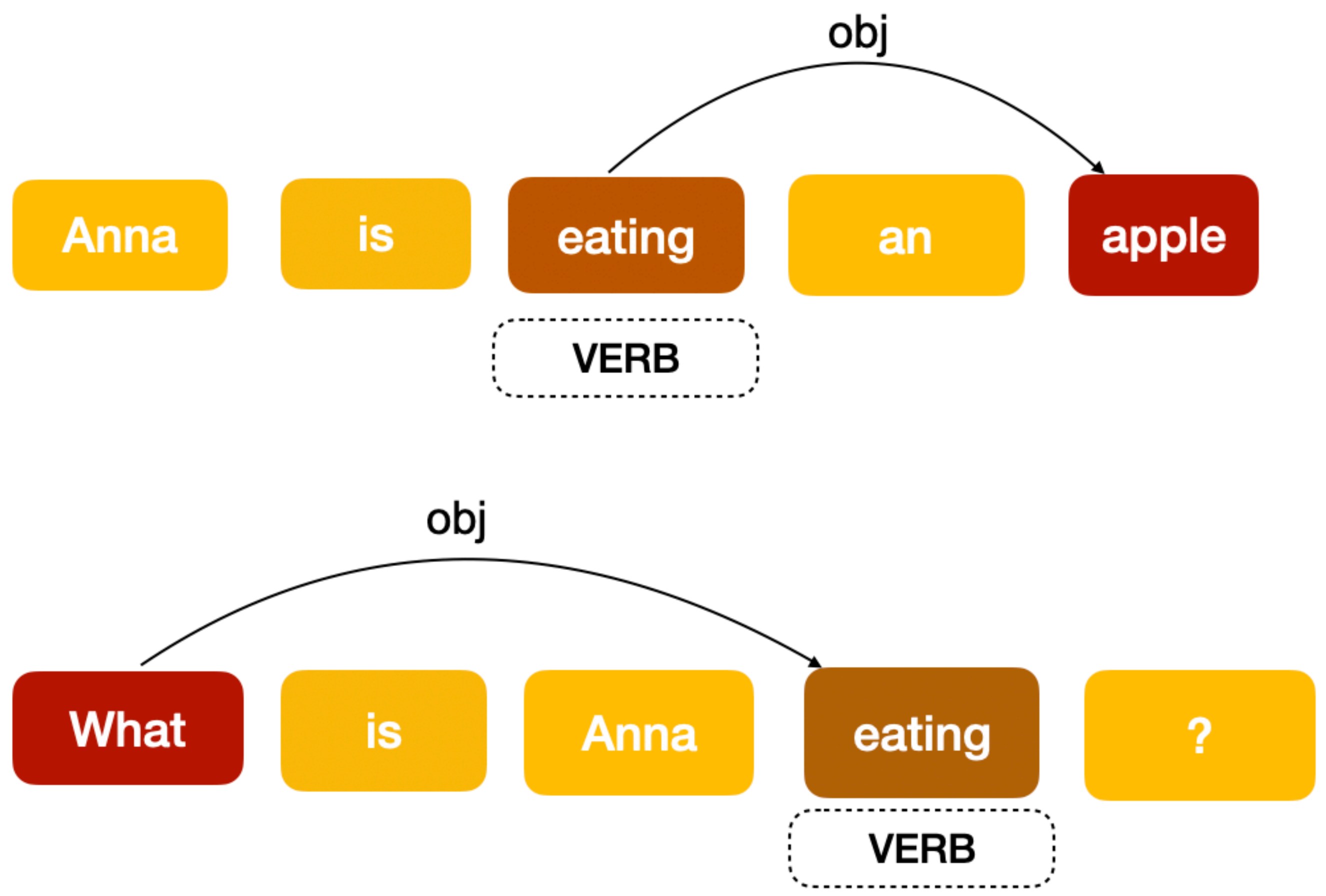
Input	Label



Word Order: Formulate Linguistic Question



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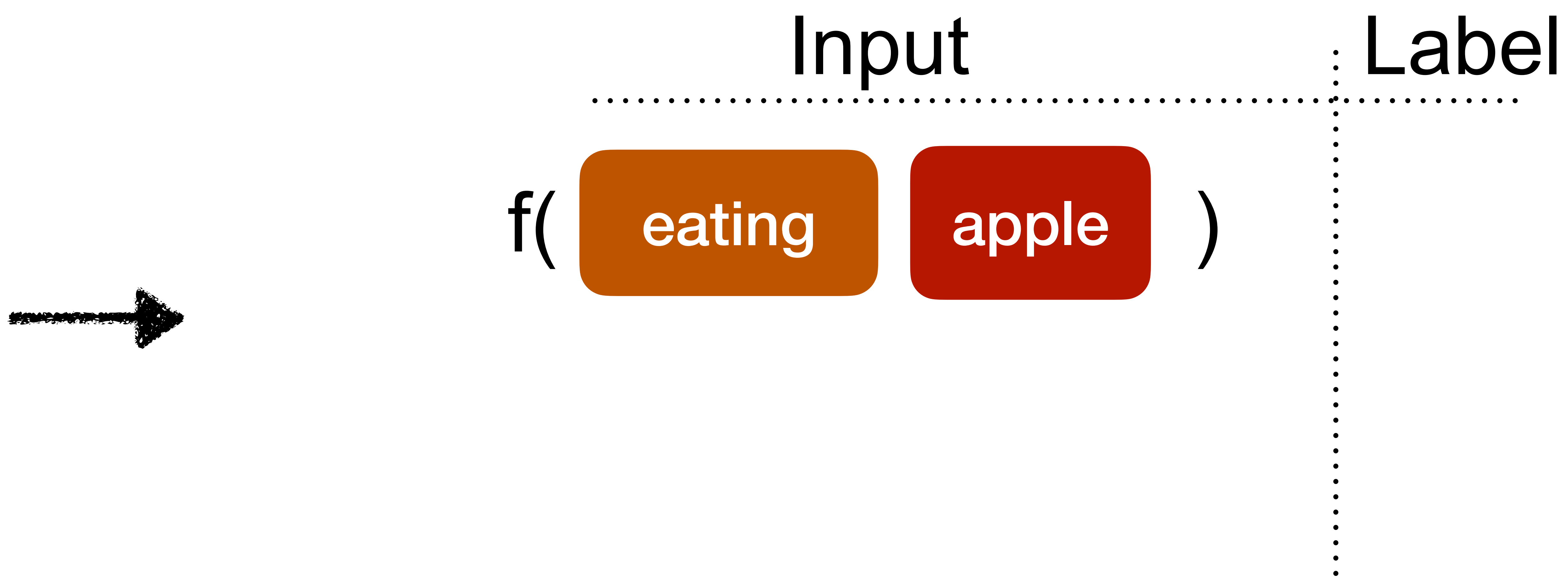

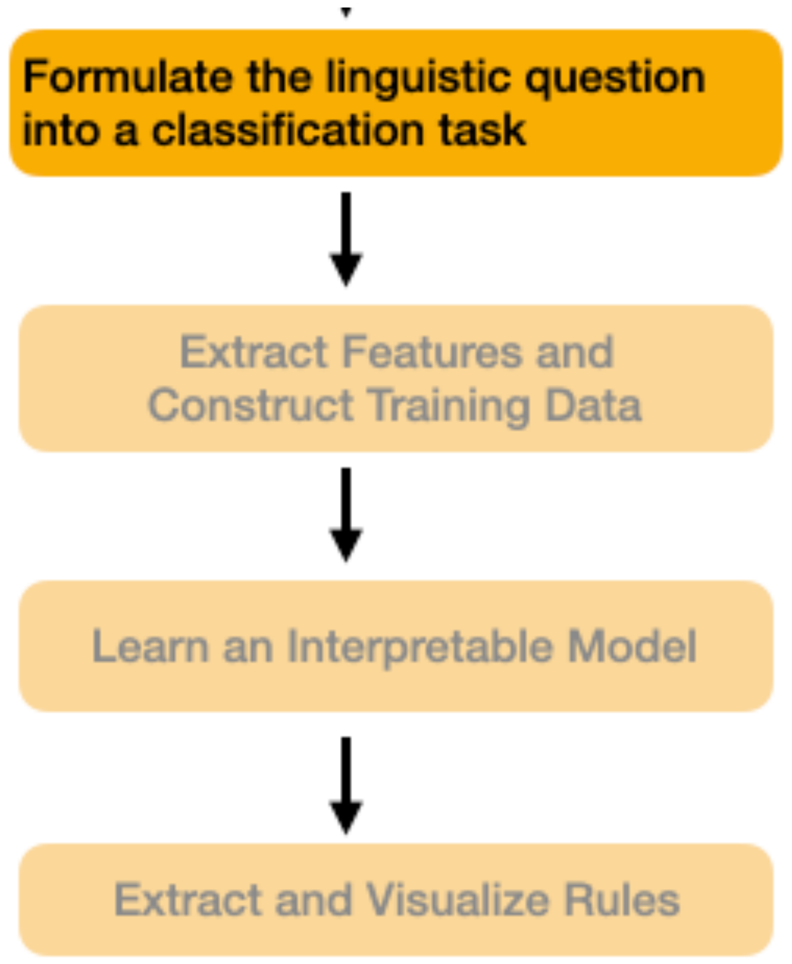

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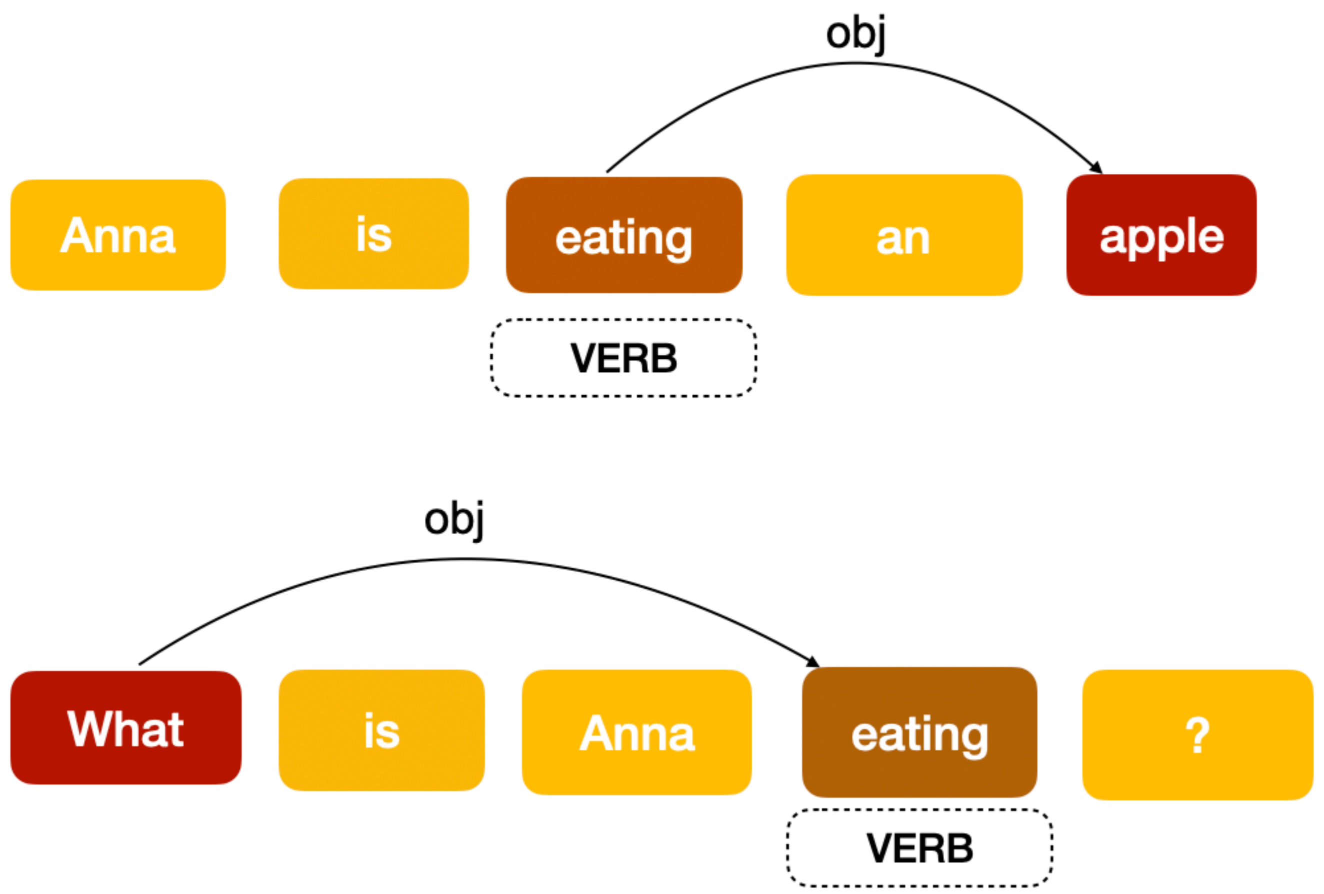

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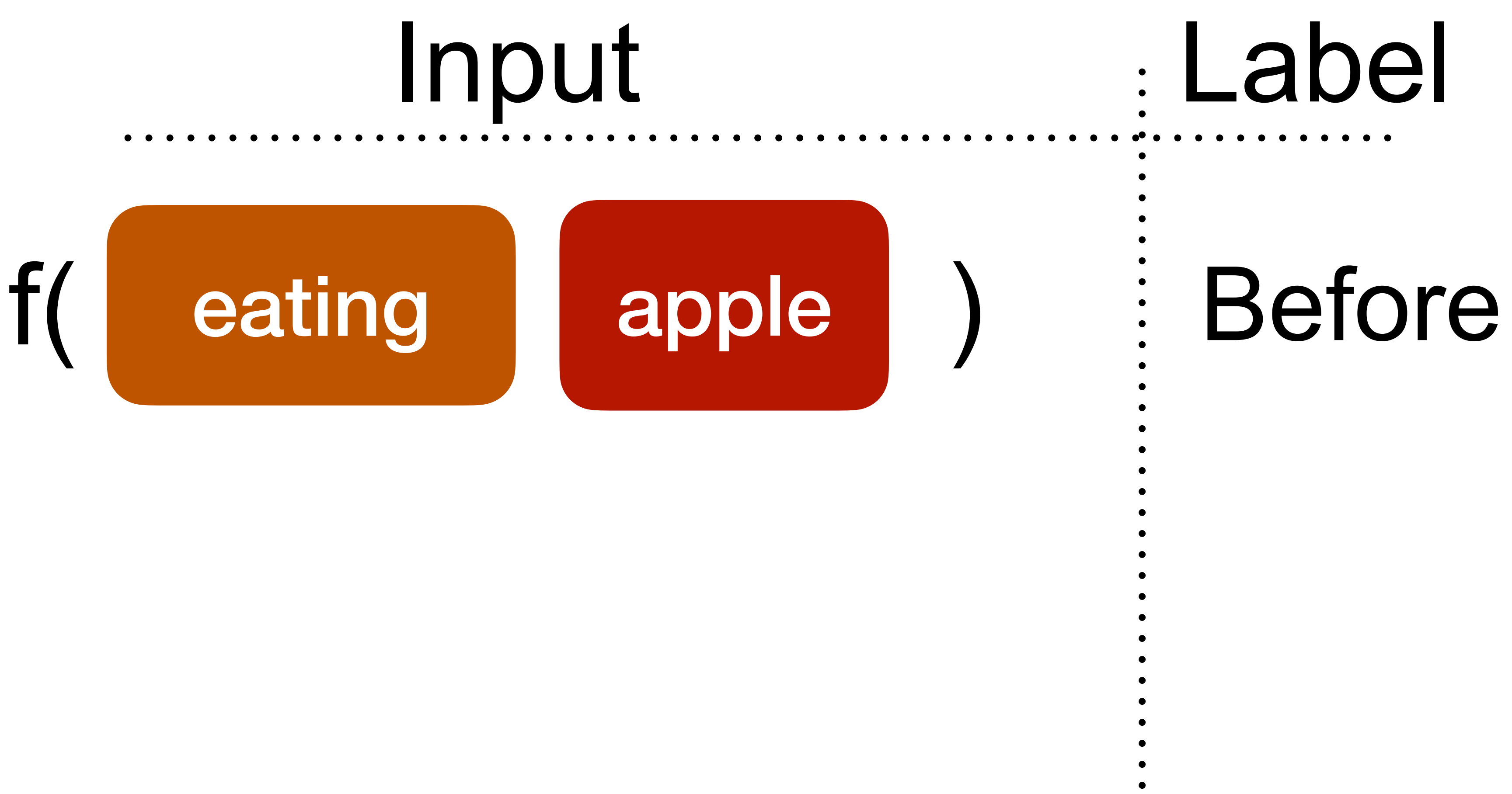

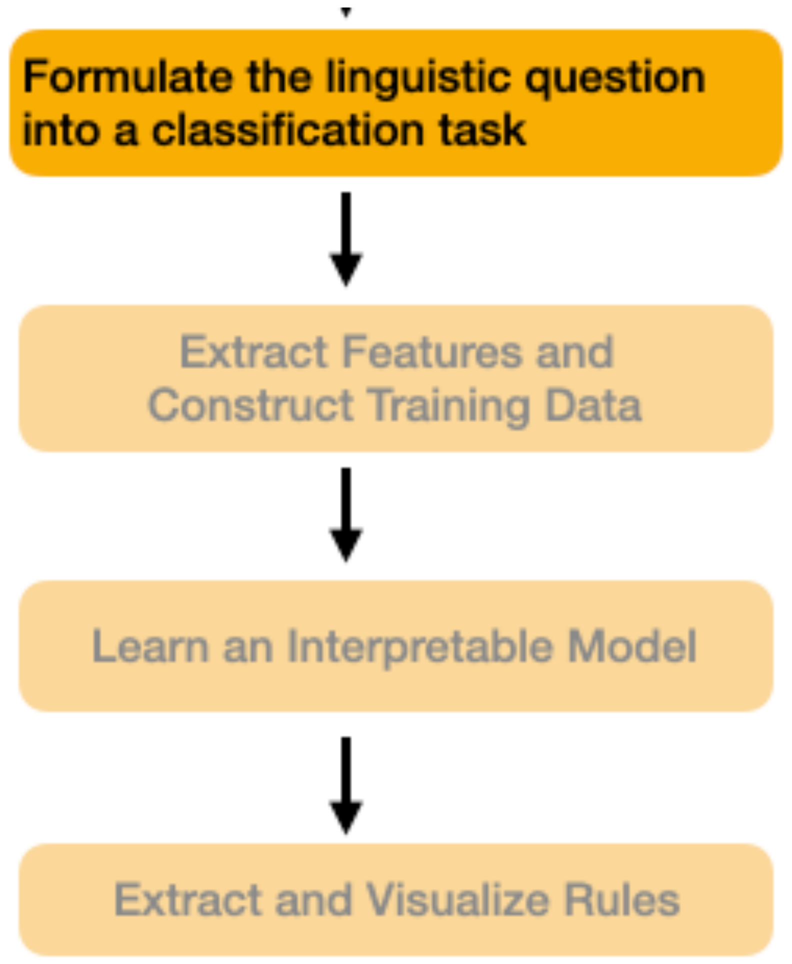

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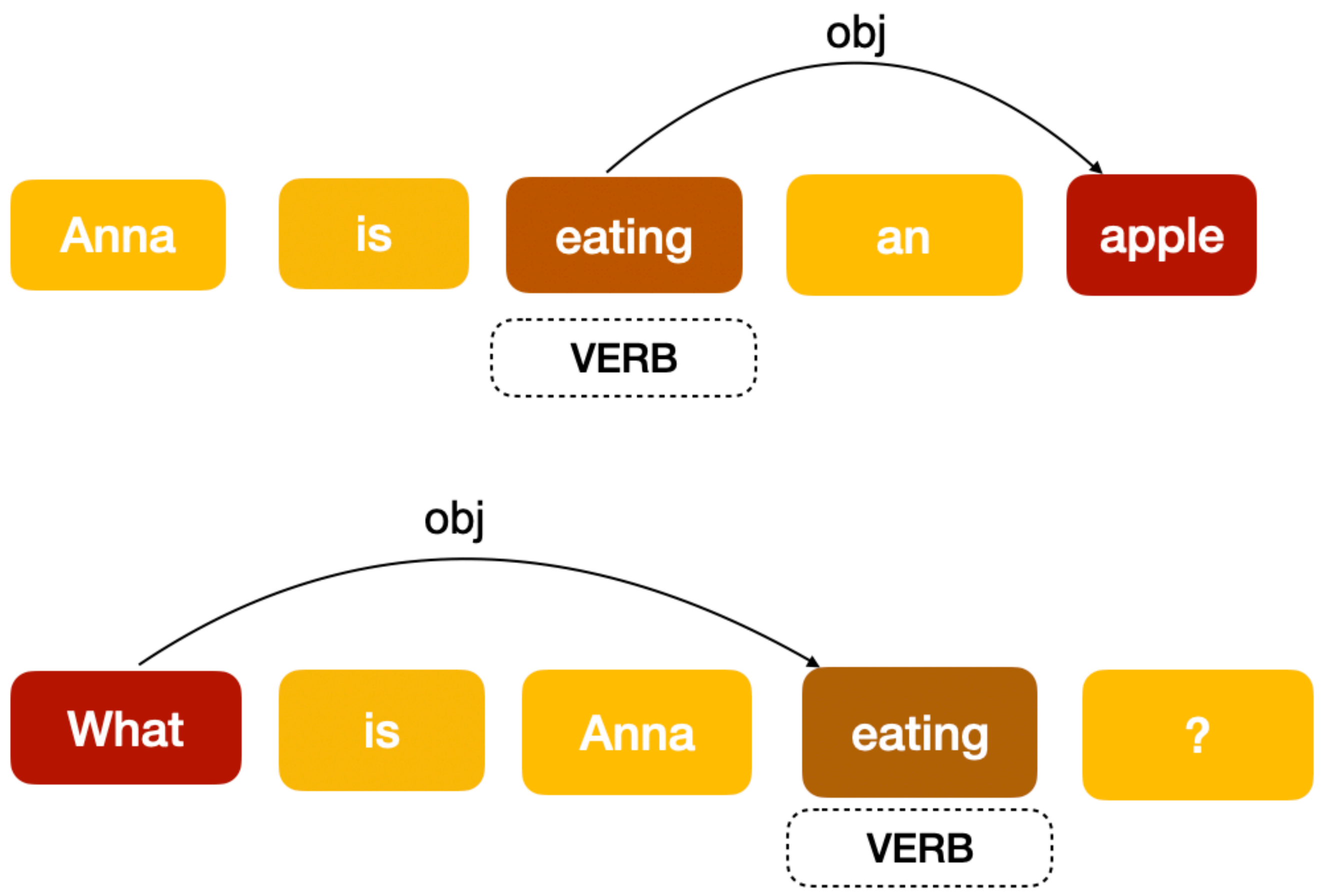

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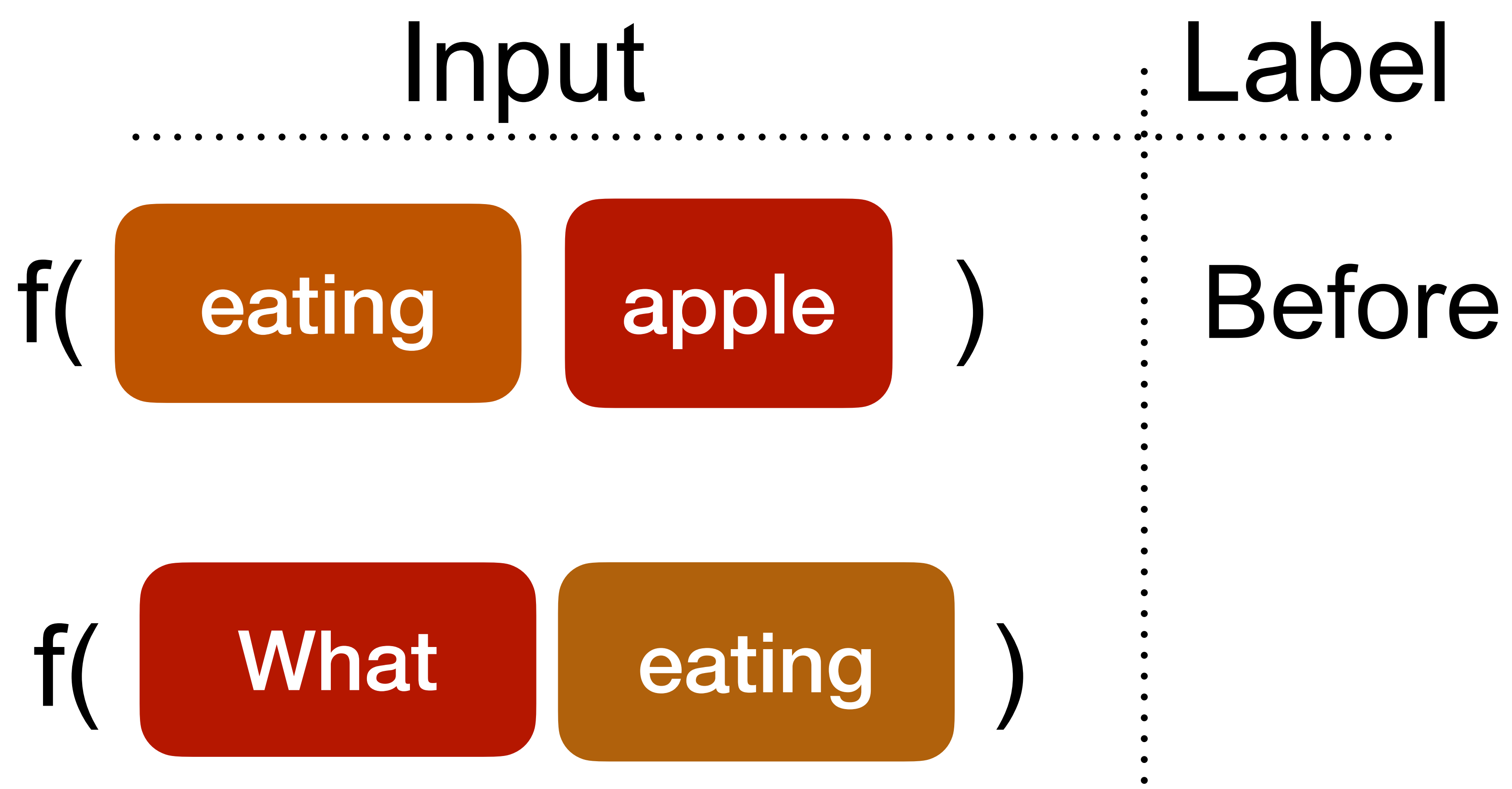

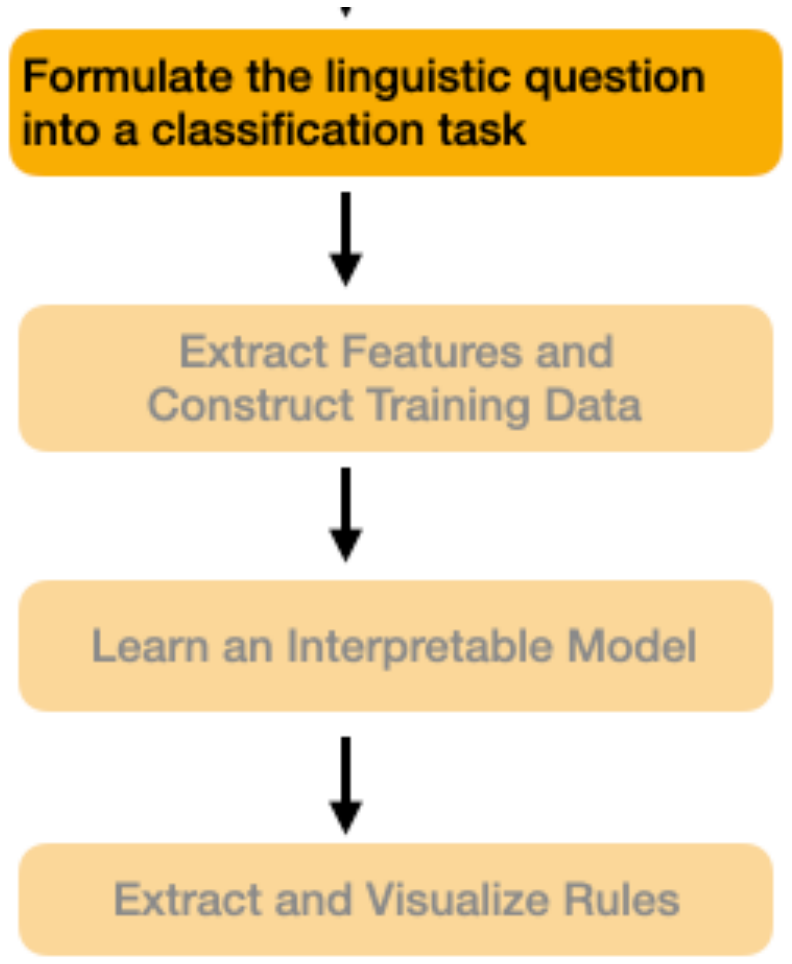

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Extract Features and Construct Training Data

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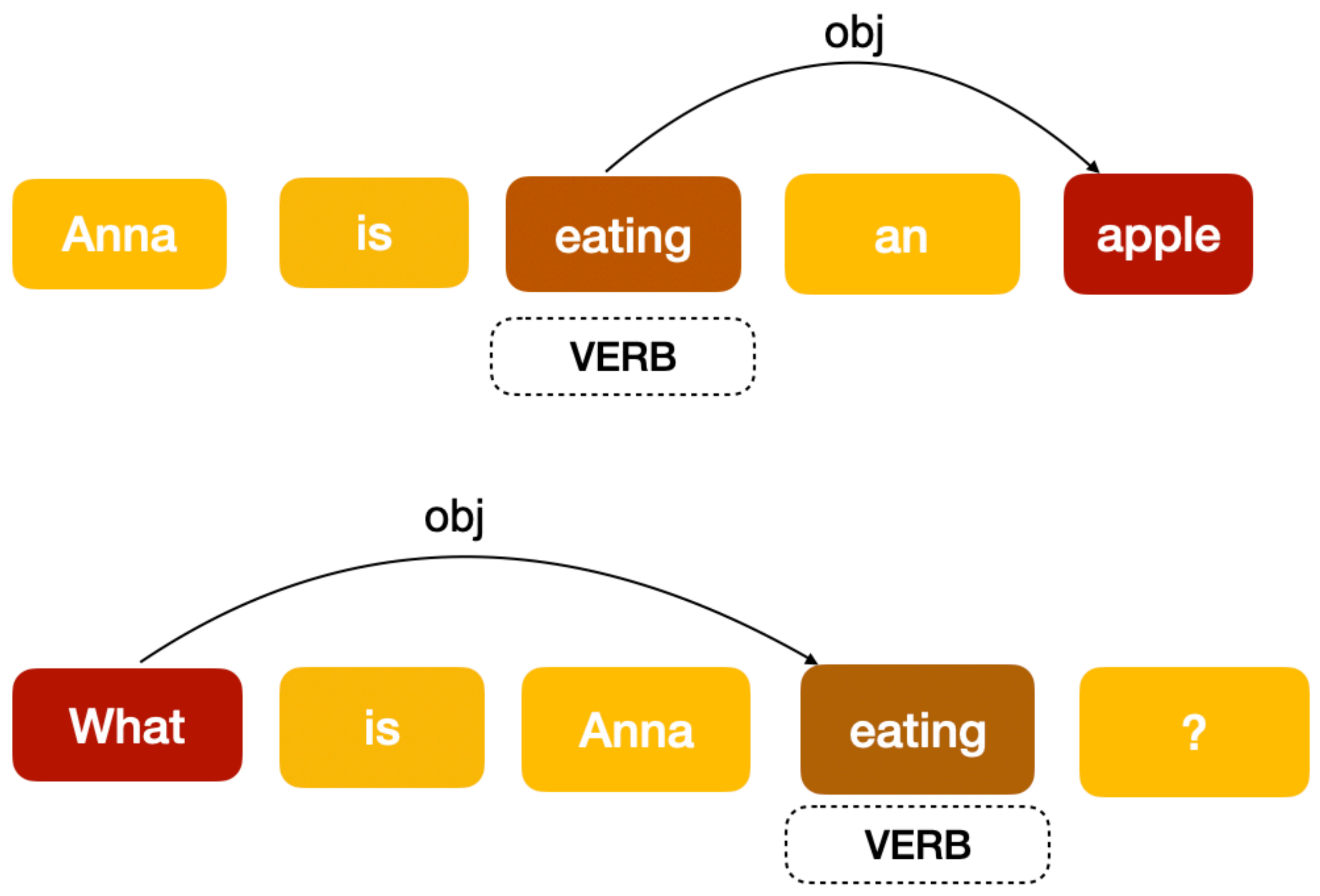
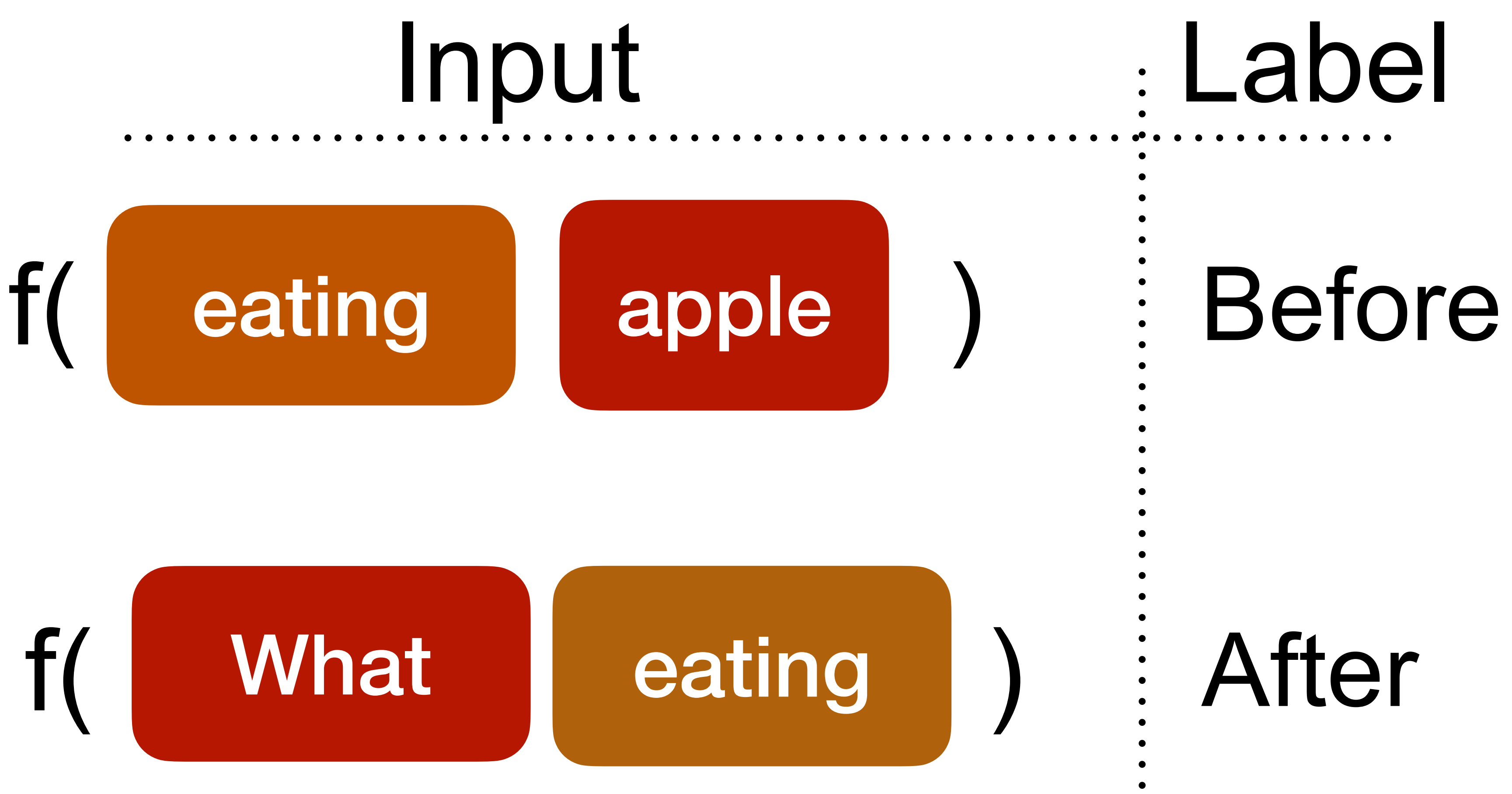
Extract and Visualize Rules

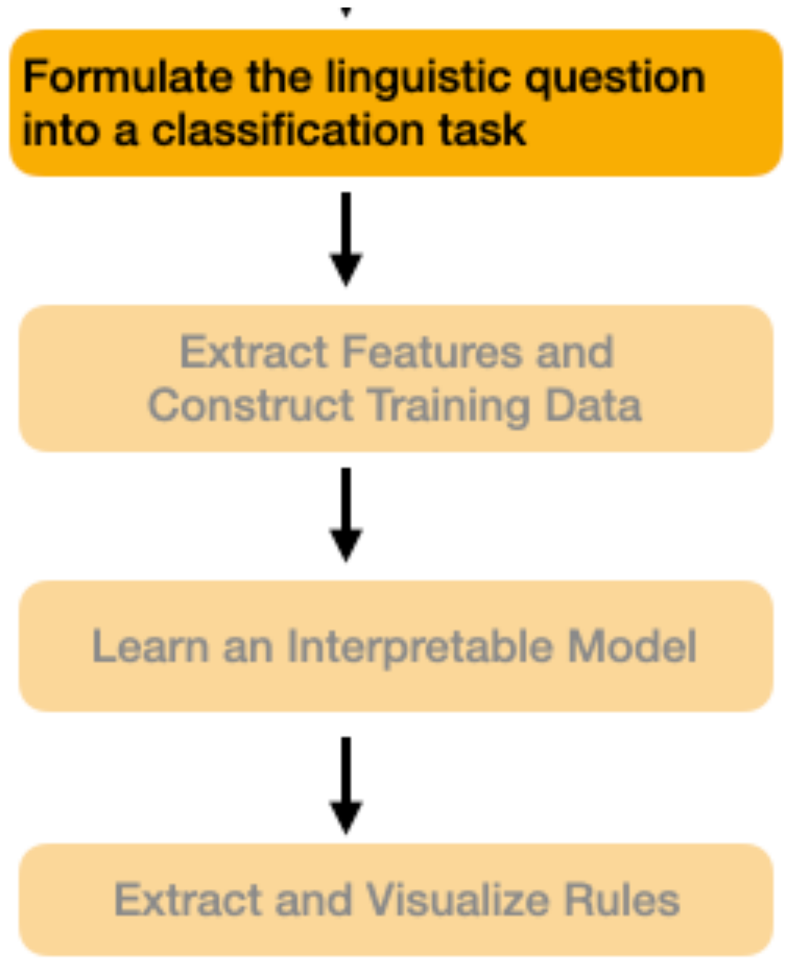
Word Order: Formulate Linguistic Question



When are **objects** before or after the **verbs**?



Input	Label
f(eating apple)	Before
f(What eating)	After



Formulate the linguistic question into a classification task

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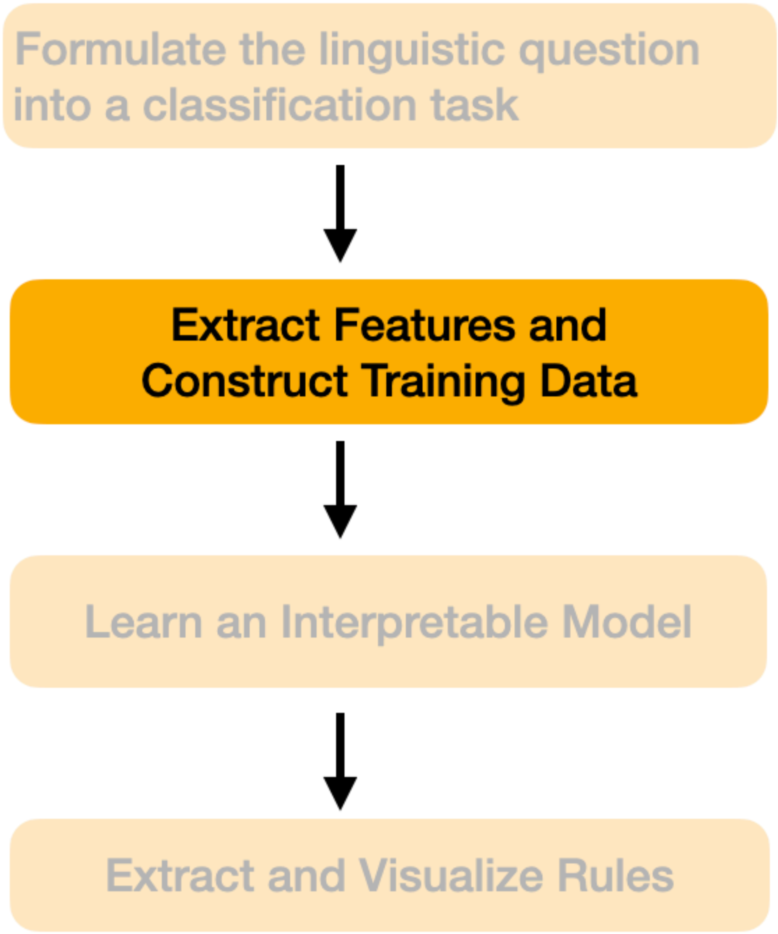
Word Order: Formulate Linguistic Question

When are **objects** before or after the **verbs** in English?



Formulate the linguistic question into a classification task

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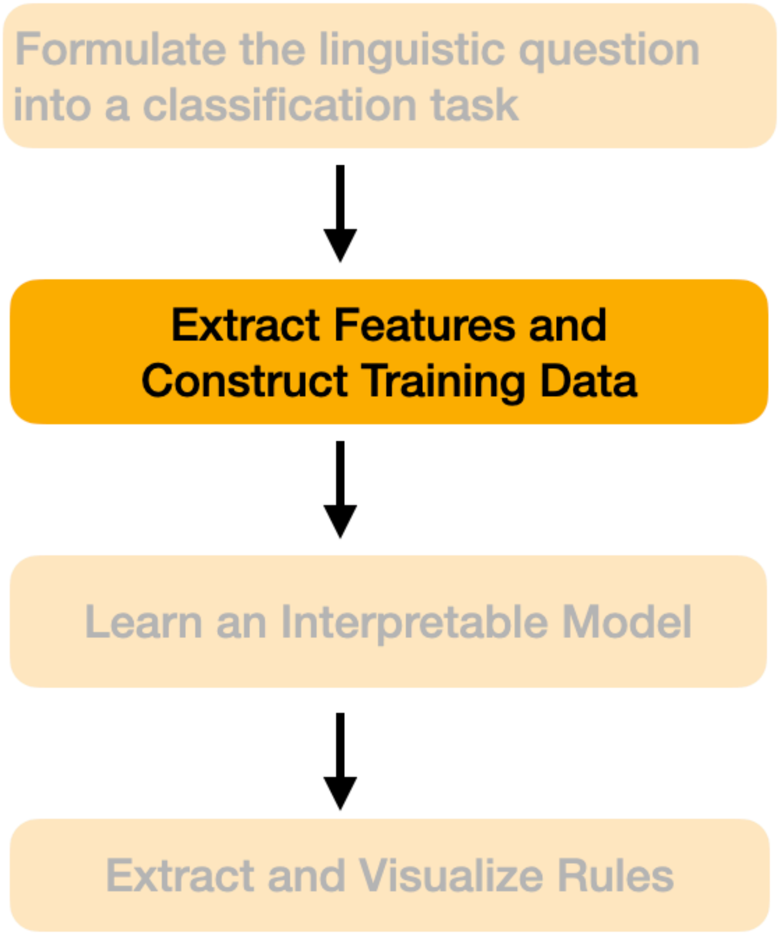
Word Order: Formulate Linguistic Question

When are **objects** before or after the **verbs** in English?

Anna is eating an apple



Formulate the linguistic question into a classification task

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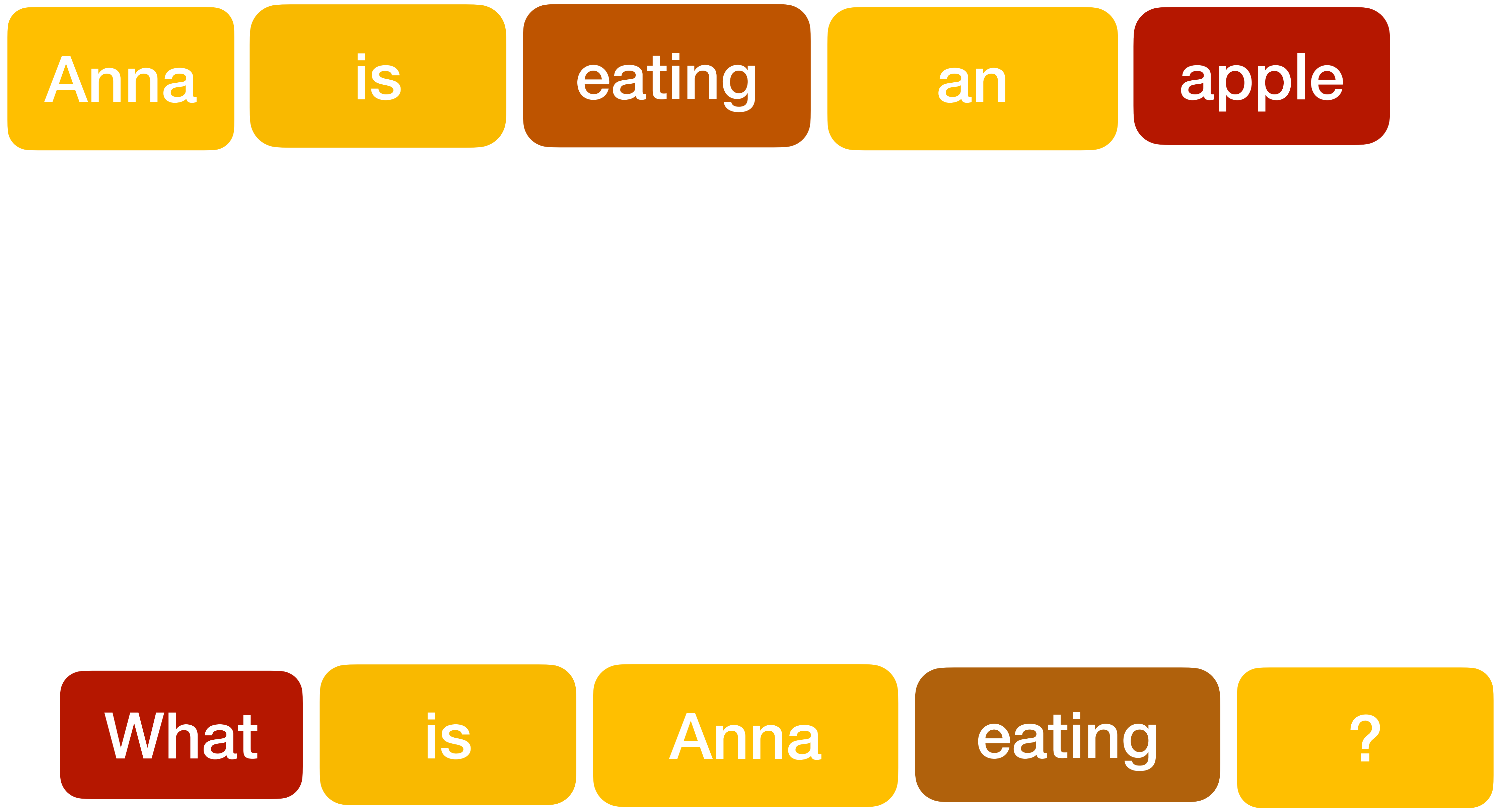
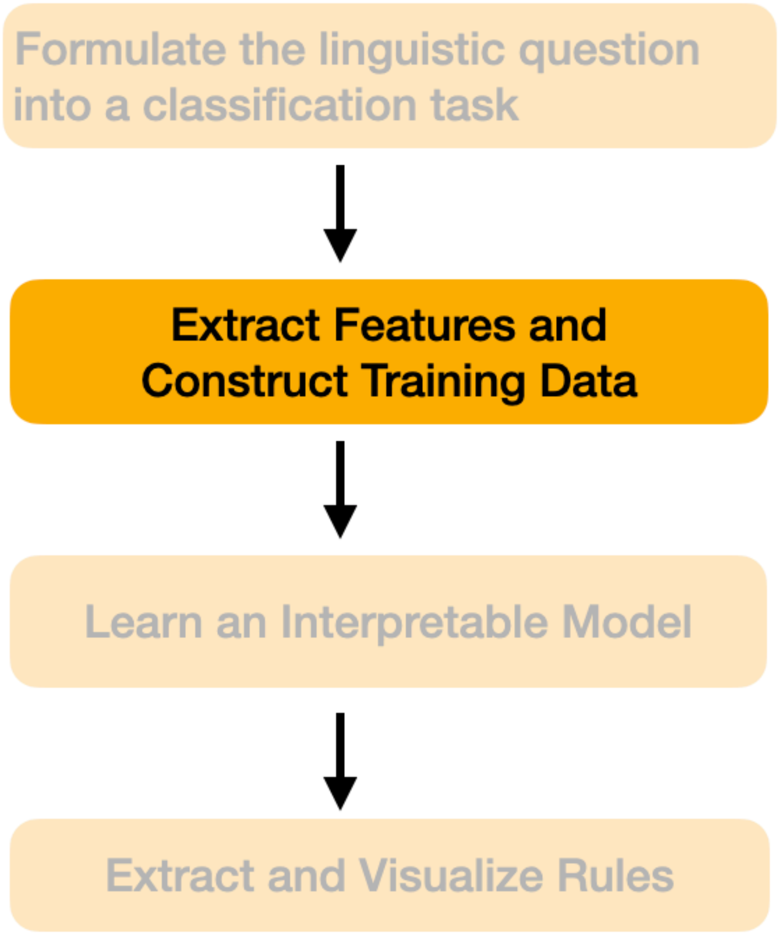
Word Order: Formulate Linguistic Question

When are **objects** before or after the **verbs** in English?





Formulate the linguistic question into a classification task

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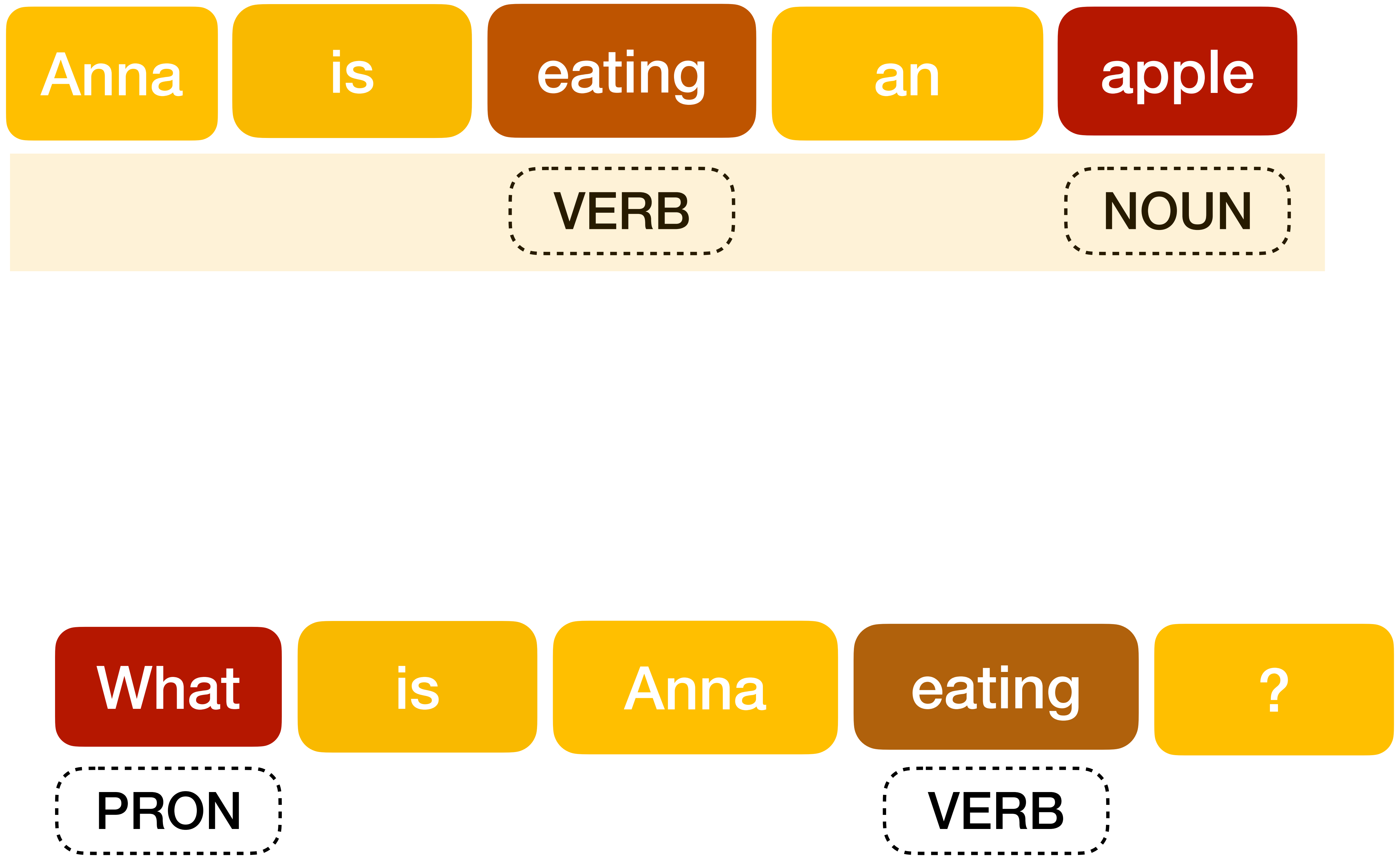
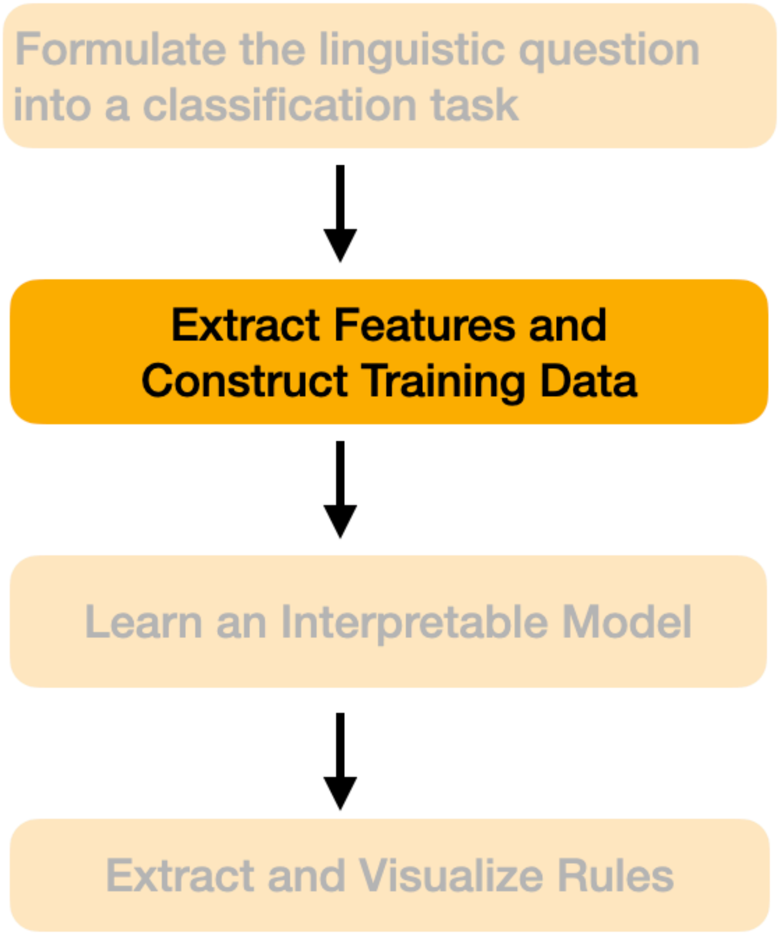
Word Order: Formulate Linguistic Question

When are **objects** before or after the **verbs** in English?

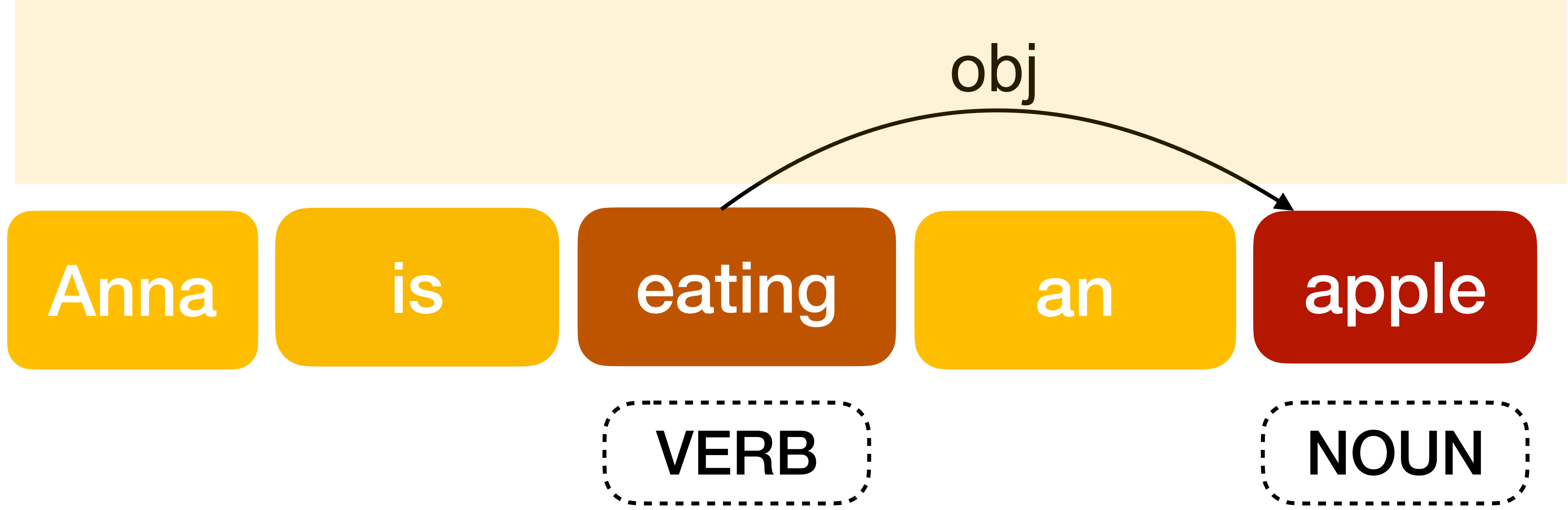


POS Tagging



Word Order: Formulate Linguistic Question

When are **objects** before or after the **verbs** in English?



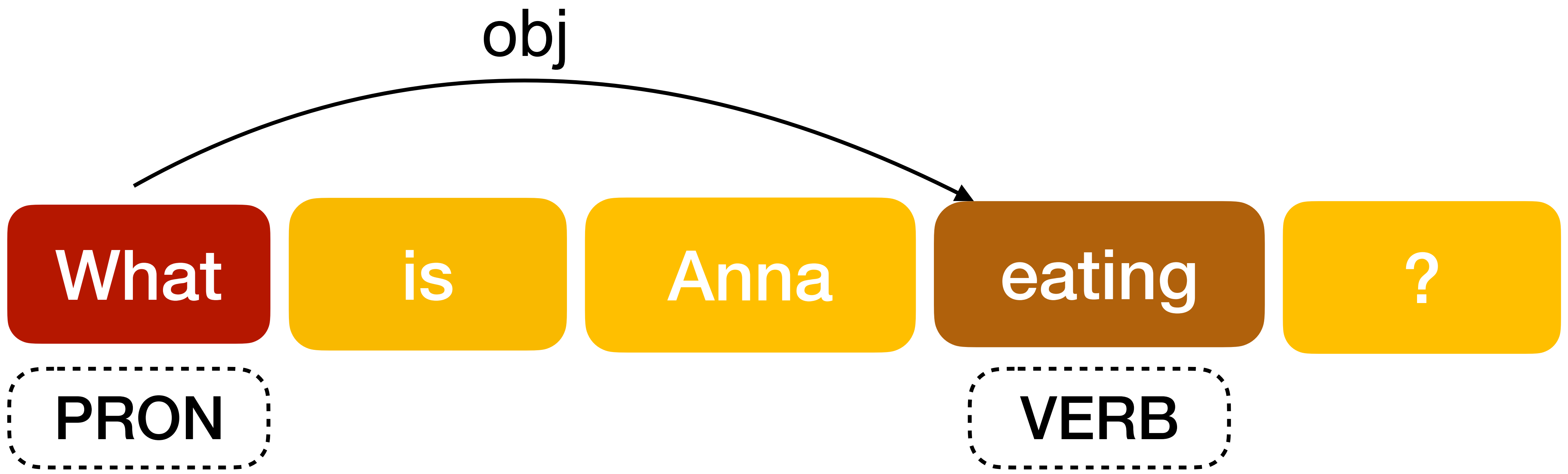
obj

Anna is eating an apple

VERB NOUN

Dependency Parsing

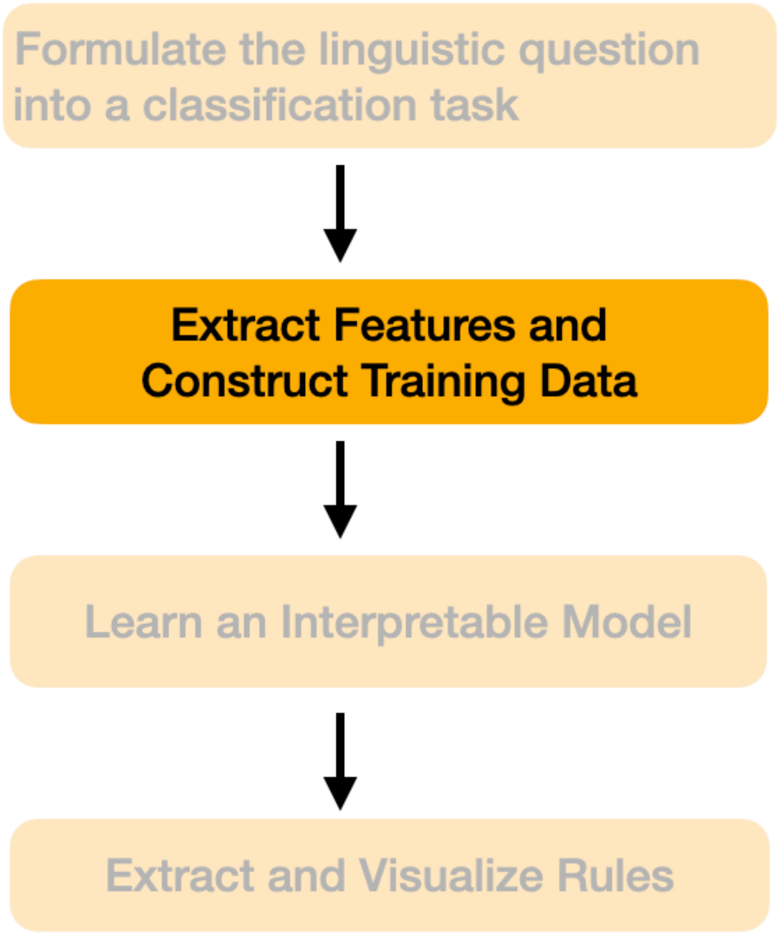
POS Tagging



obj

What is Anna eating ?

PRON VERB



Formulate the linguistic question into a classification task

Extract Features and Construct Training Data

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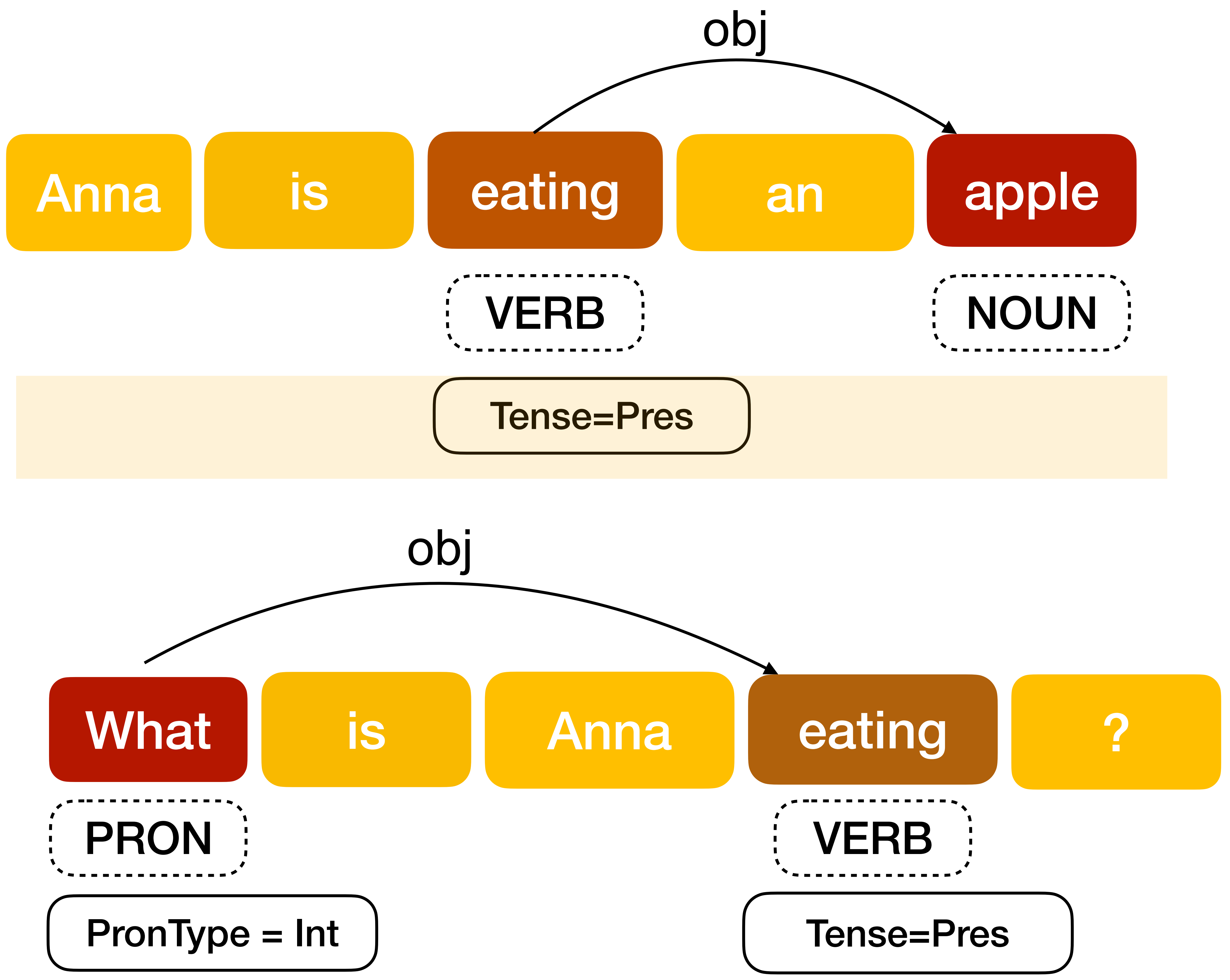
Word Order: Formulate Linguistic Question

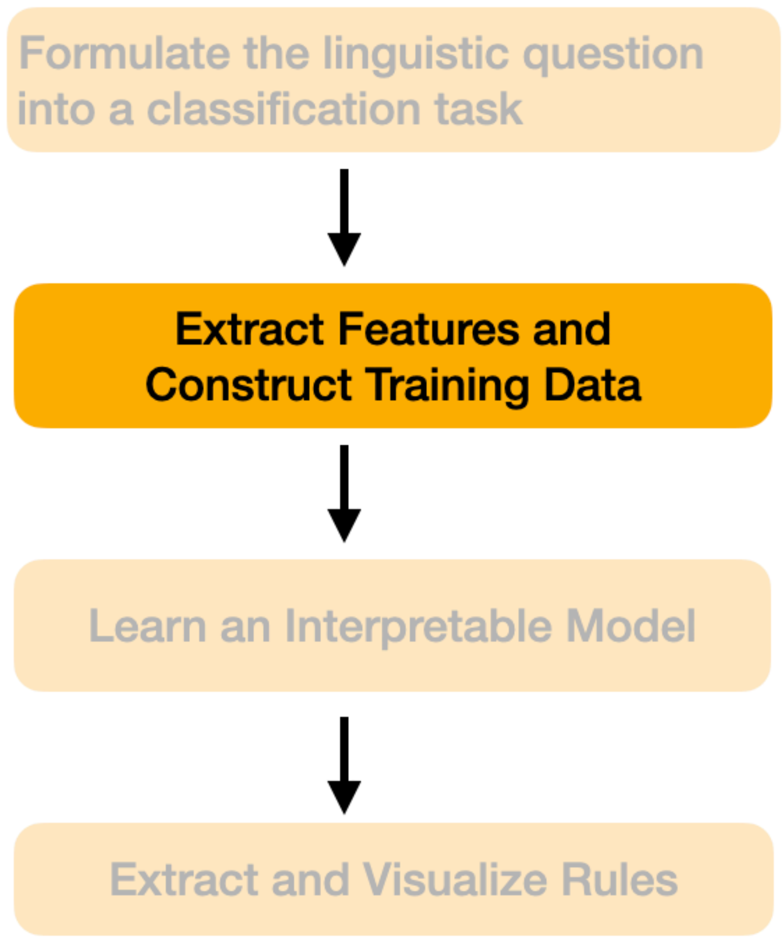
When are **objects** before or after the **verbs** in English?



Dependency Parsing

POS Tagging

Morphological Analysis



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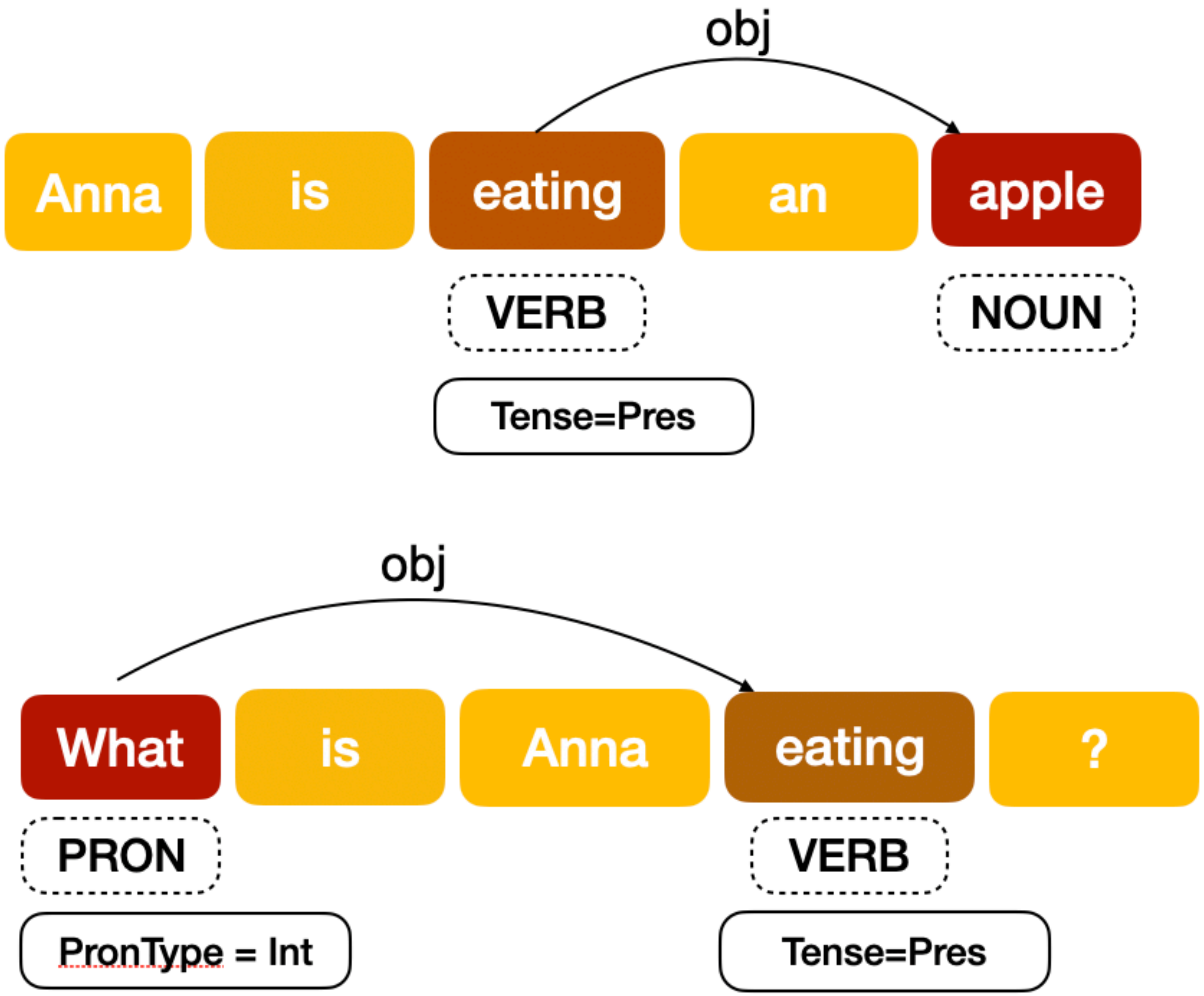
Word Order: Extract Features and Training Data

When are **objects** before or after the **verbs** in English?



Formulate the linguistic question into a classification task

Extract Features and Construct Training Data

Learn an Interpretable Model

Extract and Visualize Rules

Carnegie Mellon University

Word Order: Extract Features and Training Data

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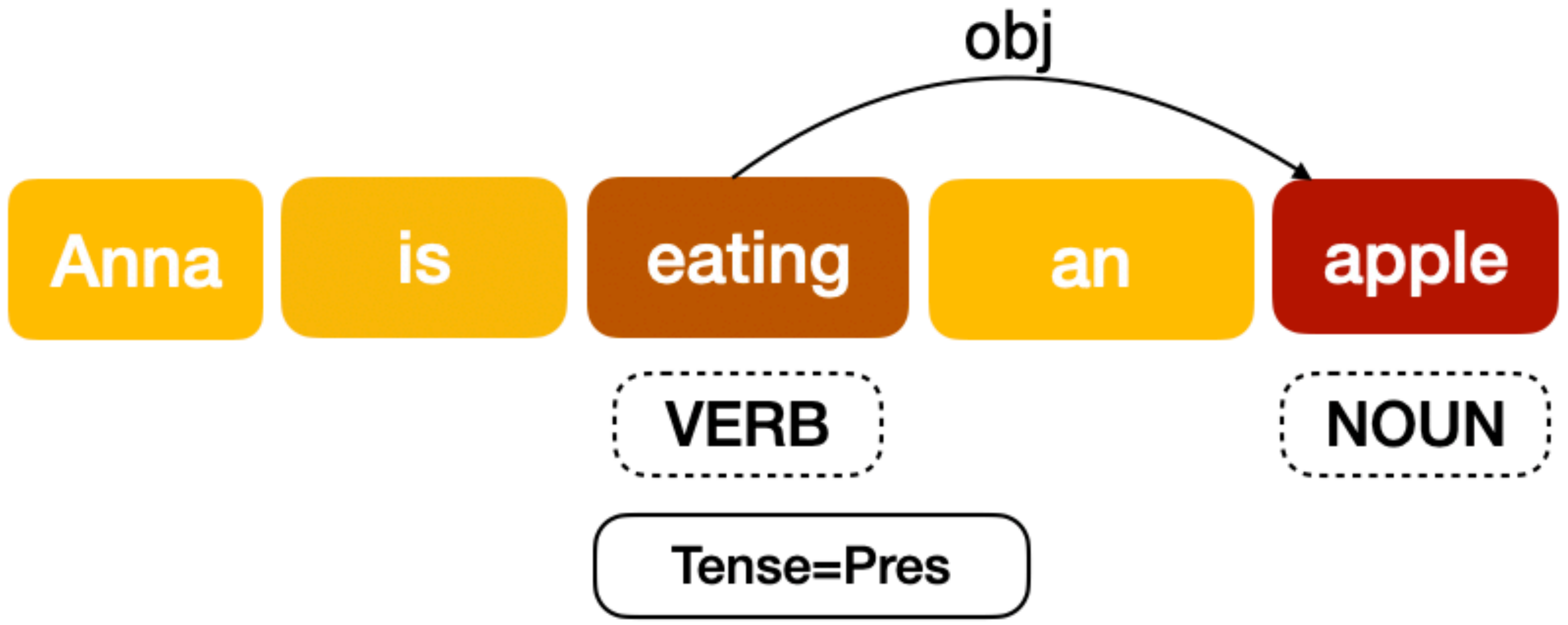
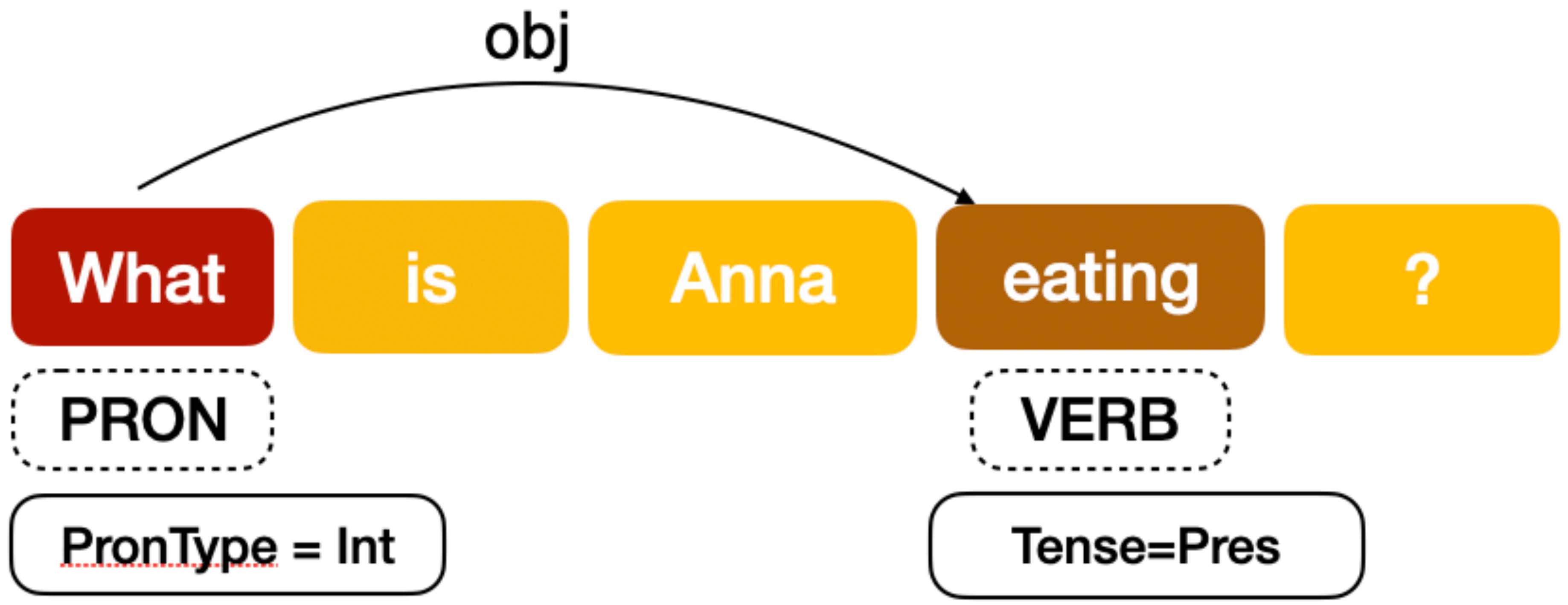
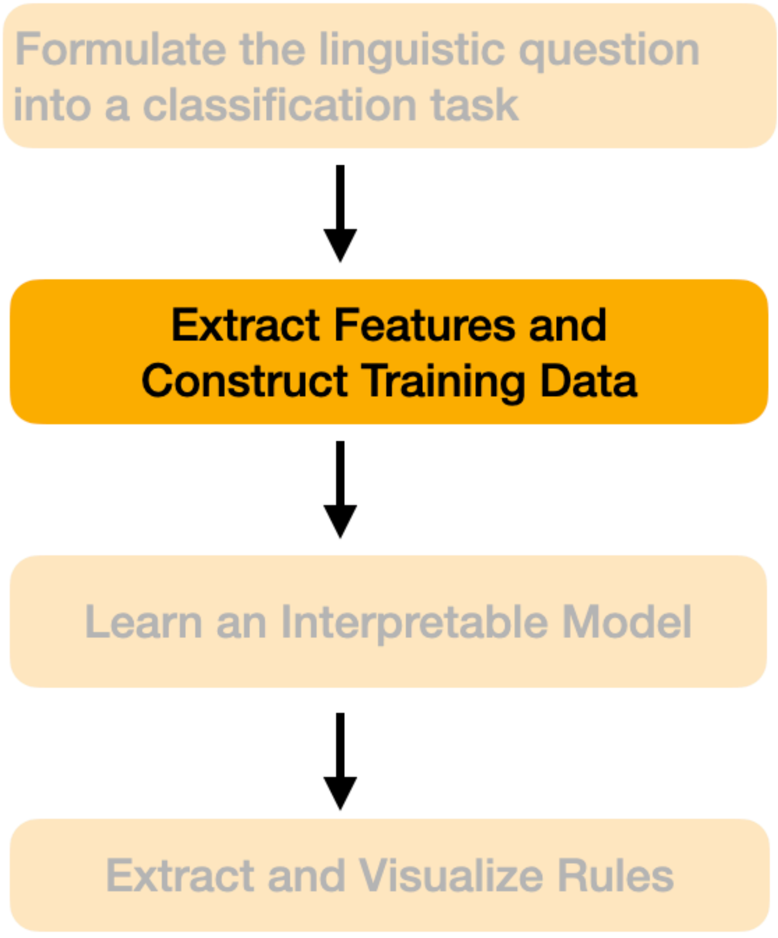






Formulate the linguistic question into a classification task

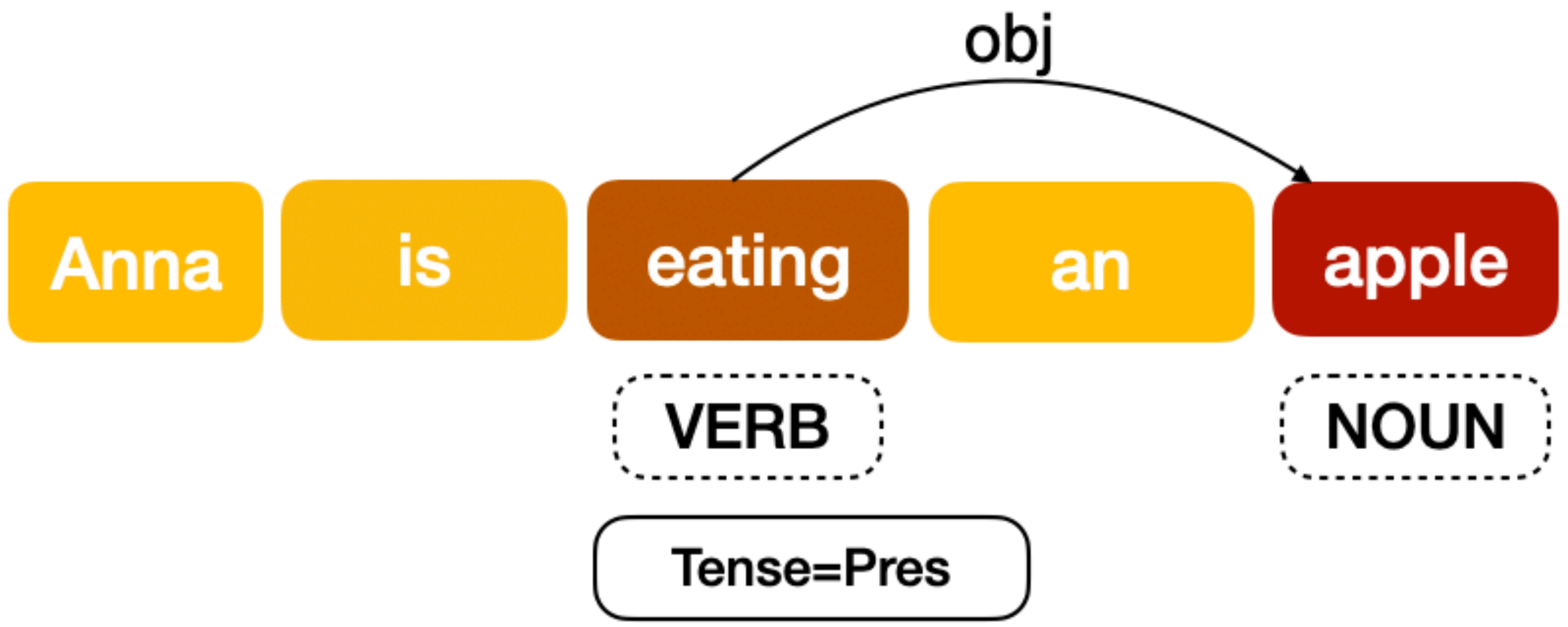
Extract Features and Construct Training Data

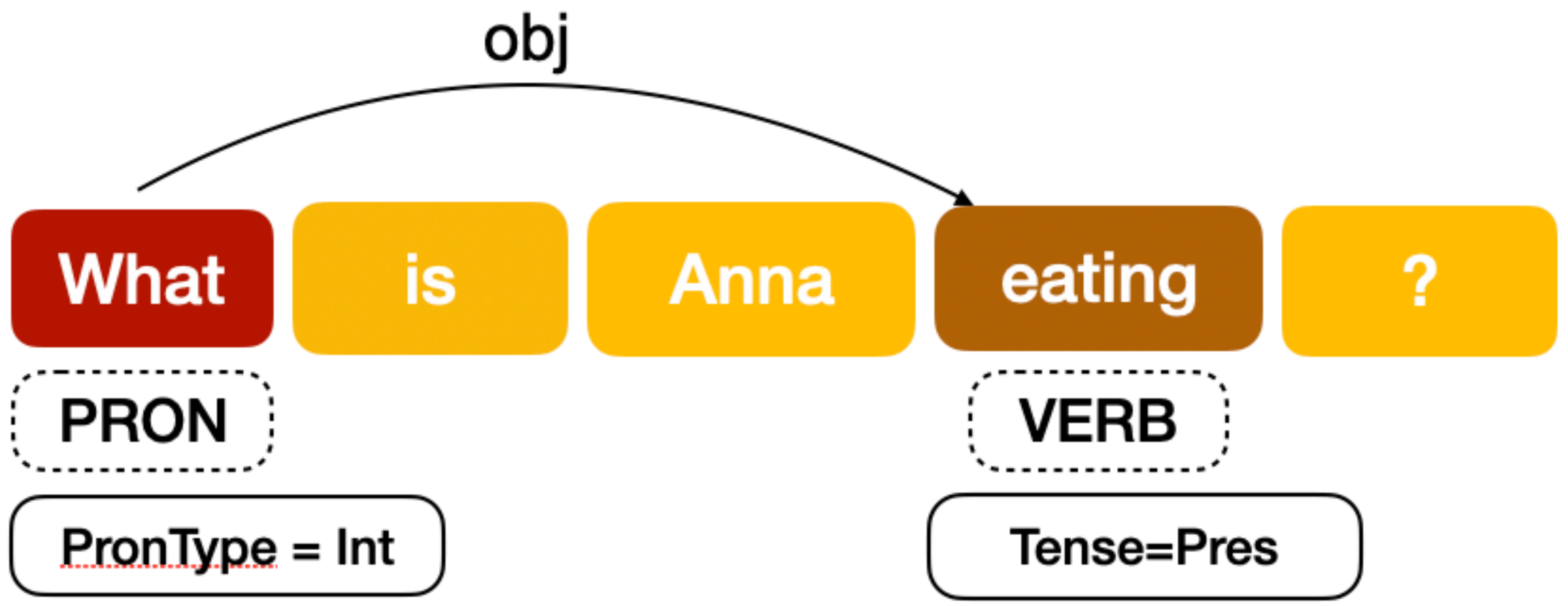
Learn an Interpretable Model

Extract and Visualize Rules

Word Order: Extract Features and Training Data

When are **objects** before or after the **verbs** in English?





Input	Features	Label

Formulate the linguistic question into a classification task

↓

Extract Features and Construct Training Data

↓

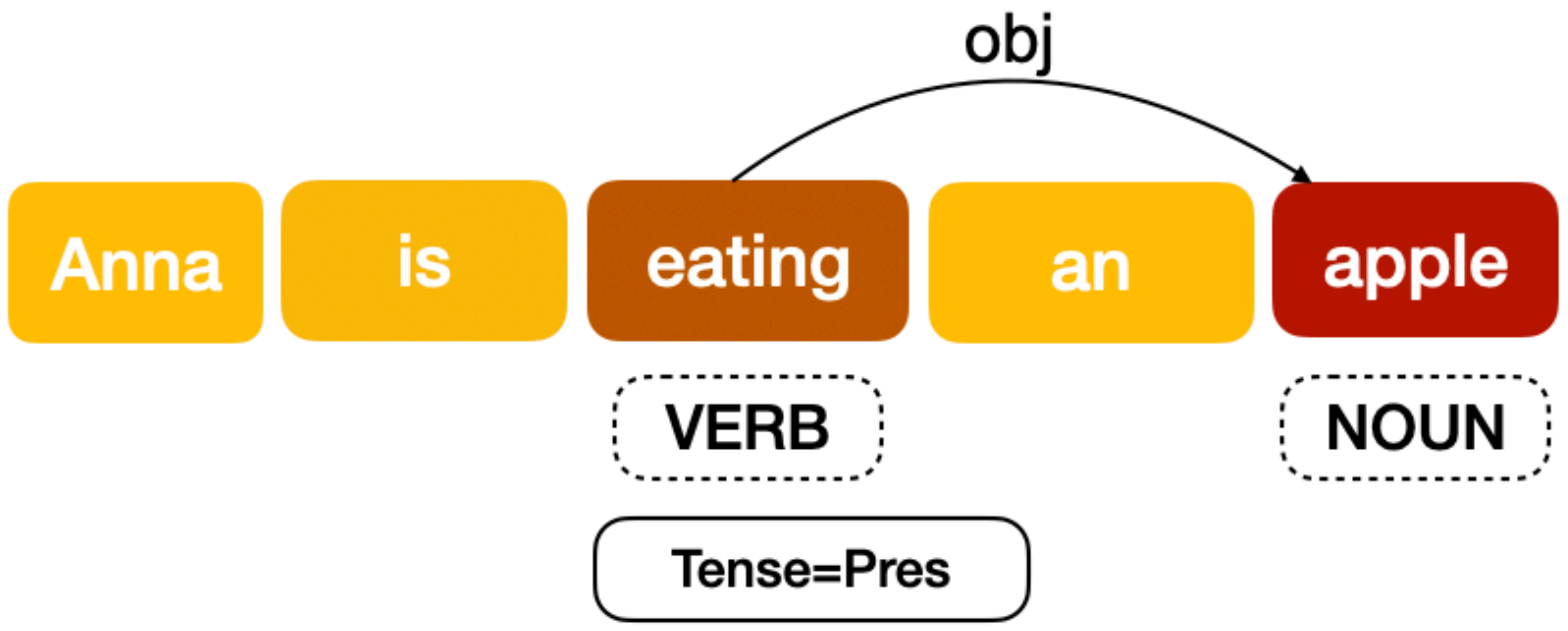
Learn an Interpretable Model

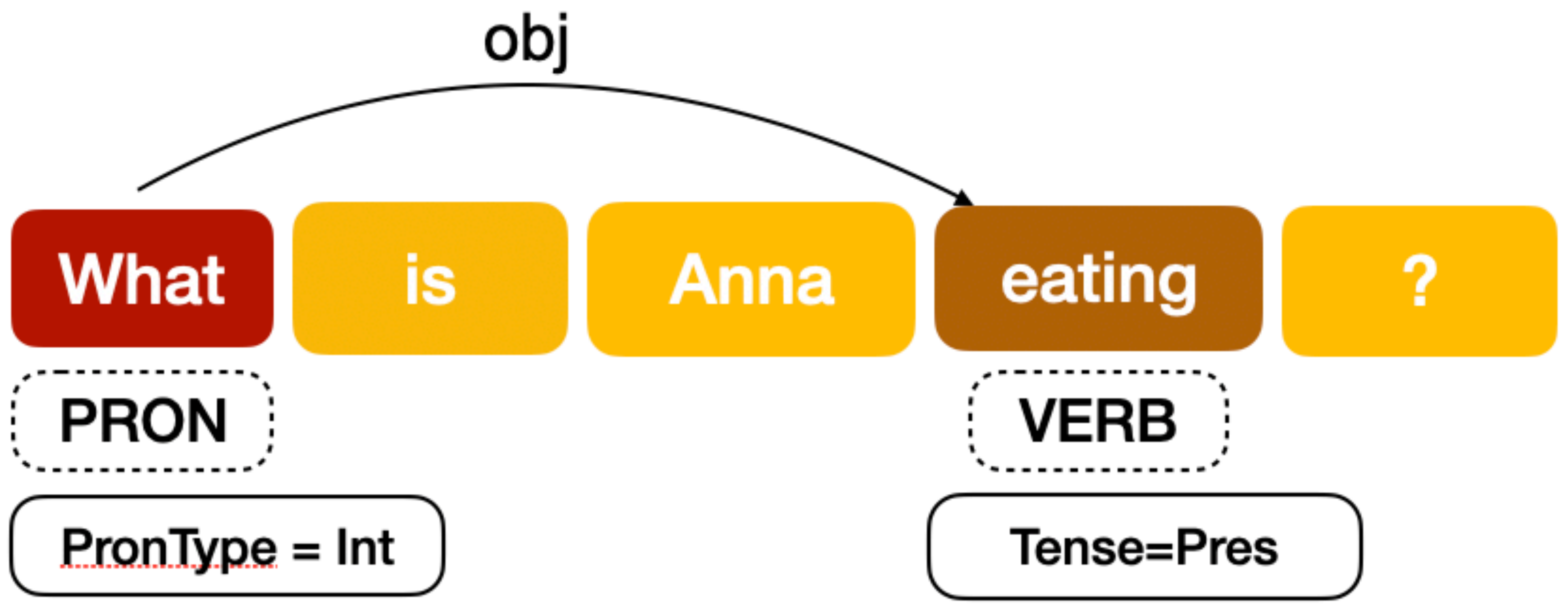
↓

Extract and Visualize Rules

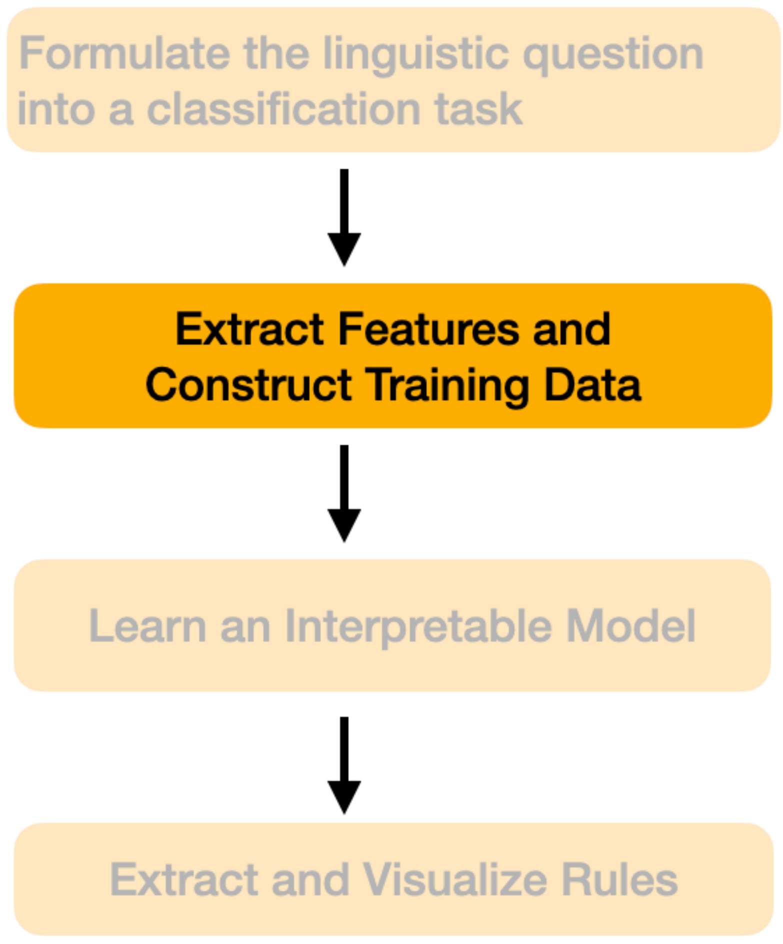
Word Order: Extract Features and Training Data

When are **objects** before or after the **verbs** in English?





Input	Features	Label
f(eating apple)		Before



Formulate the linguistic question into a classification task

↓

Extract Features and Construct Training Data

↓

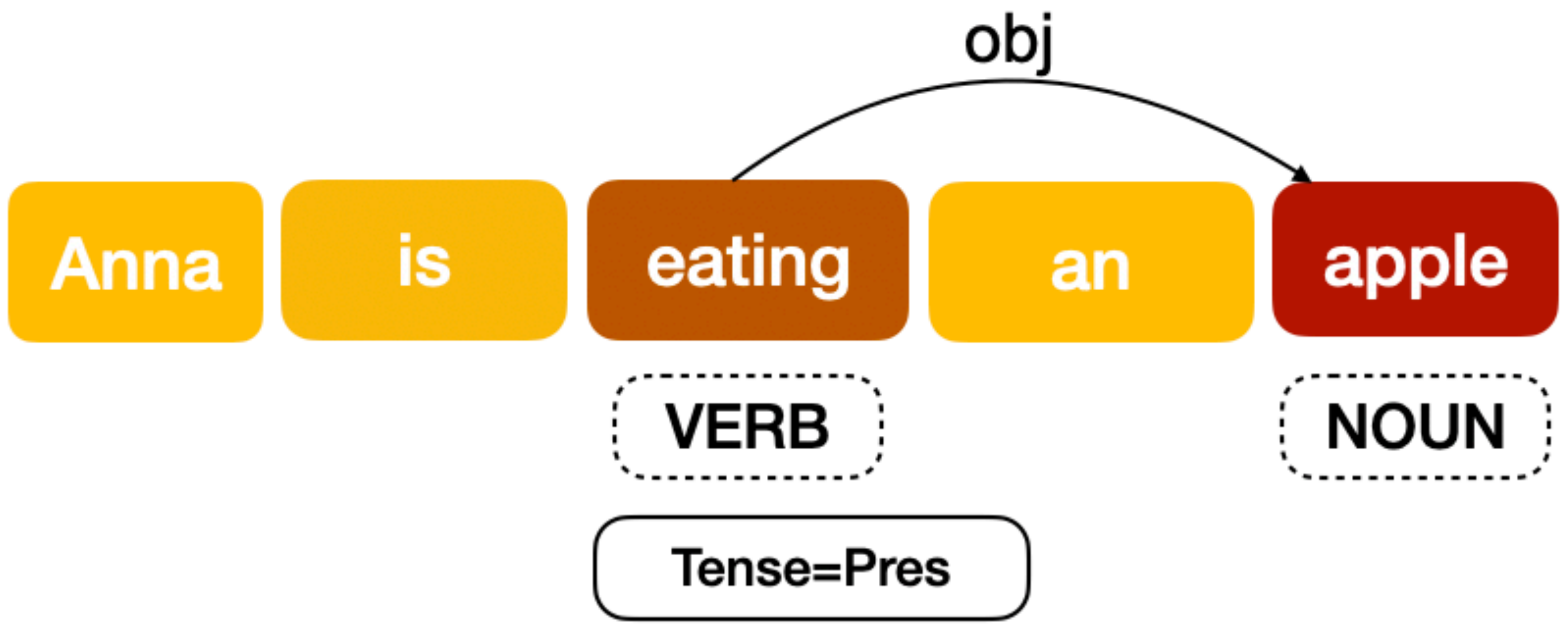
Learn an Interpretable Model

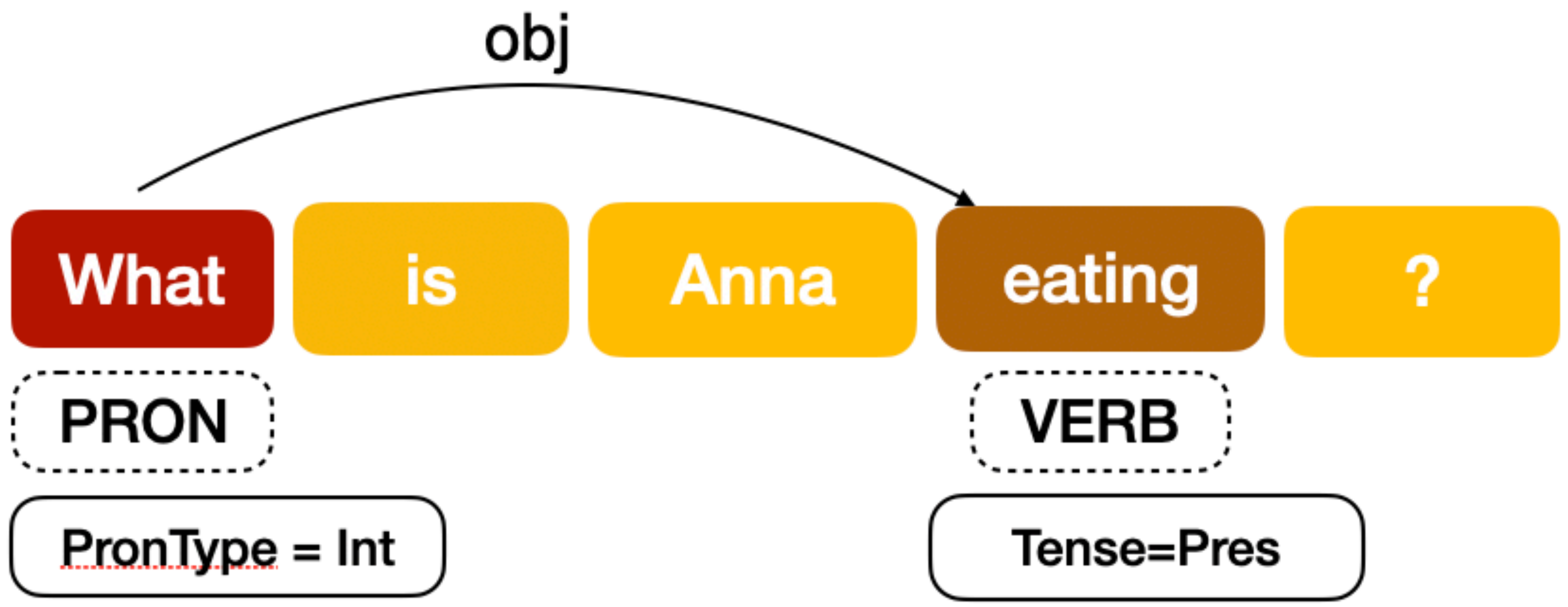
↓

Extract and Visualize Rules

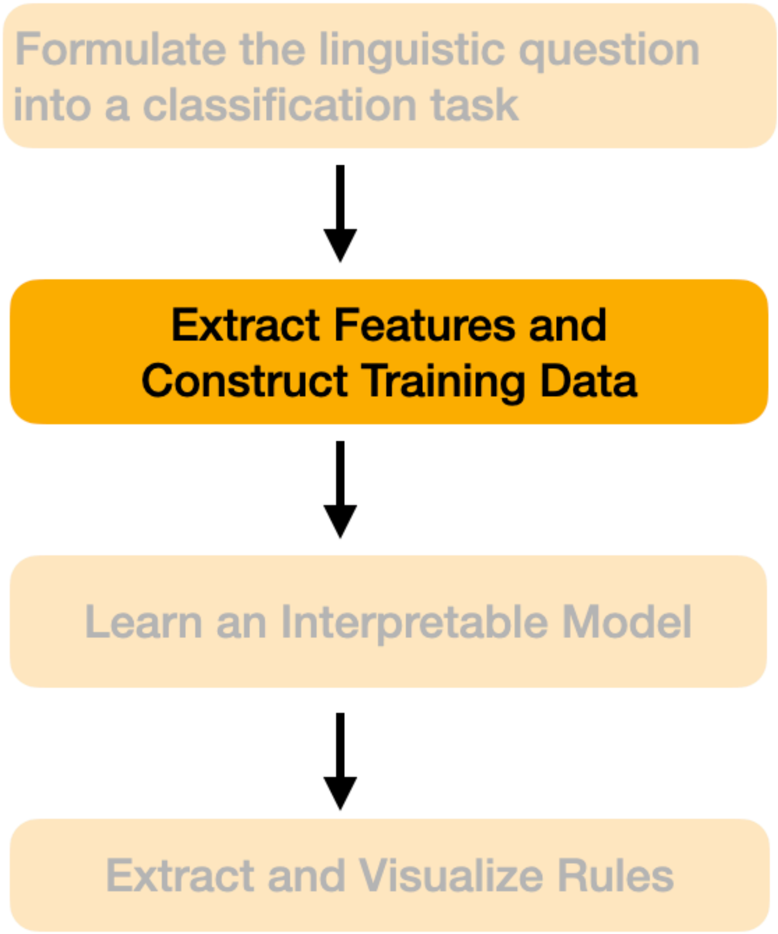
Word Order: Extract Features and Training Data

When are **objects** before or after the **verbs** in English?





Input	Features	Label
f(eating apple)		Before
f(What eating)		After


Formulate the linguistic question into a classification task

Extract Features and Construct Training Data

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Extract and Visualize Rules

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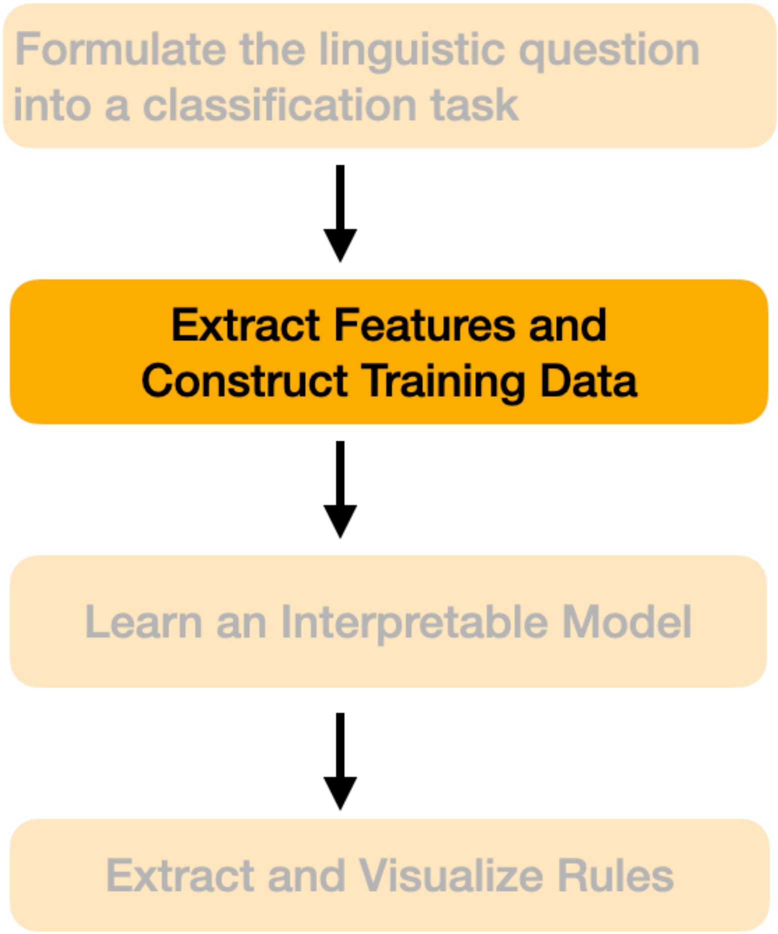
Chaudhary**, Sheikh, Mortensen, Anastasopoulos, Neubig.* ***In Submission

Word Order: Extract Features and Training Data

When are **objects** before or after the **verbs** in English?

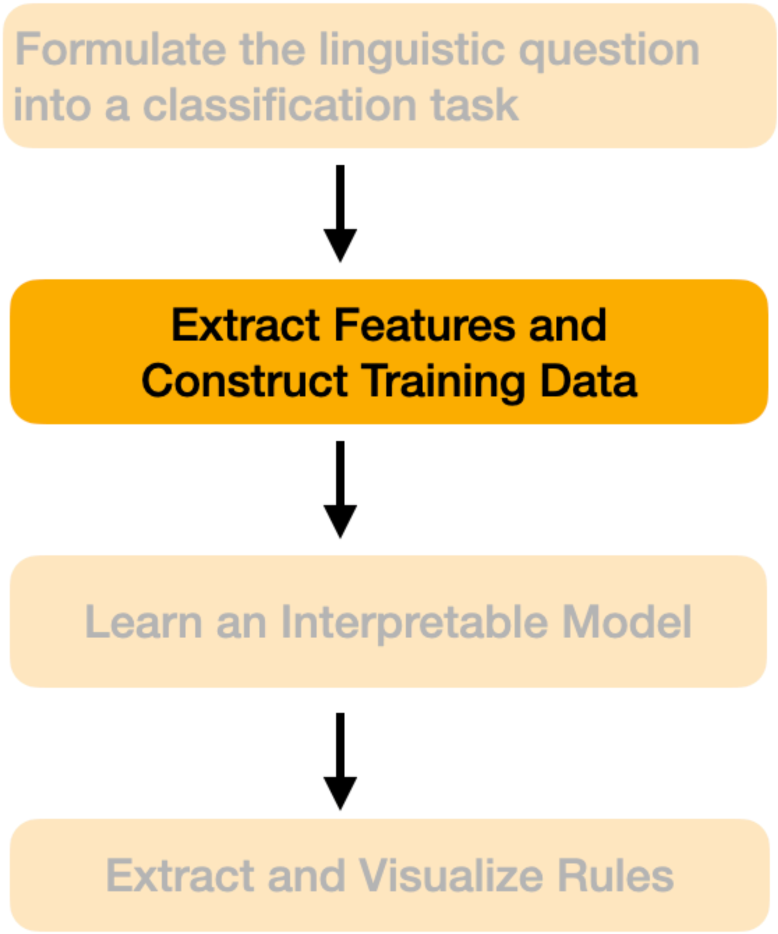
Input	Features	Label
f(eating apple)	is-object-NOUN	Before
f(What eating)	is-object-PRON	After



Word Order: Extract Features and Training Data

When are **objects** before or after the **verbs** in English?

Input	Features	Label
f(eating apple)	is-object-NOUN is-verb-tense-present	Before
f(What eating)	is-object-PRON is-object-Interrogative is-verb-tense-present	After



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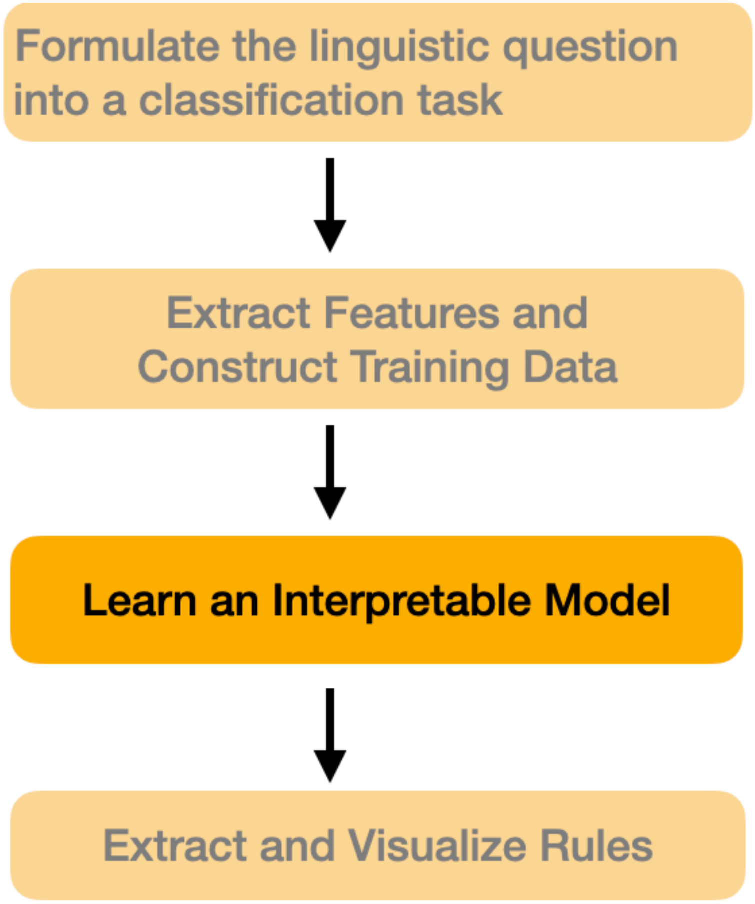
Word Order: Learn a Model

When are **objects** before or after the **verbs** in English?



Formulate the linguistic question into a classification task

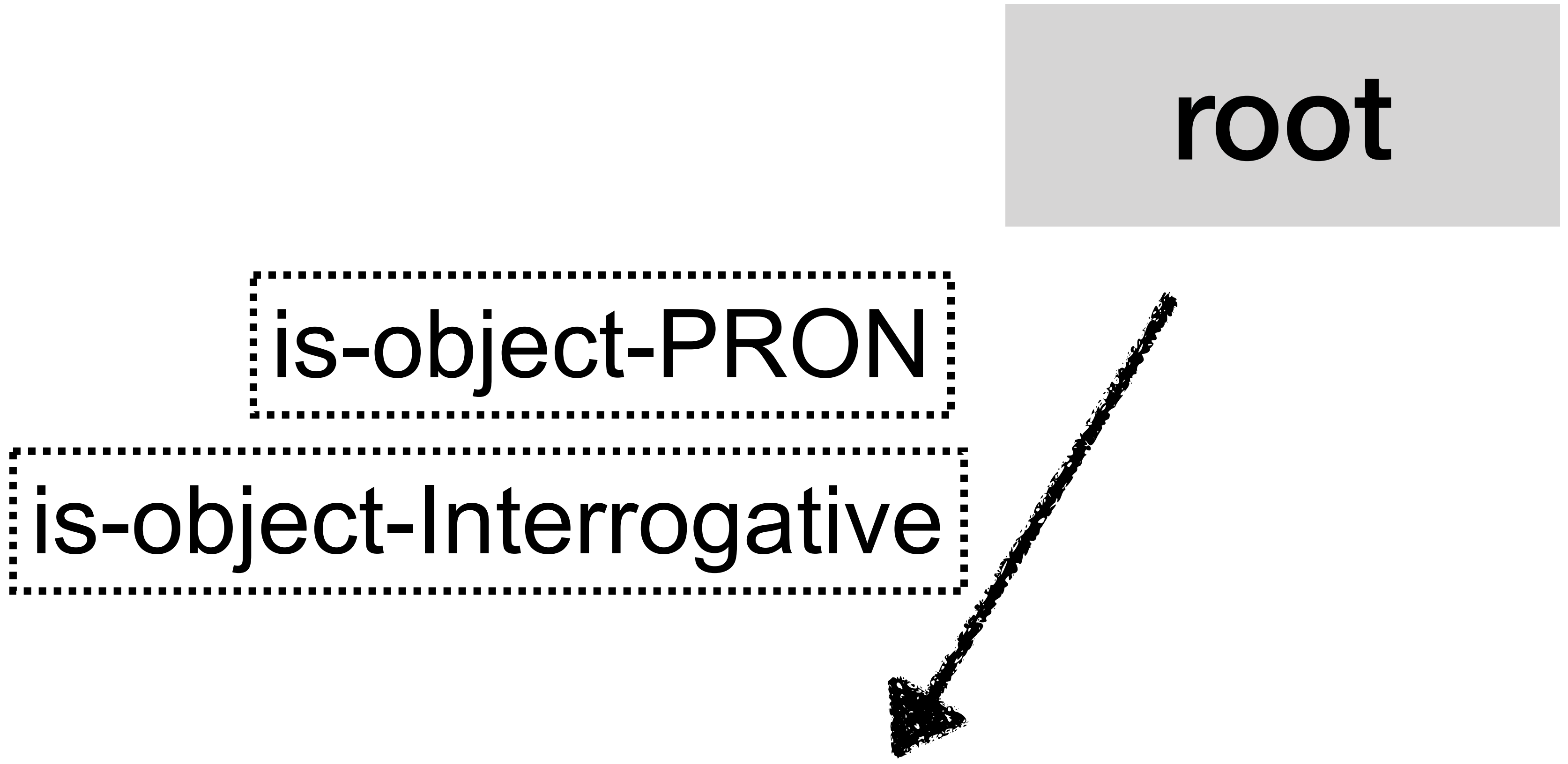
Extract Features and Construct Training Data

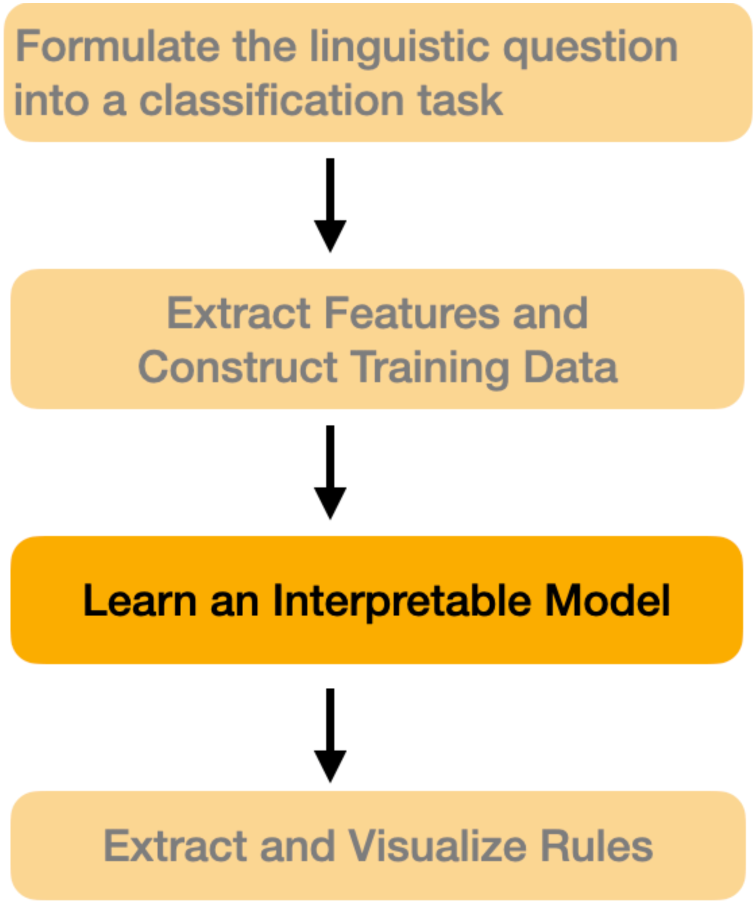
Learn an Interpretable Model

Extract and Visualize Rules

Word Order: Learn a Model

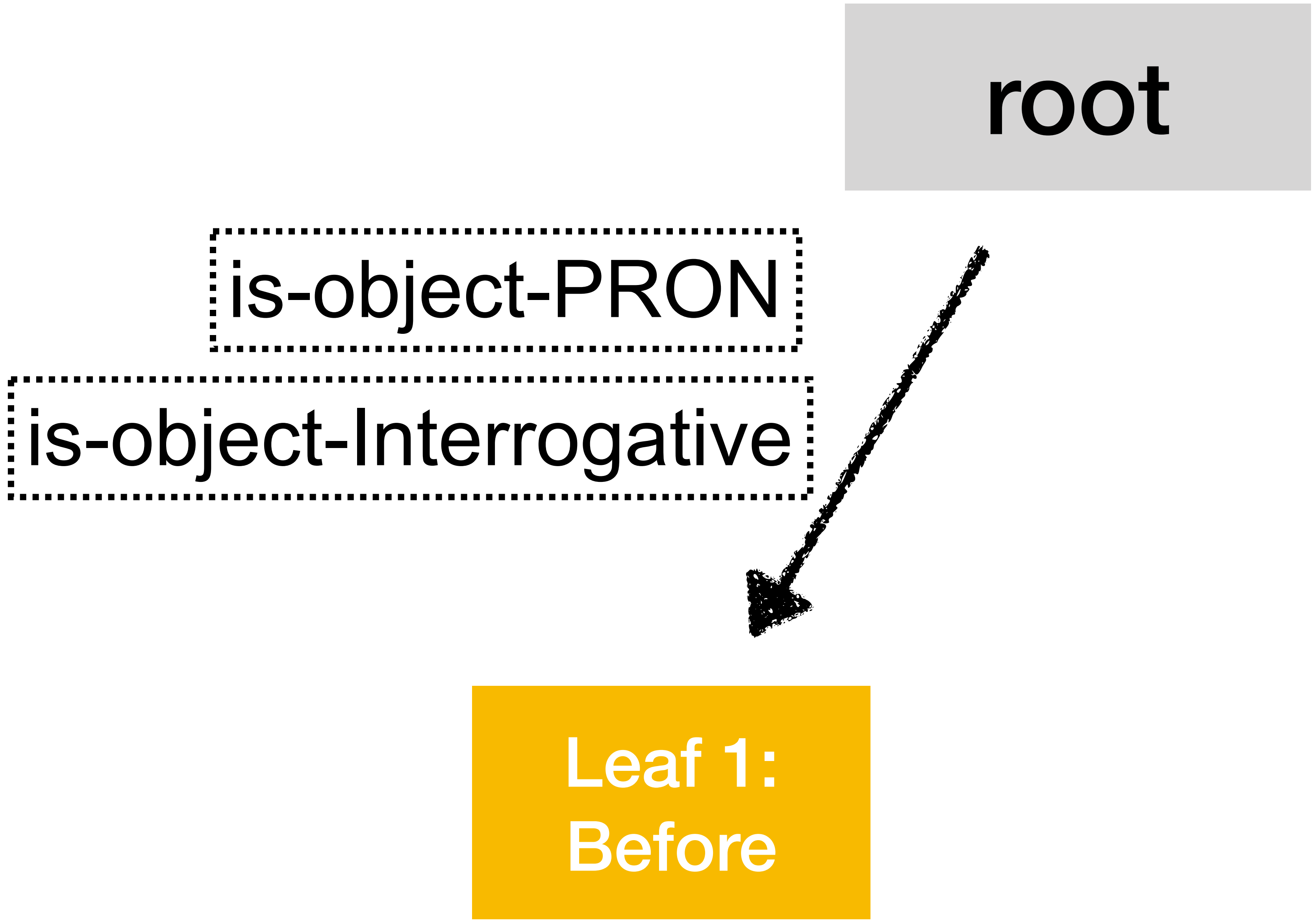
When are **objects** before or after the **verbs** in English?





Word Order: Learn a Model

When are **objects** before or after the **verbs** in English?



root

is-object-PRON

is-object-Interrogative

Leaf 1: Before

Formulate the linguistic question into a classification task

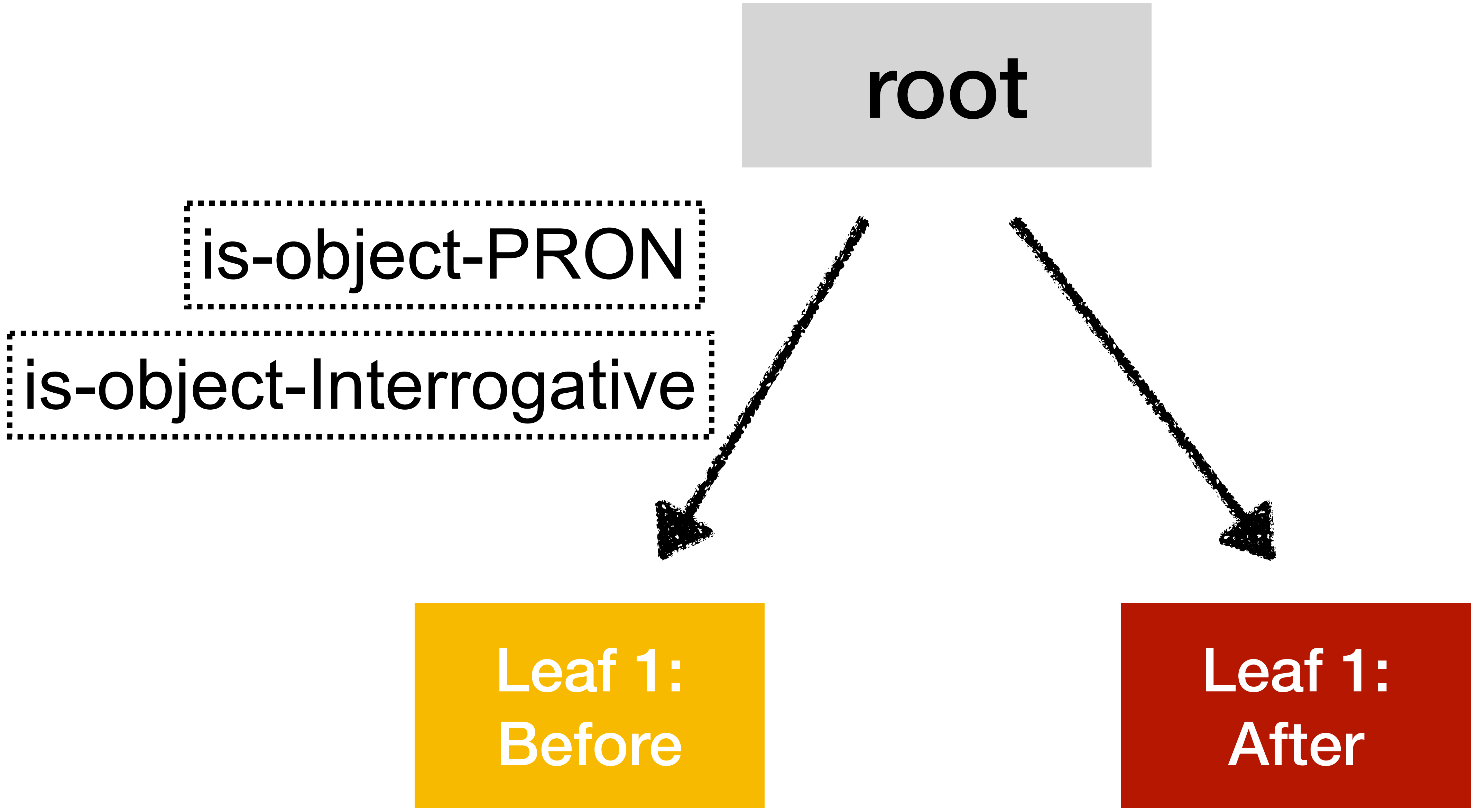
Extract Features and Construct Training Data

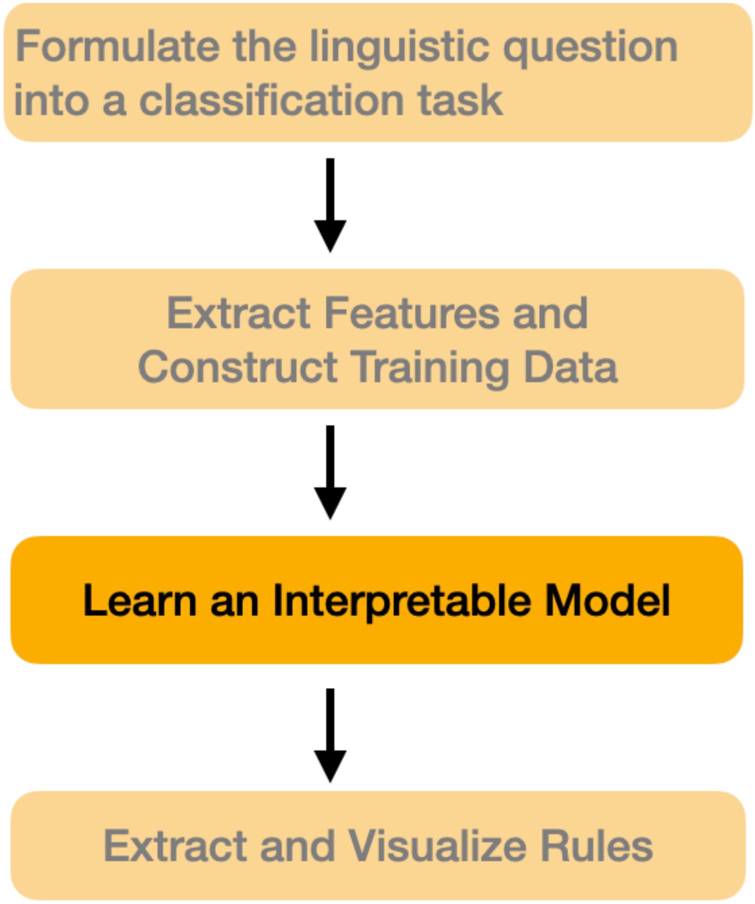
Learn an Interpretable Model

Extract and Visualize Rules

Word Order: Learn a Model

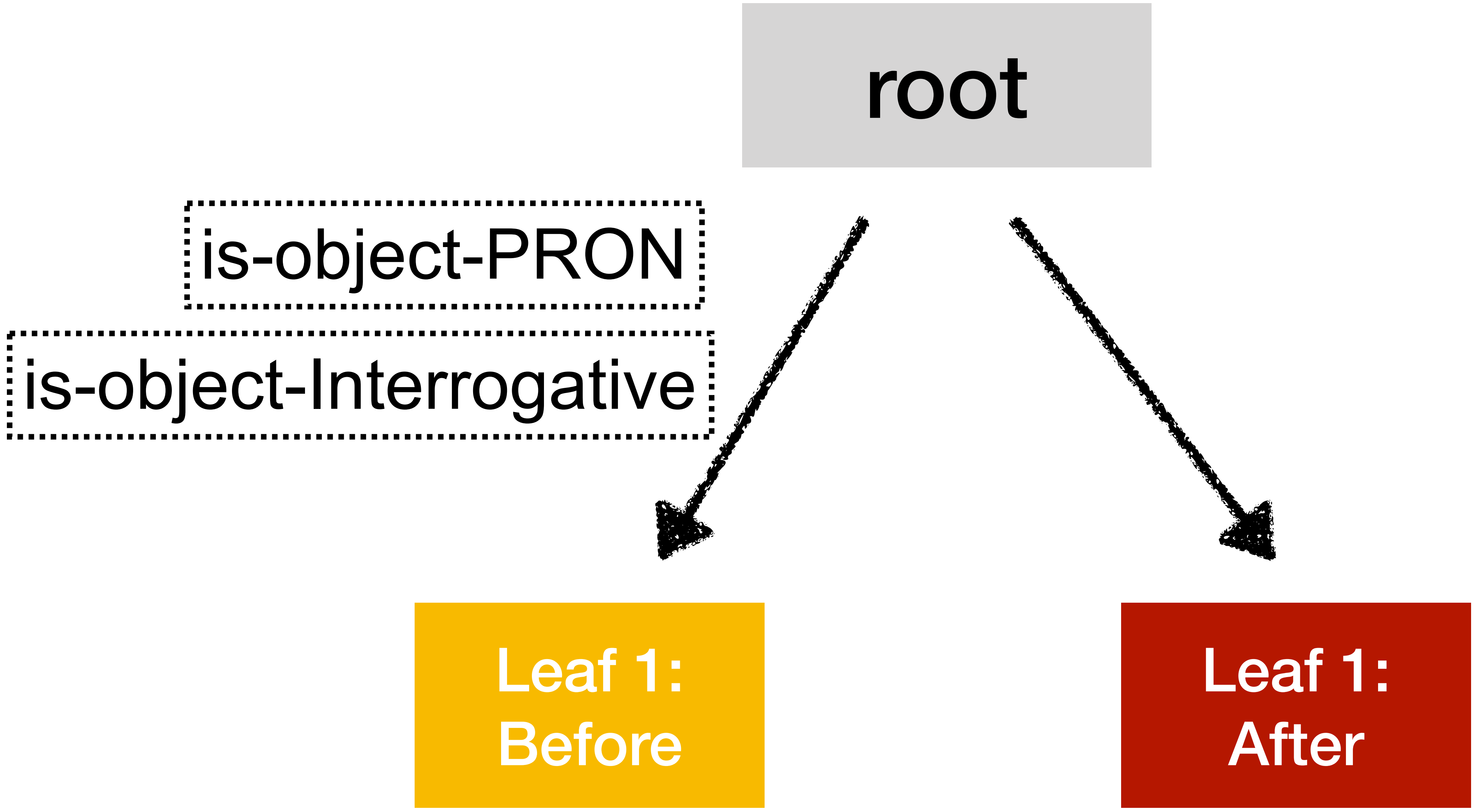
When are **objects** before or after the **verbs** in English?



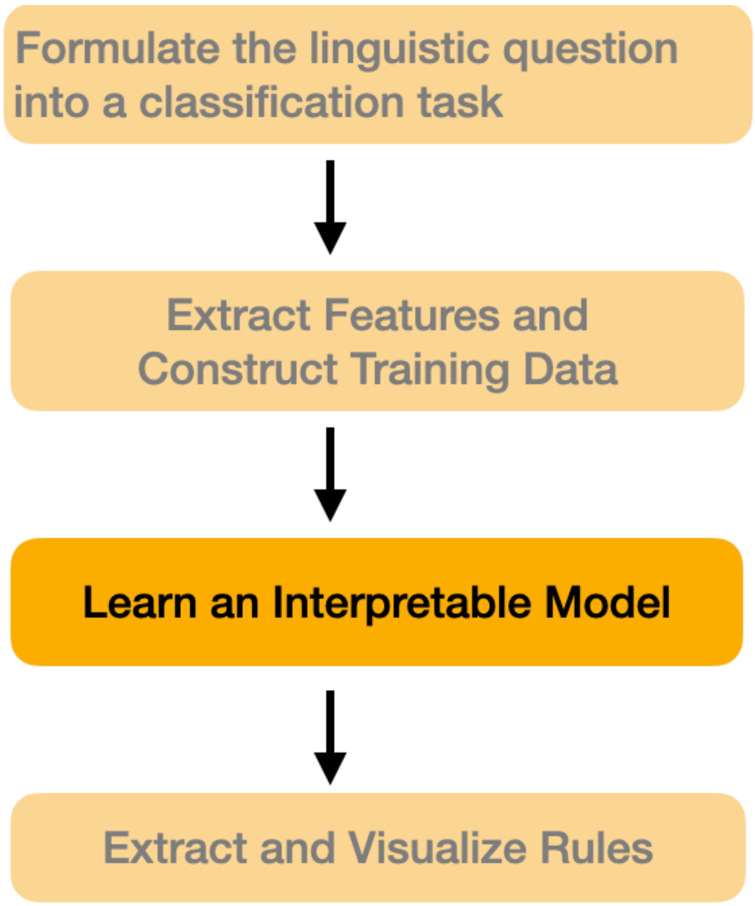


Word Order: Learn a Model

When are **objects** before or after the **verbs** in English?



Rule: When object is an interrogative pronoun, it comes **BEFORE** the verb.



Word Order: Data

When are **objects** before or after the **verbs** in English?

Formulate the linguistic question into a classification task

↓

Extract Features and Construct Training Data

↓

Learn an Interpretable Model

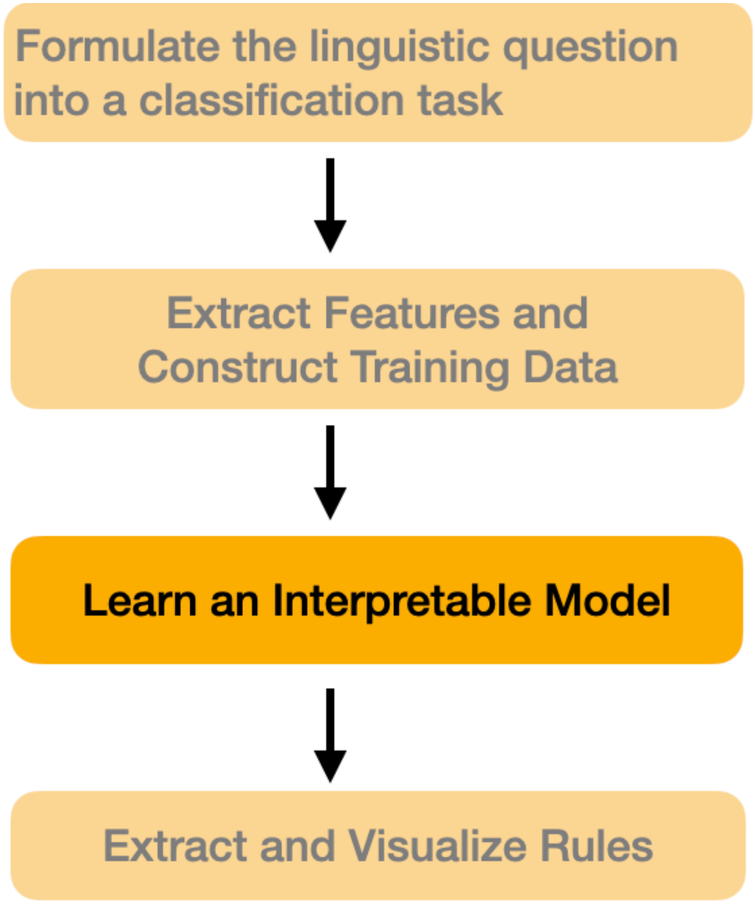
↓

Extract and Visualize Rules

Word Order: Data

When are **objects** before or after the **verbs** in English?

- Compare the model in a clean setting ⟶ **Syntactic Universal Dependencies (SUD)**



Formulate the linguistic question into a classification task

Extract Features and Construct Training Data

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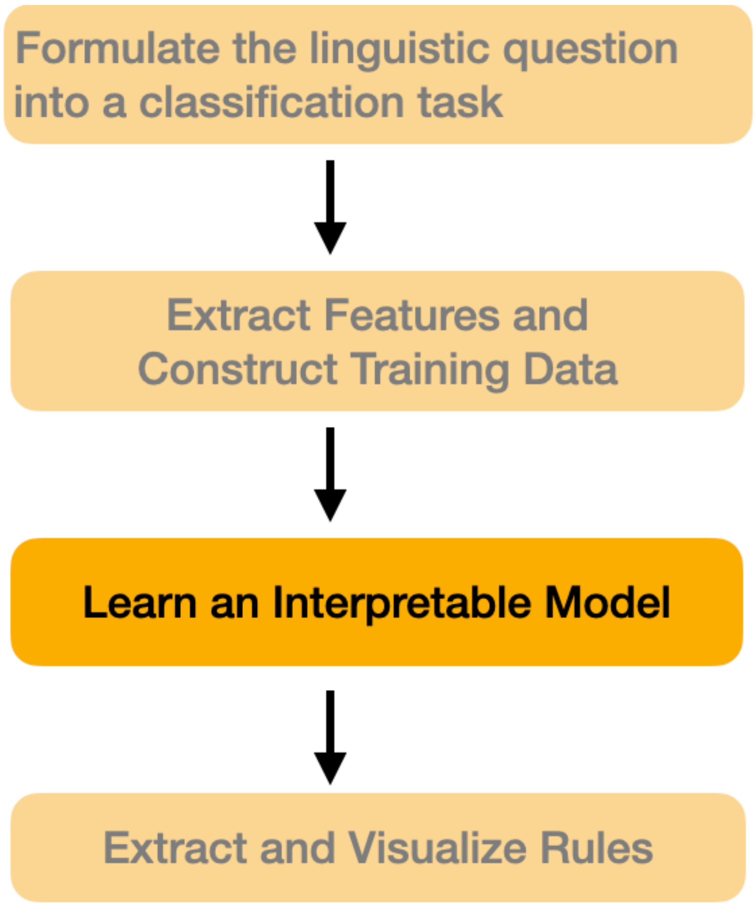
Extract and Visualize Rules

Word Order: Data

When are **objects** before or after the **verbs** in English?

- Compare the model in a clean setting ⟶ **Syntactic Universal Dependencies (SUD)**

- **Prefers syntactic heads** over content heads ⟶ more conducive to our goal of rule extraction



Formulate the linguistic question into a classification task

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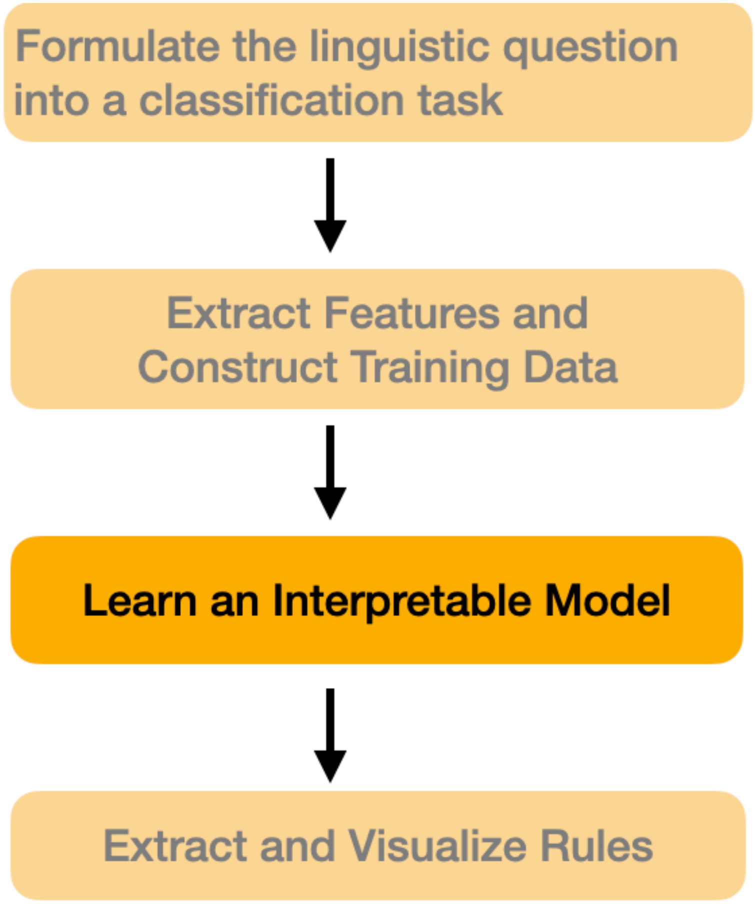
Word Order: Data

When are **objects** before or after the **verbs** in English?

- Compare the model in a clean setting ⟶ **Syntactic Universal Dependencies (SUD)**

- **Prefers syntactic heads** over content heads ⟶ more conducive to our goal of rule extraction

- Expert-annotated syntactic analysis for **>60 languages**



Formulate the linguistic question into a classification task

Extract Features and Construct Training Data

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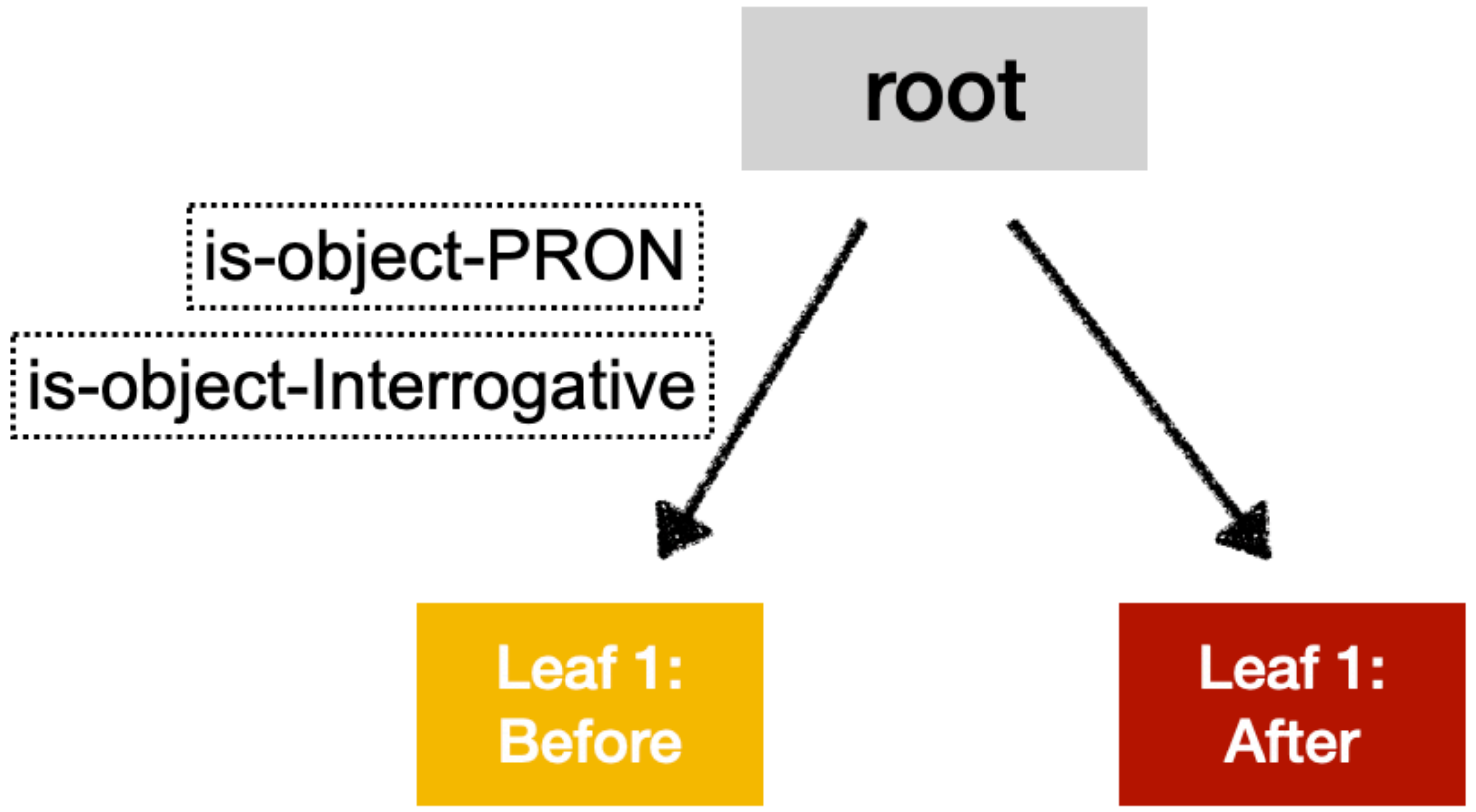
Extract and Visualize Rules

Word Order: Automated Evaluation

When are **objects** before or after the **verbs** in English?



root

is-object-PRON

is-object-Interrogative

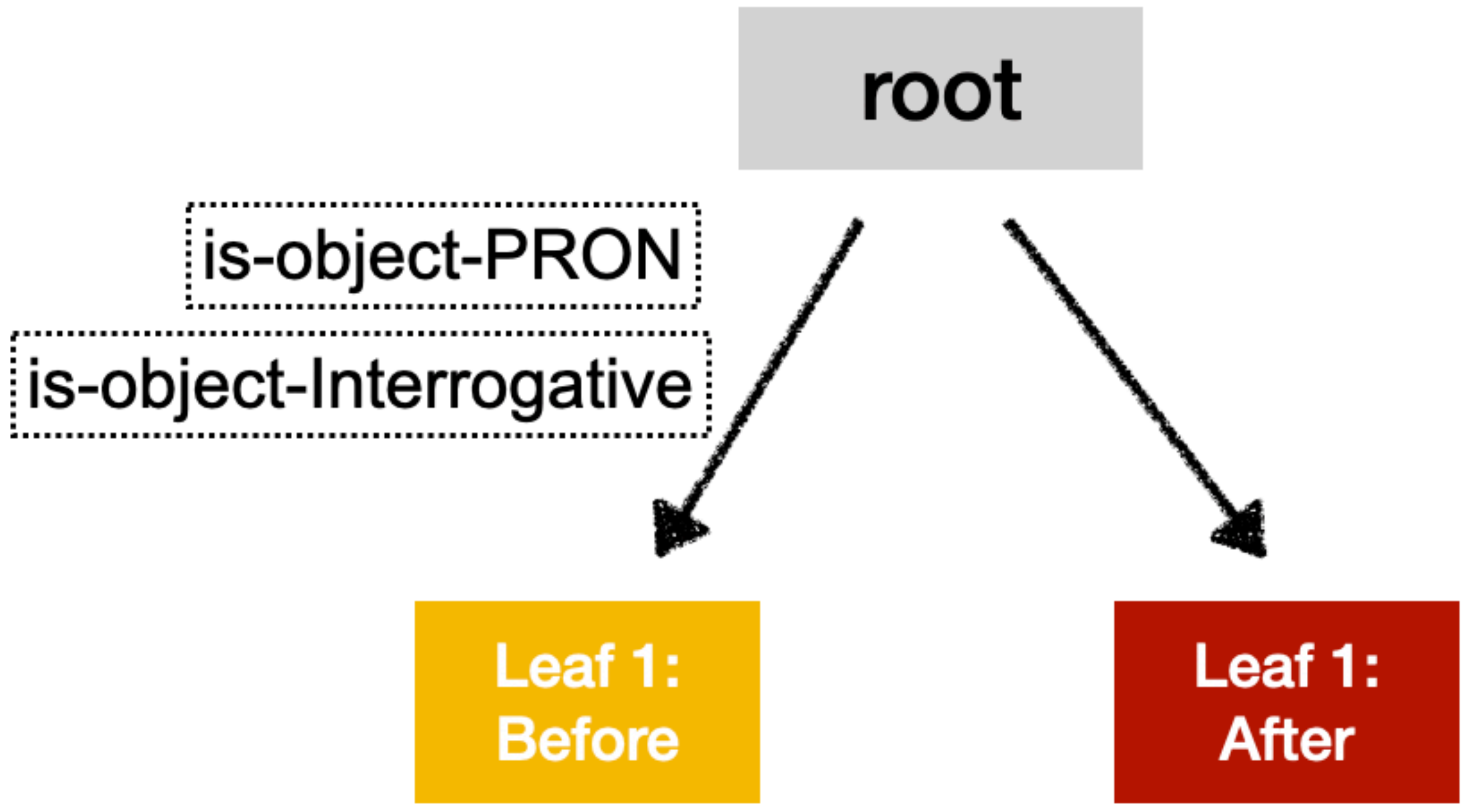
Leaf 1: Before

Leaf 1: After

Apply model
on held-out sentences

Word Order: Automated Evaluation

When are **objects** before or after the **verbs** in English?



root

is-object-PRON

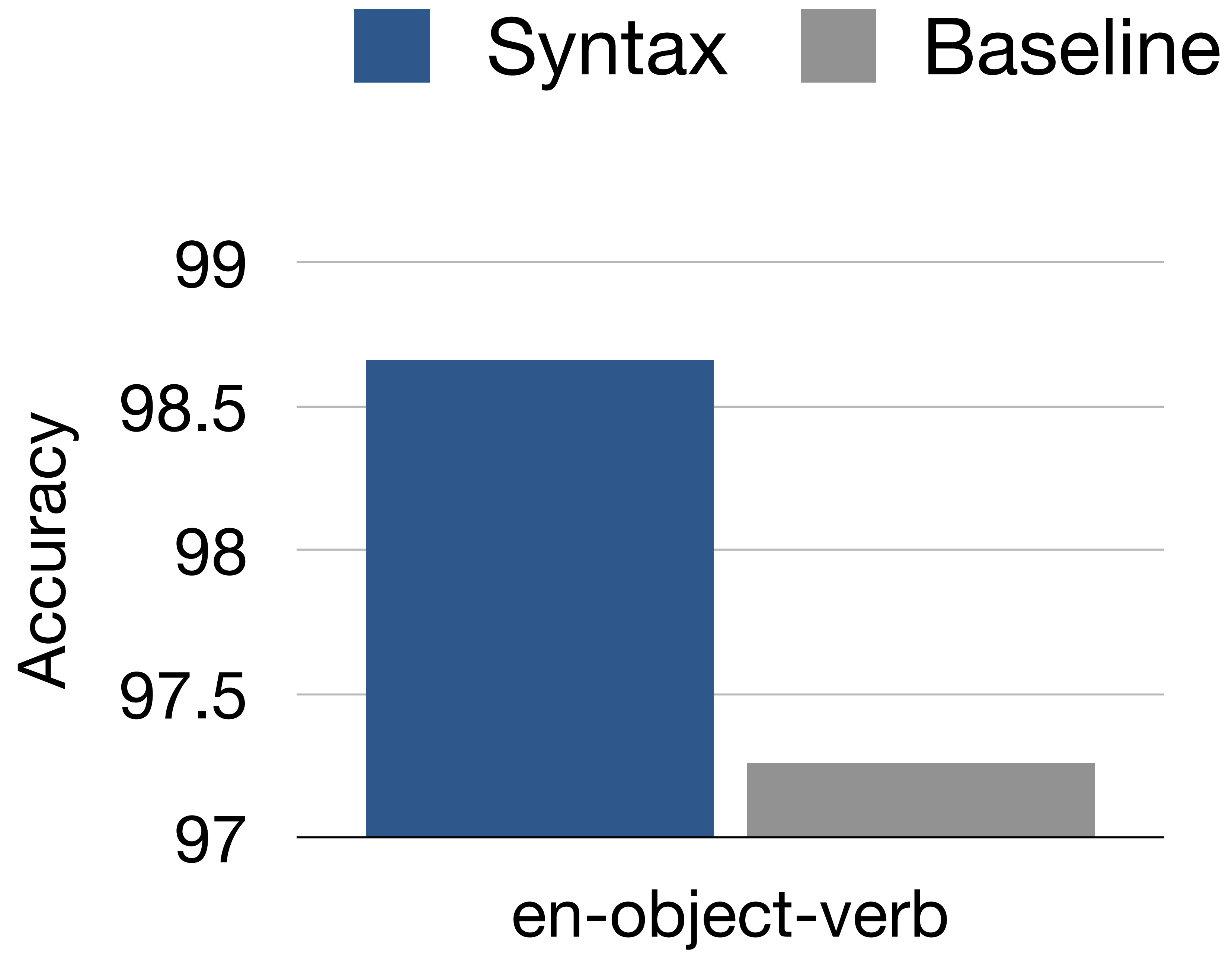
is-object-Interrogative

Leaf 1: Before

Leaf 1: After

Apply model
on held-out sentences

Baseline: most frequent
label in test data



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Word Order: Automated Evaluation

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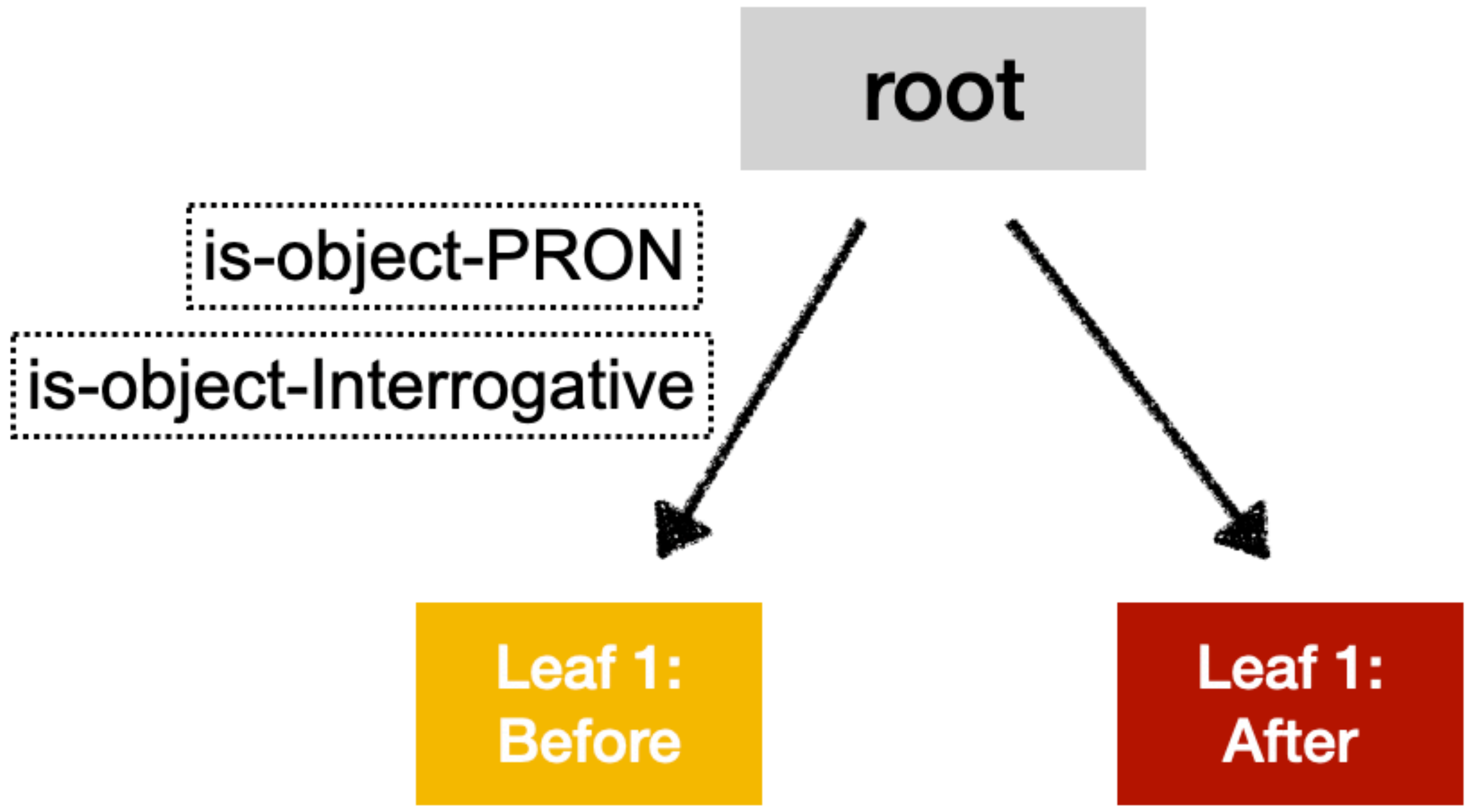

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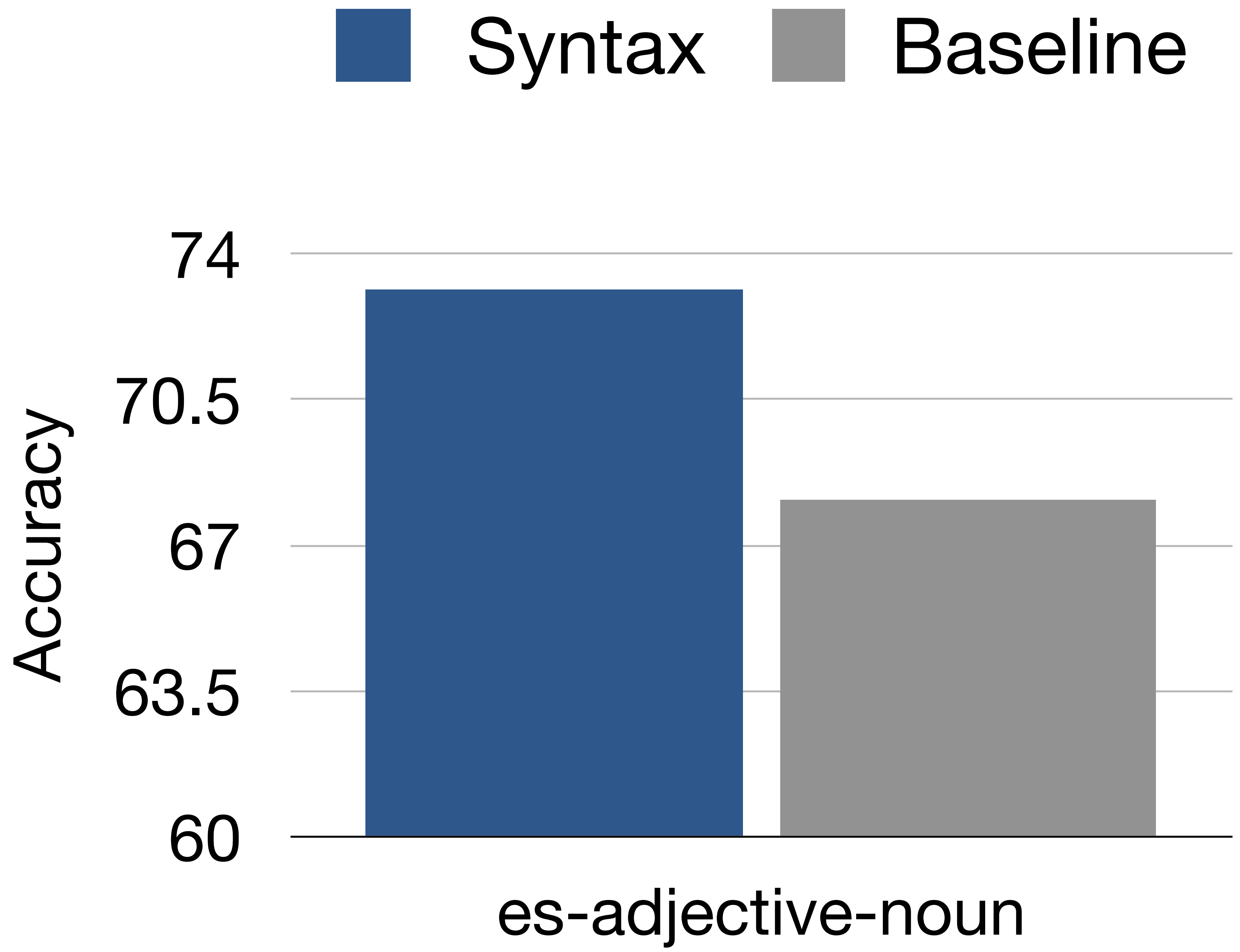
is-object-Interrogative

Leaf 1: Before

Leaf 1: After

Apply model on held-out sentences →

Baseline: most frequent label in test data



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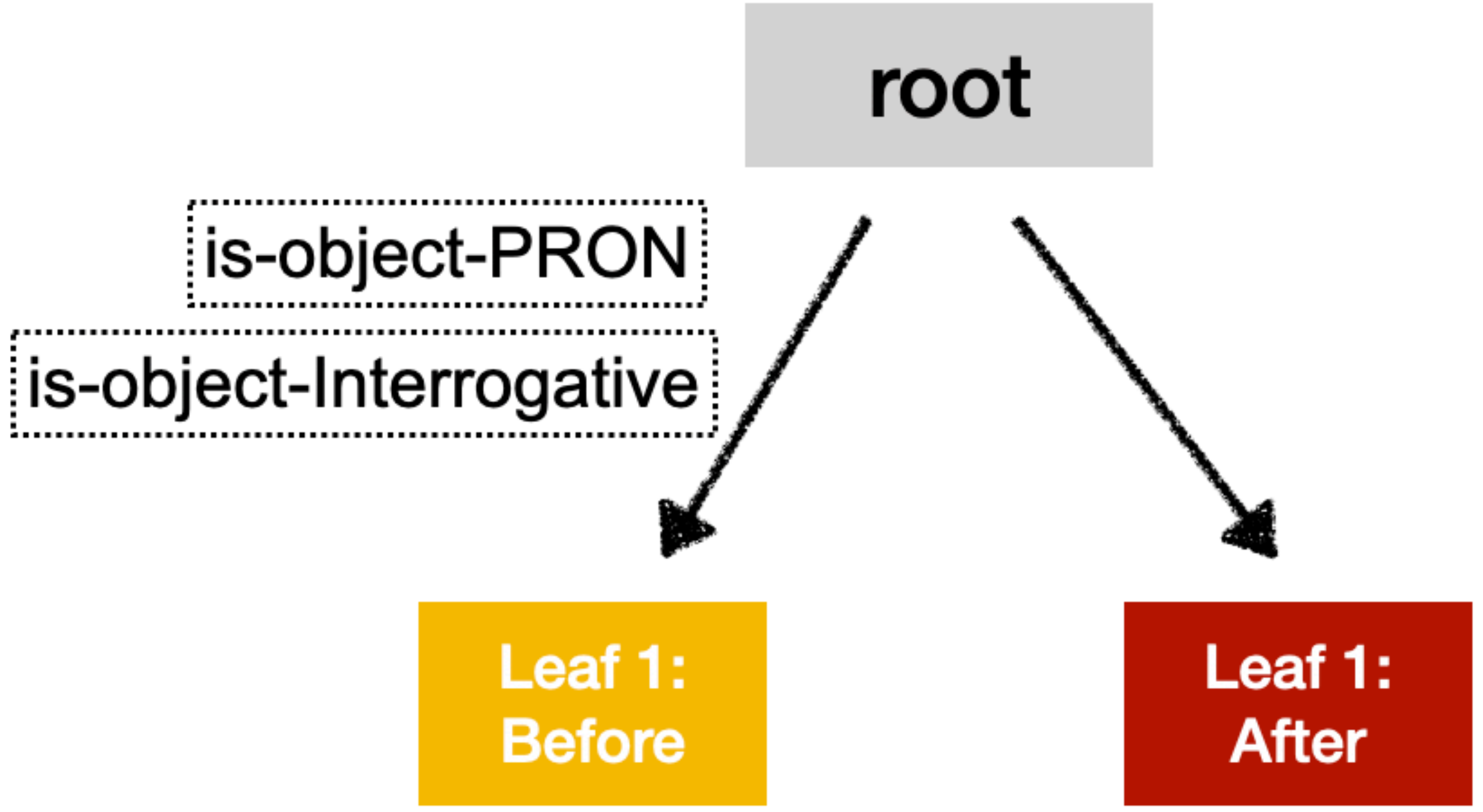
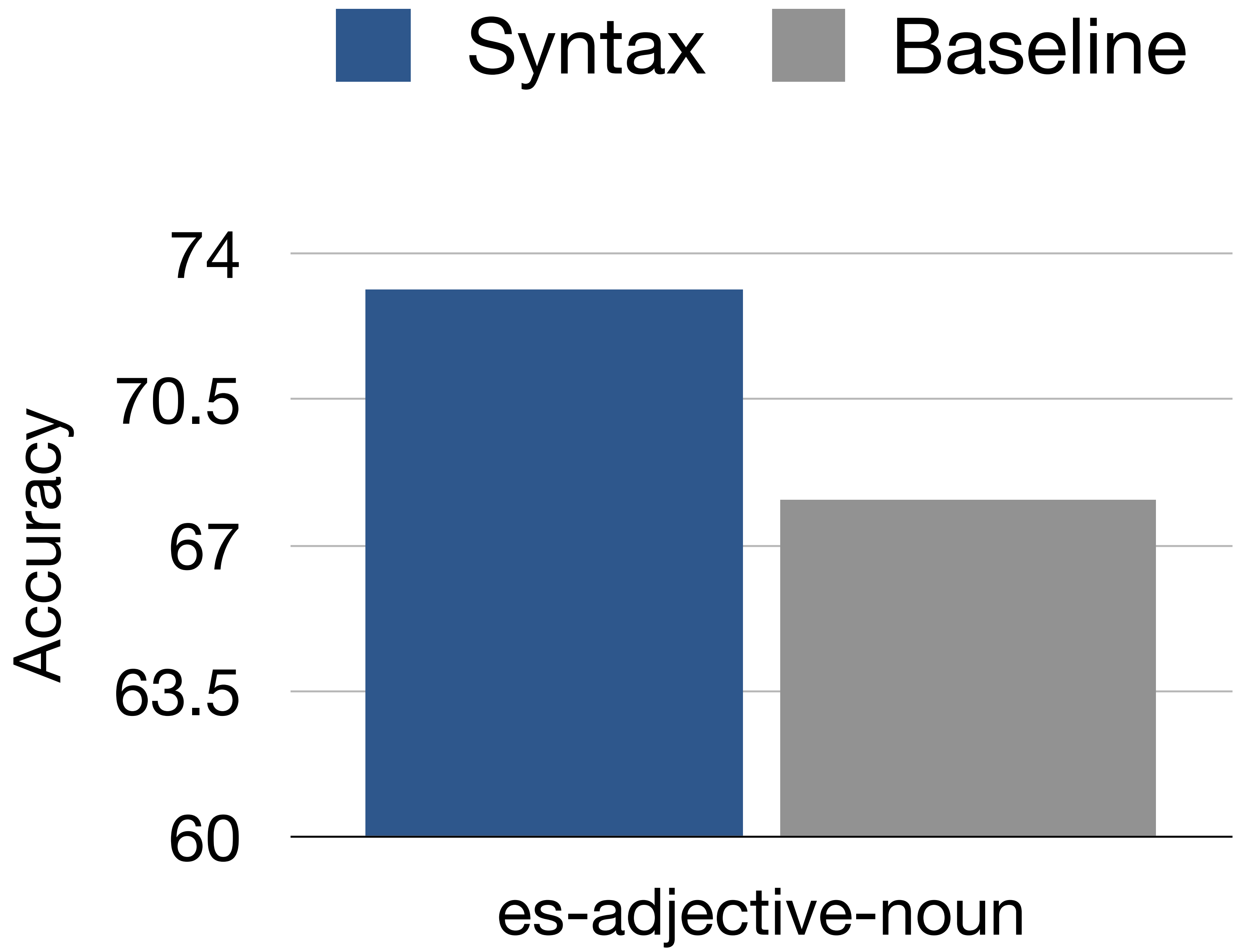


Apply model
on held-out sentences

Baseline: most frequent
label in test data



Using syntactic signals **insufficient**!

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Word Order: Types of Features

grandes	libros	fueron	comprados	por	la	niña	pequeña
great	*books*	*were*	*bought*	*by*	*the*	*girl*	*small*

Word Order: Types of Features

grandes	libros	fueron	comprados	por	la	niña	pequeña
great	*books*	*were*	*bought*	*by*	*the*	*girl*	*small*
ADJ	NOUN					NOUN	ADJ

Word Order: Types of Features

mod

mod

grandes *great* ADJ

libros *books* NOUN

fueron *were*

comprados *bought*

por *by*

la *the*

niña *girl* NOUN

pequeña *small* ADJ

Word Order: Types of Features

syntactic

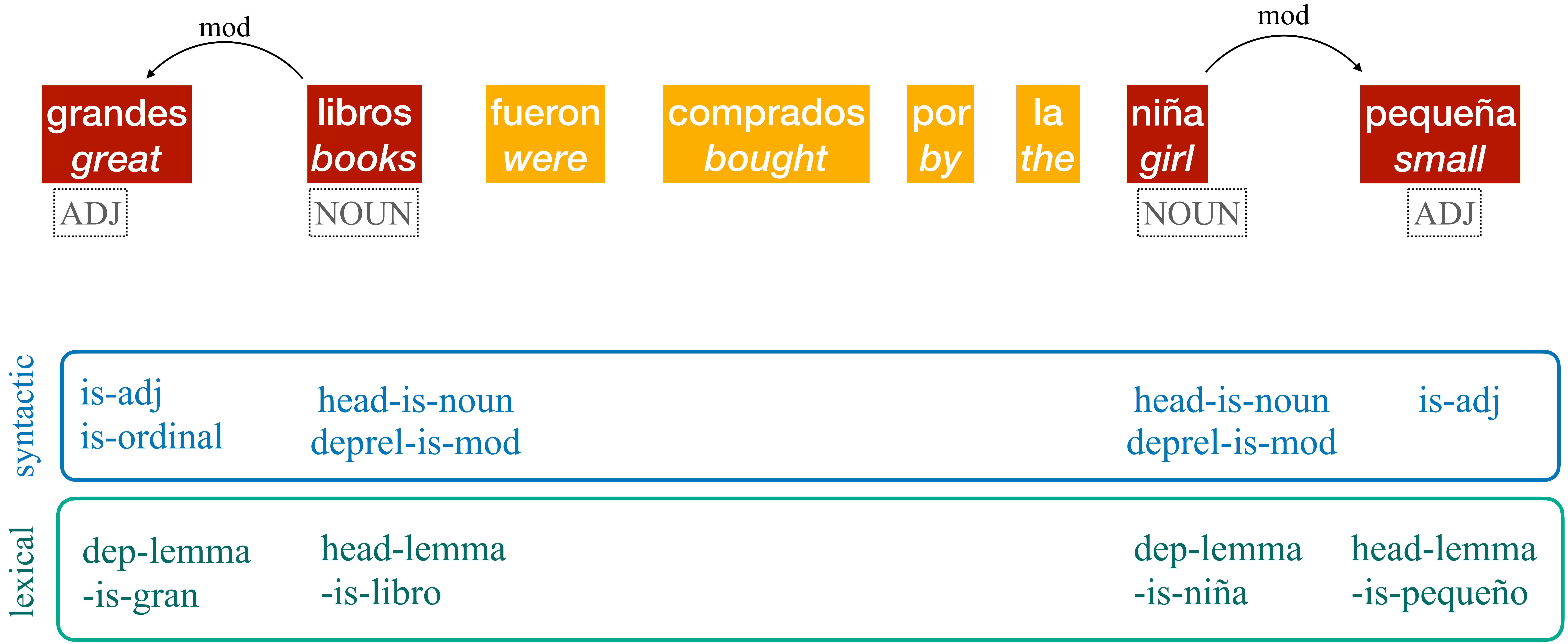
is-adj
is-ordinal

head-is-noun
deprel-is-mod

head-is-noun
deprel-is-mod

is-adj

Word Order: Types of Features



mod

mod

grandes *great* ADJ

libros *books* NOUN

fueron *were*

comprados *bought*

por *by*

la *the*

niña *girl* NOUN

pequeña *small* ADJ

syntactic

is-adj
is-ordinal

head-is-noun
deprel-is-mod

head-is-noun
deprel-is-mod

is-adj

lexical

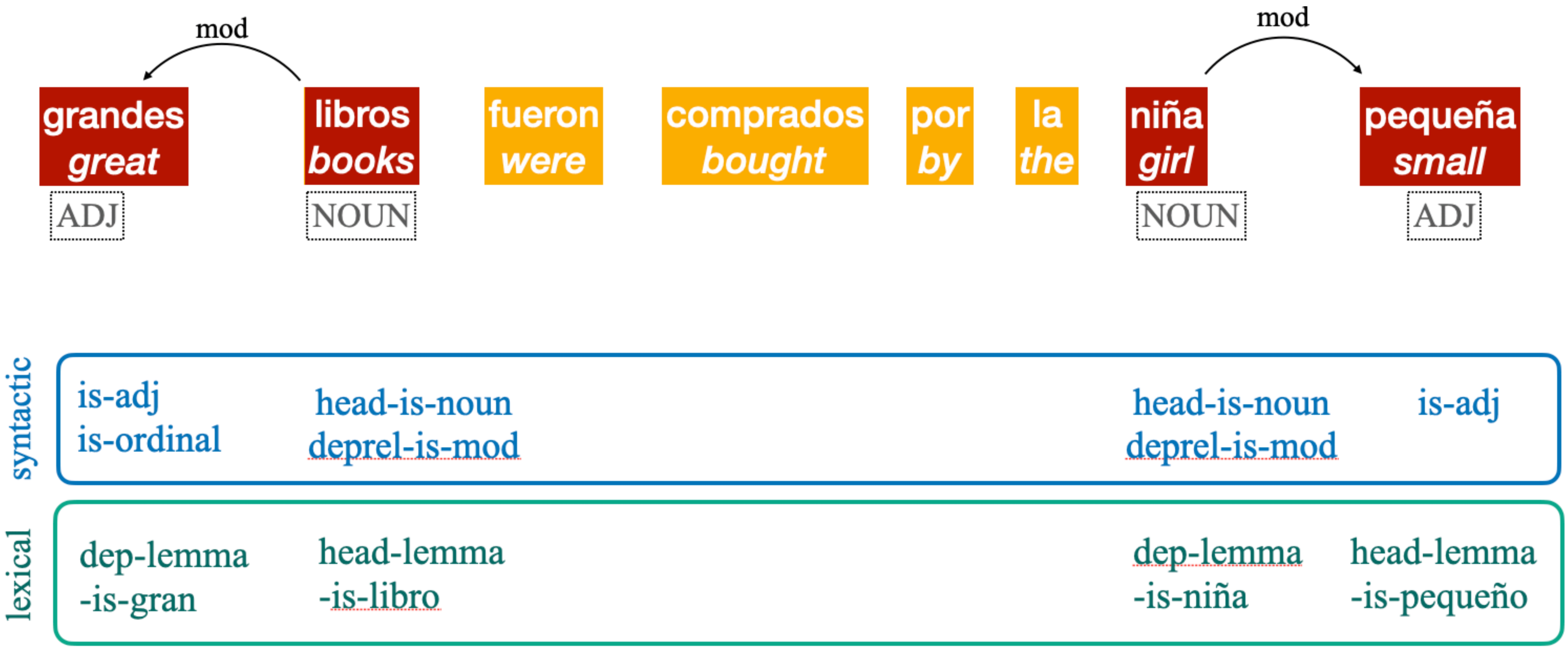
dep-lemma
-is-gran

head-lemma
-is-libro

dep-lemma
-is-niña

head-lemma
-is-pequeño

Word Order: Types of Features



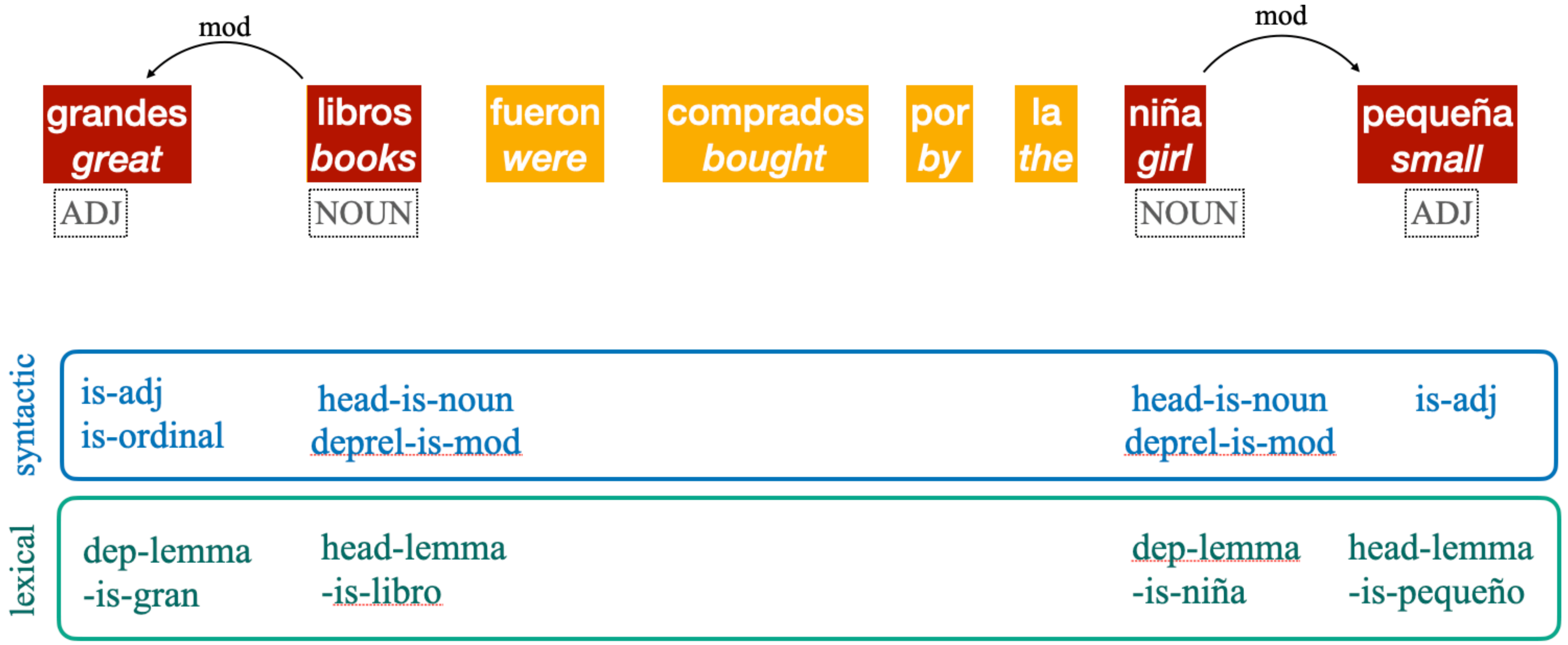
mod

mod

grandes *great*	libros *books*	fueron *were*	comprados *bought*	por *by*	la *the*	niña *girl*	pequeña *small*
ADJ	NOUN					NOUN	ADJ

syntactic	is-adj is-ordinal	head-is-noun deprel-is-mod	head-is-noun deprel-is-mod	is-adj
lexical	dep-lemma -is-gran	head-lemma -is-libro	dep-lemma -is-niña	head-lemma -is-pequeño

Word Order: Types of Features



mod

mod

grandes *great* ADJ

libros *books* NOUN

fueron *were*

comprados *bought*

por *by*

la *the*

niña *girl* NOUN

pequeña *small* ADJ

syntactic

is-adj
is-ordinal

head-is-noun
deprel-is-mod

head-is-noun
deprel-is-mod

is-adj

lexical

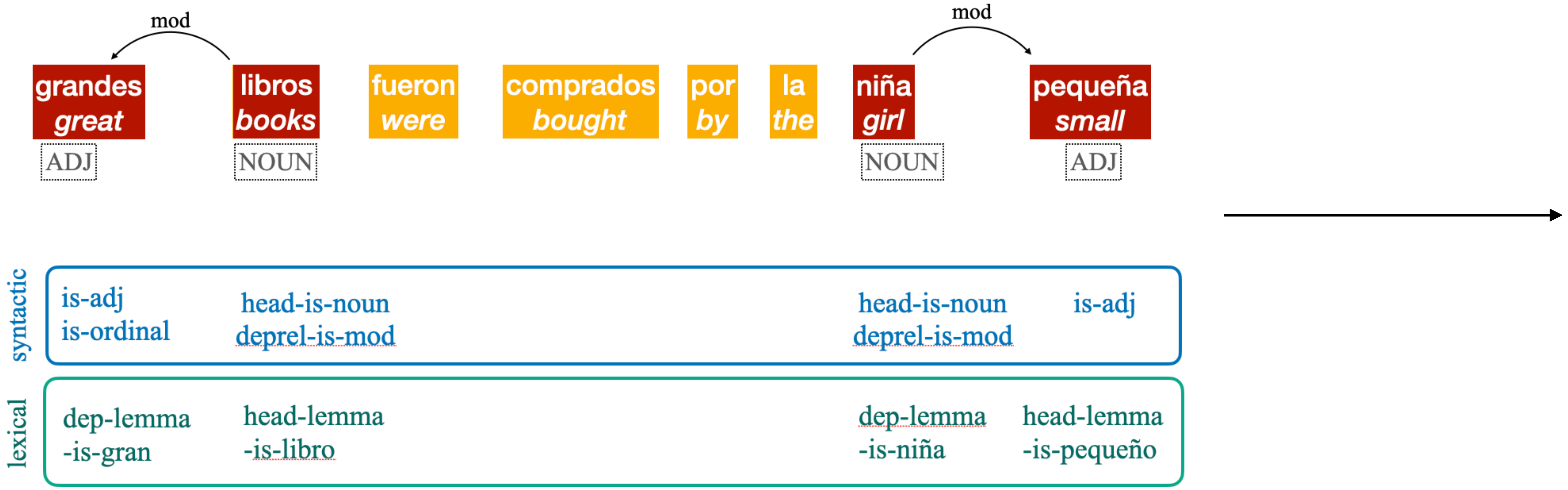
dep-lemma
-is-gran

head-lemma
-is-libro

dep-lemma
-is-niña

head-lemma
-is-pequeño

Word Order: Types of Features



syntactic: is-adj is-ordinal | head-is-noun deprel-is-mod | head-is-noun deprel-is-mod | is-adj

lexical: dep-lemma-is-gran | head-lemma-is-libro | dep-lemma-is-niña | head-lemma-is-pequeño

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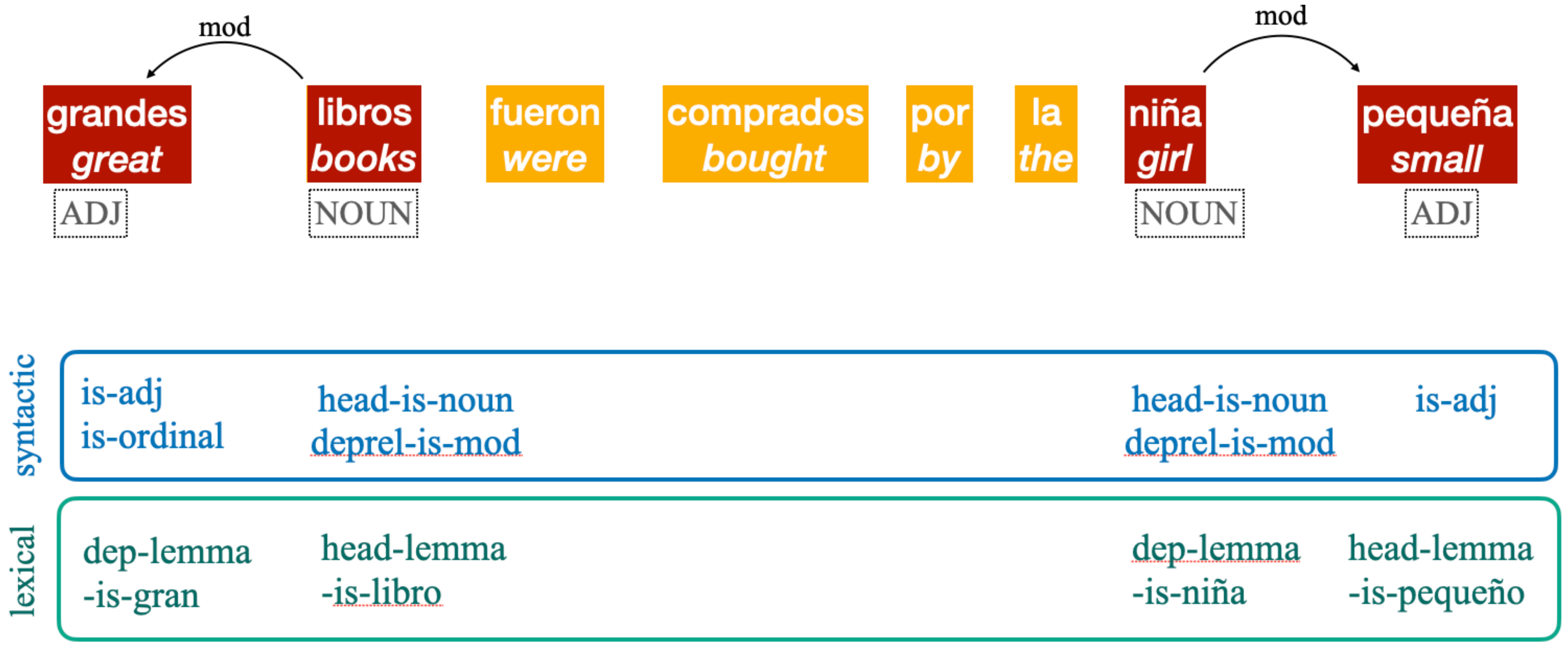
Chaudhary**, Sheikh, Mortensen, Anastasopoulos, Neubig.* ***In Submission

Word Order: Types of Features



mod

grandes *great* ADJ

libros *books* NOUN

fueron *were*

comprados *bought*

por *by*

la *the*

mod

niña *girl* NOUN

pequeña *small* ADJ

syntactic

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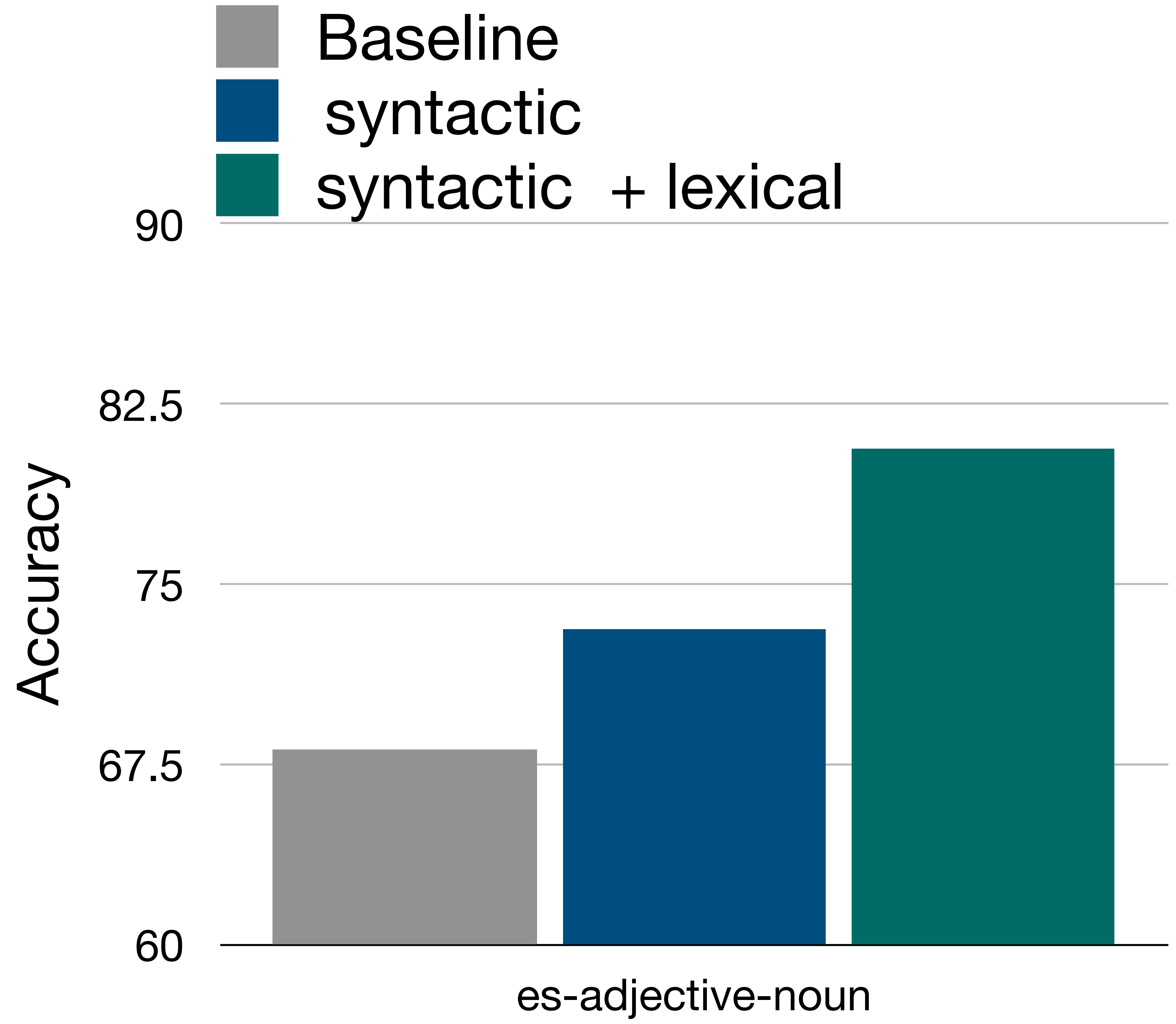

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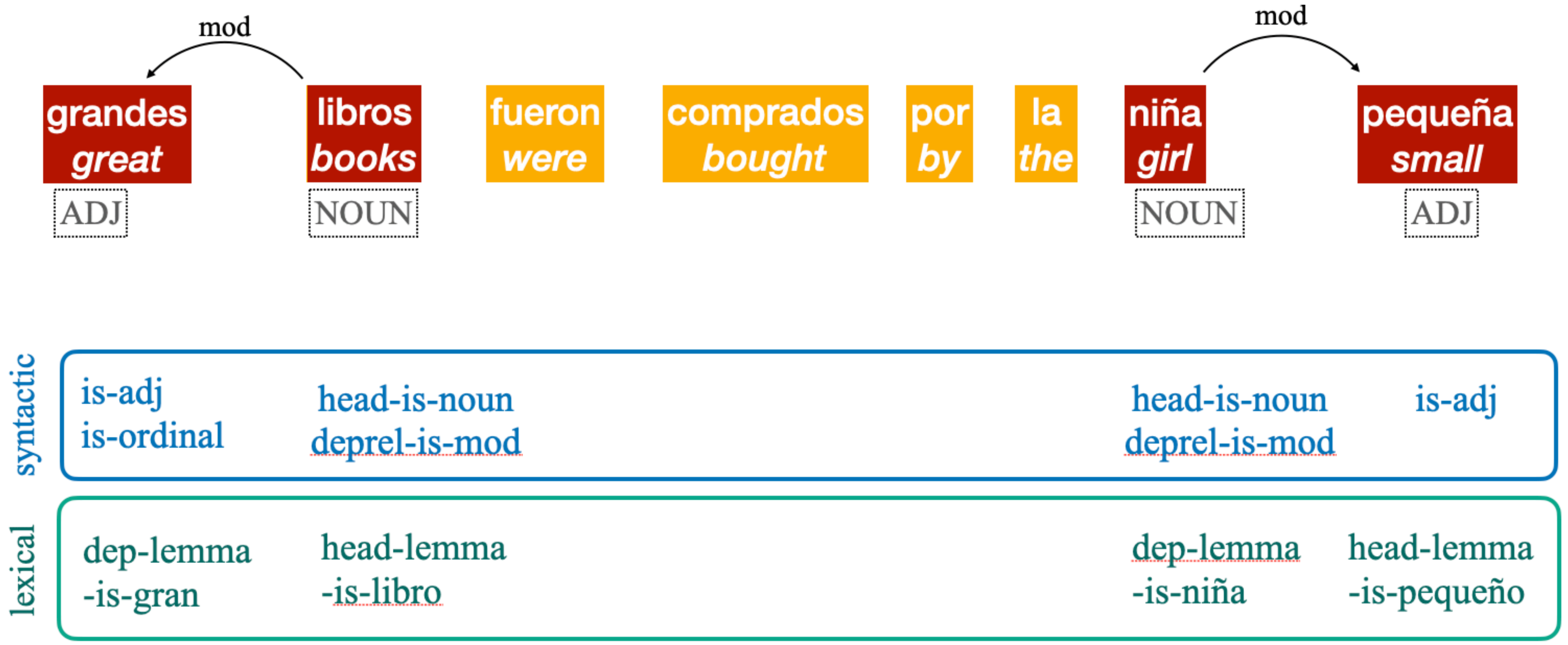
Word Order: Types of Features



mod
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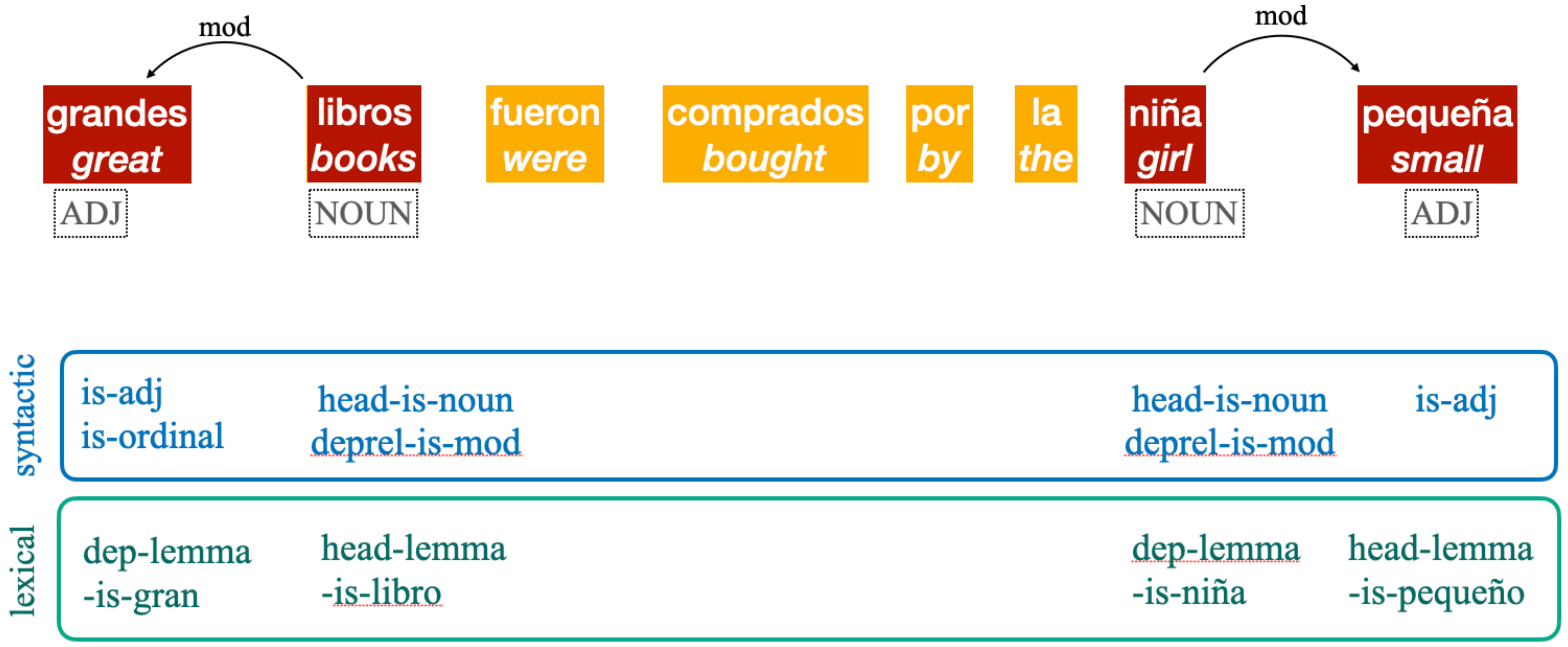
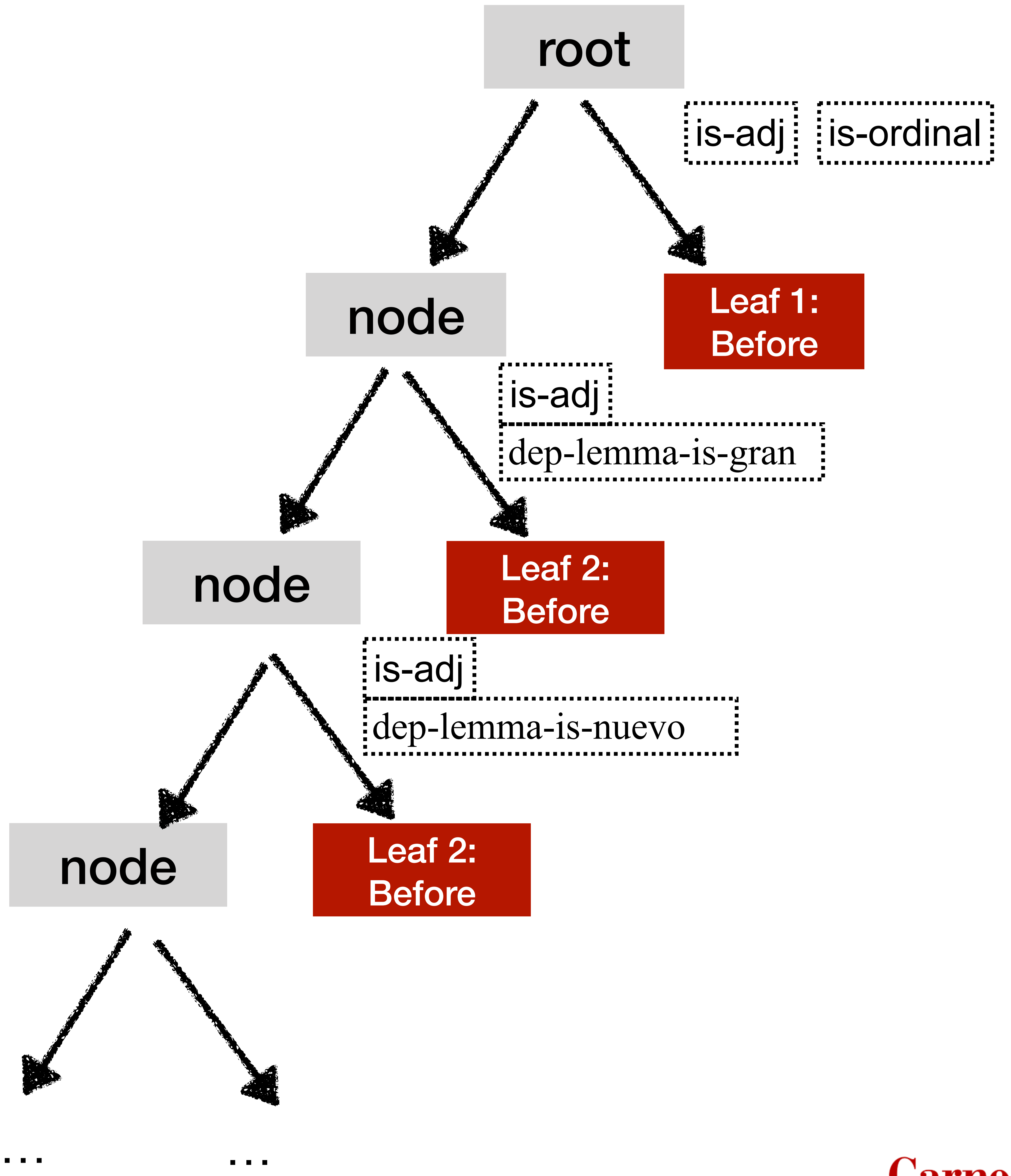
Word Order: Types of Features





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Word Order: Types of Features

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[1] SPINE: SParse Interpretable Neural Embeddings
Anant Subramanian, Danish Pruthi, Harsh Jhamtani, Taylor Berg-Kirkpatrick, Eduard Hovy

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dim-0: wrist, shoulder, ligament, ankle, thigh

Semantic similarity

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dim-0: wrist, shoulder, ligament, ankle, thigh

Semantic similarity

dim-1: extensively, adequately, traditionally, royally, fully

Syntactic similarity

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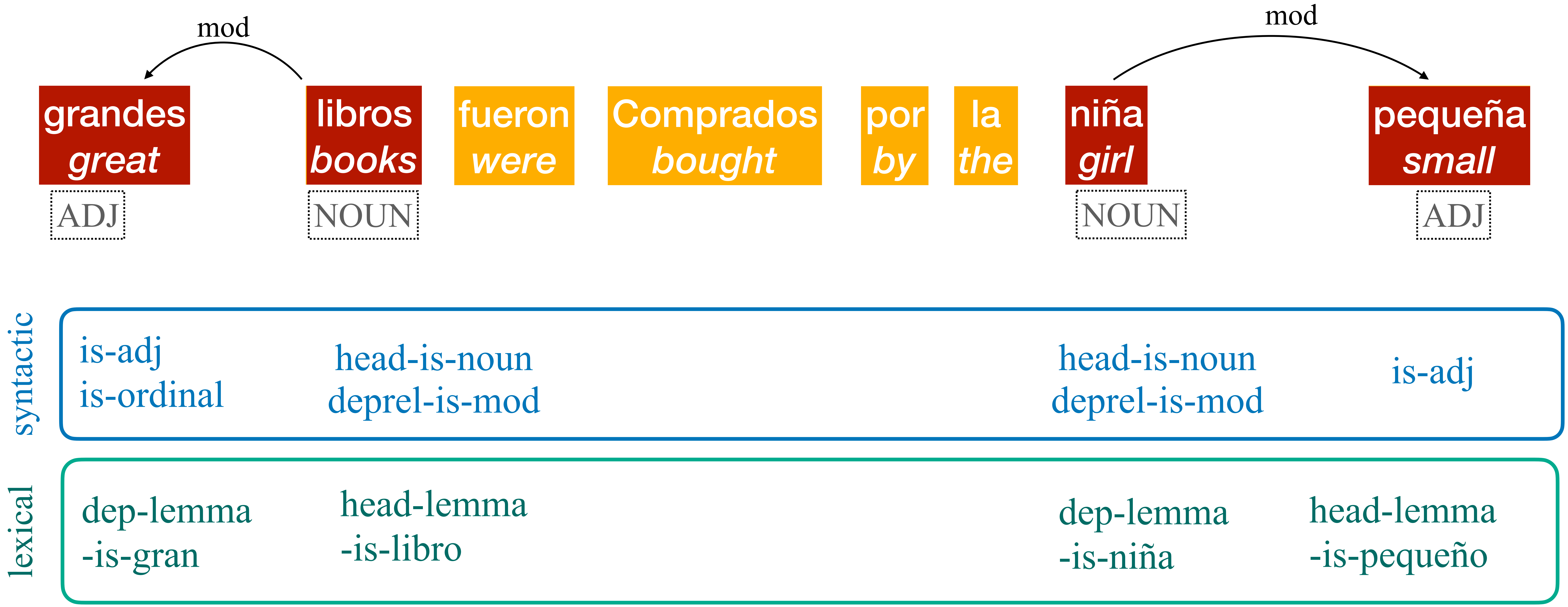
Word Order: Types of Features



mod

mod

grandes *great*	libros *books*	fueron *were*	Comprados *bought*	por *by*	la *the*	niña *girl*	pequeña *small*
ADJ	NOUN					NOUN	ADJ

syntactic	is-adj is-ordinal	head-is-noun deprel-is-mod	head-is-noun deprel-is-mod	is-adj
lexical	dep-lemma -is-gran	head-lemma -is-libro	dep-lemma -is-niña	head-lemma -is-pequeño

Word Order: Types of Features

grandes	libros	fueron	Comprados	por	la	niña	pequeña
great	*books*	*were*	*bought*	*by*	*the*	*girl*	*small*
ADJ	NOUN					NOUN	ADJ

syntactic	is-adj is-ordinal	head-is-noun deprel-is-mod	head-is-noun deprel-is-mod	is-adj
lexical	dep-lemma -is-gran	head-lemma -is-libro	dep-lemma -is-niña	head-lemma -is-pequeño
semantic	word-is-like-primera	head-word-is-like-págin, publicación	word-is-like-niño	head-word-is-like-nueva, vuelta

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Word Order: Types of Features

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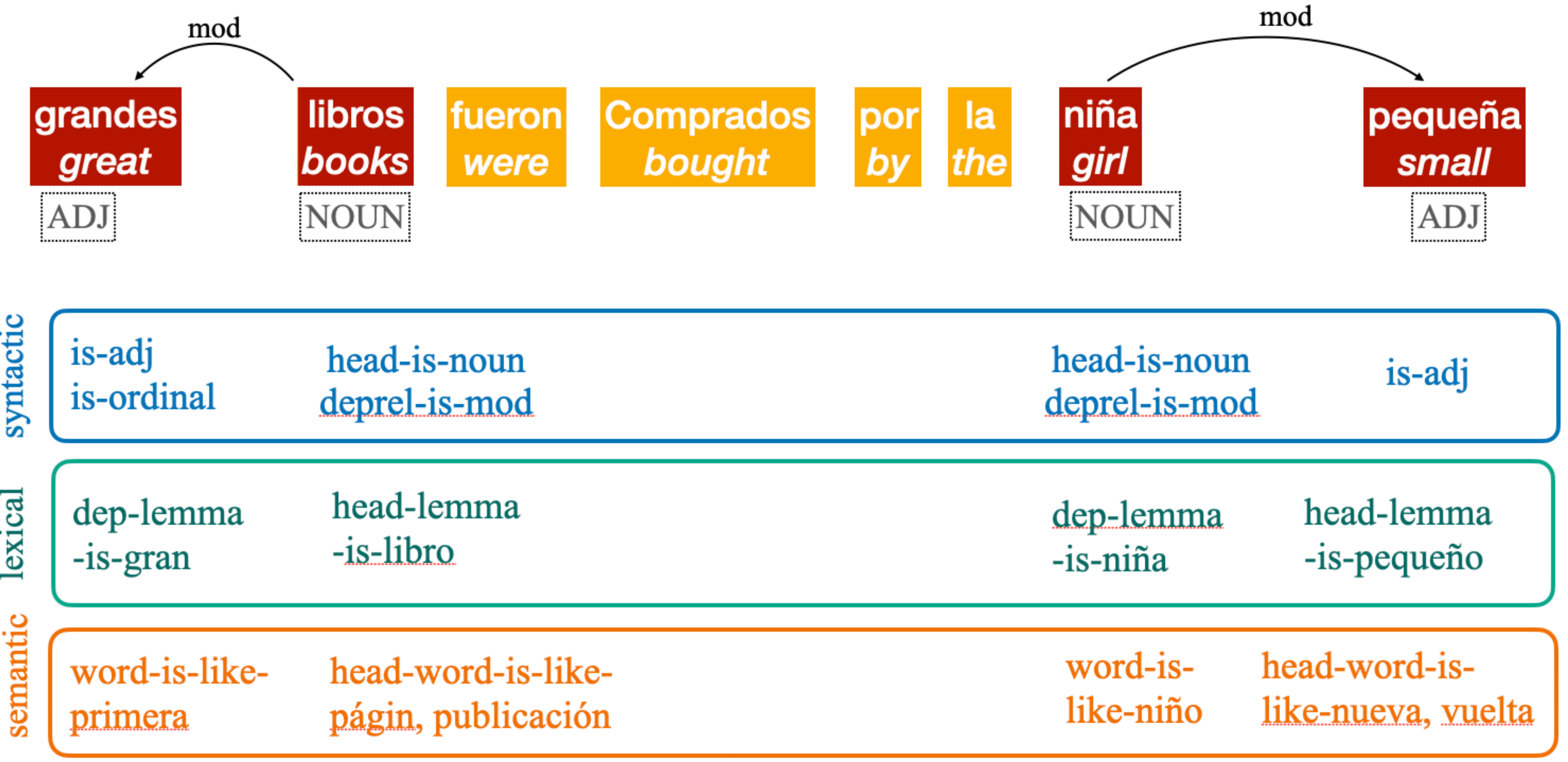

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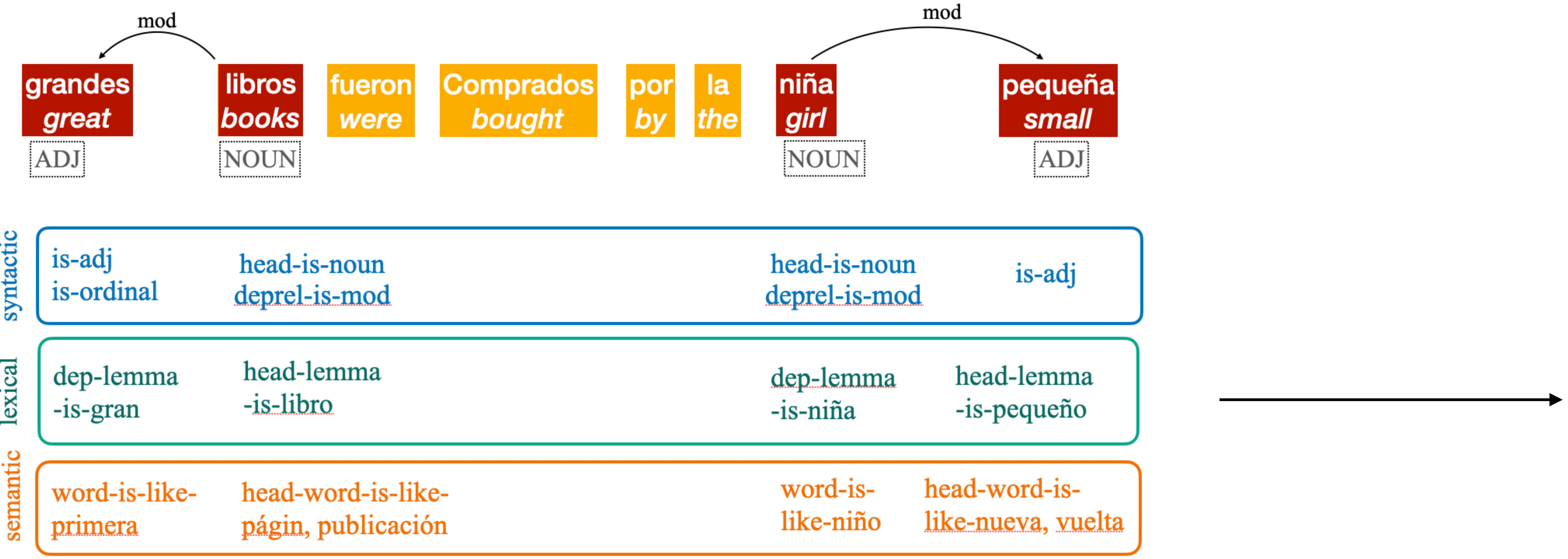

is-adj
is-ordinal

head-is-noun
deprel-is-mod

head-is-noun
deprel-is-mod

is-adj

dep-lemma -is-gran

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head-lemma -is-pequeño

word-is-like-primera

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word-is-like-niño

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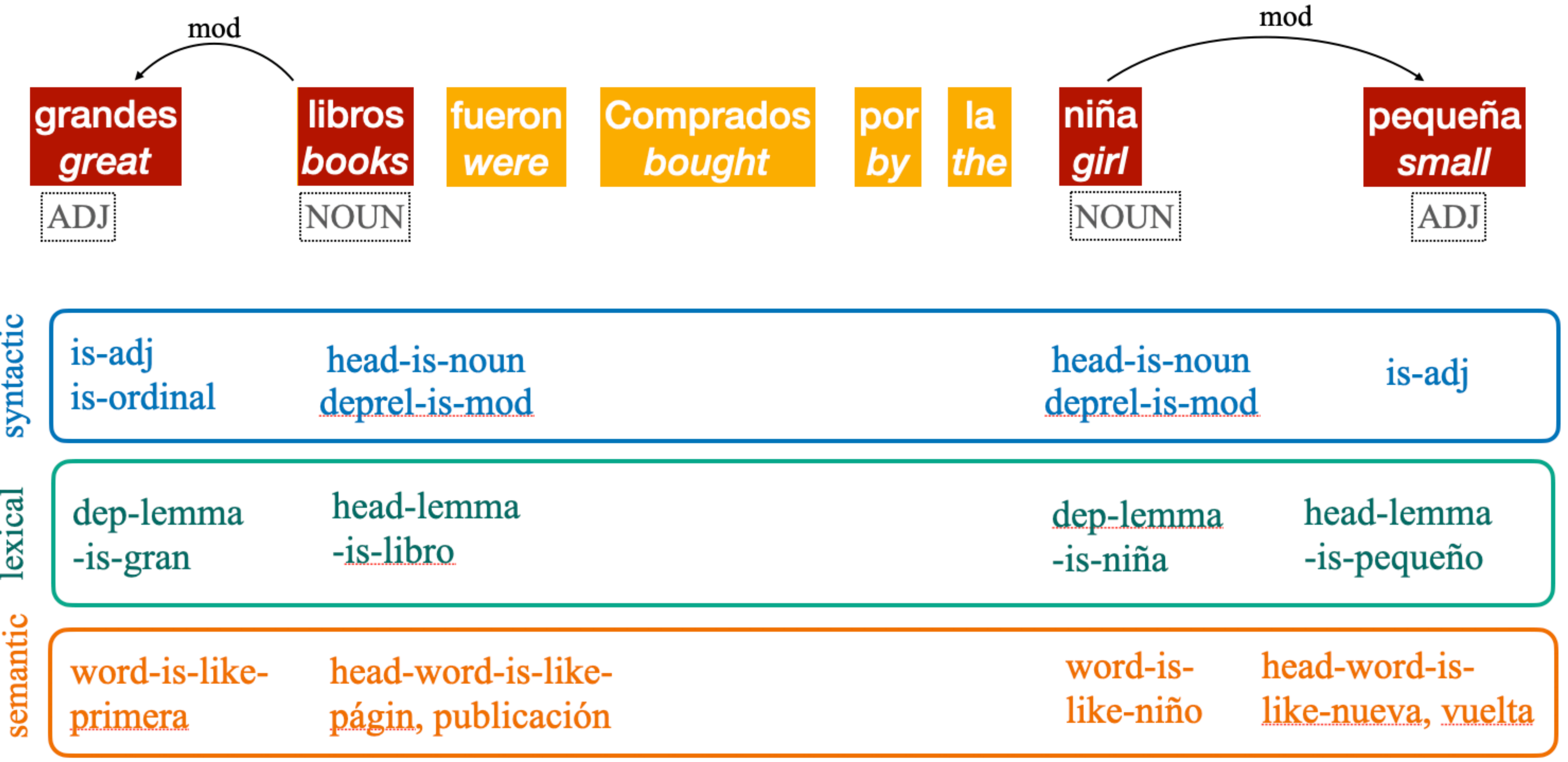

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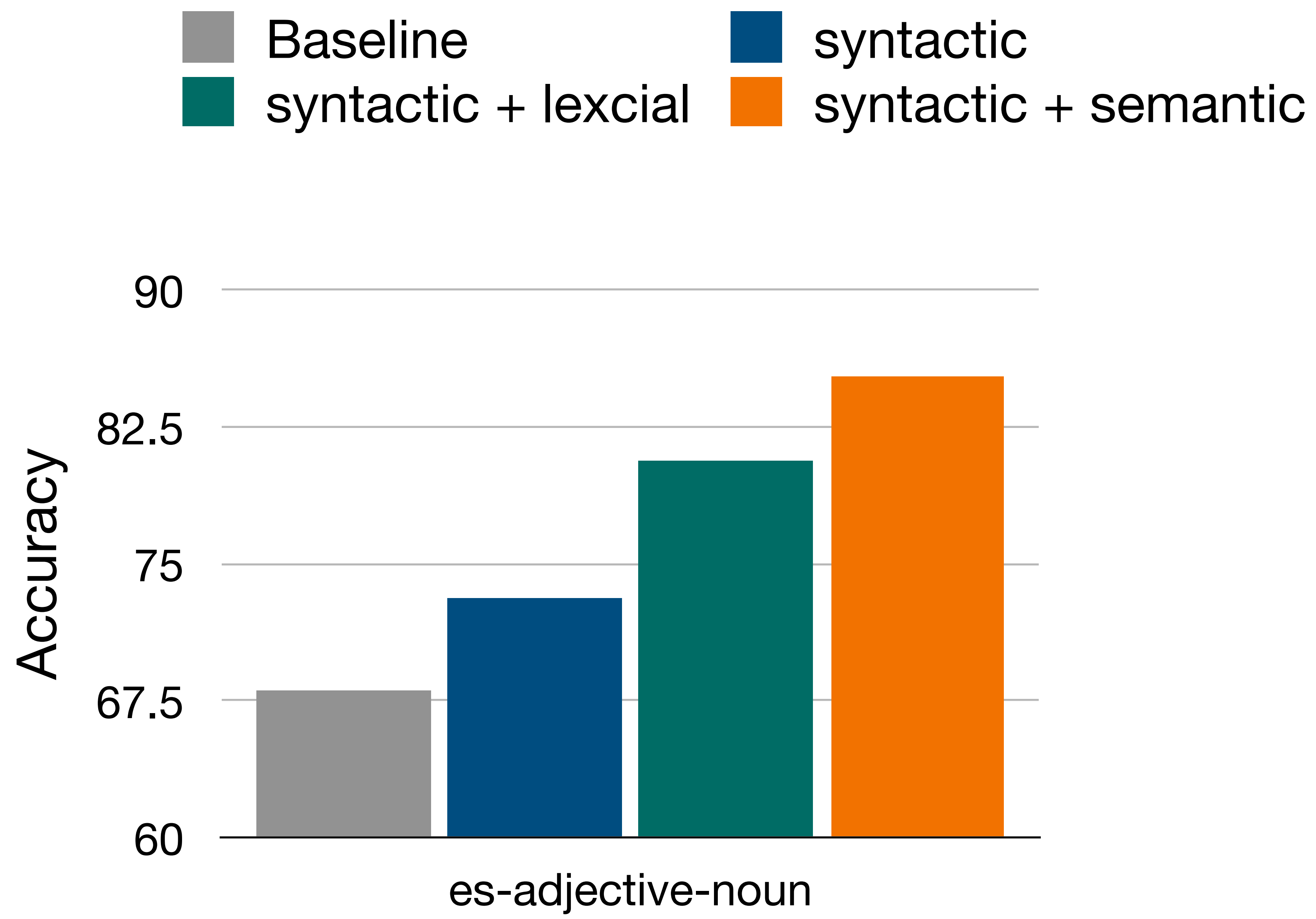

AUTOLEX: An Automatic Framework for Linguistic Exploration
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Word Order: Extract rules

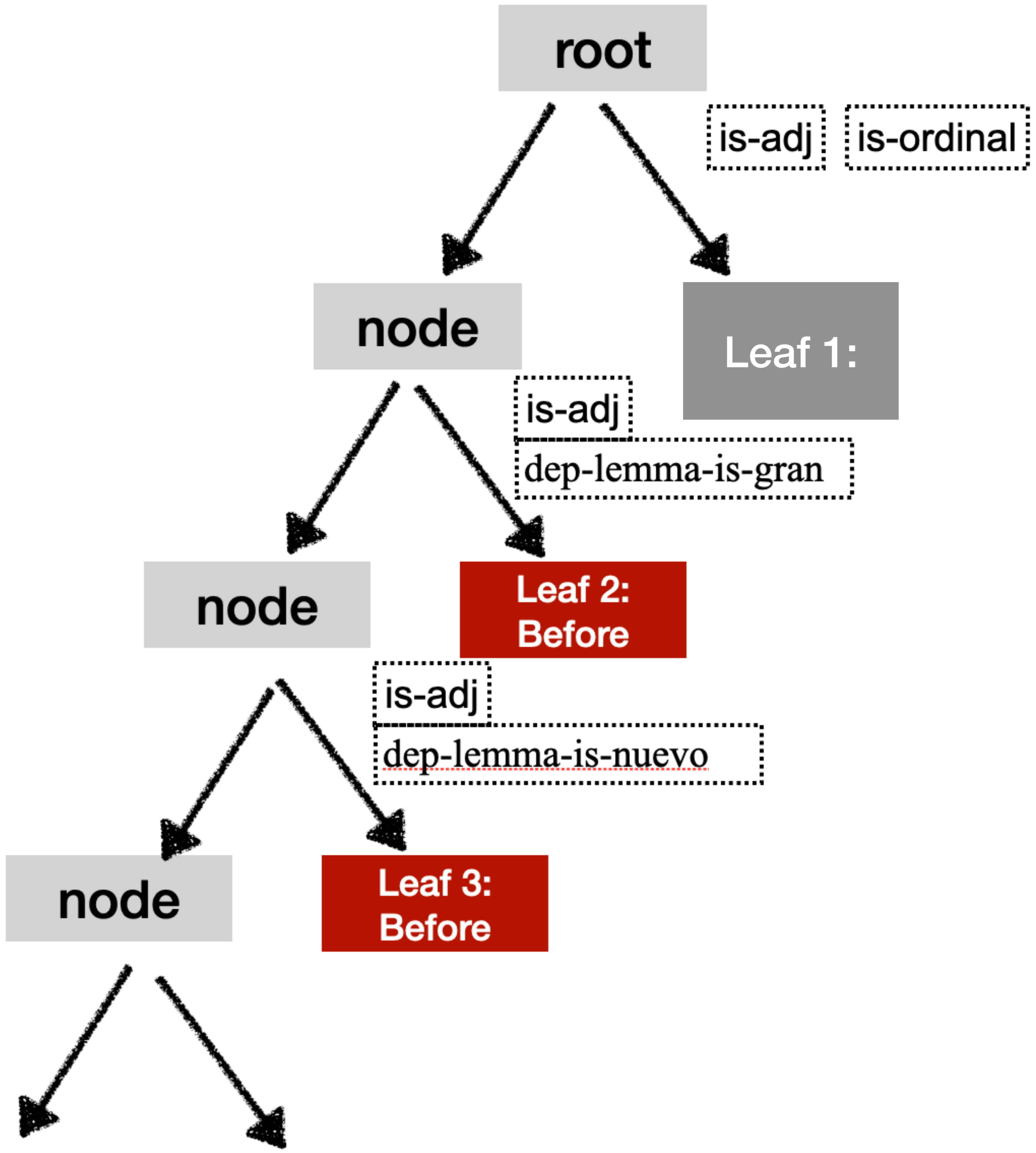
Formulate the linguistic question into a classification task

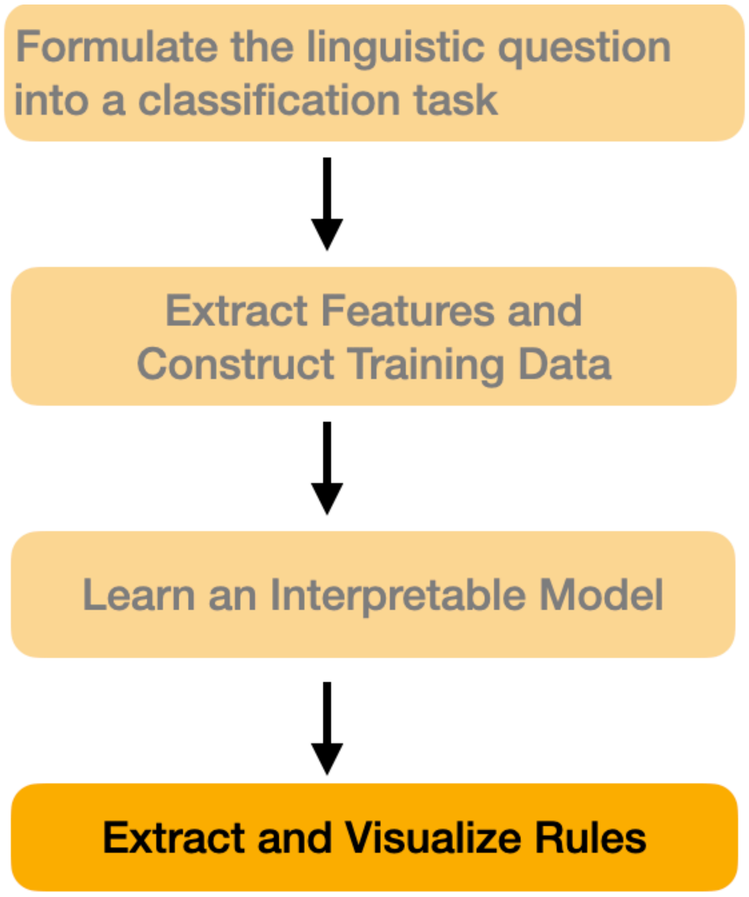
Extract Features and Construct Training Data

Learn an Interpretable Model

Extract and Visualize Rules

Word Order: Extract rules





Formulate the linguistic question into a classification task

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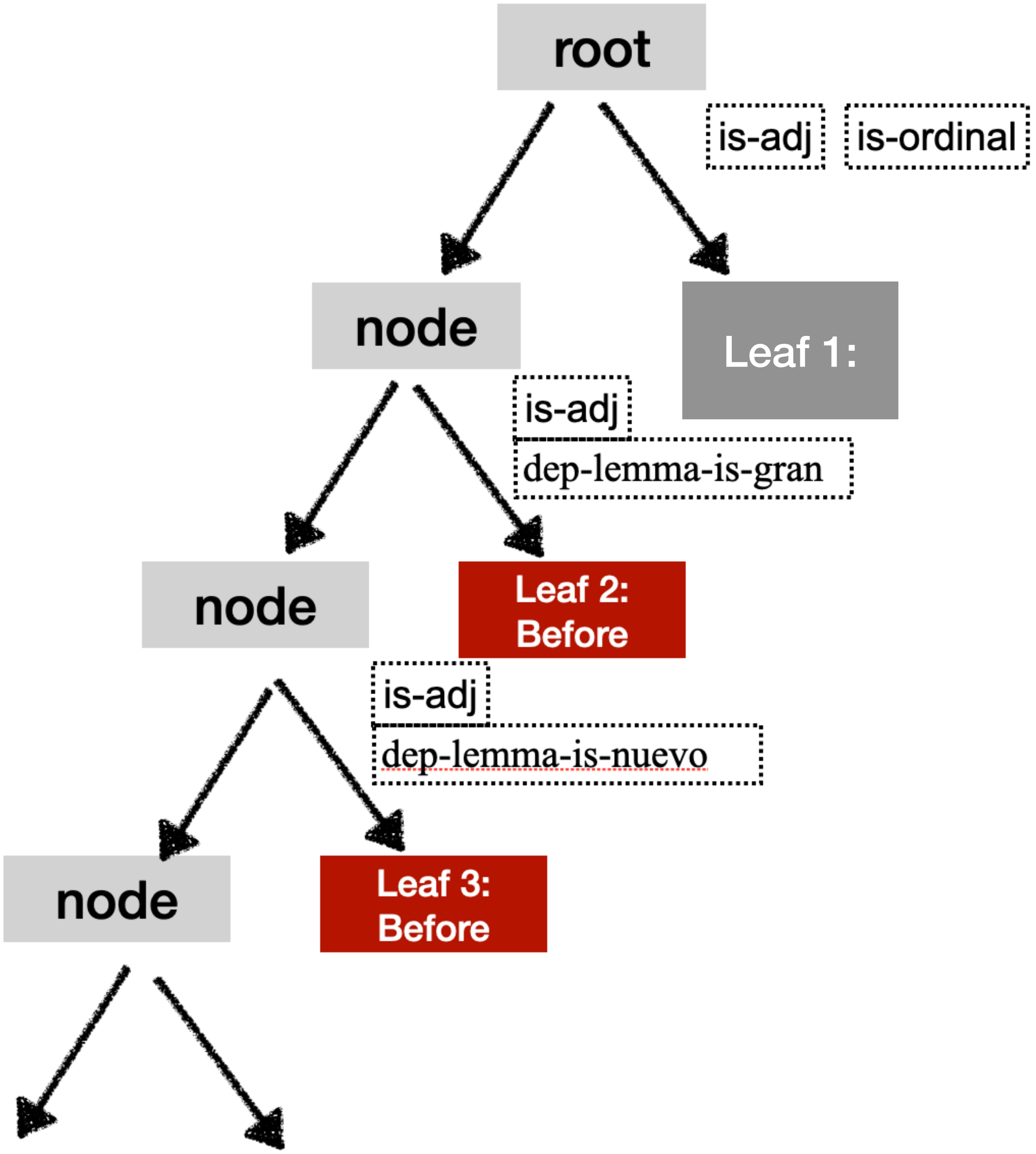
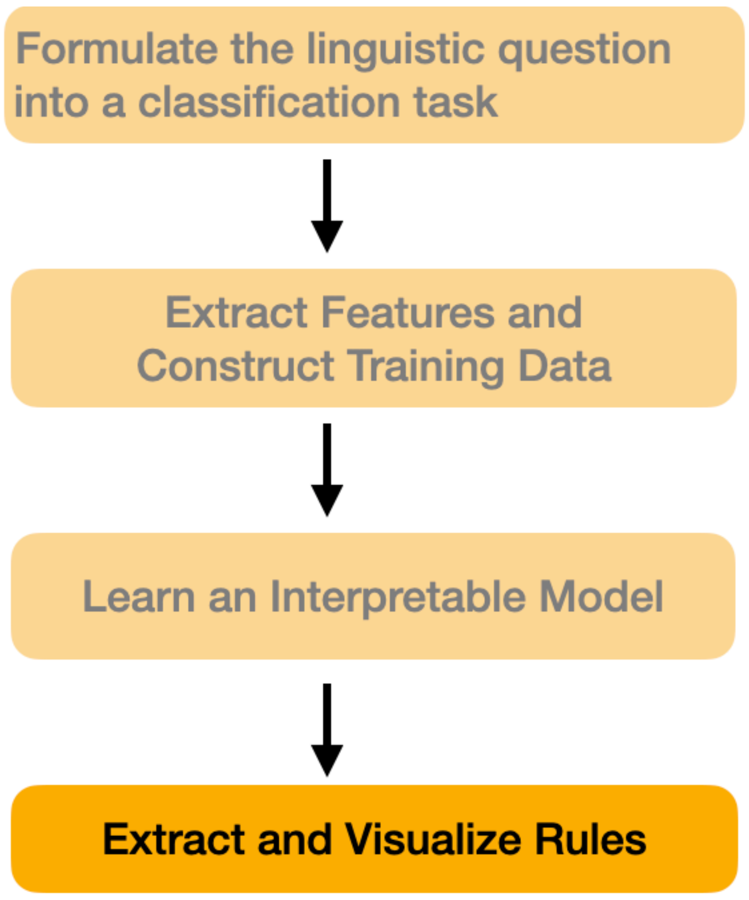
Word Order: Extract rules


root
is-adj
is-ordinal
node
Leaf 1:
is-adj
dep-lemma-is-gran
node
Leaf 2: Before
is-adj
dep-lemma-is-nuevo
node
Leaf 3: Before

Leaf 1:

After: 1000 **Before**: 8000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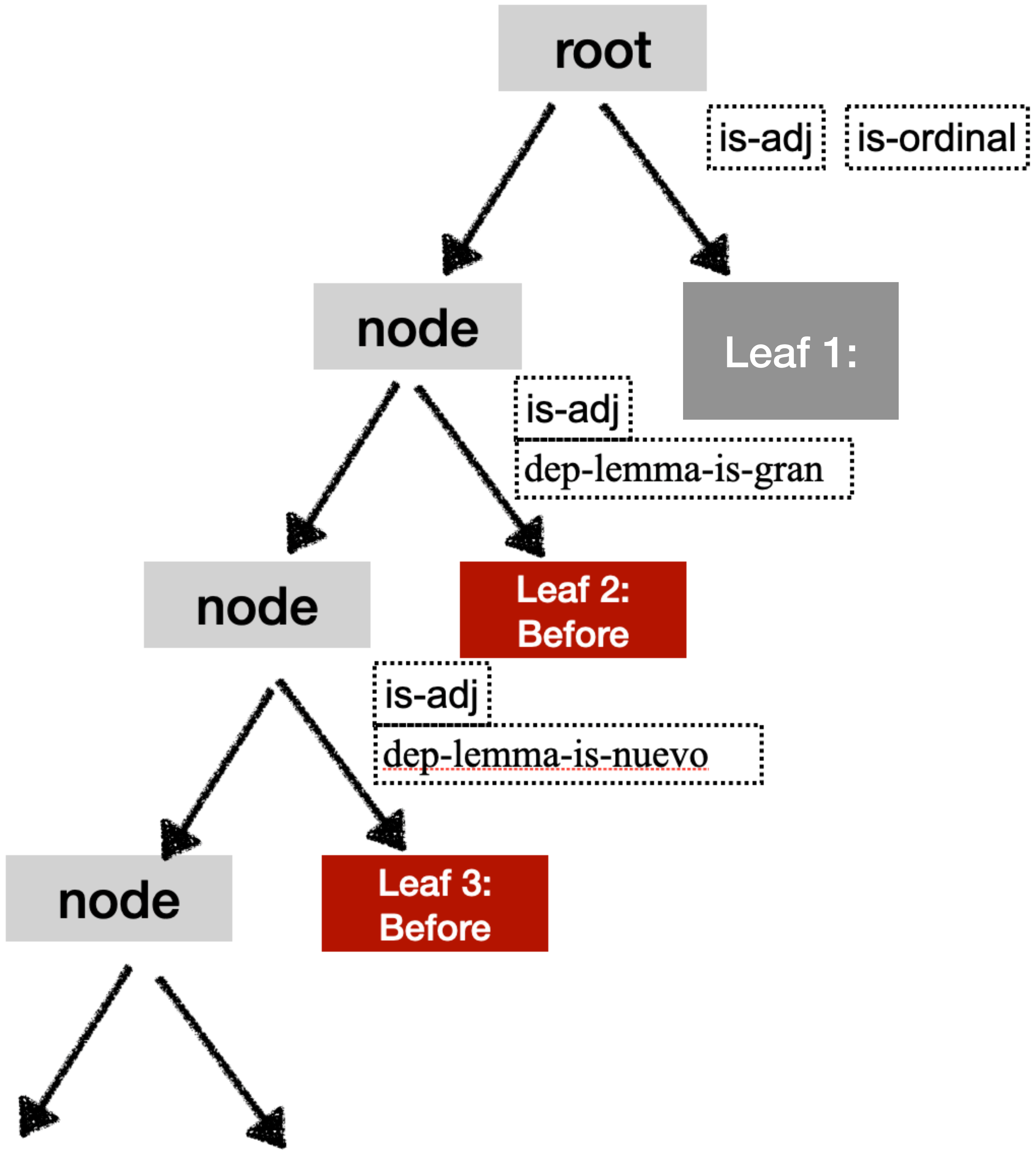
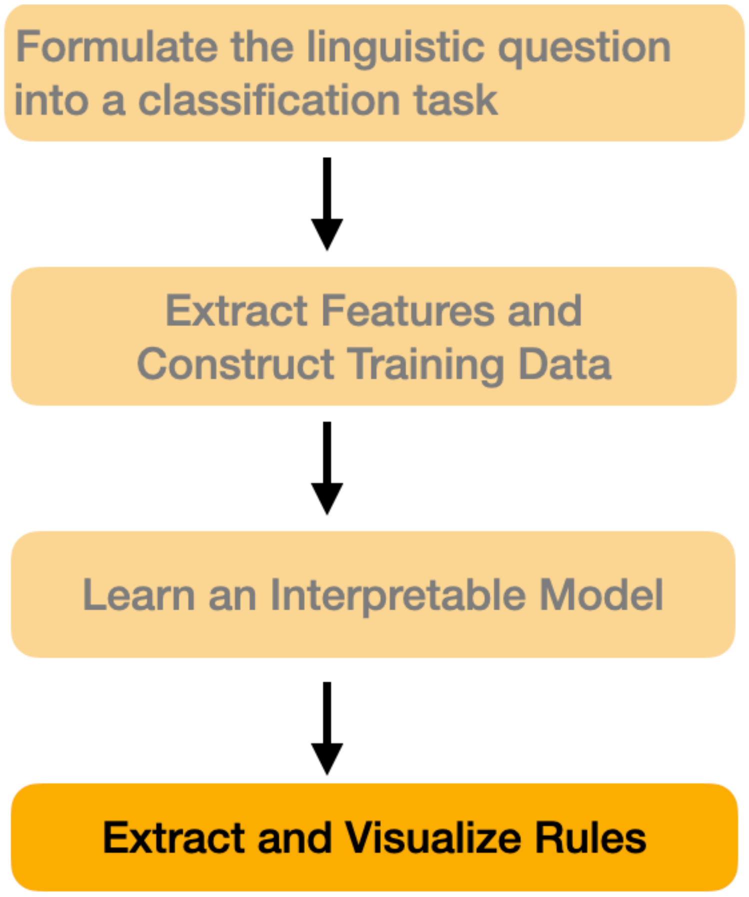


Leaf 1:

After: 1000 **Before**: 1800



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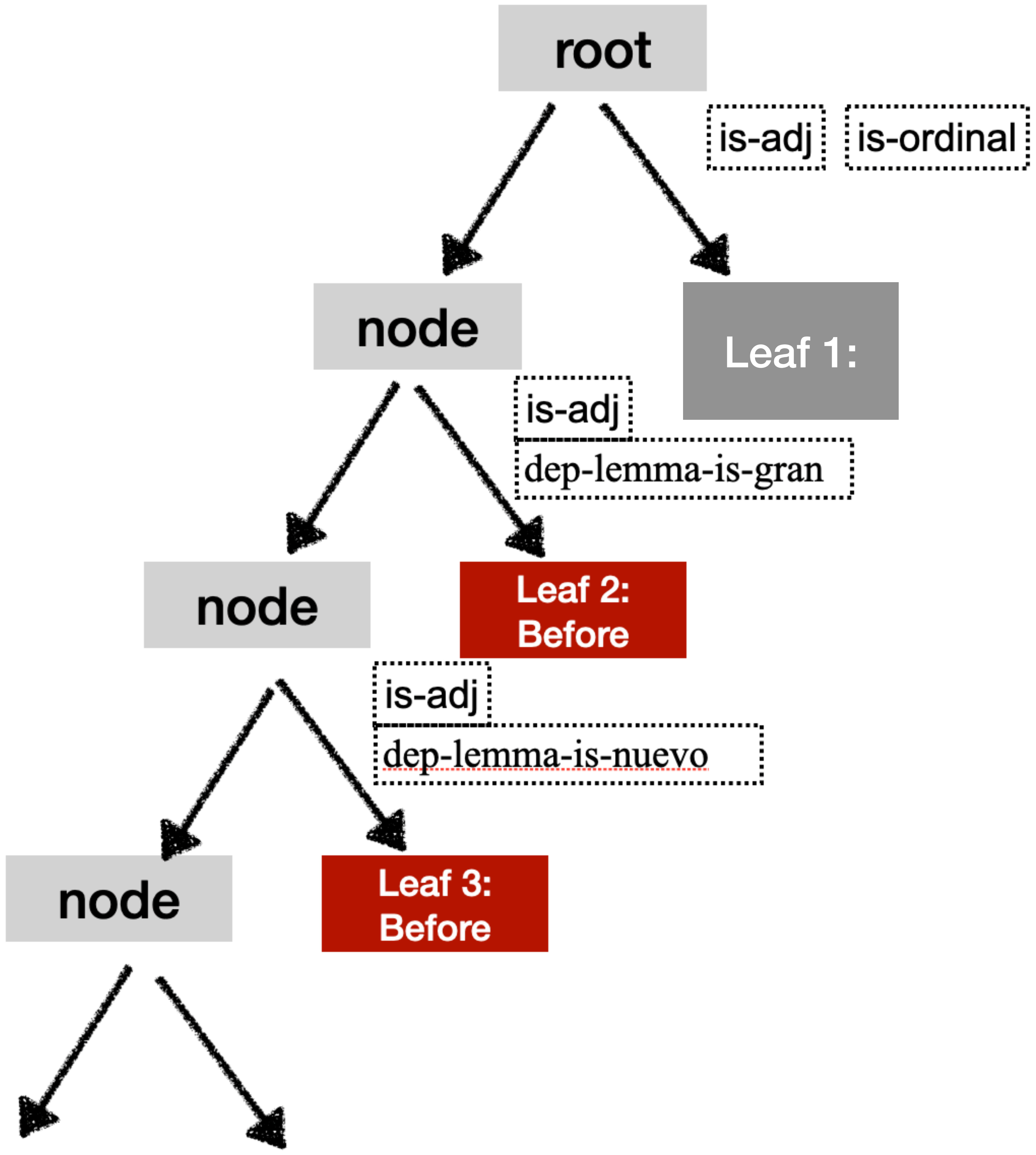

Leaf 1:

After: 1000 **Before**: 1800

↓ Statistical threshold

Significance test χ^2 + **Effect Size**

Observed distribution is significant

Magnitude of significance is large

Formulate the linguistic question into a classification task
↓
Extract Features and Construct Training Data
↓
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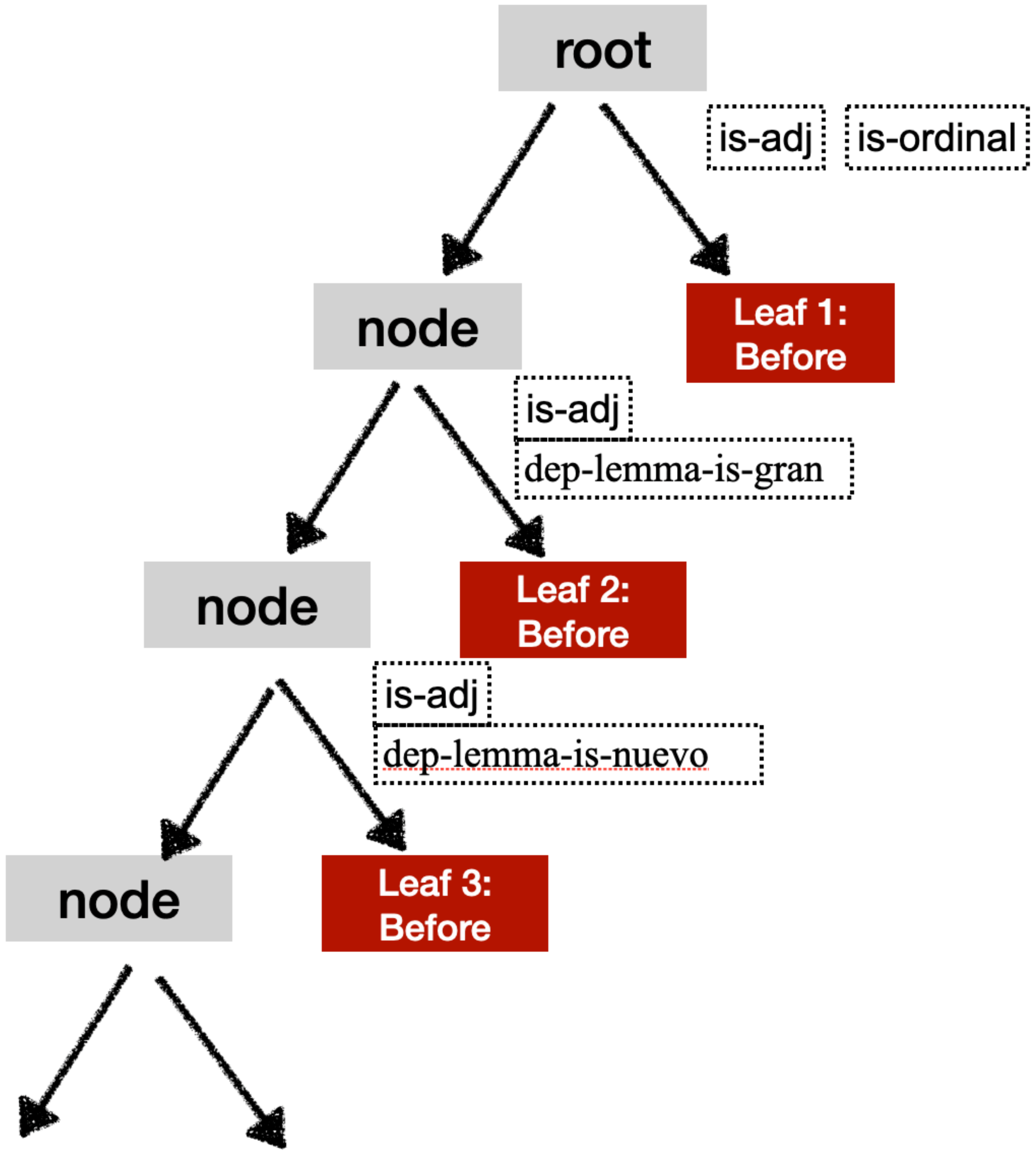

Leaf 1:

After: 1000 **Before**: 1800

Label: **Before**

↓ Statistical threshold

Significance test χ^2 + **Effect Size**

Observed distribution is significant

Magnitude of significance is large

Formulate the linguistic question into a classification task

↓

Extract Features and Construct Training Data

↓

Learn an Interpretable Model

↓

Extract and Visualize Rules

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Word Order: Visualize rules

Formulate the linguistic question into a classification task

Extract Features and Construct Training Data

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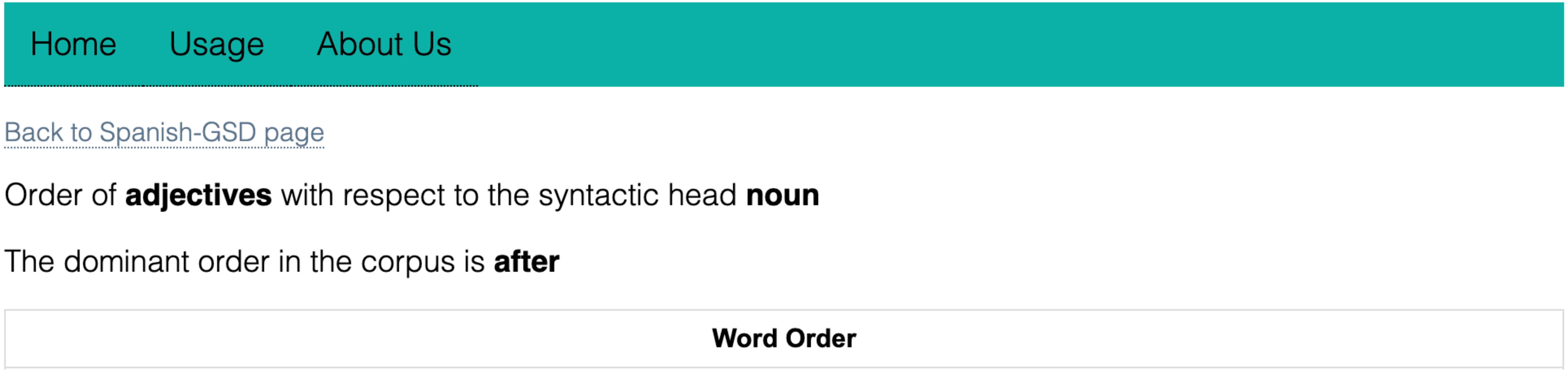
Extract and Visualize Rules

Word Order: Visualize rules

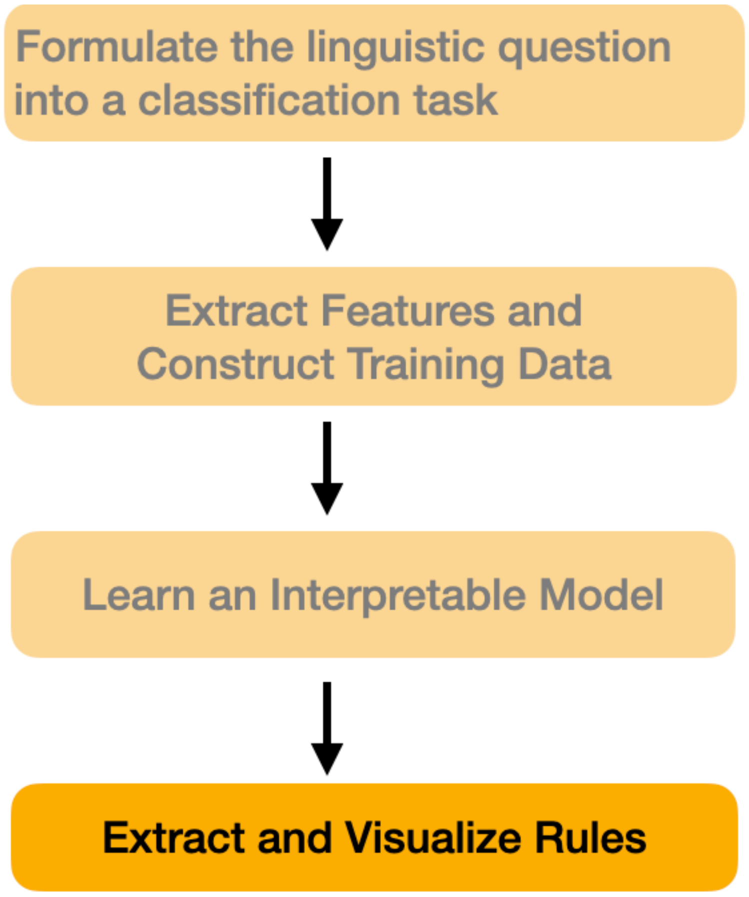


Back to Spanish-GSD page

Order of **adjectives** with respect to the syntactic head **noun**

The dominant order in the corpus is **after**

Word Order



Formulate the linguistic question into a classification task

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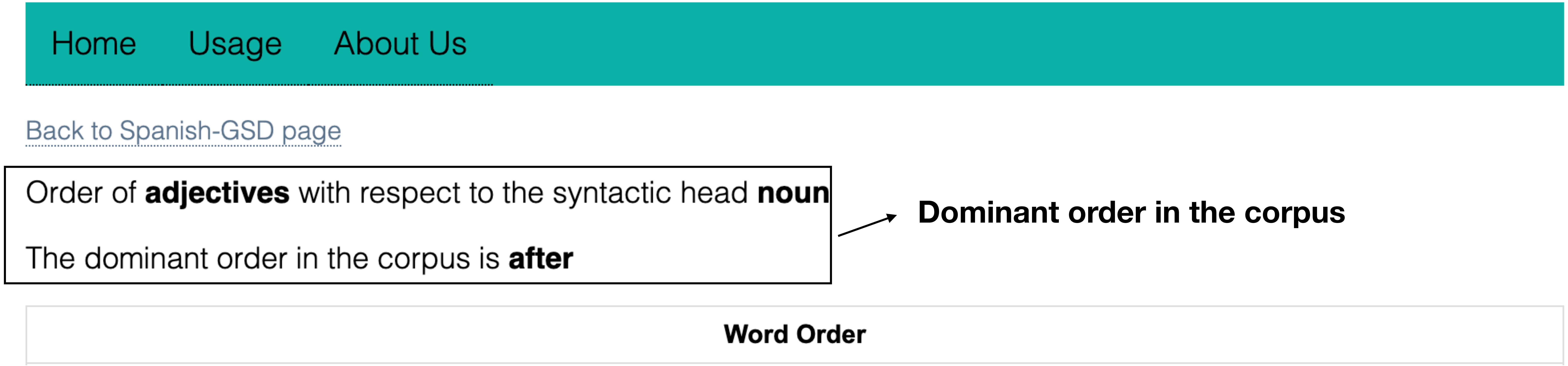
Word Order: Visualize rules



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Order of **adjectives** with respect to the syntactic head **noun**

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Word Order

Dominant order in the corpus

Formulate the linguistic question into a classification task

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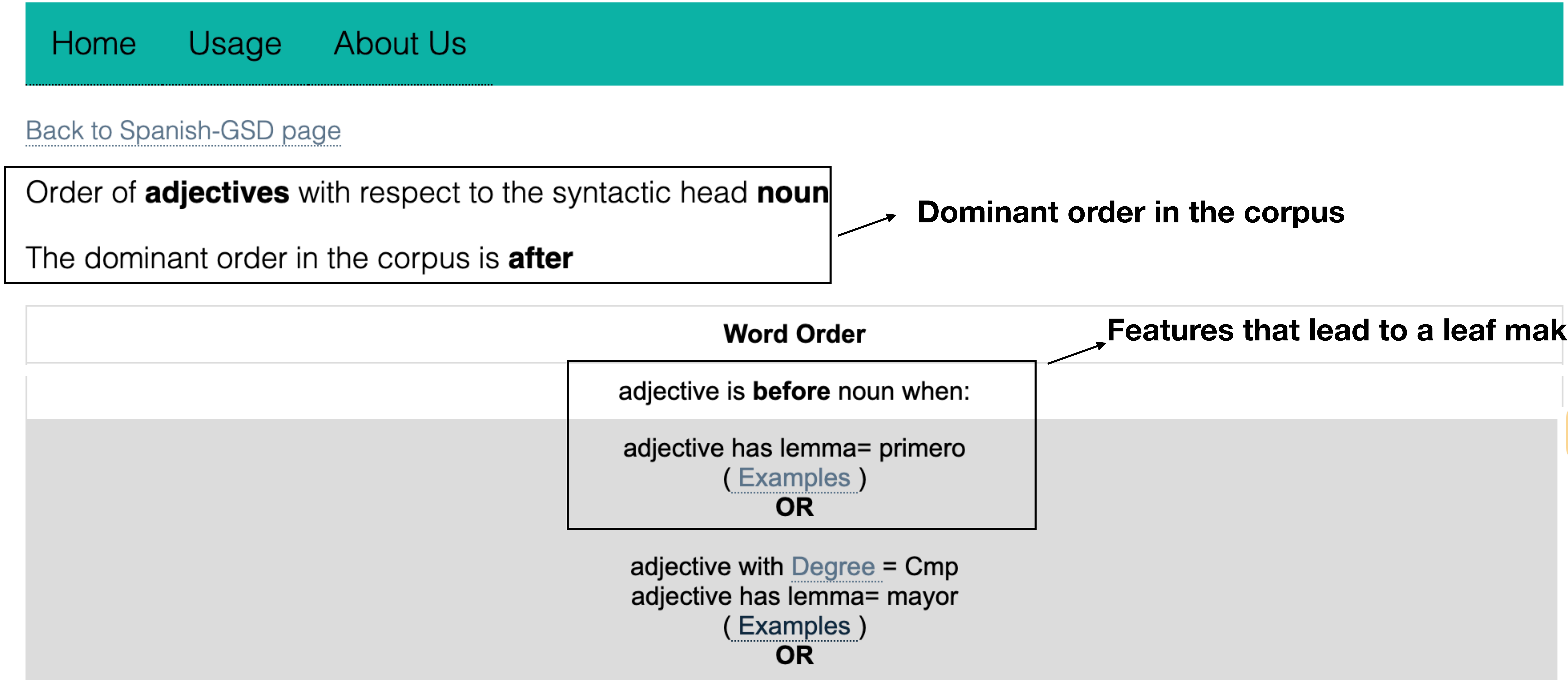


Back to Spanish-GSD page

Order of **adjectives** with respect to the syntactic head **noun**

The dominant order in the corpus is **after**

Word Order

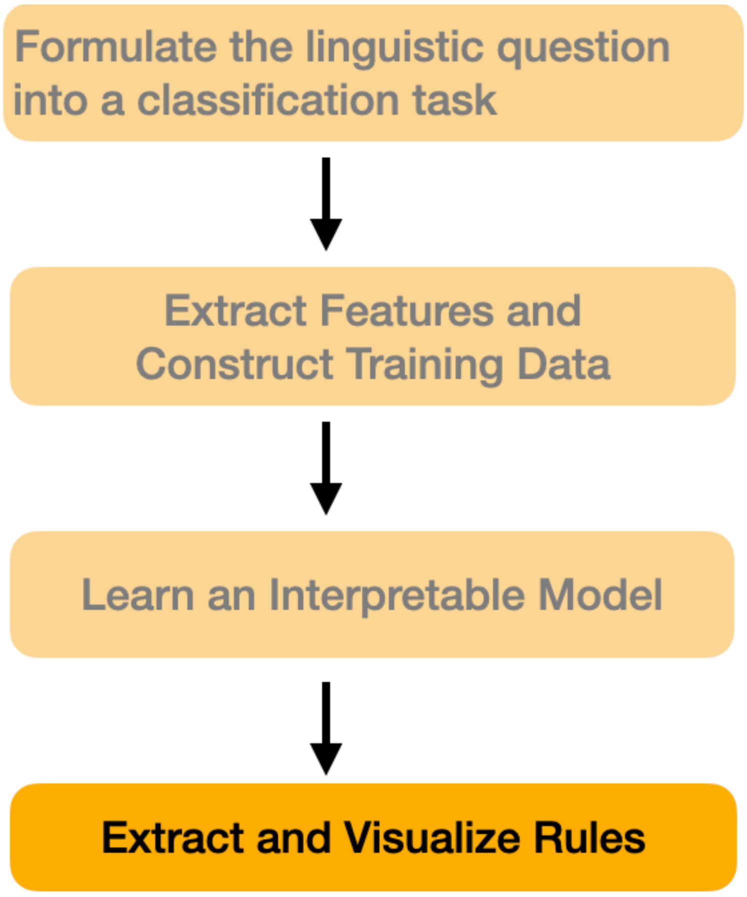
adjective is **before** noun when:

adjective has lemma= primero
(Examples)
OR

adjective with Degree = Cmp
adjective has lemma= mayor
(Examples)
OR

Dominant order in the corpus

Features that lead to a leaf makes a rule



Word Order: Visualize rules

Rule: Adjective like “Primera” come **before** noun

Word Order: Visualize rules

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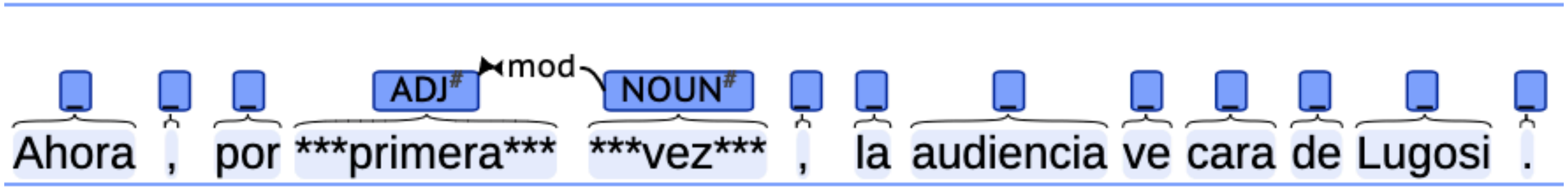


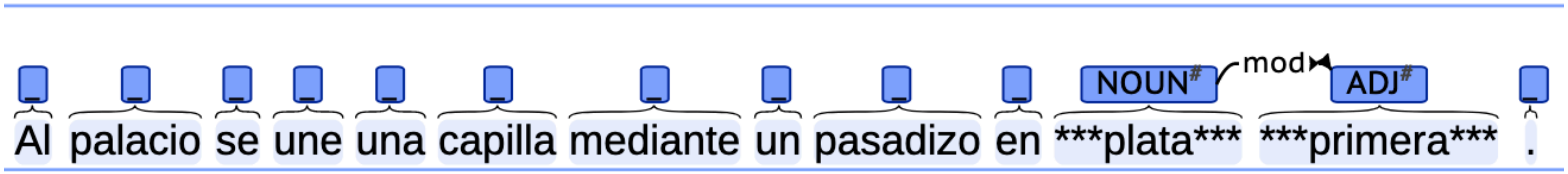
Ahora , por ***primera*** ***vez*** , la audiencia ve cara de Lugosi .

Word Order: Visualize rules

Rule: Adjective like “Primera” come **before** noun

Ahora , por ***primera*** ***vez*** , la audiencia ve cara de Lugosi .

Exceptions!



Al palacio se une una capilla mediante un pasadizo en ***plata*** ***primera*** .

Agreement

Agreement

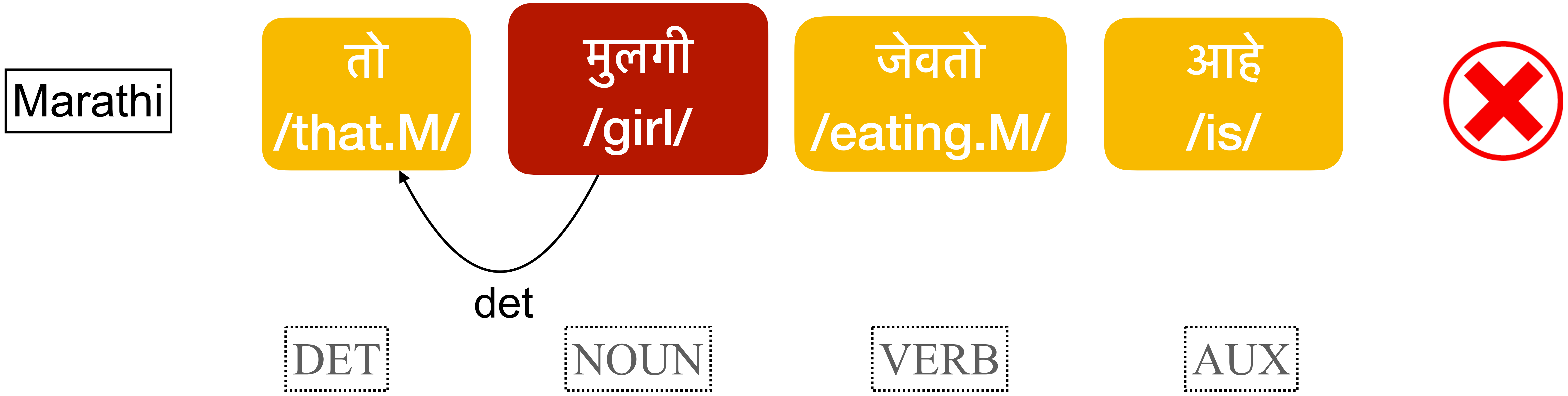
Agreement

Marathi	तो /that.M/	मुलगा /boy/	जेवतो /eating.M/	आहे /is/	✓

Agreement

Marathi	तो	मुलगी	जेवतो	आहे	✗
	/that.M/	/girl/	/eating.M/	/is/	

Agreement



Marathi

तो /that.M/

मुलगी /girl/

जेवतो /eating.M/

आहे /is/

✗

det

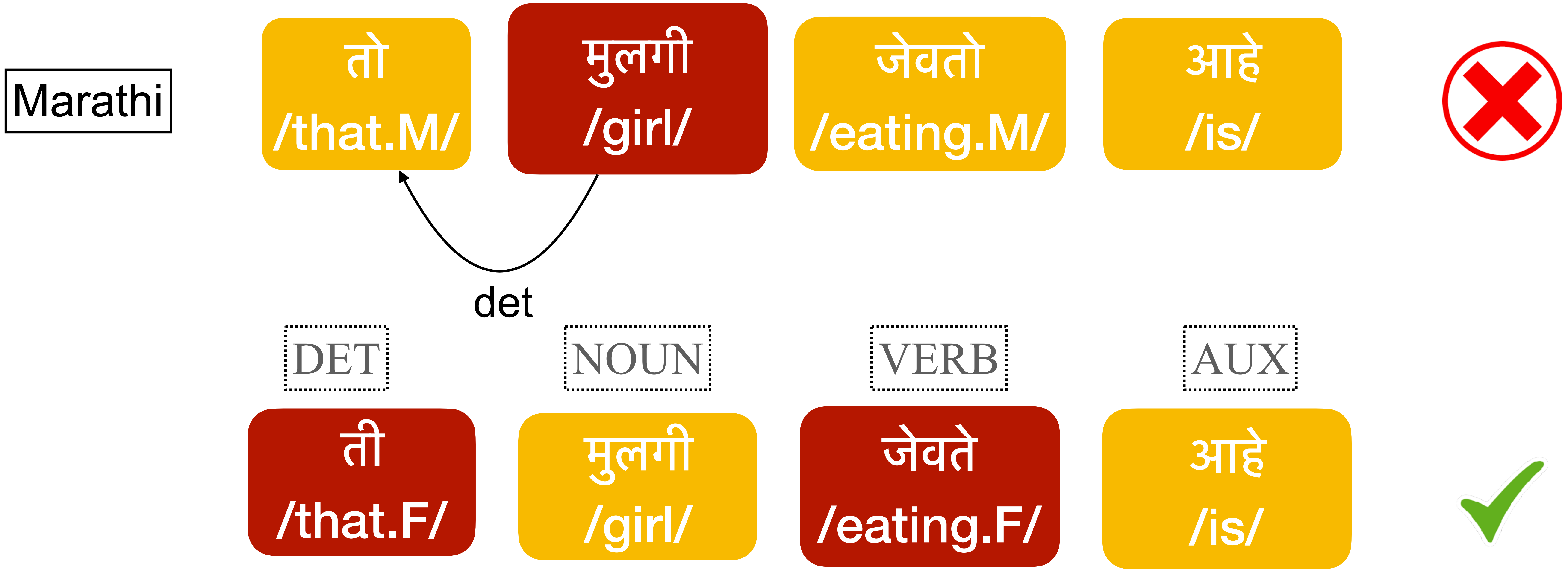
DET

NOUN

VERB

AUX

Agreement



Marathi

तो /that.M/ मुलगी /girl/ जेवतो /eating.M/ आहे /is/ ✗

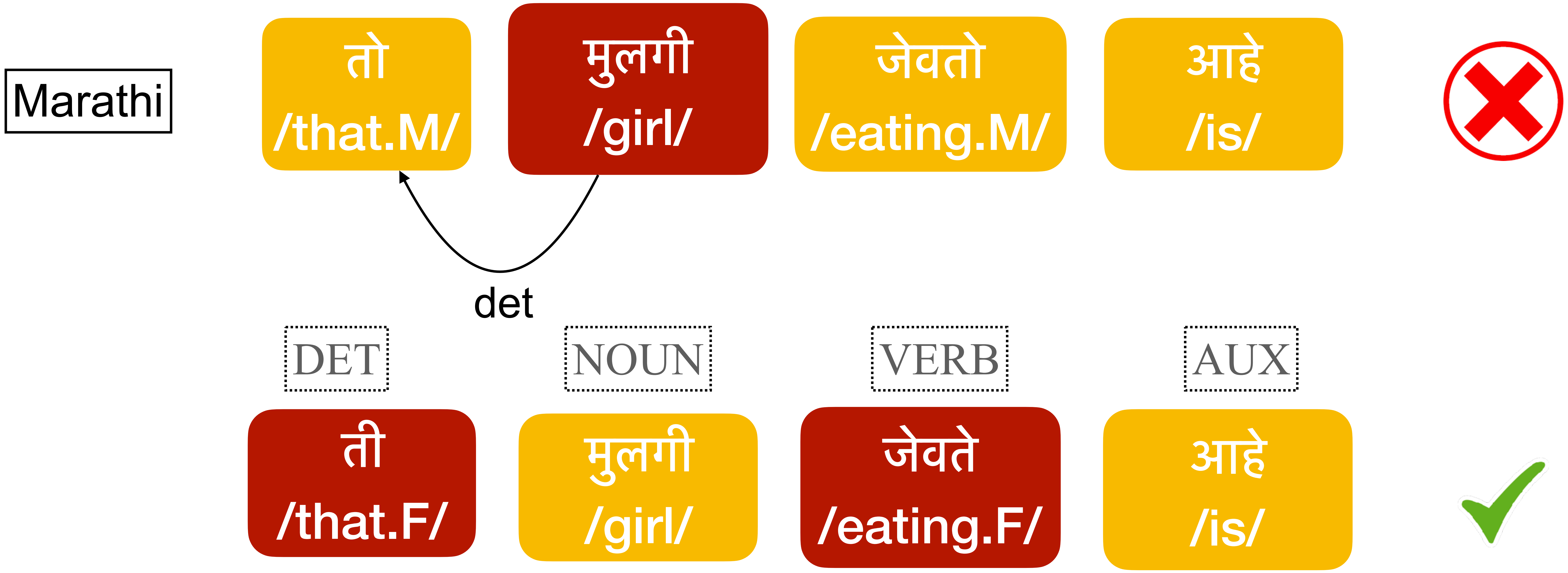
det

DET NOUN VERB AUX

ती /that.F/ मुलगी /girl/ जेवते /eating.F/ आहे /is/ ✓

Agreement

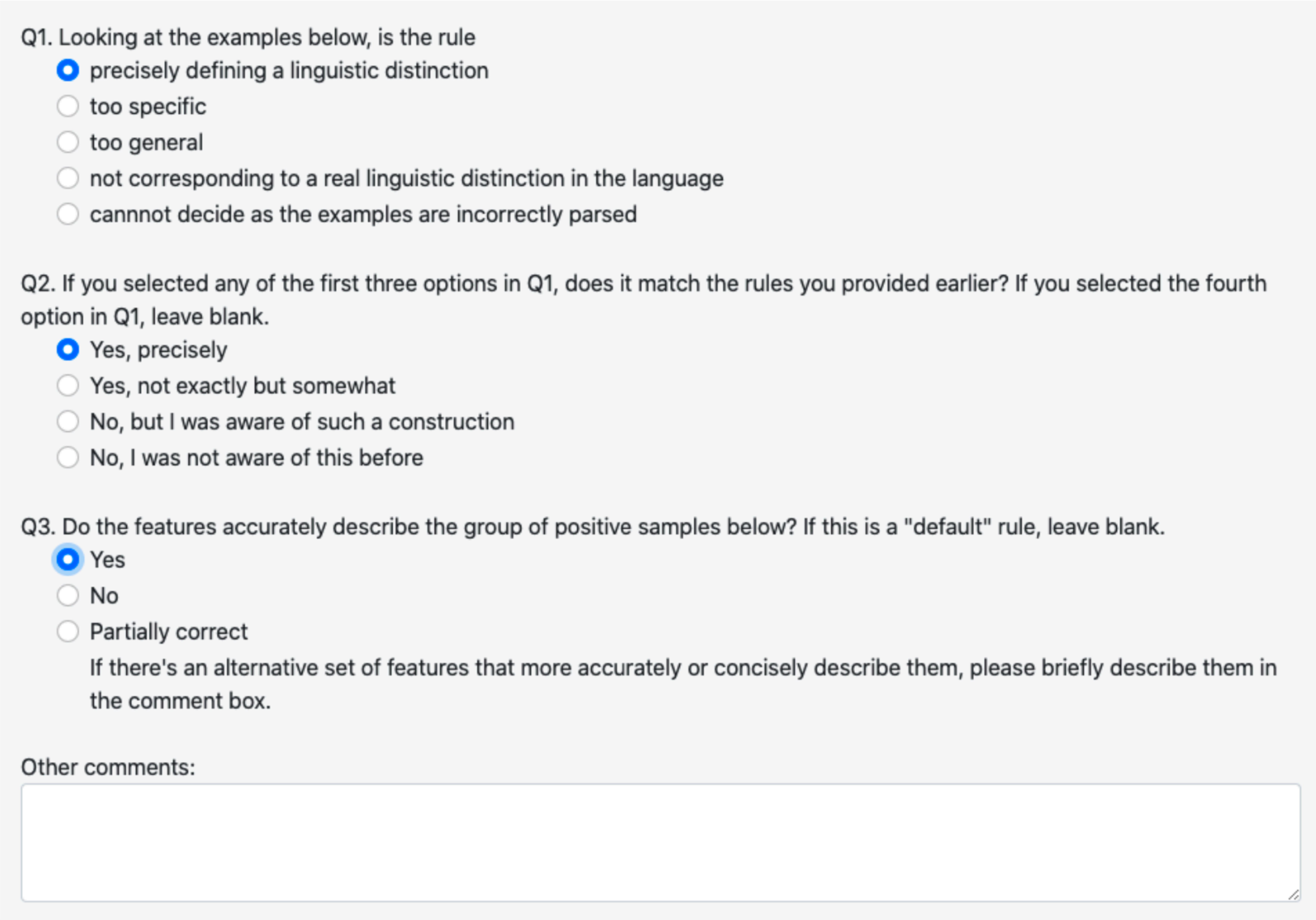
When should a head-dependent agree on gender and when it shouldn't?



Marathi

तो /that.M/	मुलगी /girl/	जेवतो /eating.M/	आहे /is/	✗
DET	NOUN	VERB	AUX	
ती /that.F/	मुलगी /girl/	जेवते /eating.F/	आहे /is/	✓

Quality Evaluation



Q1. Looking at the examples below, is the rule

- ● precisely defining a linguistic distinction
- ○ too specific
- ○ too general
- ○ not corresponding to a real linguistic distinction in the language
- ○ cannnot decide as the examples are incorrectly parsed

Q2. If you selected any of the first three options in Q1, does it match the rules you provided earlier? If you selected the fourth option in Q1, leave blank.

- ● Yes, precisely
- ○ Yes, not exactly but somewhat
- ○ No, but I was aware of such a construction
- ○ No, I was not aware of this before

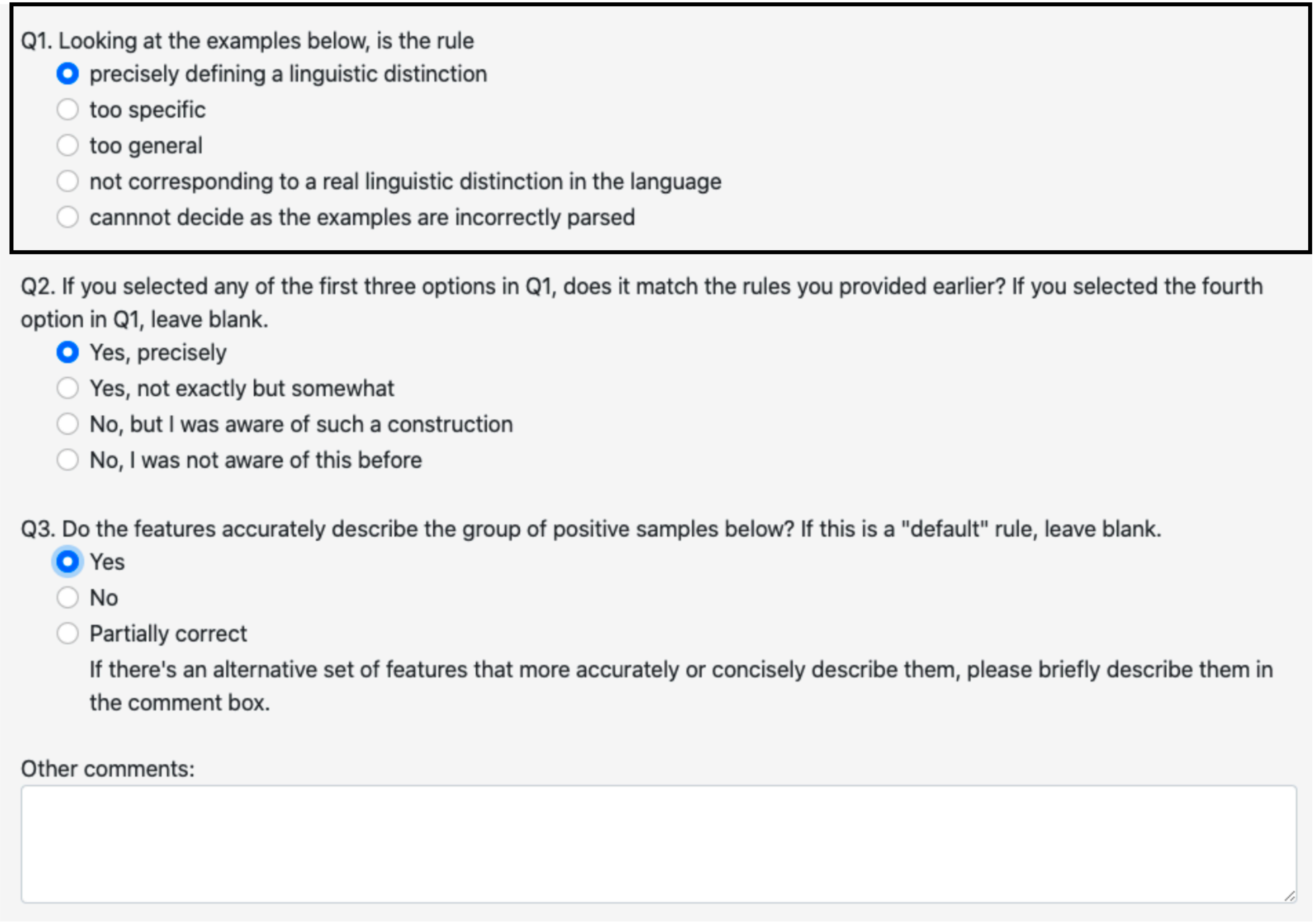
Q3. Do the features accurately describe the group of positive samples below? If this is a "default" rule, leave blank.

- ● Yes
- ○ No
- ○ Partially correct

If there's an alternative set of features that more accurately or concisely describe them, please briefly describe them in the comment box.

Other comments:

Quality Evaluation



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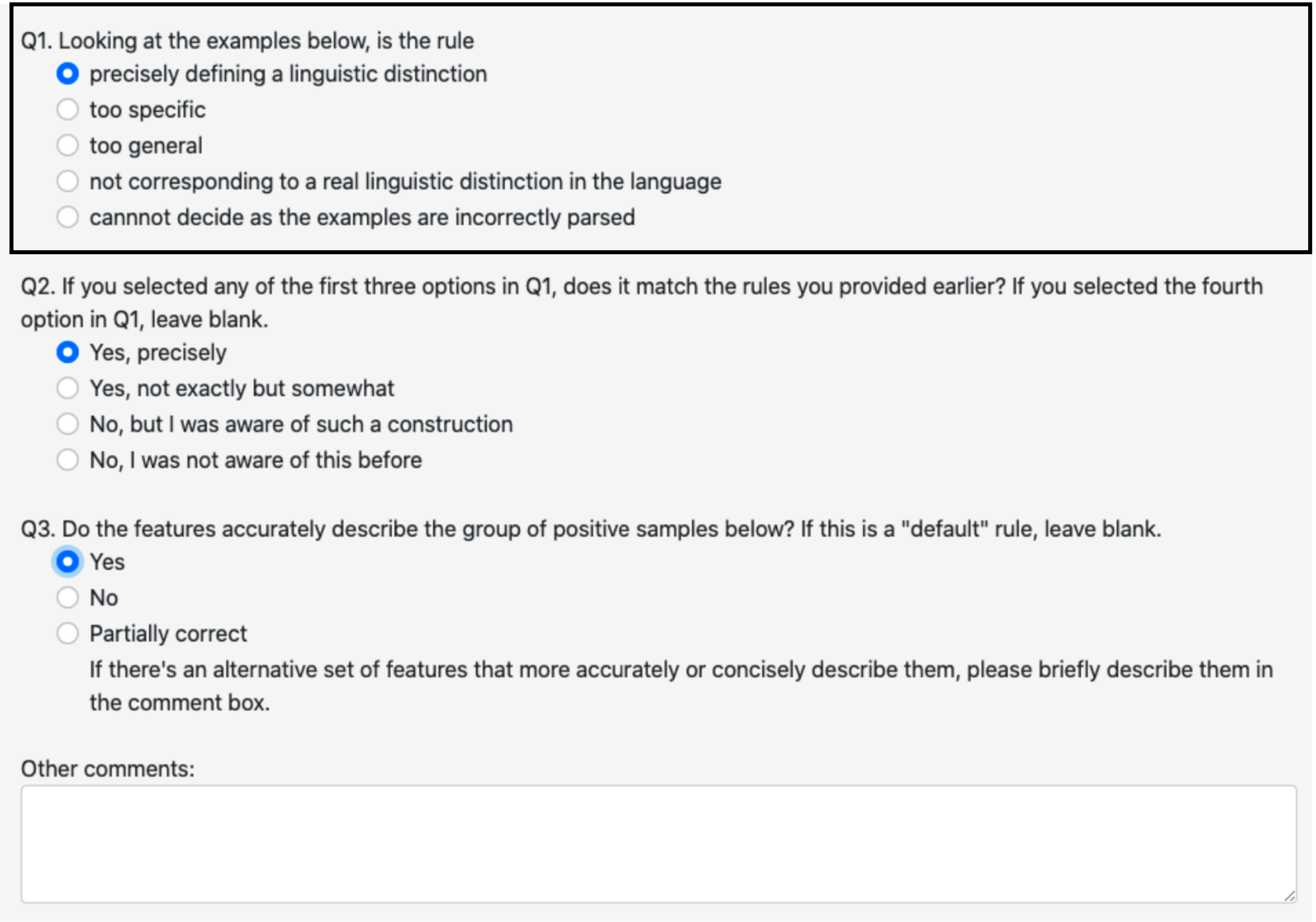

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- ○ too specific
- ○ too general
- ○ not corresponding to a real linguistic distinction in the language
- ○ cannnot decide as the examples are incorrectly parsed

Q2. If you selected any of the first three options in Q1, does it match the rules you provided earlier? If you selected the fourth option in Q1, leave blank.

- ● Yes, precisely
- ○ Yes, not exactly but somewhat
- ○ No, but I was aware of such a construction
- ○ No, I was not aware of this before

Q3. Do the features accurately describe the group of positive samples below? If this is a "default" rule, leave blank.

- ● Yes
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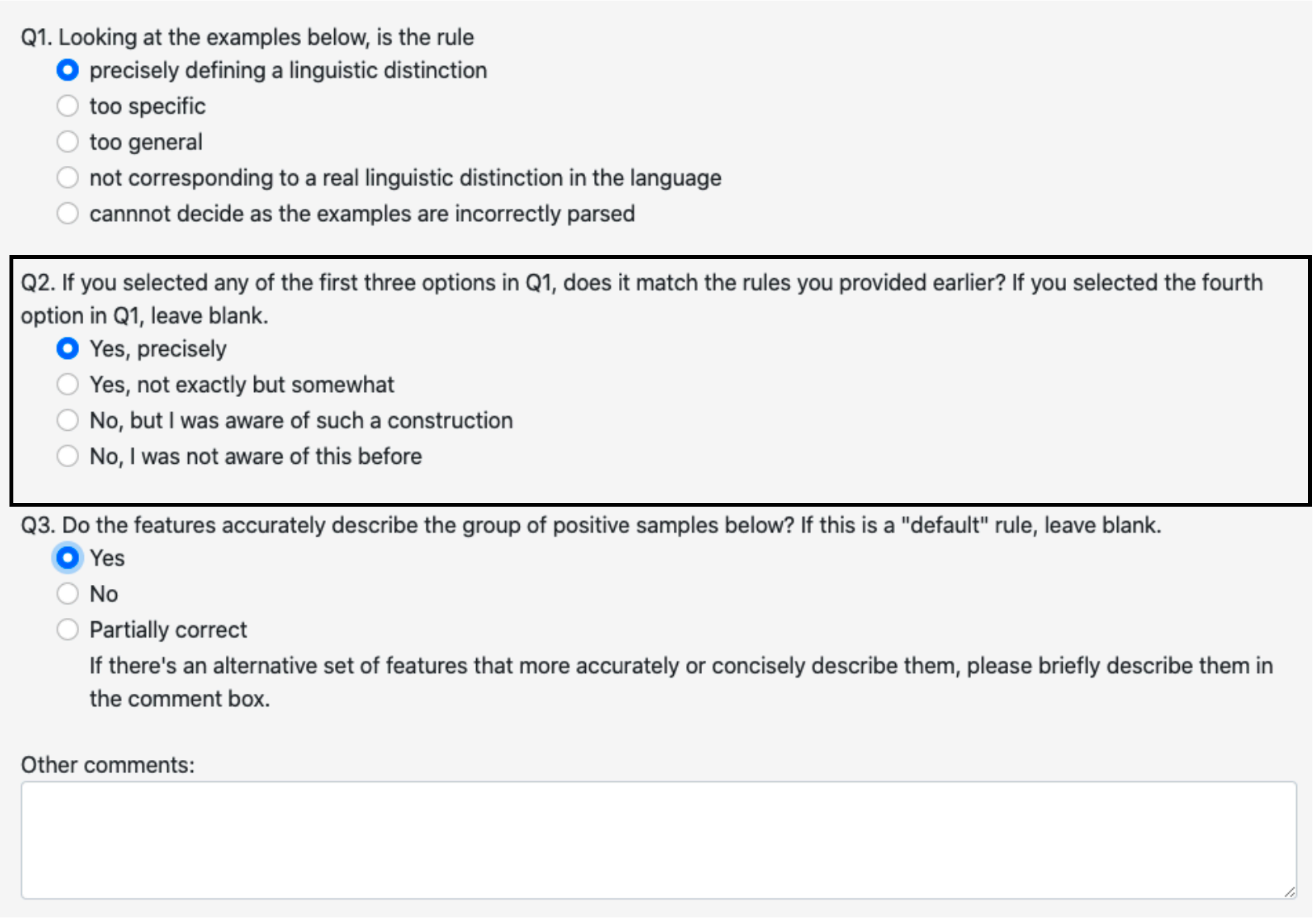
- ○ Partially correct

If there's an alternative set of features that more accurately or concisely describe them, please briefly describe them in the comment box.

Other comments:

Correctness

Quality Evaluation



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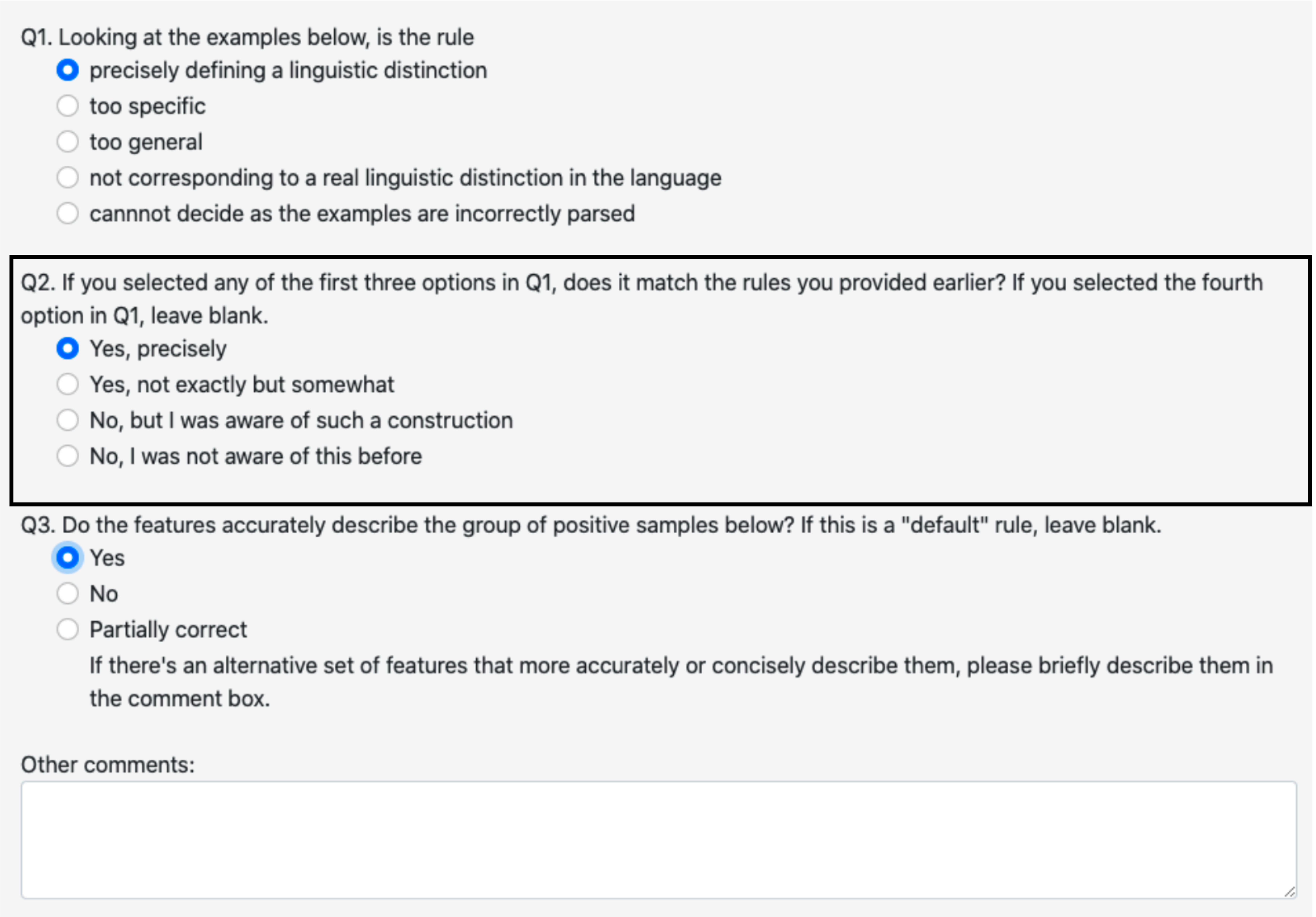

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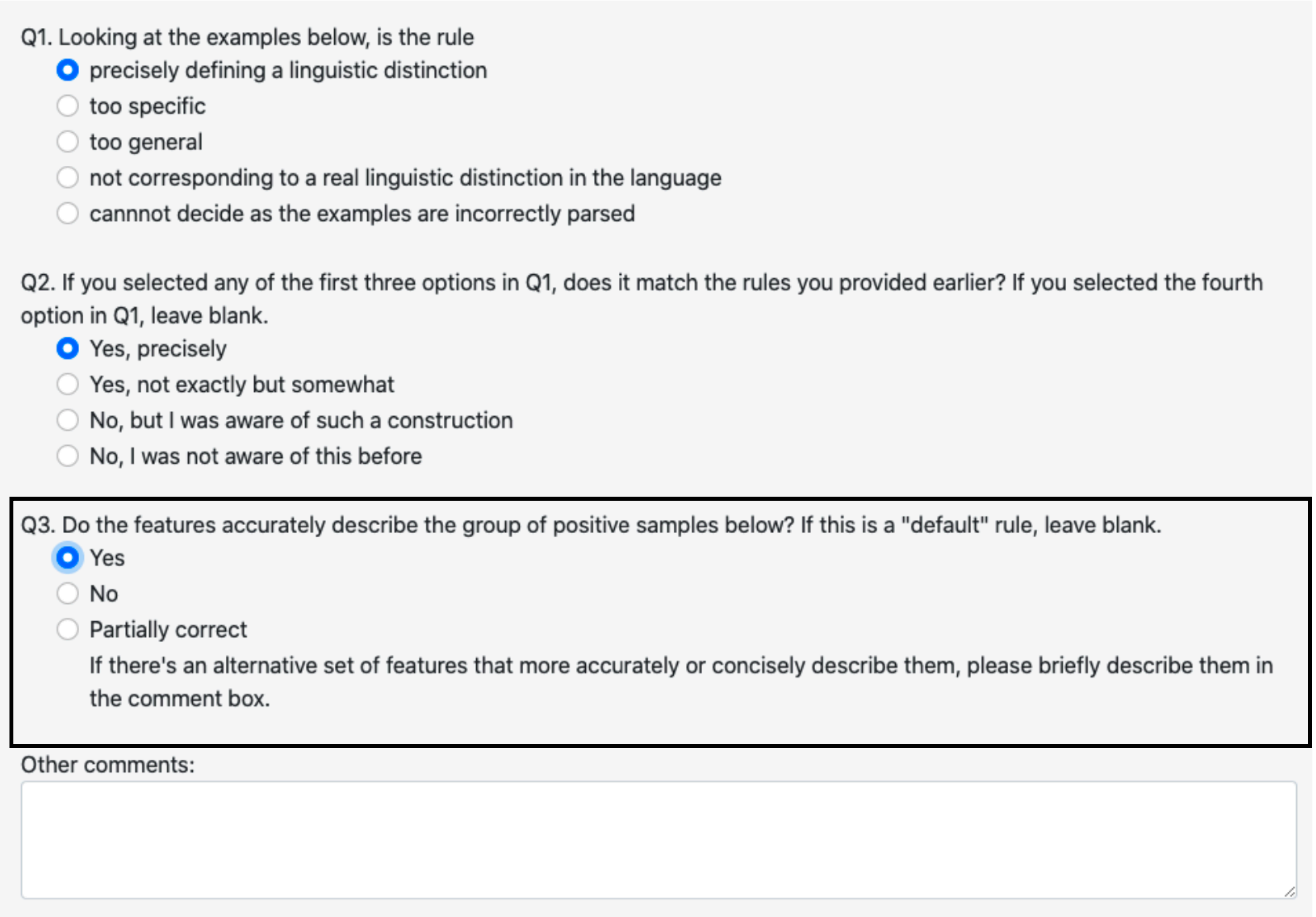

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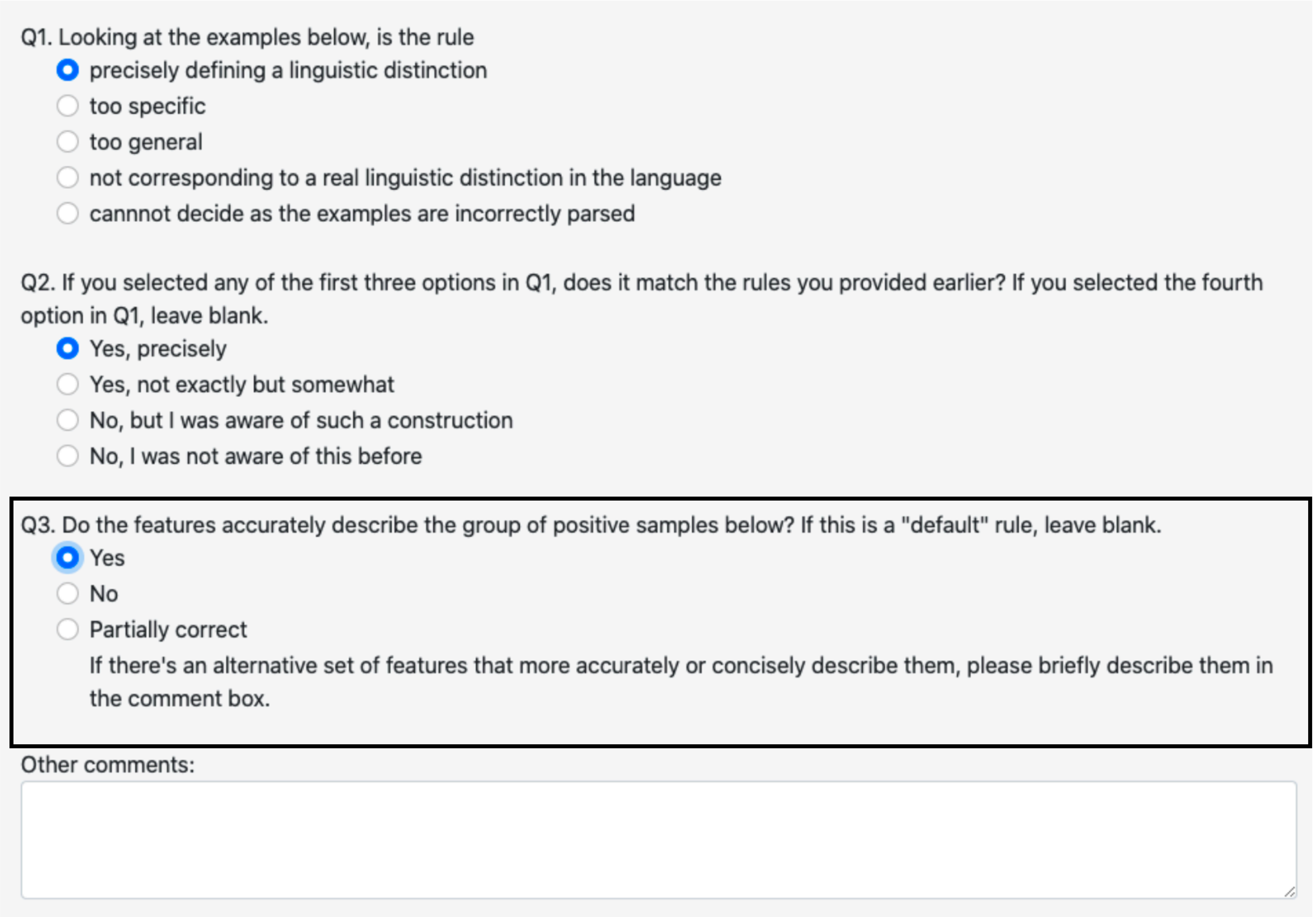

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Correctness

Prior knowledge

Readability

Results: Quality Evaluation for Greek

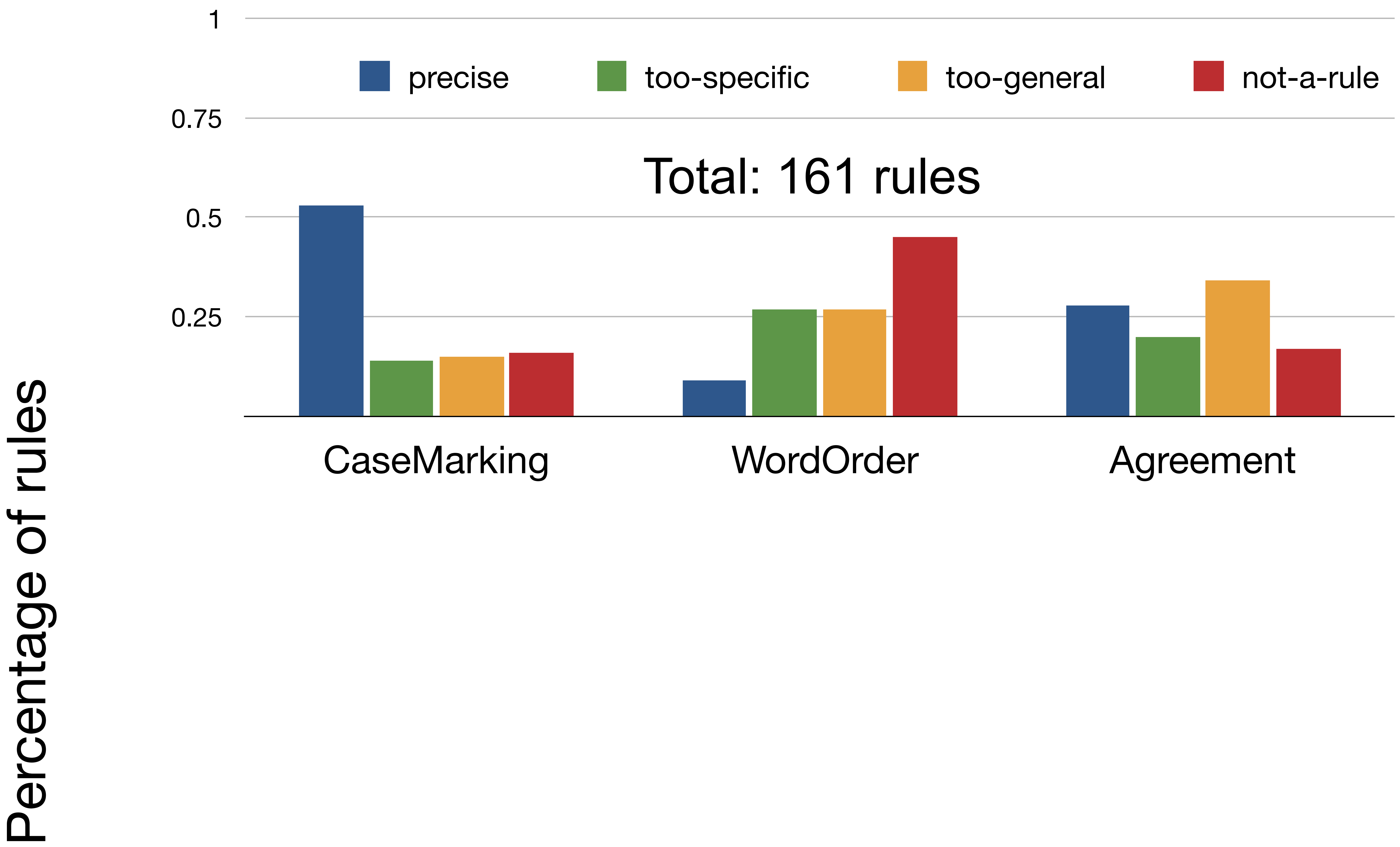
Percentage of rules

Results: Quality Evaluation for Greek

Does model discover grammatically valid rules?

Percentage of rules

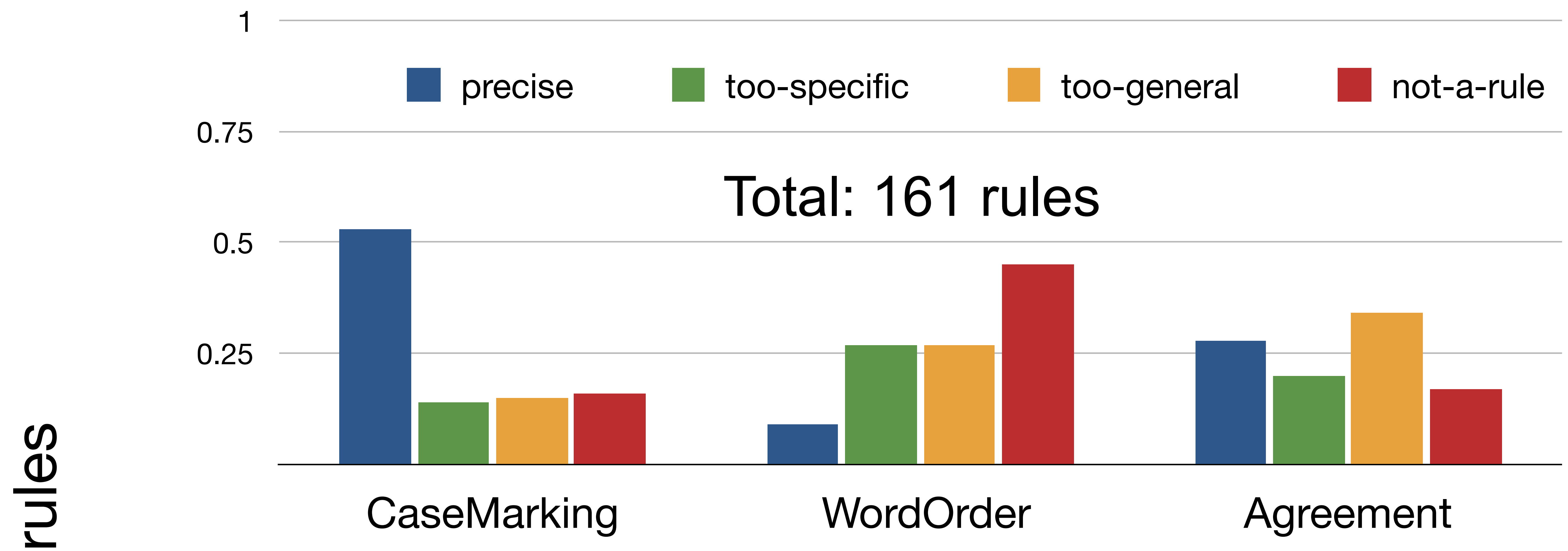
Results: Quality Evaluation for Greek



Does model discover grammatically valid rules?

80% rules are valid,
40% valid rules too specific/general

Results: Quality Evaluation for Greek



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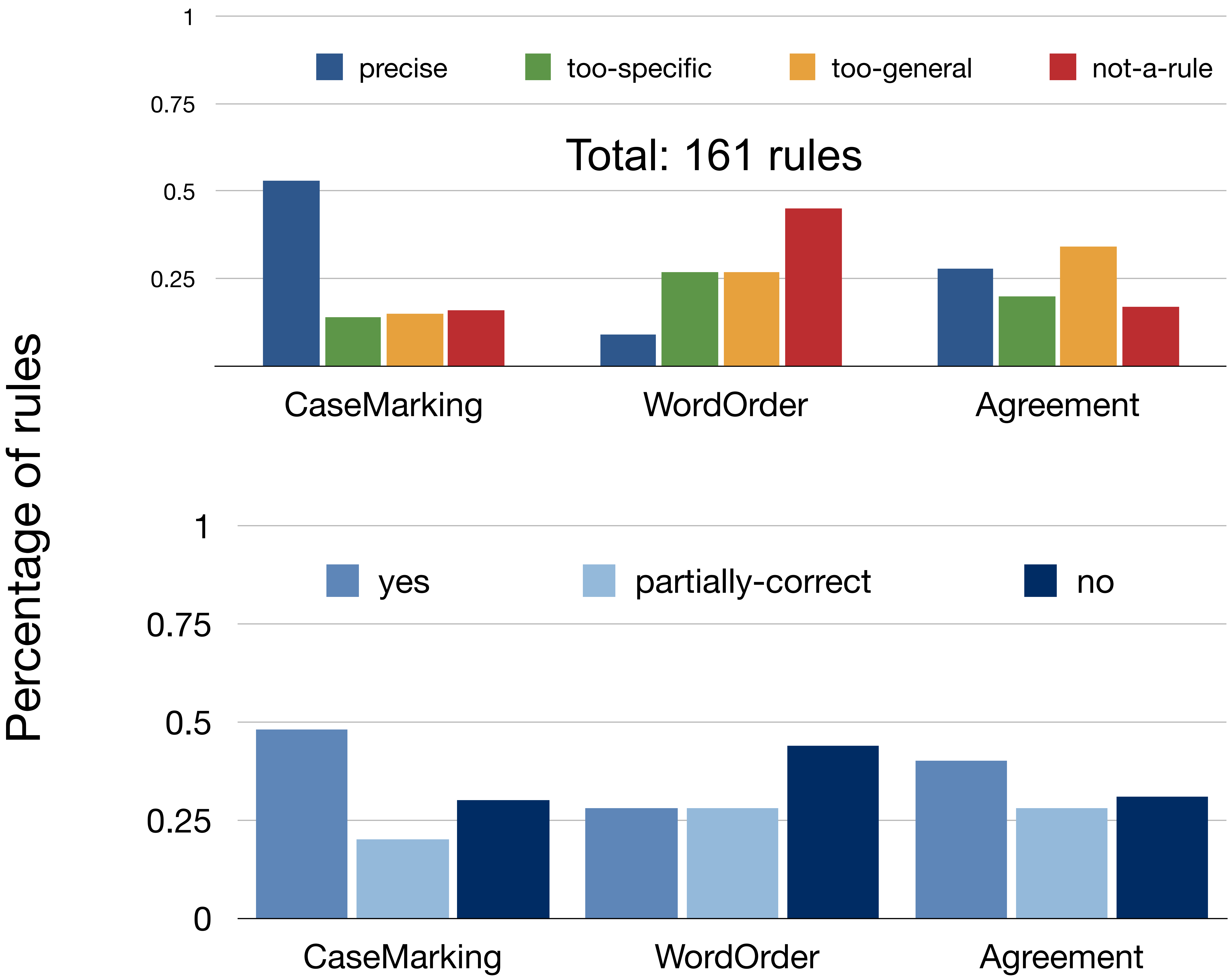
Are the rules human-readable?

Results: Quality Evaluation for Greek



Does model discover grammatically valid rules?

80% rules are valid,
40% valid rules too specific/general

Are the rules human-readable?

69% rules are informative and readable

Results: Quality Evaluation

Does the model discover *new rules?

Results: Quality Evaluation

Does the model discover *new rules?

adjective is **after** its head **noun**

Features that make up this rule	
Active Features	**Inactive Features**
adjective's head is a= PRON	-

Even for well studied languages, system discovers *new rules

Examples that agree with label: **after**: The **adjective** is denoted by ***

1 please let me know if you need anything ***else***

2 Please let us know if you need anything ***else*** .

3 No pancreatitis or anything ***abnormal*** .

4 Then take the leash off and do nothing ***else*** but that .

An aside: Parser quality matters a lot!

---

[1] 75 Languages, 1 Model: Parsing Universal Dependencies Universally, Kondratyuk and Straka, 2019

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With improvements in syntactic parser, quality of rules also improves!

---

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Revisiting our research goal

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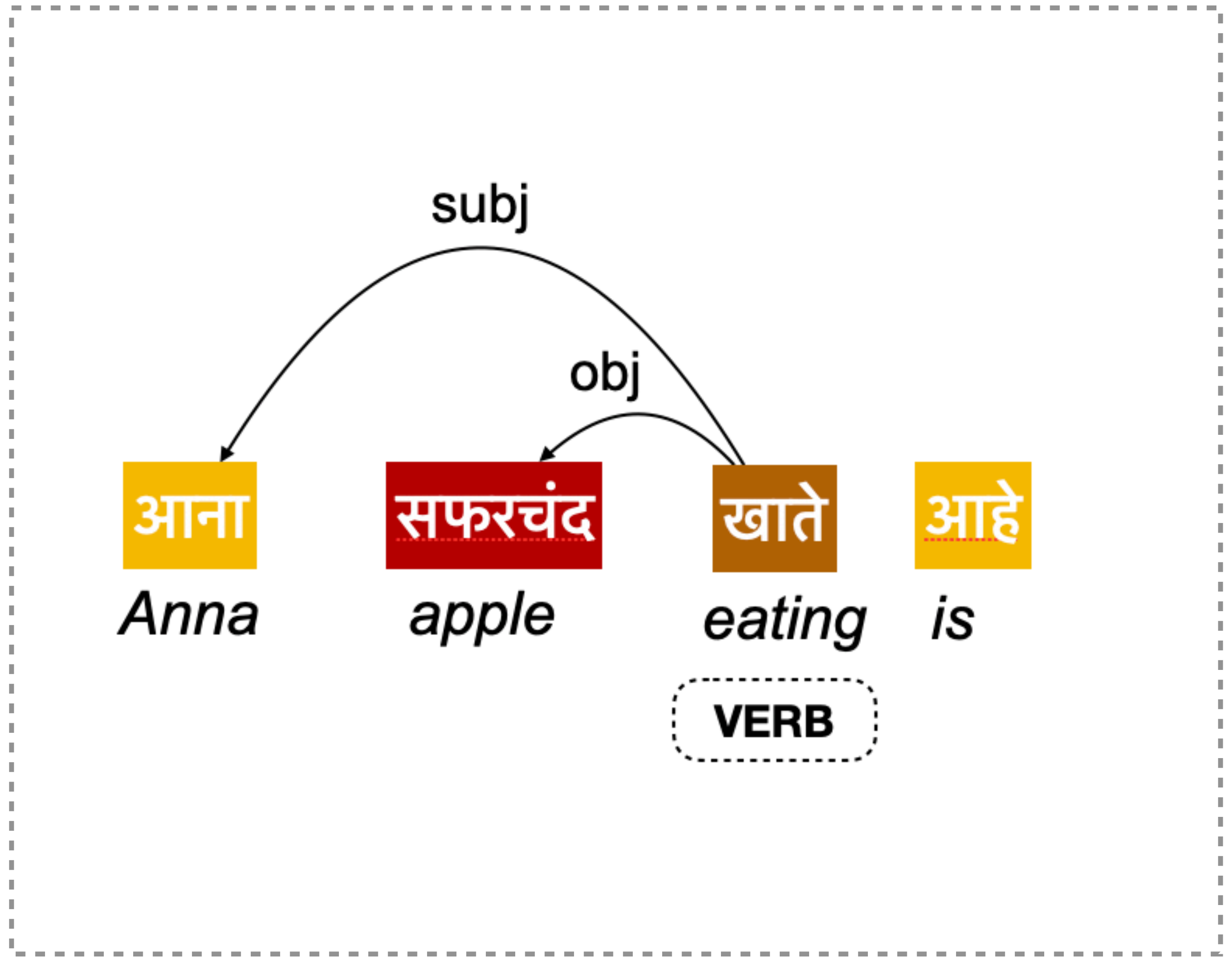
(Low-resource) Language Analysis



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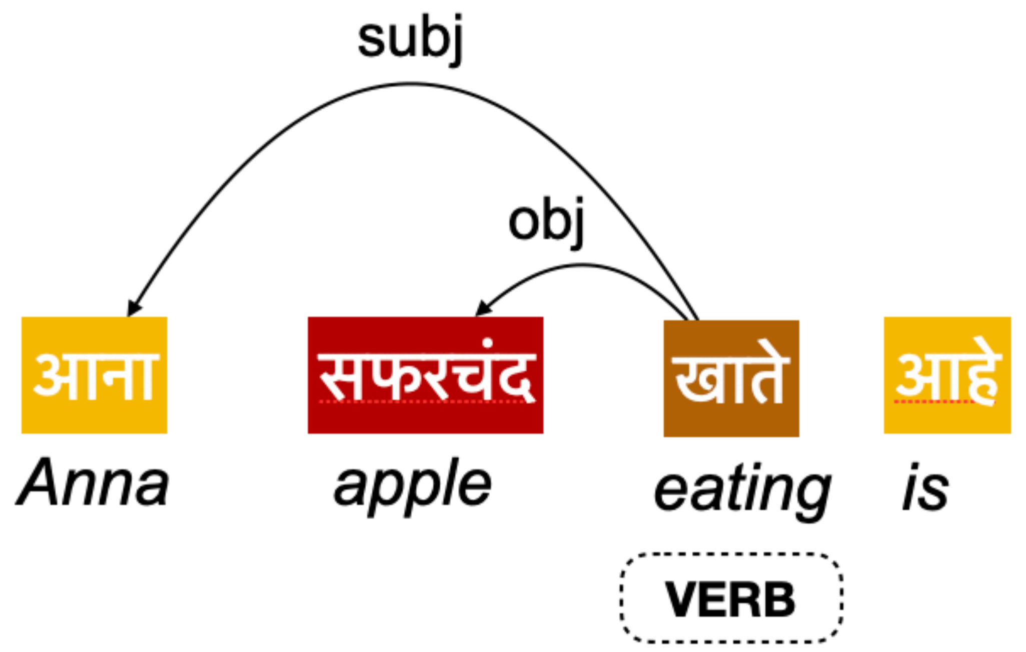

subj

obj

आना *Anna*

सफरचंद *apple*

खाते *eating*

आहे *is*

VERB

AutoLEX: Automatic Language Explorer

Subject Object Verb

तांदूळ
/tandul/
‘raw rice’

भात
/bhaat/
‘cooked rice’

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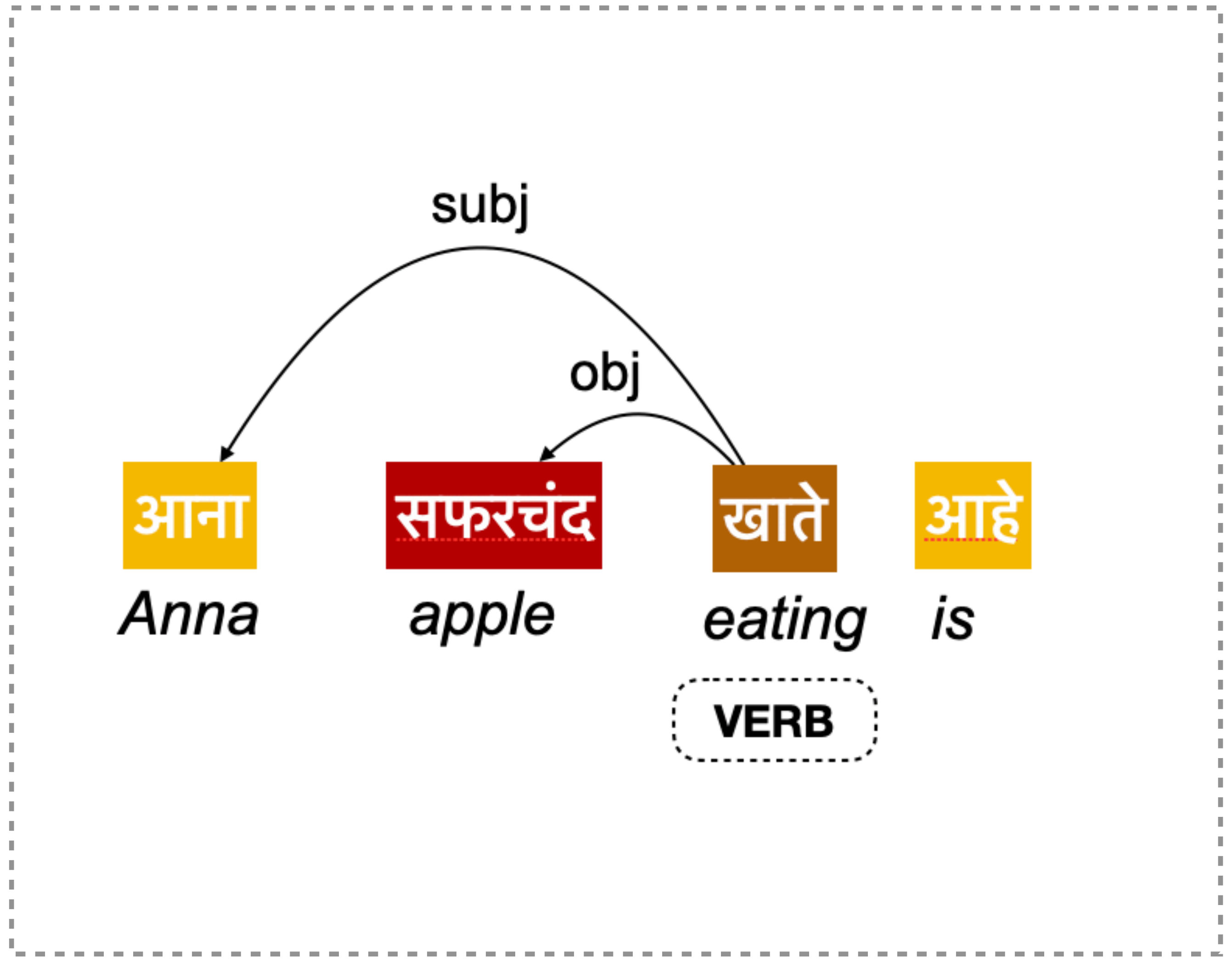

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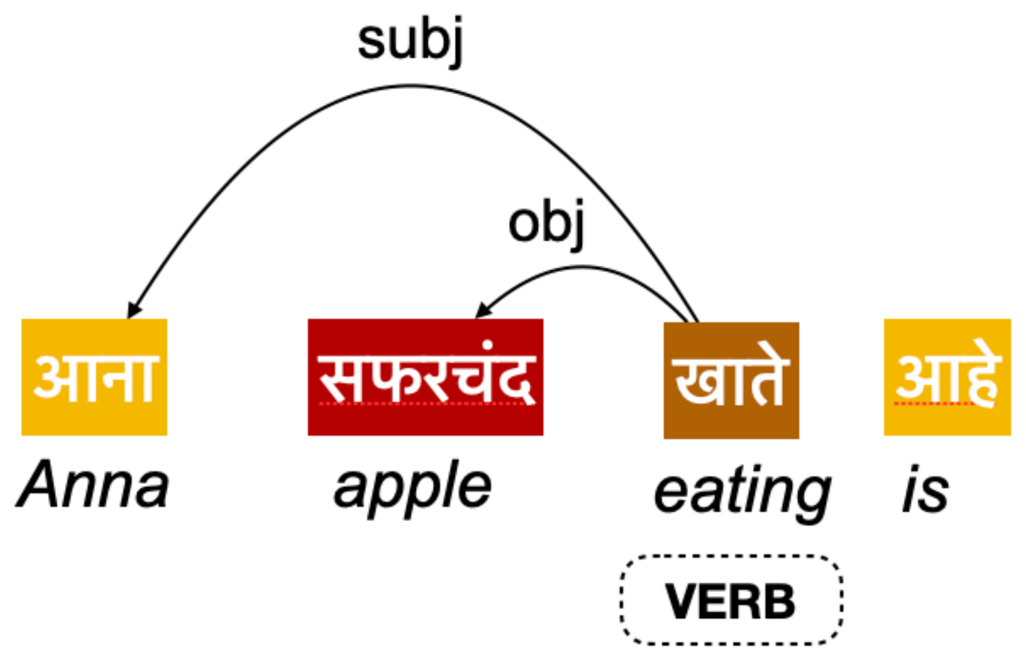

AutoLEX: Automatic Language Explorer

Subject **Object** **Verb**

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Applications

Language Education and Documentation

Language Education

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Language Education

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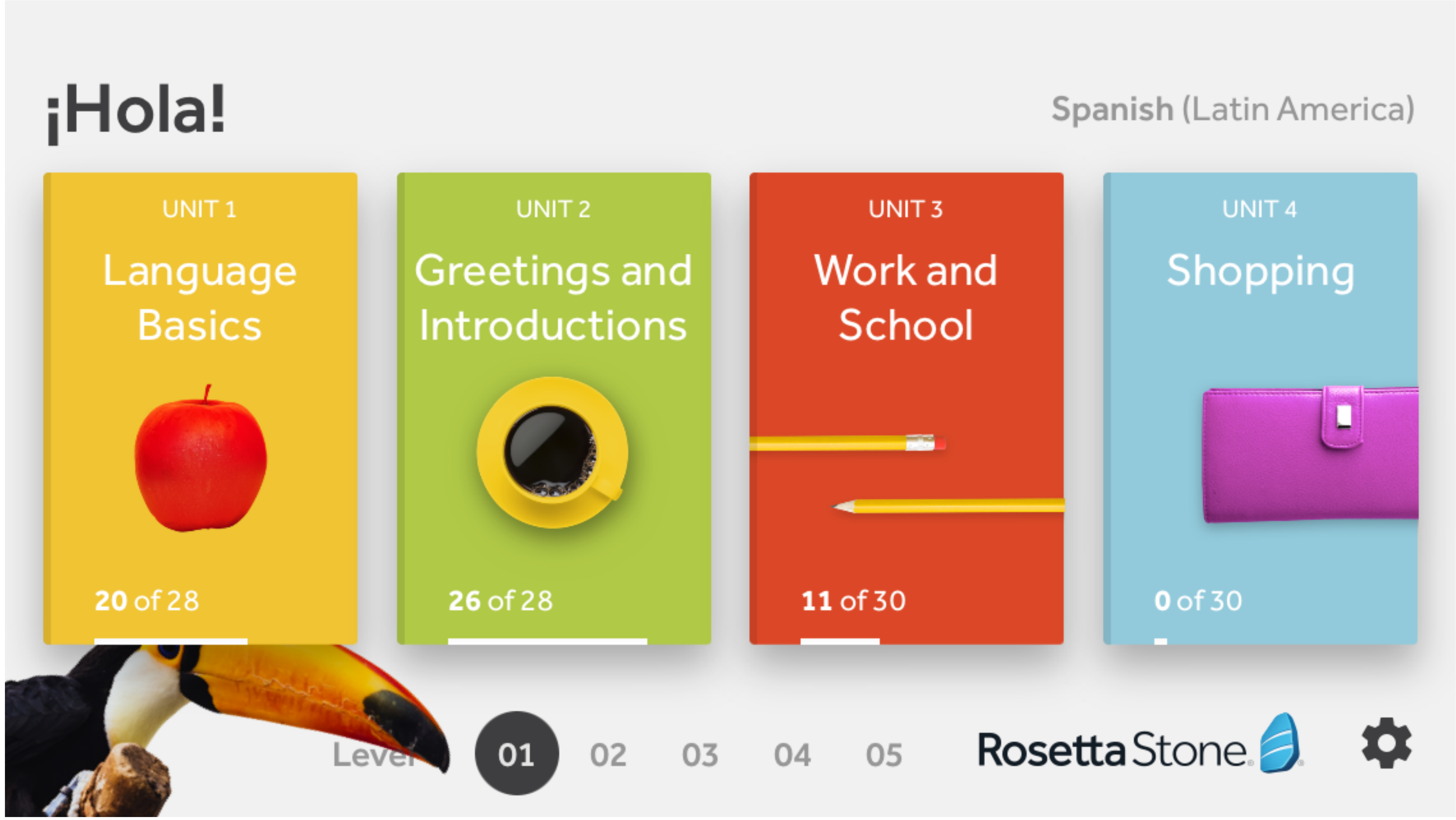

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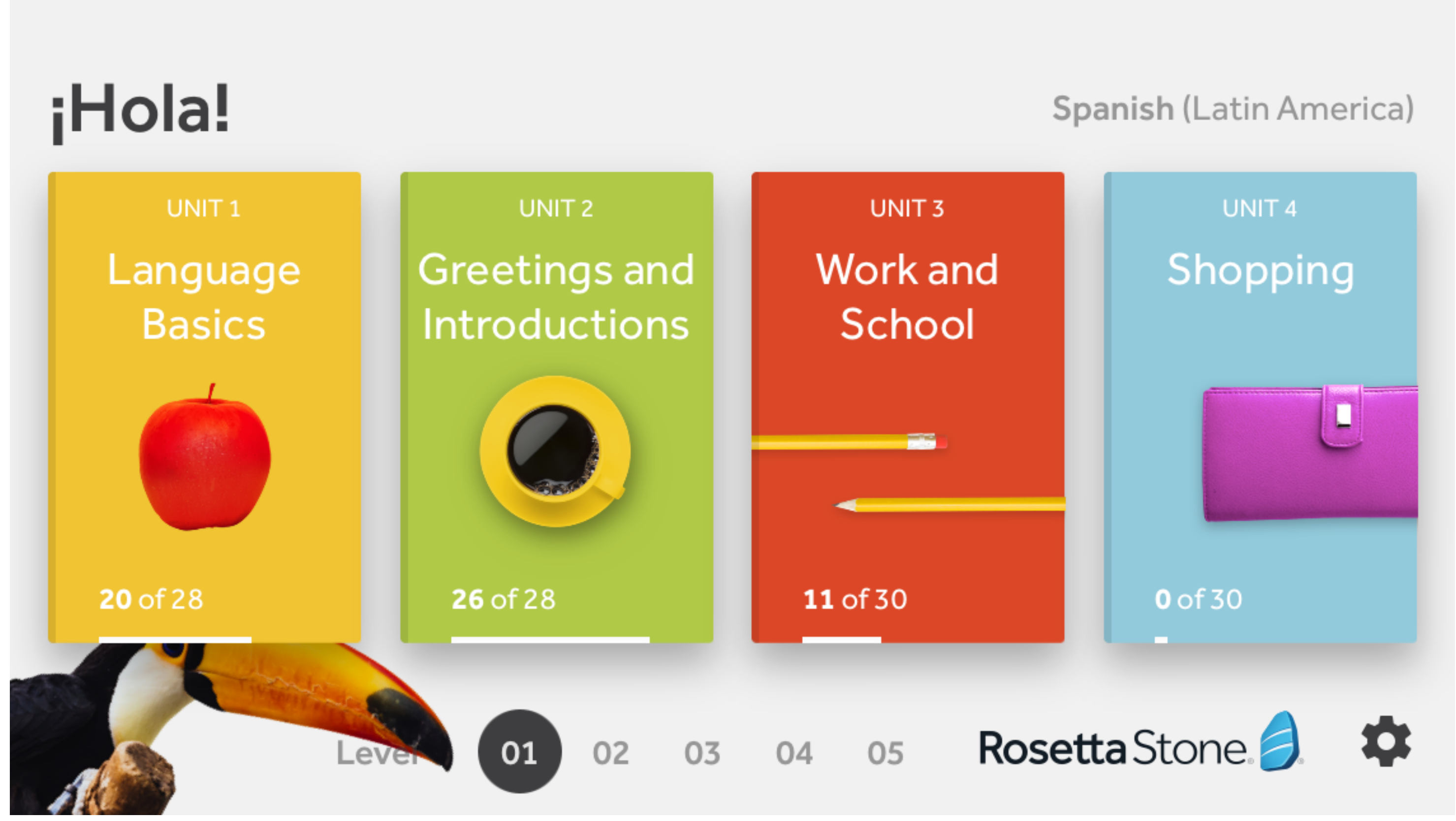
Limited in language coverage!



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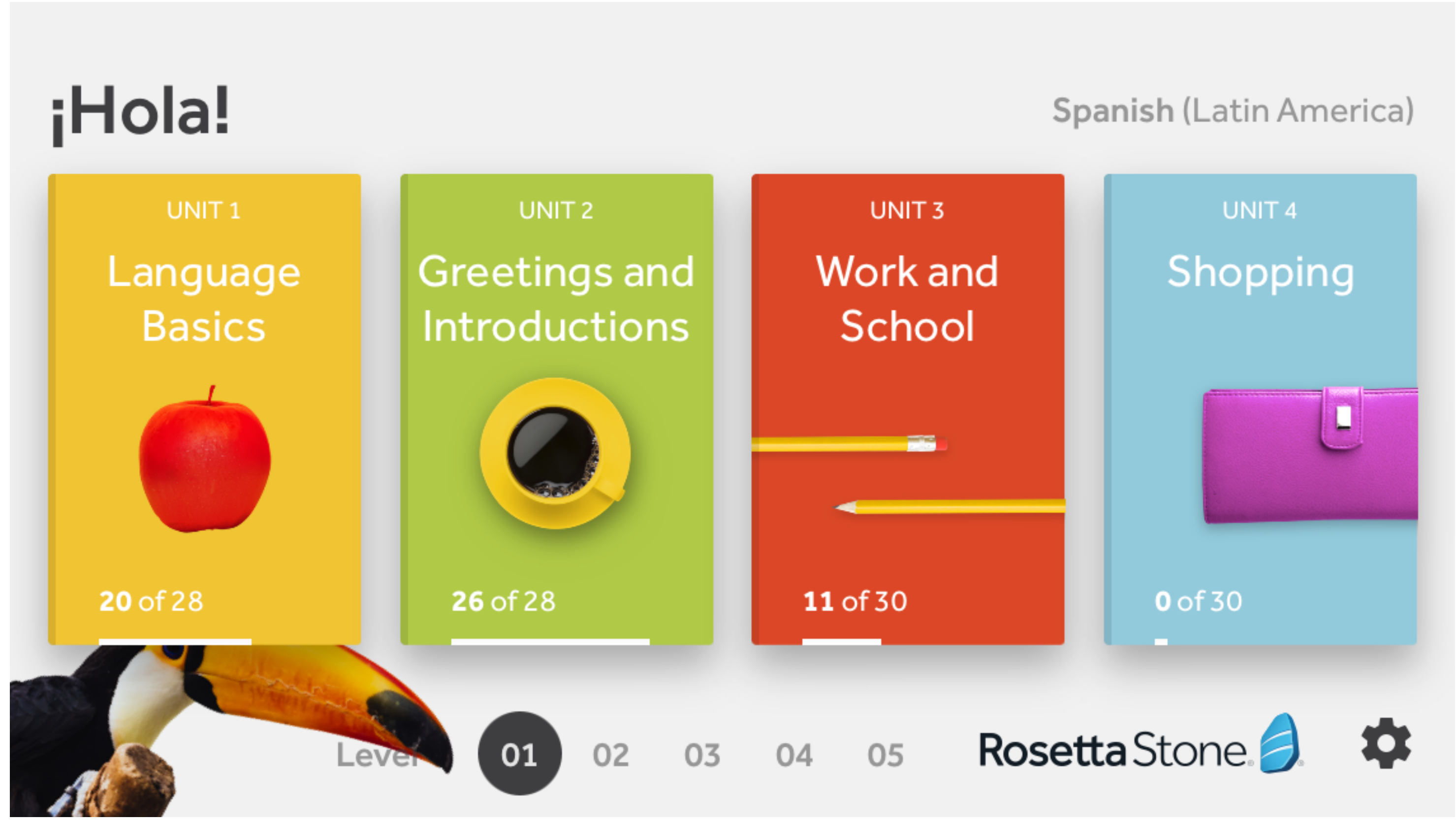

- Creating a curriculum is a **challenging process** ⟶ grammar coverage, examples, exercises …

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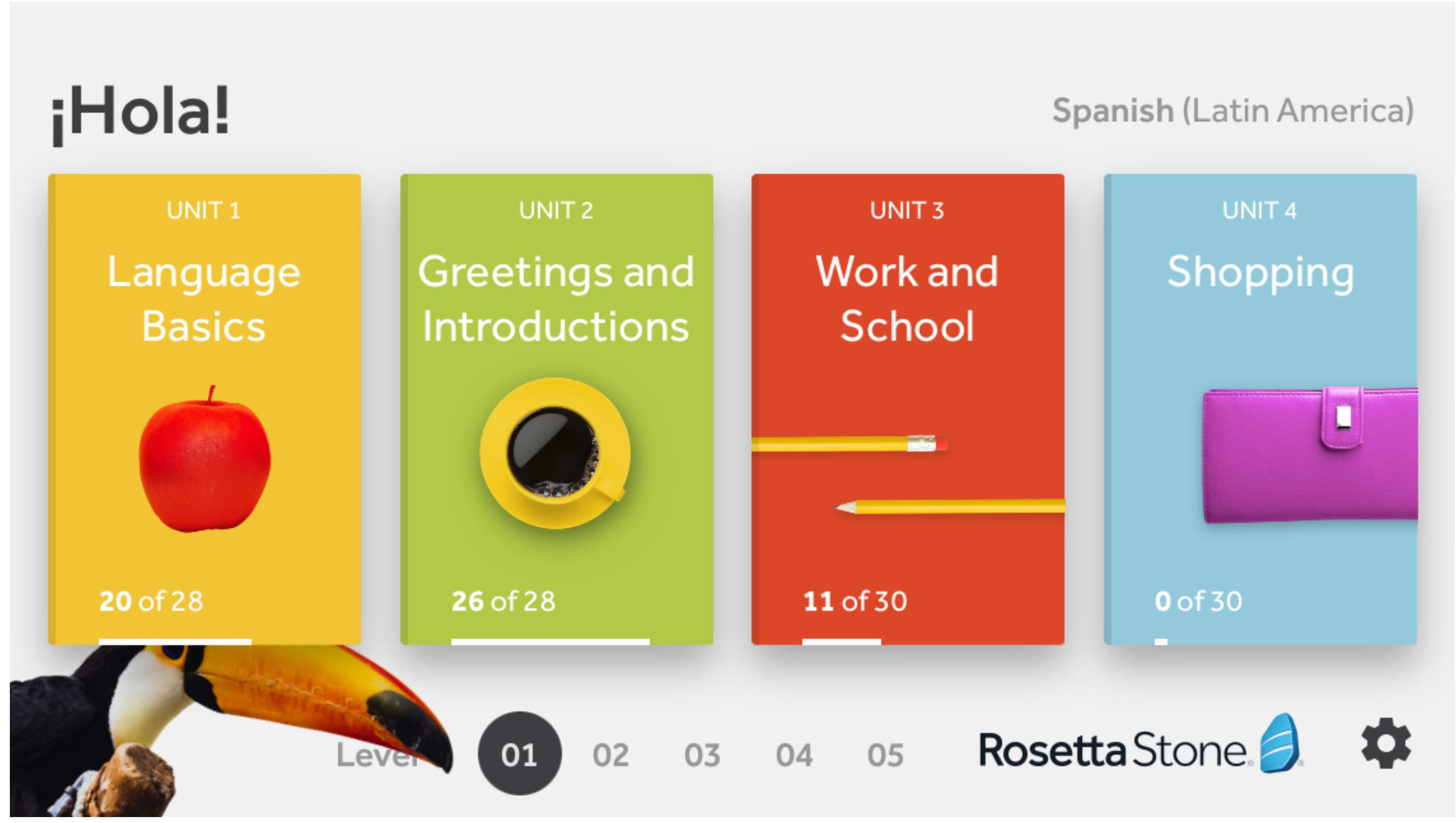

- Creating a curriculum is a **challenging process** ⟶ grammar coverage, examples, exercises …

- **AutoLEX** has shown potential in doing some aspects of this **automatically**

Word Usage: Semantic Subdivisions

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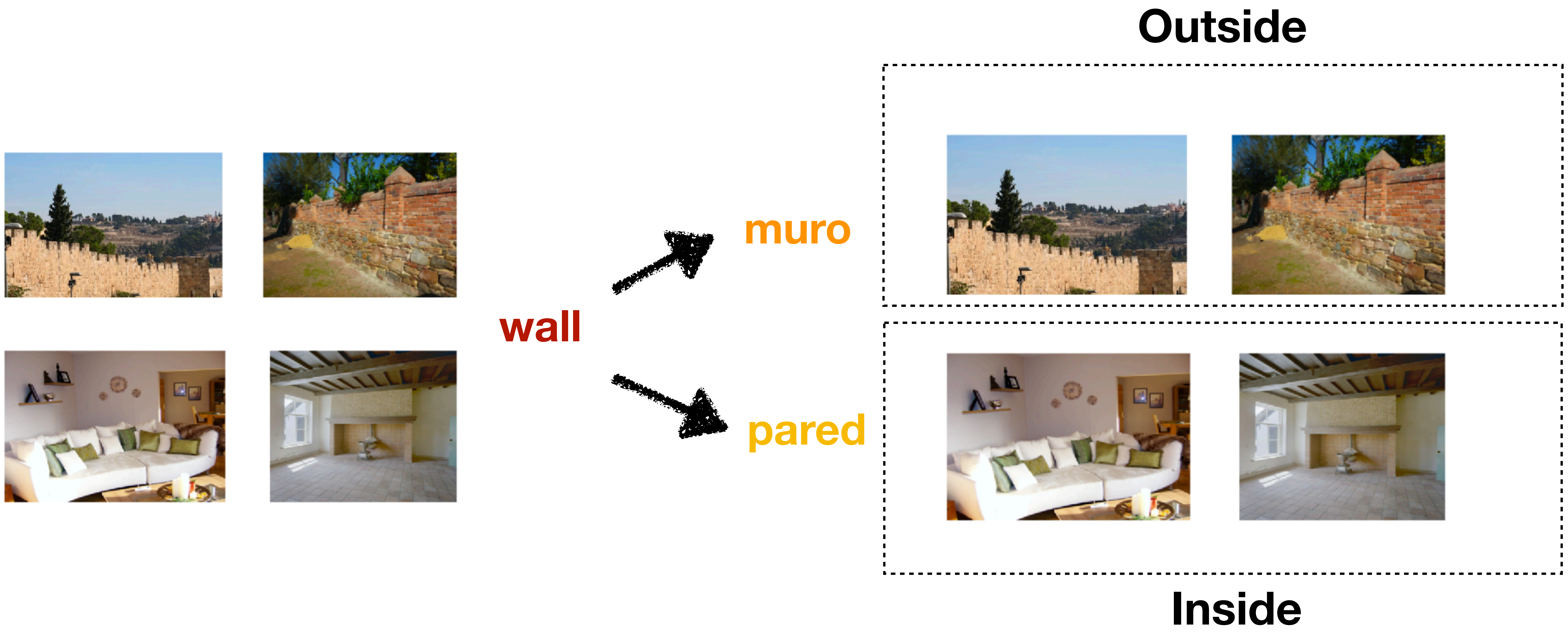

Outside

wall

muro

pared

Inside

When is Wall a Pared and when a Muro? Extracting Rules Governing Lexical Selection
Chaudhary**, Yin, Anastasopoulos, Neubig.* ***EMNLP 2021

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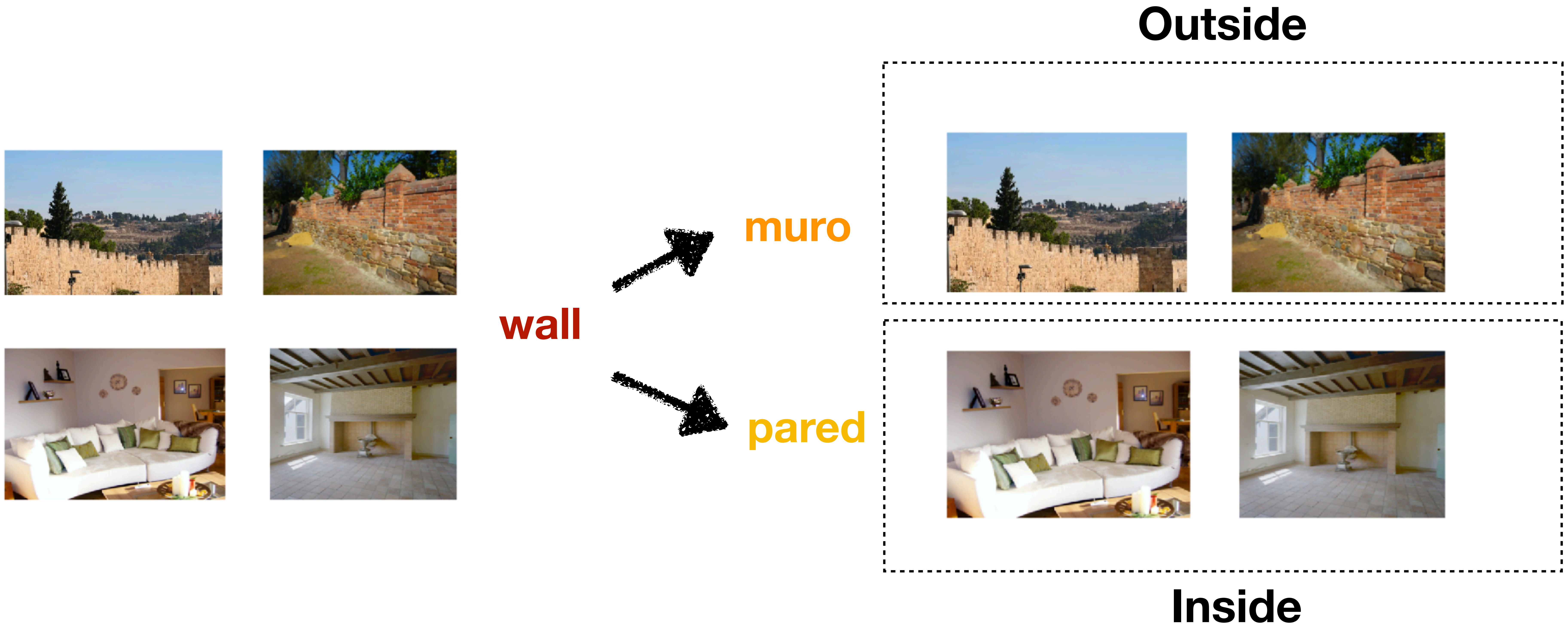

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Inside

- Crowdsourced study where participants recruited online had to predict correct word usage in context

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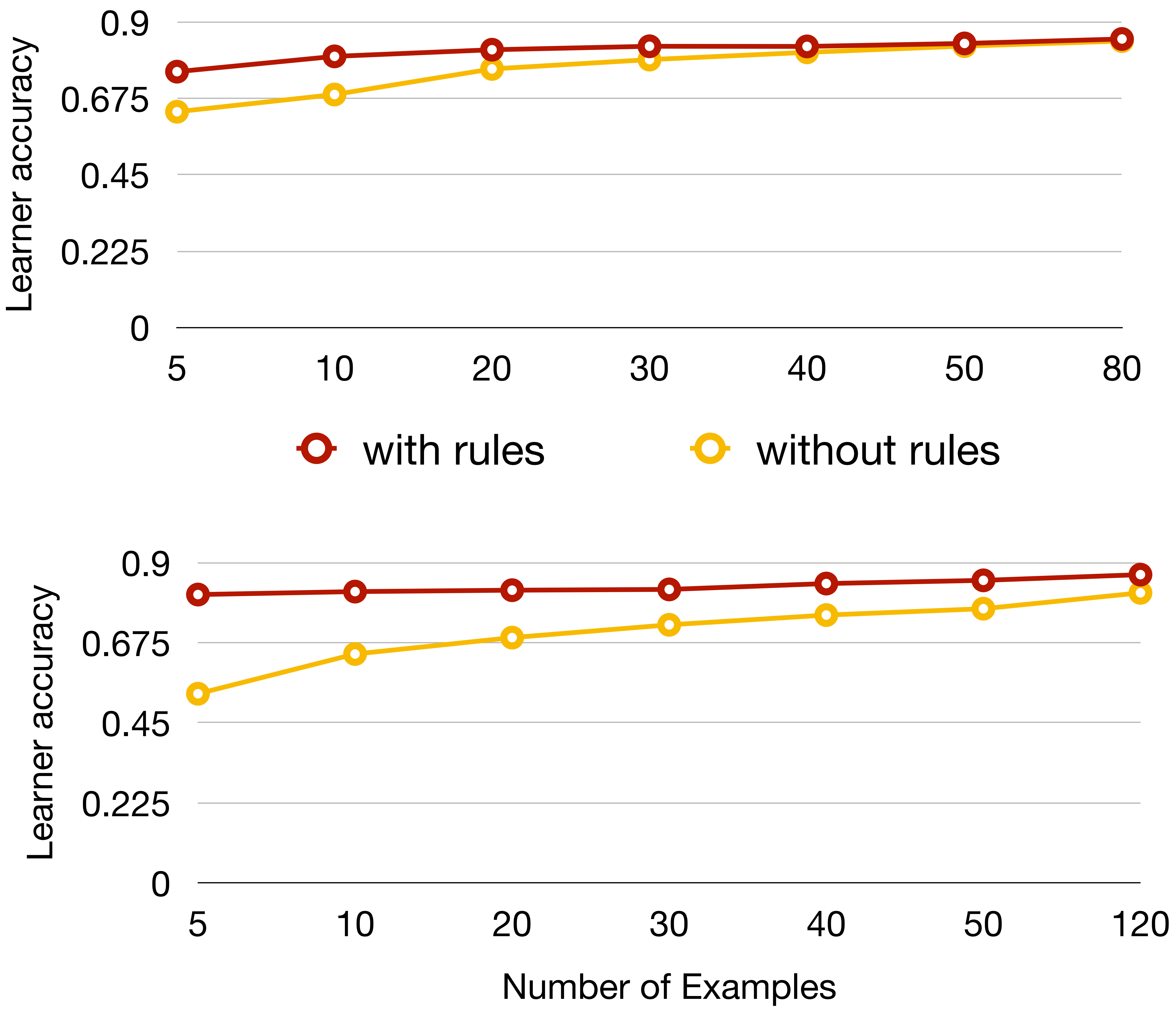
Results



Spanish

7 learners, 9 words

Greek

9 learners, 10 words

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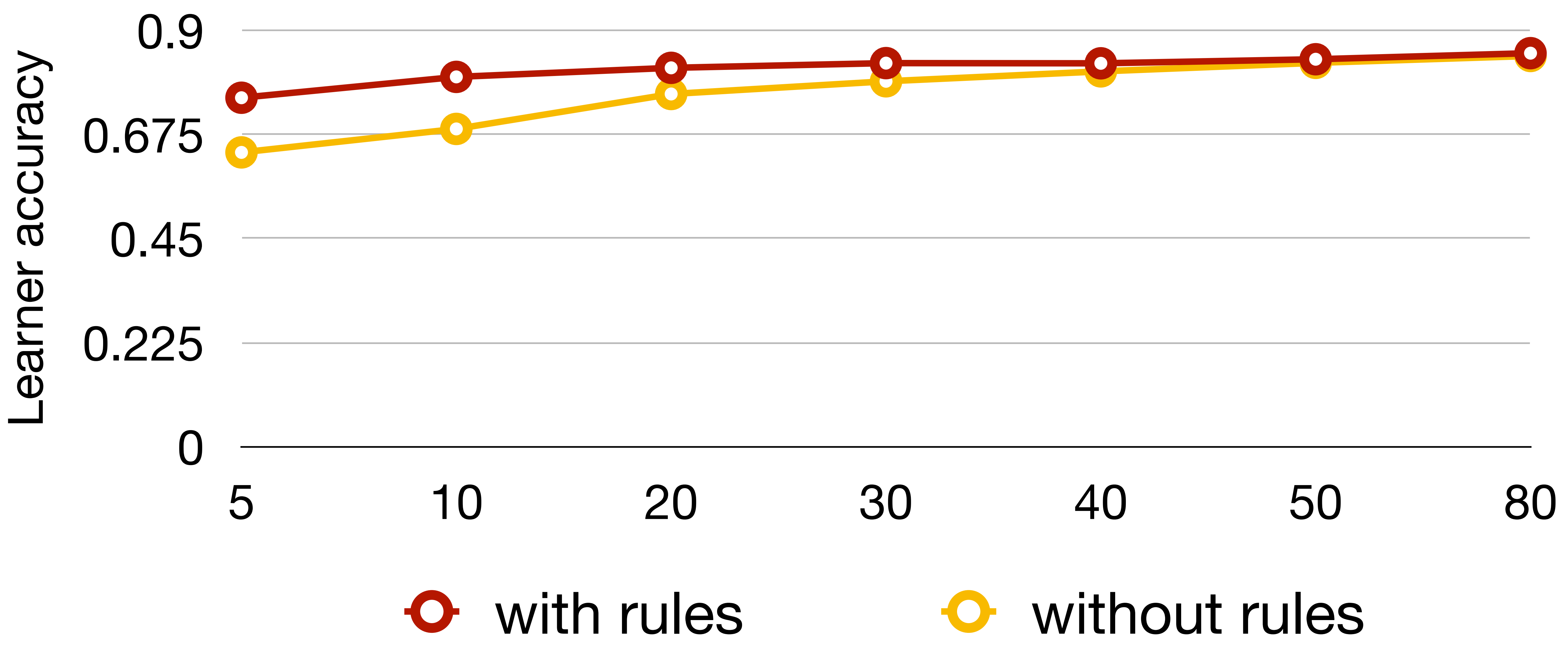

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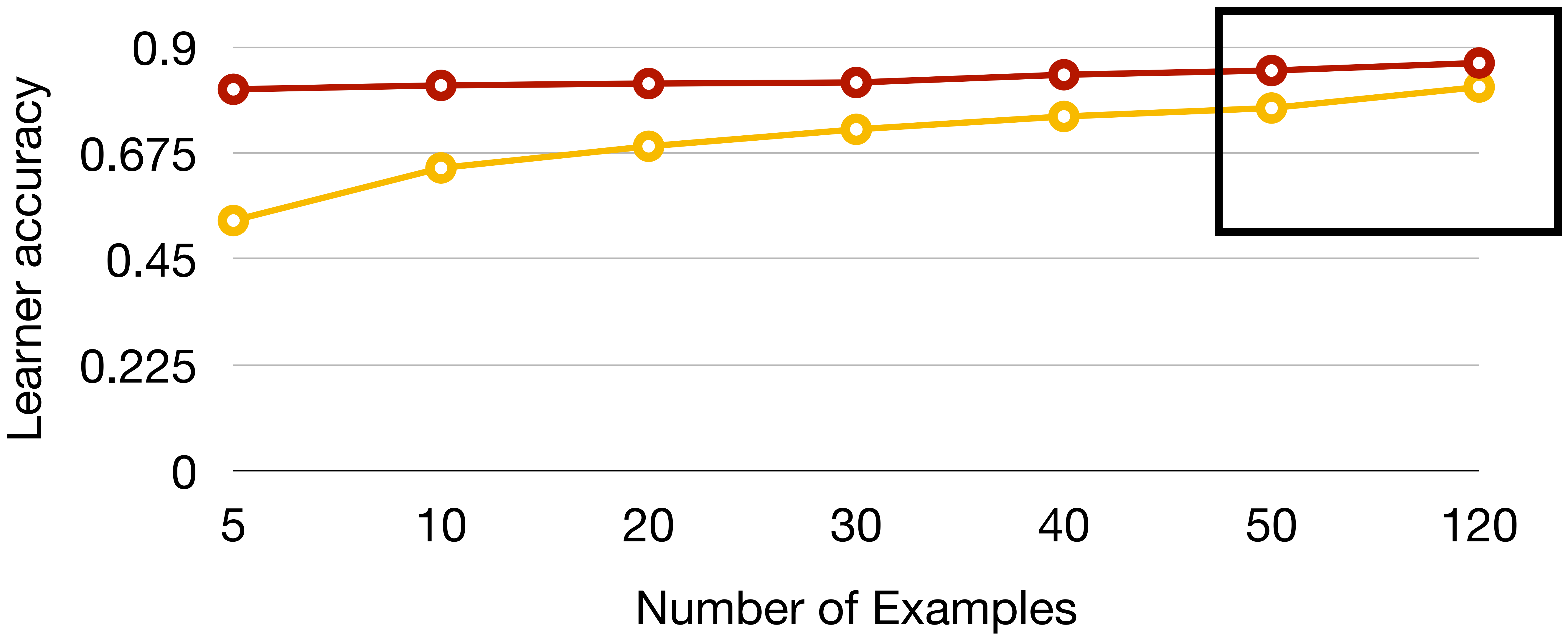

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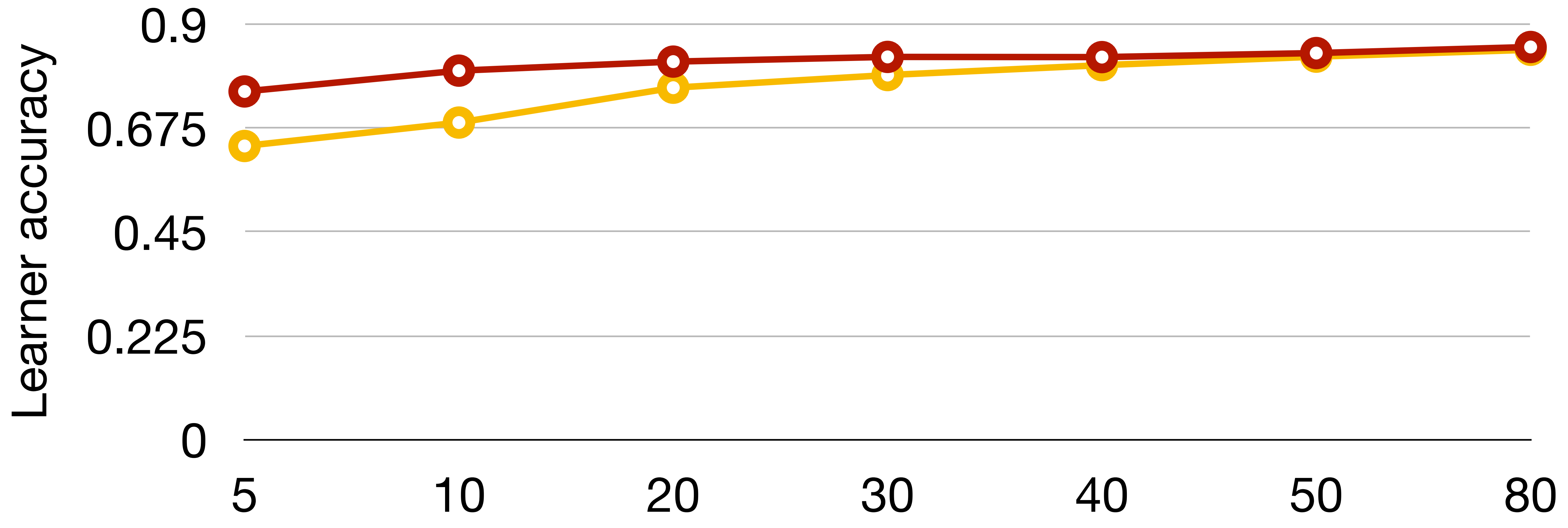

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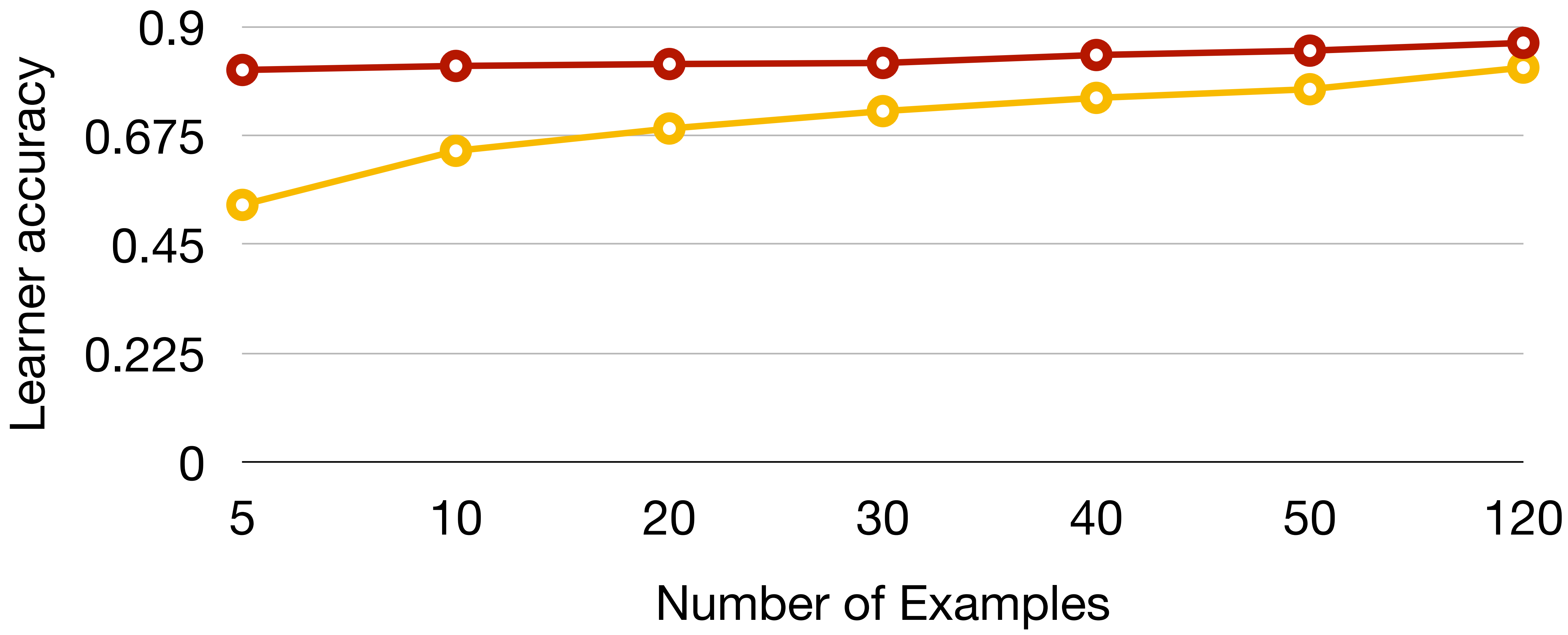
When shown rules, learners learn better and faster!



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Marathi - मराठी

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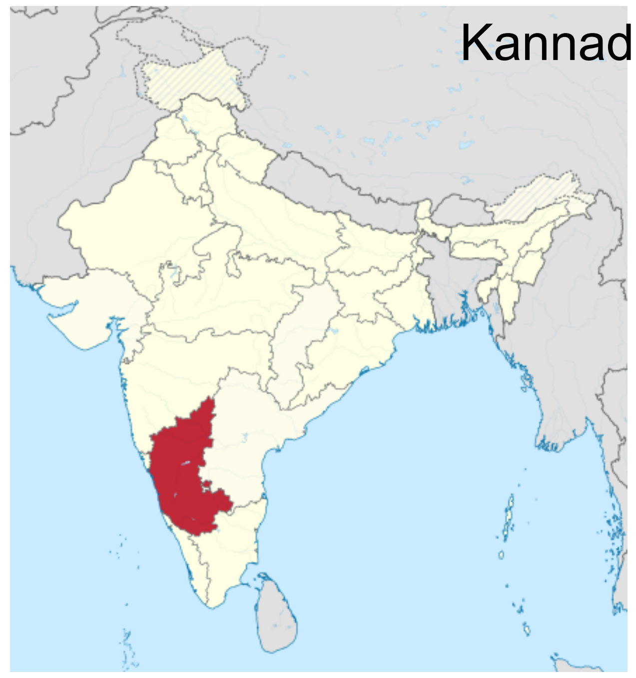

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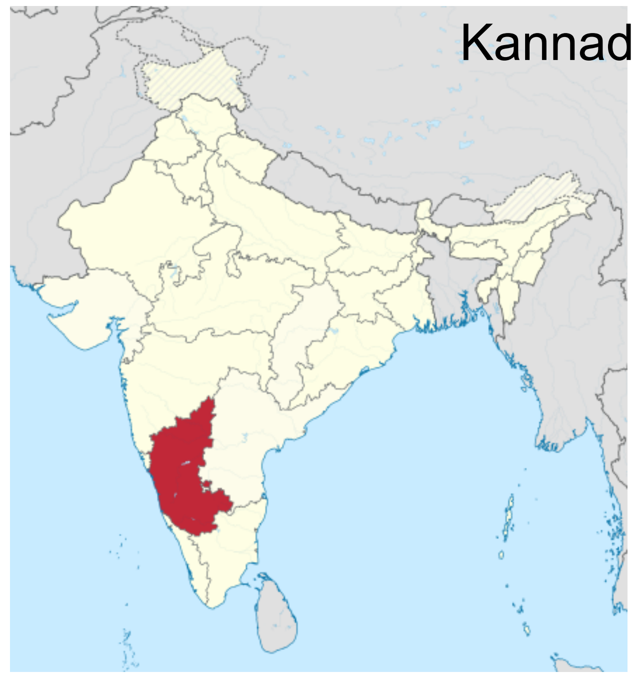

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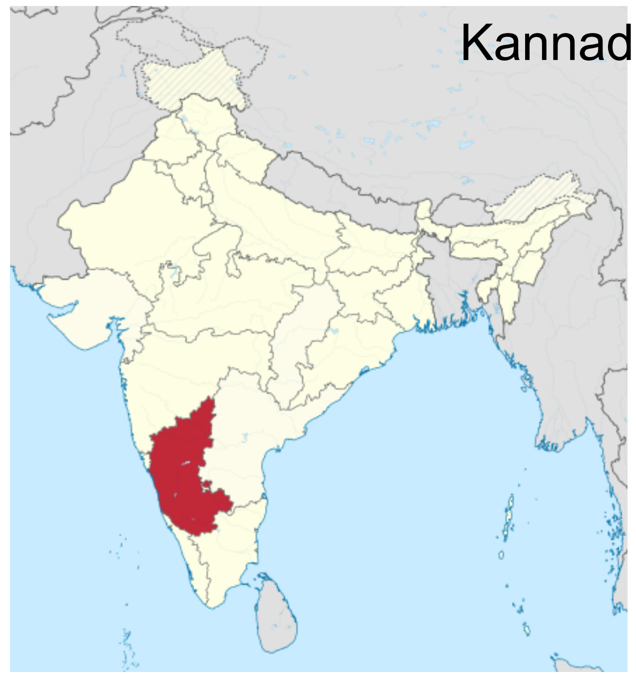

Dravidian language family

“Classical language status”

- **Under-resourced settings** w.r.t pedagogical resources as well as NLP models/resources

- **Access to in-service teachers** that teach these languages to English speakers

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  70 learning centers, 800 volunteer teachers

Arun Sampath

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- **Marathi** ⟶ Marathi Vidyalaya, Randolph, New Jersey

  Marathi Shala, Pittsburgh

  Small independent volunteer-run schools

AutoLEX: Selection of Grammar Aspects

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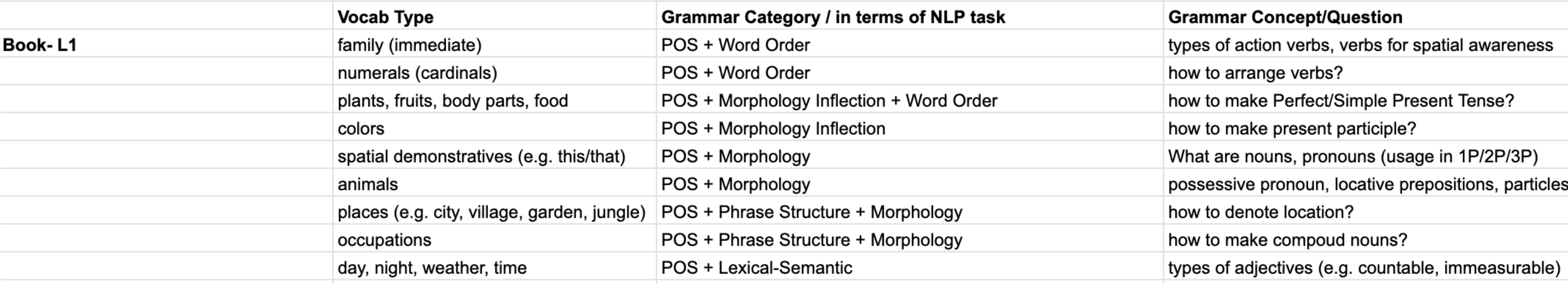

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Book- L1	family (immediate)	POS + Word Order	types of action verbs, verbs for spatial awareness
	numerals (cardinals)	POS + Word Order	how to arrange verbs?
	plants, fruits, body parts, food	POS + Morphology Inflection + Word Order	how to make Perfect/Simple Present Tense?
	colors	POS + Morphology Inflection	how to make present participle?
	spatial demonstratives (e.g. this/that)	POS + Morphology	What are nouns, pronouns (usage in 1P/2P/3P)
	animals	POS + Morphology	possessive pronoun, locative prepositions, particles
	places (e.g. city, village, garden, jungle)	POS + Phrase Structure + Morphology	how to denote location?
	occupations	POS + Phrase Structure + Morphology	how to make compound nouns?
	day, night, weather, time	POS + Lexical-Semantic	types of adjectives (e.g. countable, immeasurable)

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- Perused existing Kannada textbooks to identify popular grammar points

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	colors	POS + Morphology Inflection	how to make present participle?
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General Info

AutoLEX: Selection of Grammar Aspects

Lemma	Morphosyntactic Attributes	Gender				
		Fem	NA	Neut	Masc	
कर (kar)		-	करून (karun)	-	-	Examples
कर (kar)	2;Plur	-	करा (kara)	-	-	Examples
कर (kar)	Acc;Sing	-	-	करण्याचा (karanya)	-	Examples
कर (kar)	Nom;Sing	केली (keli)	-	करणे (karane)	केला (kelaa)	Examples
कर (kar)	3;Past;Sing	केली (keli)	-	केले (kele)	केला (kelaa)	Examples
कर (kar)	1;Plur	-	-	-	करावे (karaave)	Examples
कर (kar)	3;Sing	करावी (karavi)	-	करावे (karaave)	करावा (karawa)	Examples
कर (kar)	3;Nom;Past;Sing	-	-	-	केला (kelaa)	Examples
कर (kar)	3;Past;Plur	केल्या (kelya)	-	केली (keli)	करीत (kareet)	Examples
कर (kar)	Acc	-	केल्यामुळे (kelyamule)	-	-	Examples
कर (kar)	3;Plur;Pres	-	-	-	करतात (kartaat)	Examples

General Info

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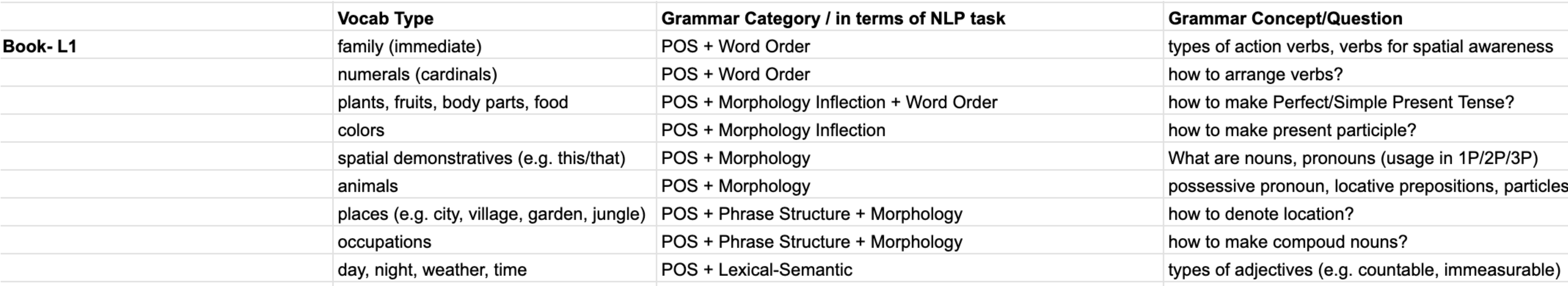

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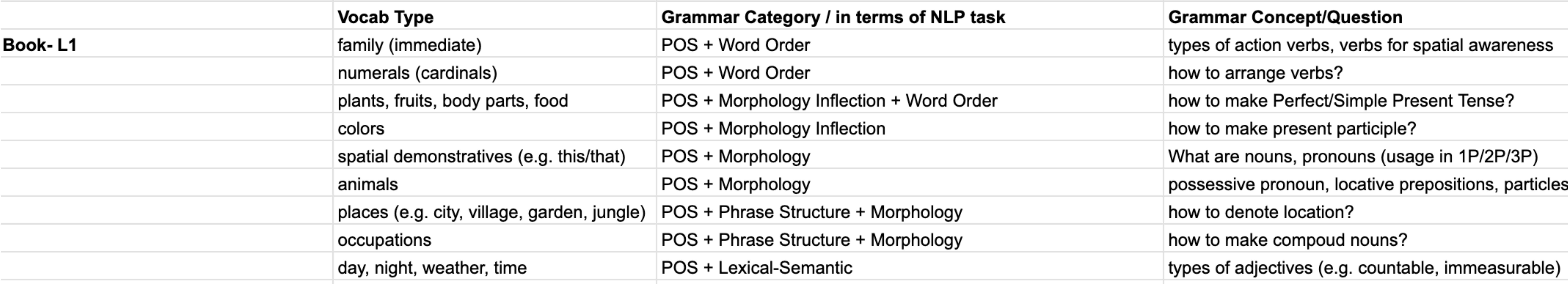

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General Info

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Word Order

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Affix Usage

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AutoLEX: Selection of Grammar Aspects

- In consultation with the curriculum designers

ला (laa) suffix is used when:

current word is in the neighborhood of the word= अटक (atak) current word is in the neighborhood of the word= सुरुवात (sruvaat) current word with Number = Sing current word with Case = Acc current word is the= oblique	Examples

चा (chaa) suffix is used when:

current word with Case = Acc current word is in the neighborhood of the word= मृत्यू (mrityu) current word is the= modifer current word's head is the= compound current word's head with Gender = Masc	Examples

General Info

Agreement

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Affix Usage

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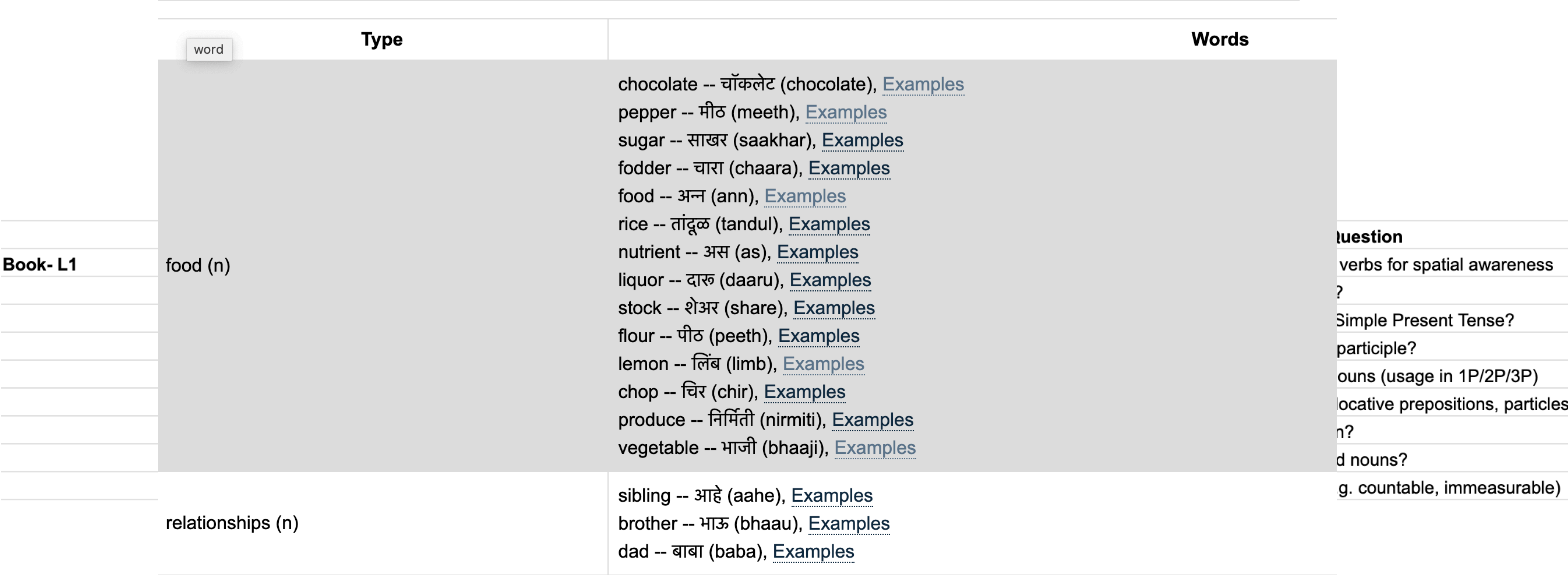

Type	Words
food (n)	chocolate -- चॉकलेट (chocolate), Examples pepper -- मीठ (meeth), Examples sugar -- साखर (saakhar), Examples fodder -- चारा (chaara), Examples food -- अन्न (ann), Examples rice -- तांदूळ (tandul), Examples nutrient -- अस (as), Examples liquor -- दारू (daaru), Examples stock -- शेअर (share), Examples flour -- पीठ (peeth), Examples lemon -- लिंब (limb), Examples chop -- चिर (chir), Examples produce -- निर्मिती (nirmiti), Examples vegetable -- भाजी (bhaaji), Examples
relationships (n)	sibling -- आहे (aahe), Examples brother -- भाऊ (bhaau), Examples dad -- बाबा (baba), Examples

Book- L1

uestion
verbs for spatial awareness
?
Simple Present Tense?
participle?
ouns (usage in 1P/2P/3P)
locative prepositions, particles
n?
d nouns?
g. countable, immeasurable)

General Info

Agreement

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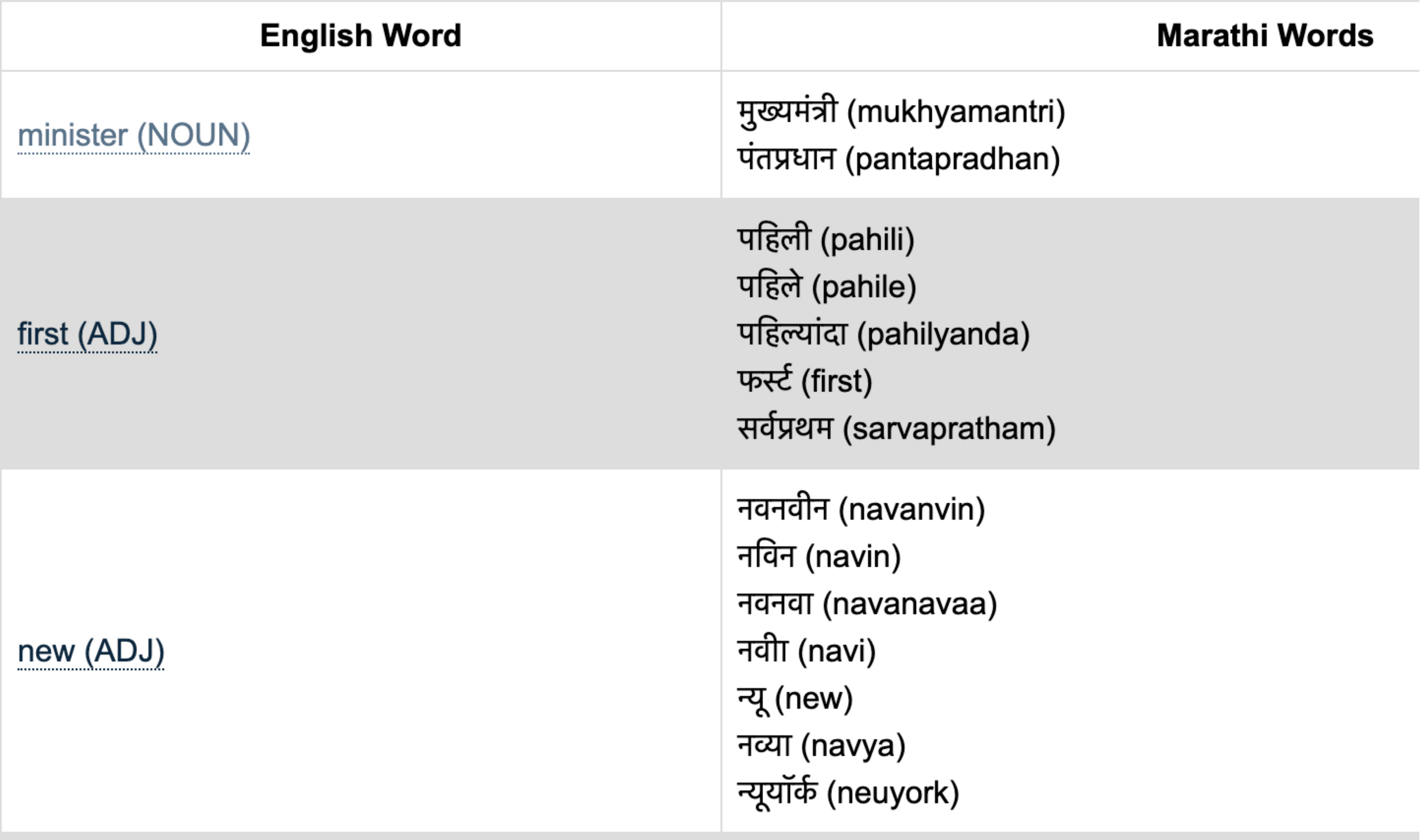

English Word	Marathi Words
minister (NOUN)	मुख्यमंत्री (mukhyamantri) पंतप्रधान (pantapradhan)
first (ADJ)	पहिली (pahili) पहिले (pahile) पहिल्यांदा (pahilyanda) फर्स्ट (first) सर्वप्रथम (sarvapratham)
new (ADJ)	नवनवीन (navanvin) नविन (navin) नवनवा (navanavaa) नवीा (navi) न्यू (new) नव्या (navya) न्यूयॉर्क (neuyork)

General Info

Agreement

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Affix Usage

Word Usage

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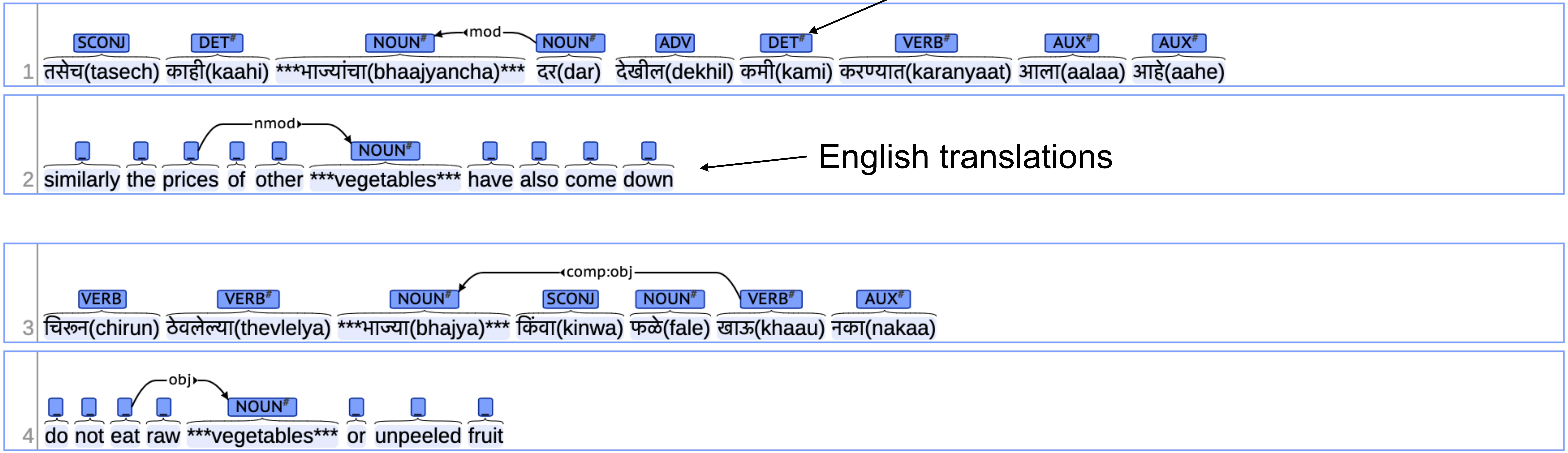
AutoLEX: Selection of Grammar Aspects

Example usages of **भाजी (bhaaji)**

Roman transliteration



1 तसेच(tasech) काही(kaahi) ***भाज्यांचा(bhaajyancha)*** दर(dar) देखील(dekhil) कमी(kami) करण्यात(karanyaat) आला(aalaa) आहे(aahe)

2 similarly the prices of other ***vegetables*** have also come down

3 चिरून(chirun) ठेवलेल्या(thevlelya) ***भाज्या(bhajya)*** किंवा(kinwa) फळे(fale) खाऊ(khaau) नका(nakaa)

4 do not eat raw ***vegetables*** or unpeeled fruit

English translations

General Info

Agreement

Word Order

Affix Usage

Word Usage

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AutoLEX: Extracting Language Descriptions

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AutoLEX: Extracting Language Descriptions

kn-en

AutoLEX: Extracting Language Descriptions

kn-en

mr-en

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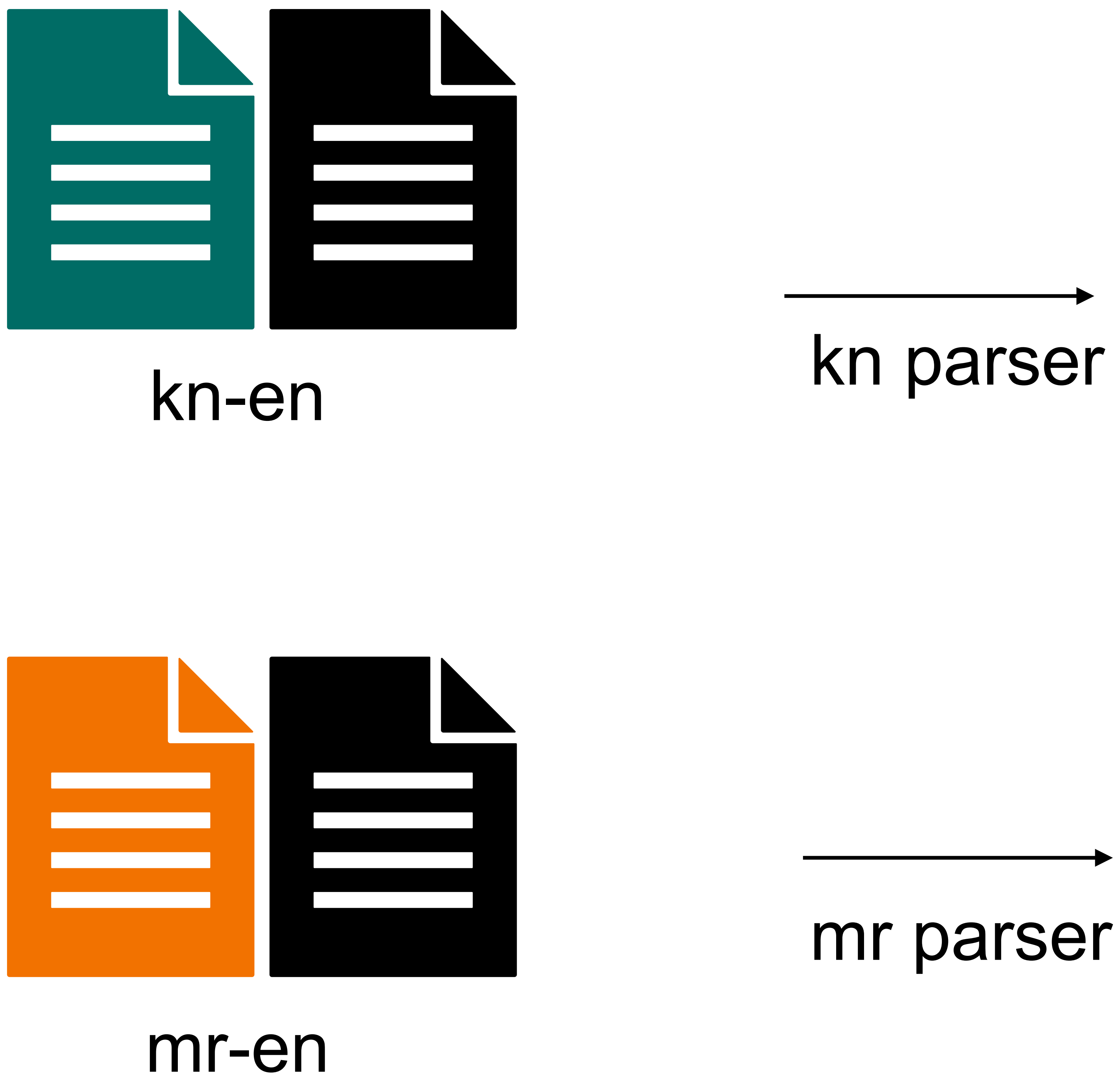

kn-en

kn parser

mr-en

mr parser

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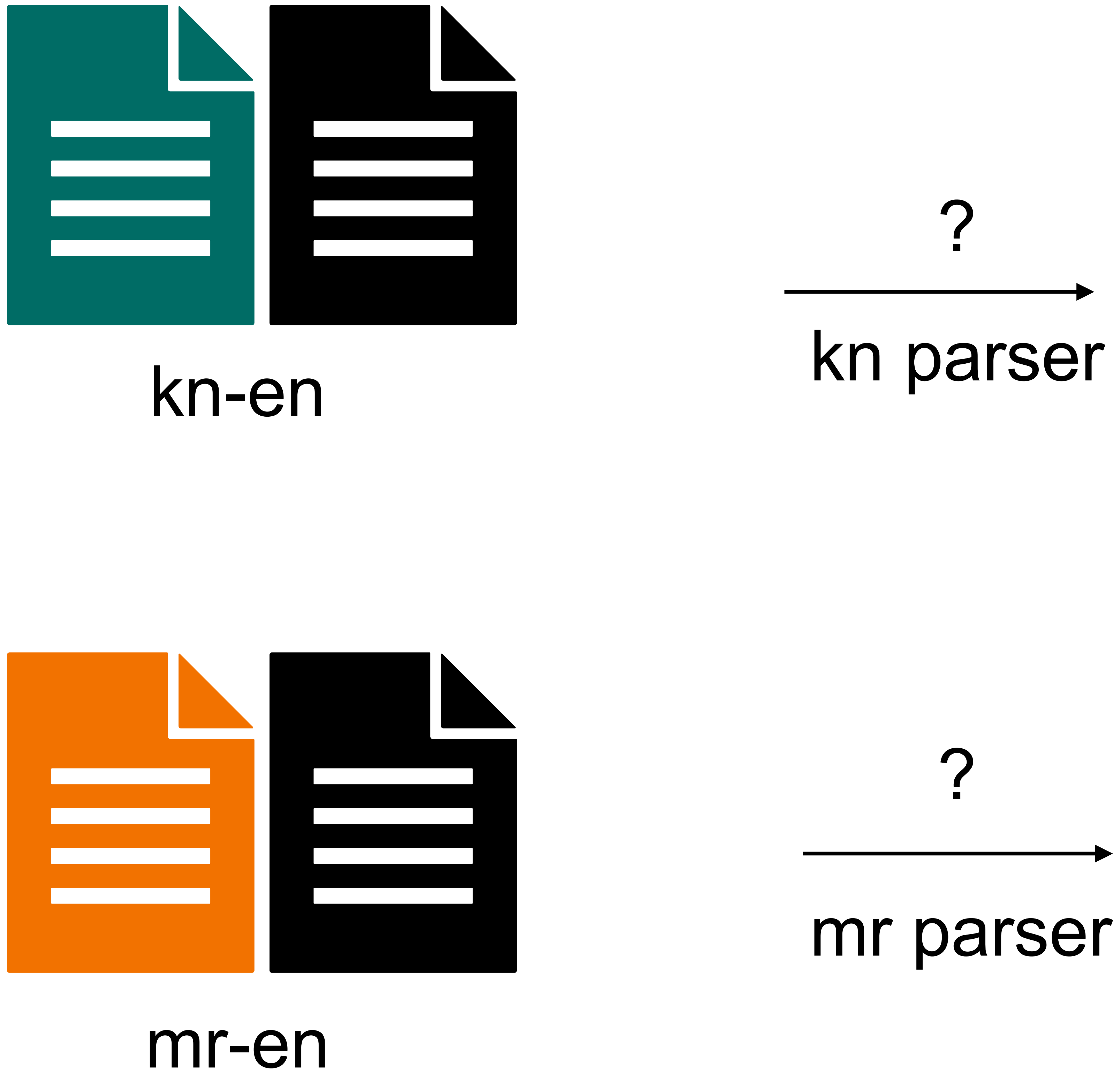

kn-en

?

kn parser

mr-en

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mr parser

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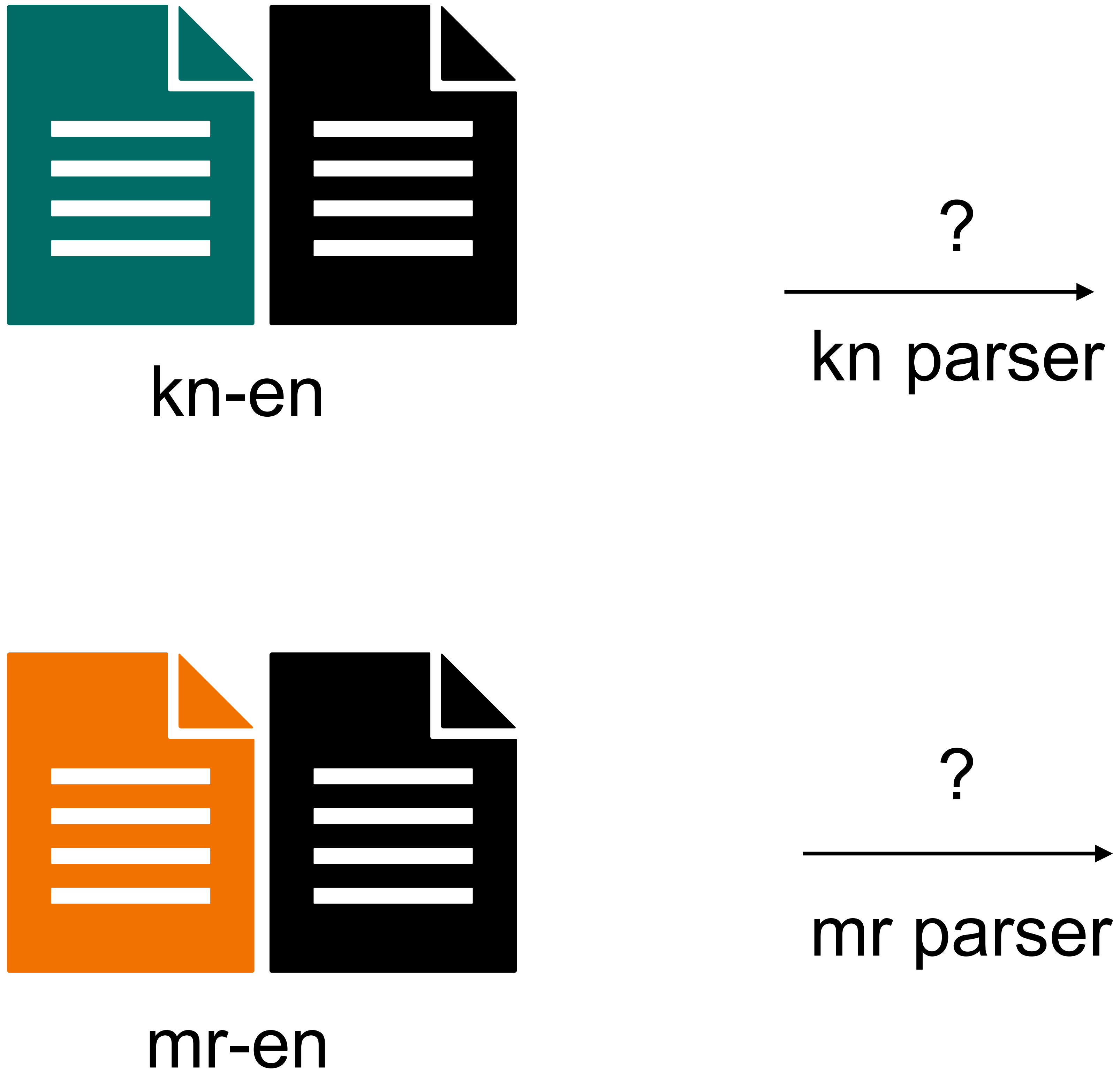

kn has **NO SUD treebank/model**

😕

mr has **VERY SMALL** and **NOISY SUD treebank/model**

AutoLEX: Extracting Language Descriptions

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AutoLEX: Extracting Language Descriptions

There is **ALWAYS** some data to be found! ☺️

AutoLEX: Extracting Language Descriptions

There is **ALWAYS** some data to be found! ☺️

Paninian Treebanks

kn

mr

INTERNATIONAL INSTITUTE OF
INFORMATION TECHNOLOGY
HYDERABAD

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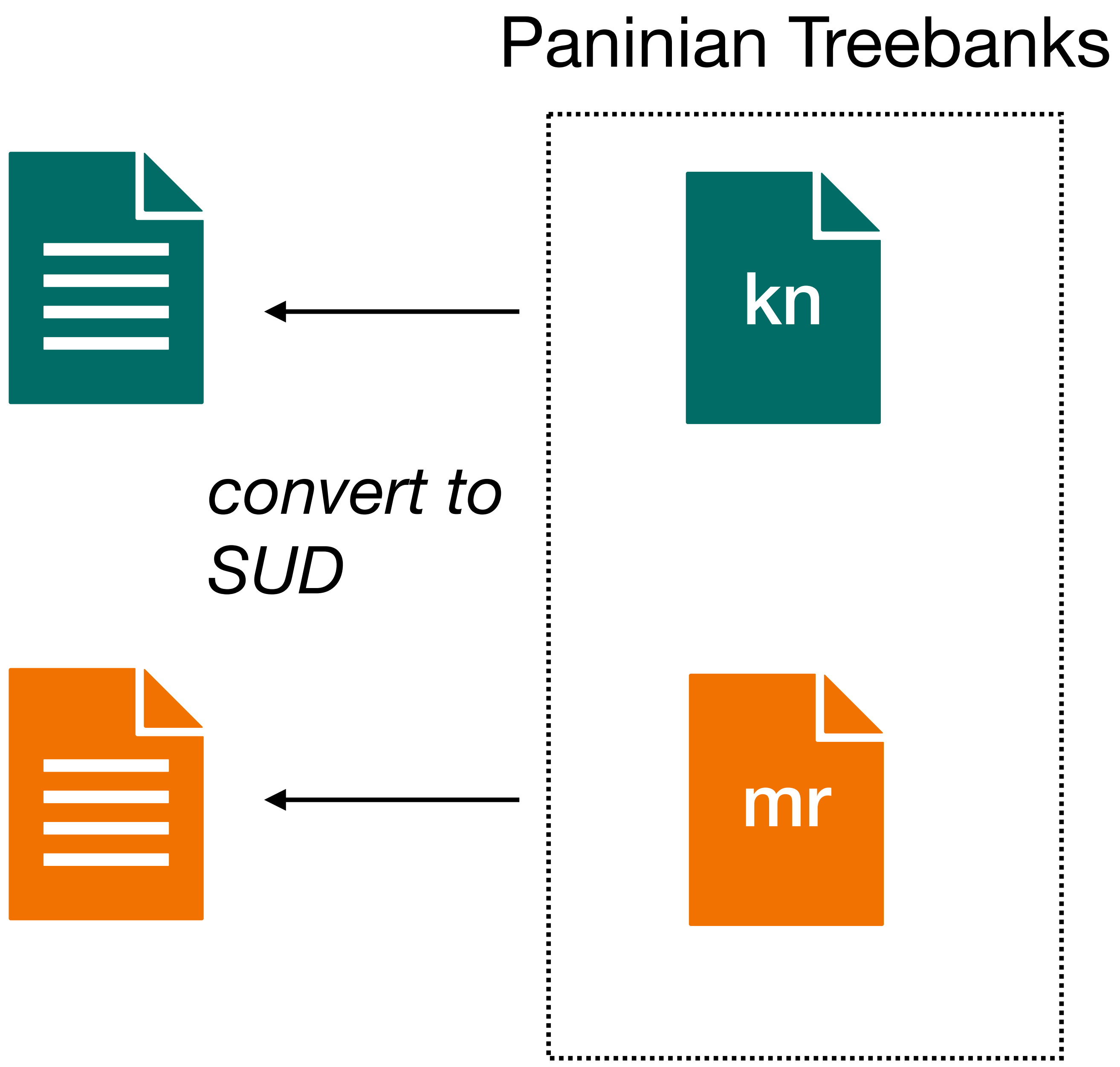

Paninian Treebanks

kn

mr

convert to SUD

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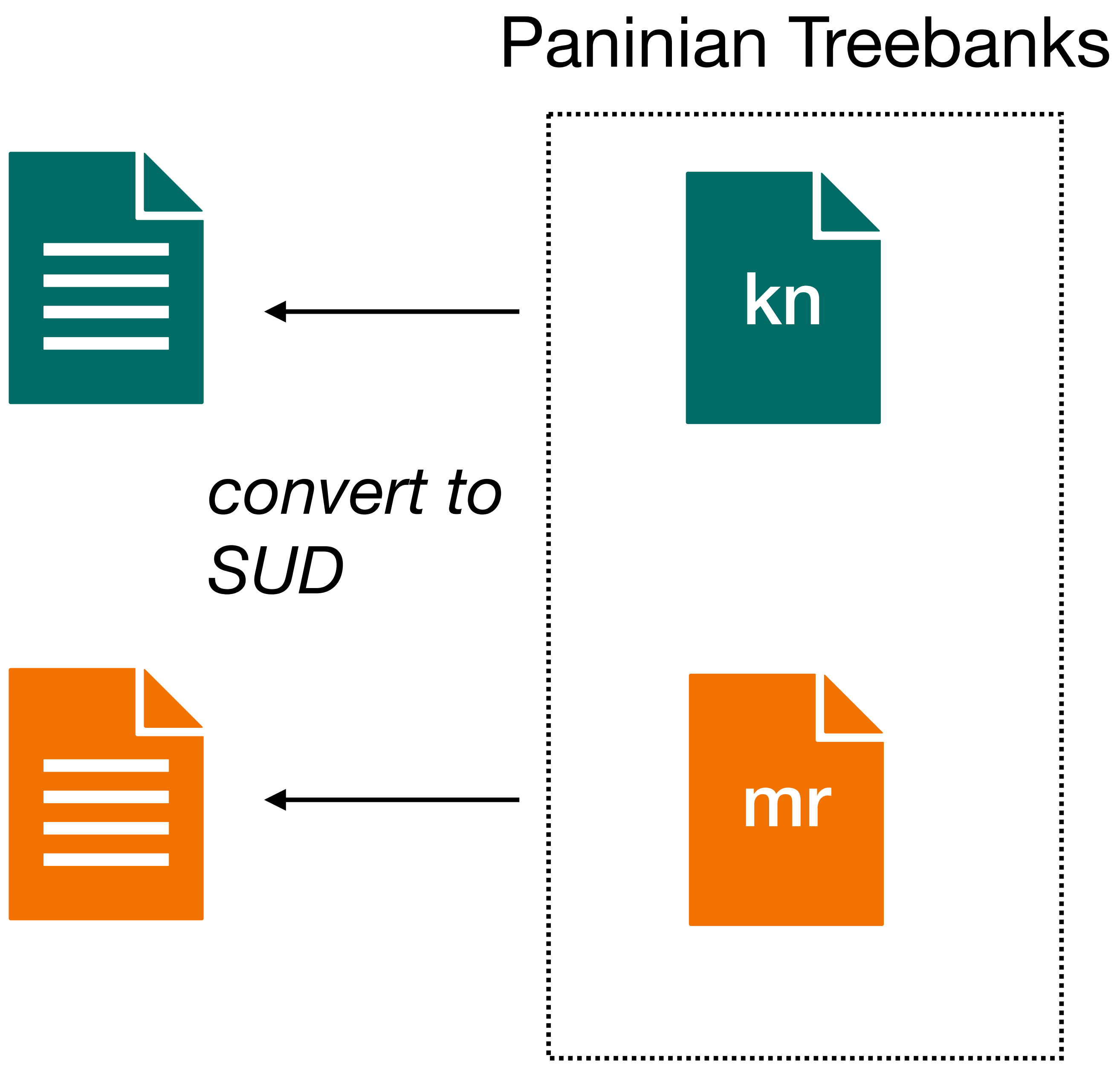

convert to SUD

train model for POS tags, lemmatization, morphological analysis

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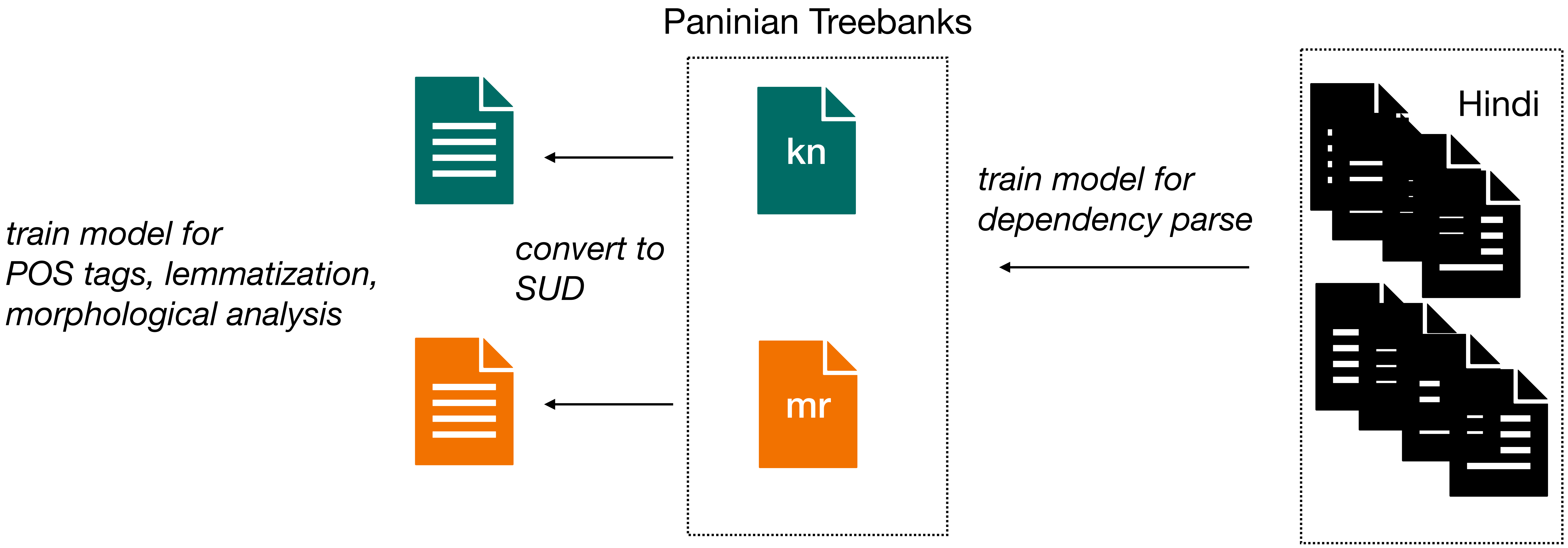

train model for POS tags, lemmatization, morphological analysis

train model for dependency parse

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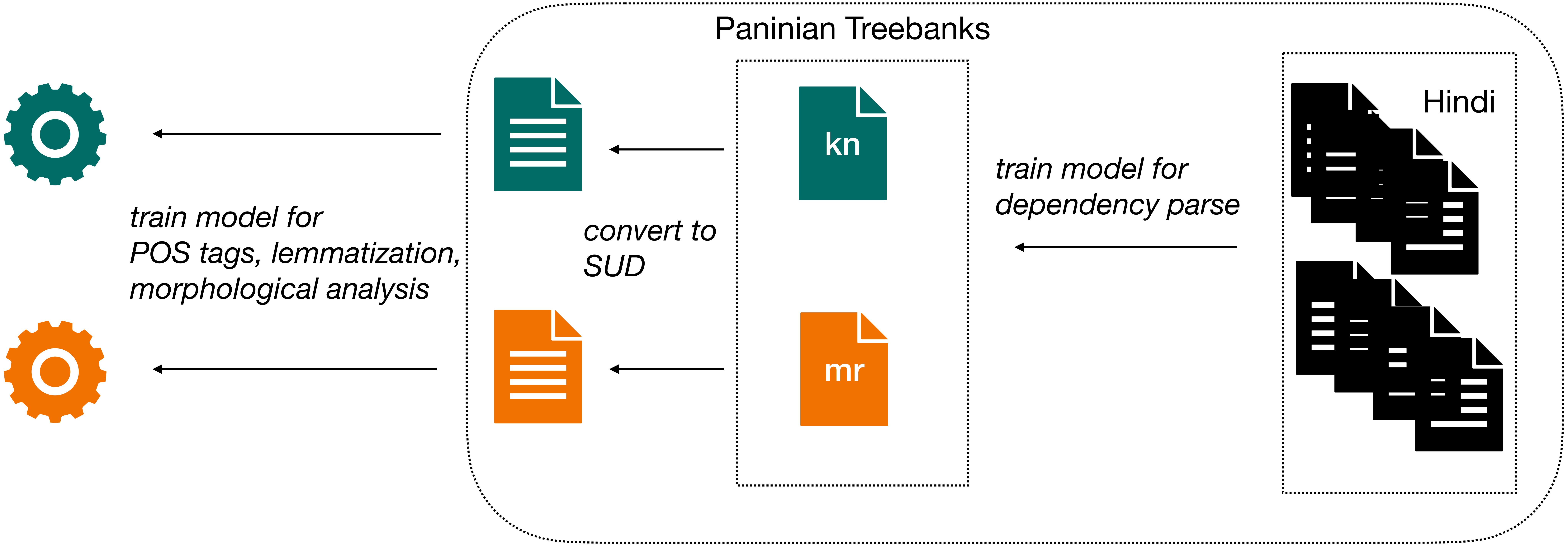

Paninian Treebanks

Hindi

train model for dependency parse

kn

mr

convert to SUD

train model for POS tags, lemmatization, morphological analysis

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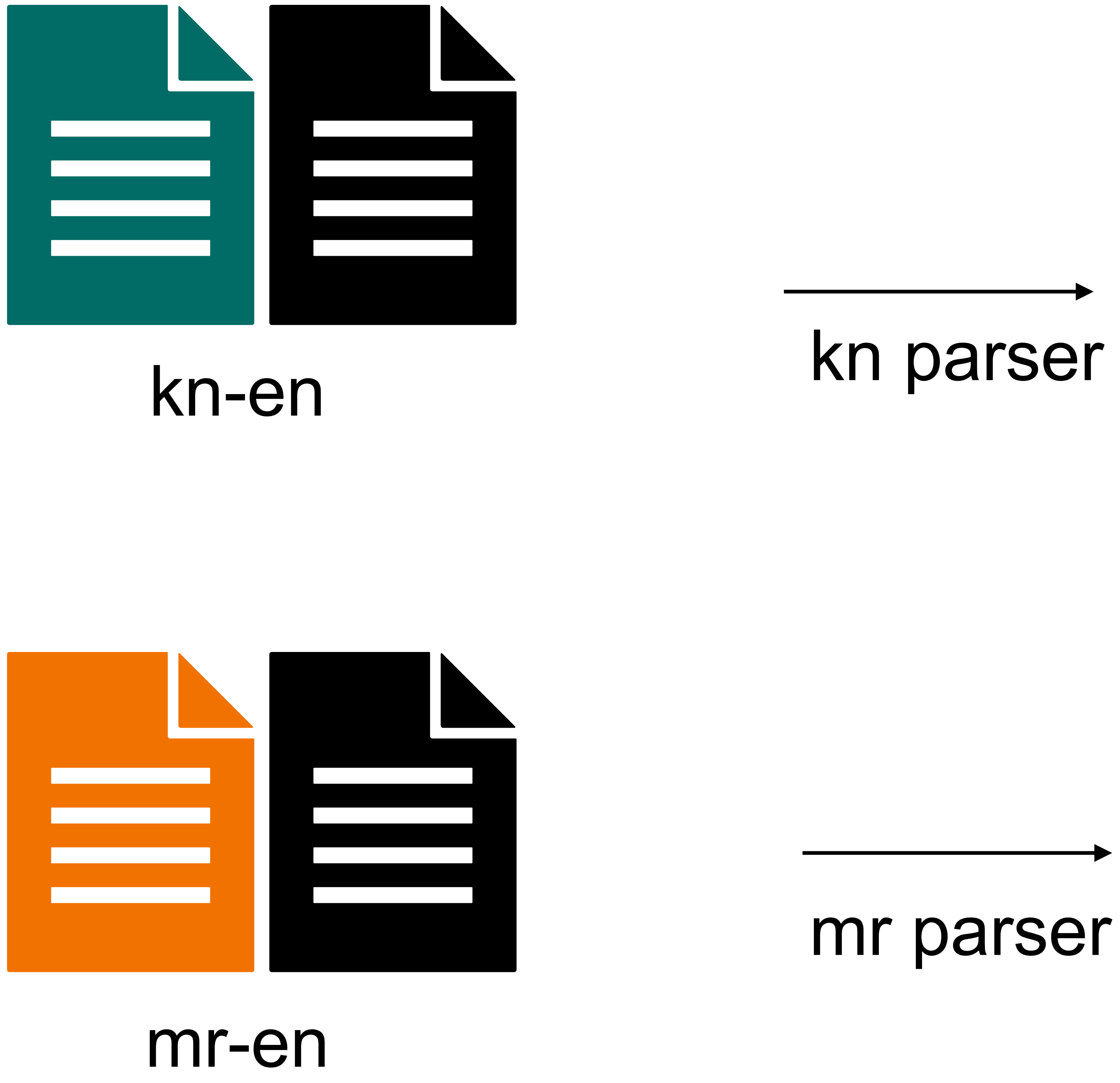


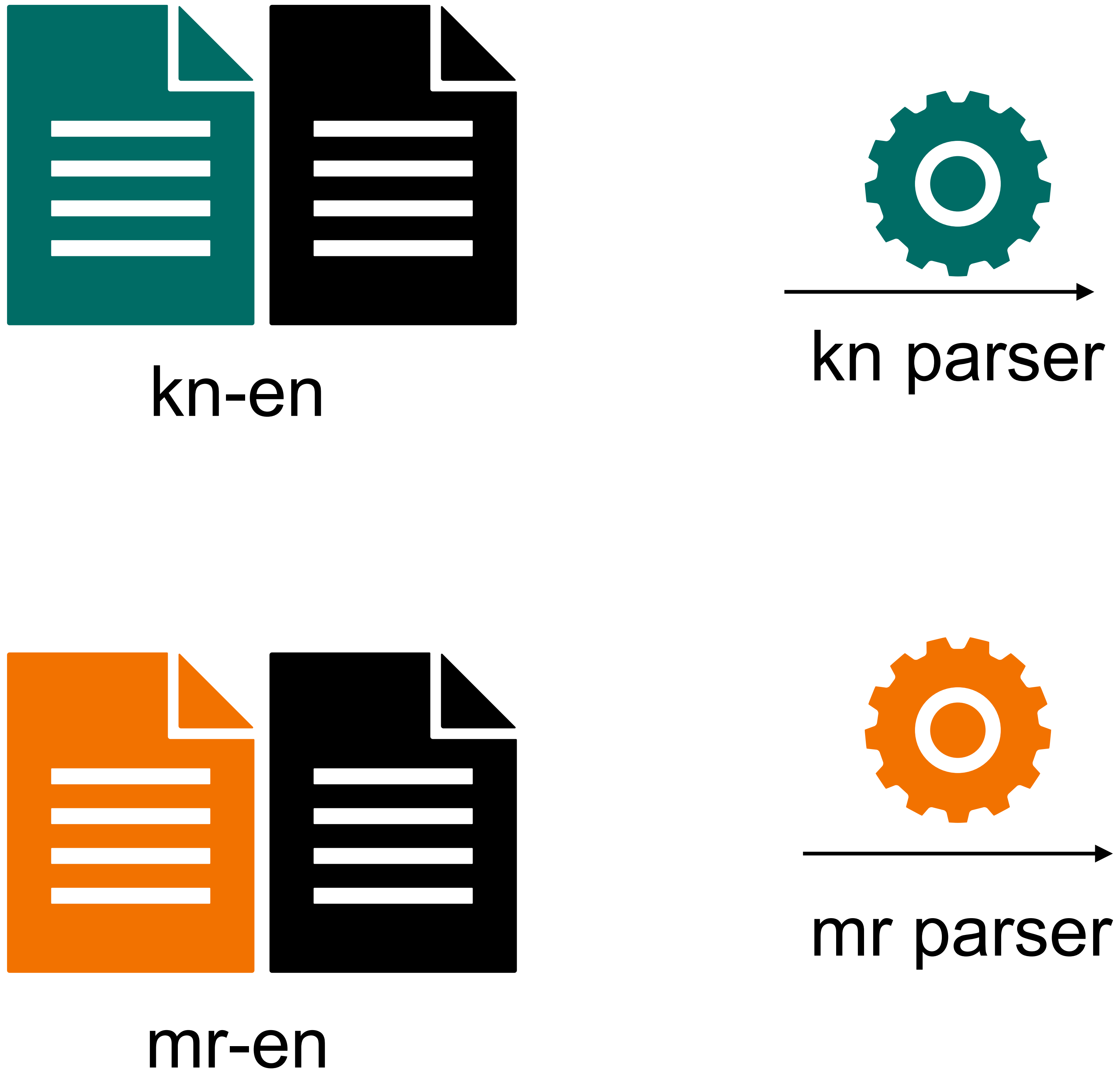
kn-en

kn parser

mr-en

mr parser

AutoLEX: Extracting Language Descriptions



kn-en

kn parser

mr-en

mr parser

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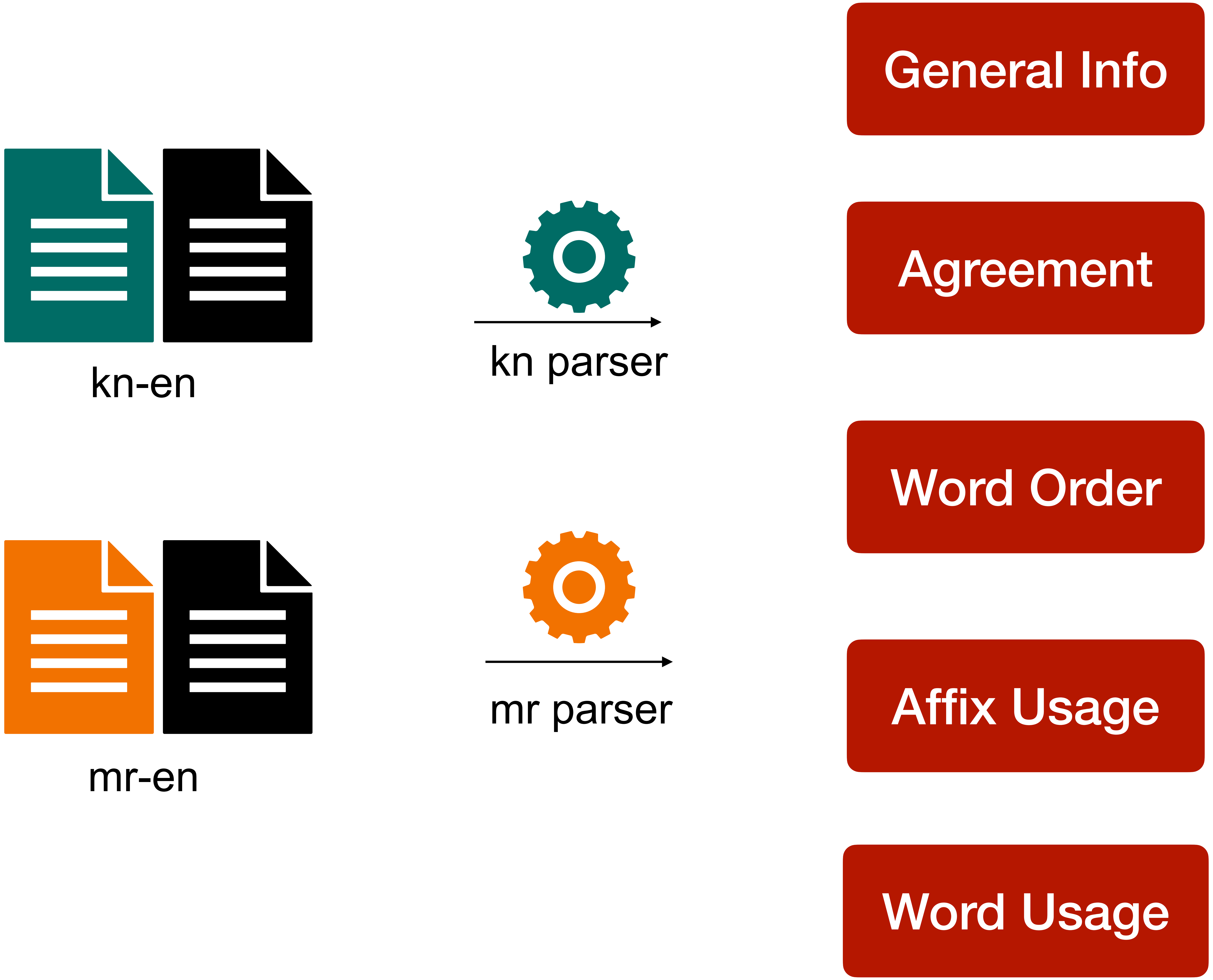

kn-en

kn parser

mr-en

mr parser

General Info

Agreement

Word Order

Affix Usage

Word Usage

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AutoLEX: Extracting Language Descriptions

kn-en

kn parser

mr-en

mr parser

General Info

Agreement

Word Order

Affix Usage

Word Usage

Linguistic Question

Formulate the linguistic question into a classification task

Extract Features and Construct Training Data

Learn an Interpretable Model

Extract and Visualize Rules

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AutoLEX: Quality Study

General Info

Agreement

Word Order

Affix Usage

Word Usage

AutoLEX: Quality Study

Affix Usage

AutoLEX: Quality Study

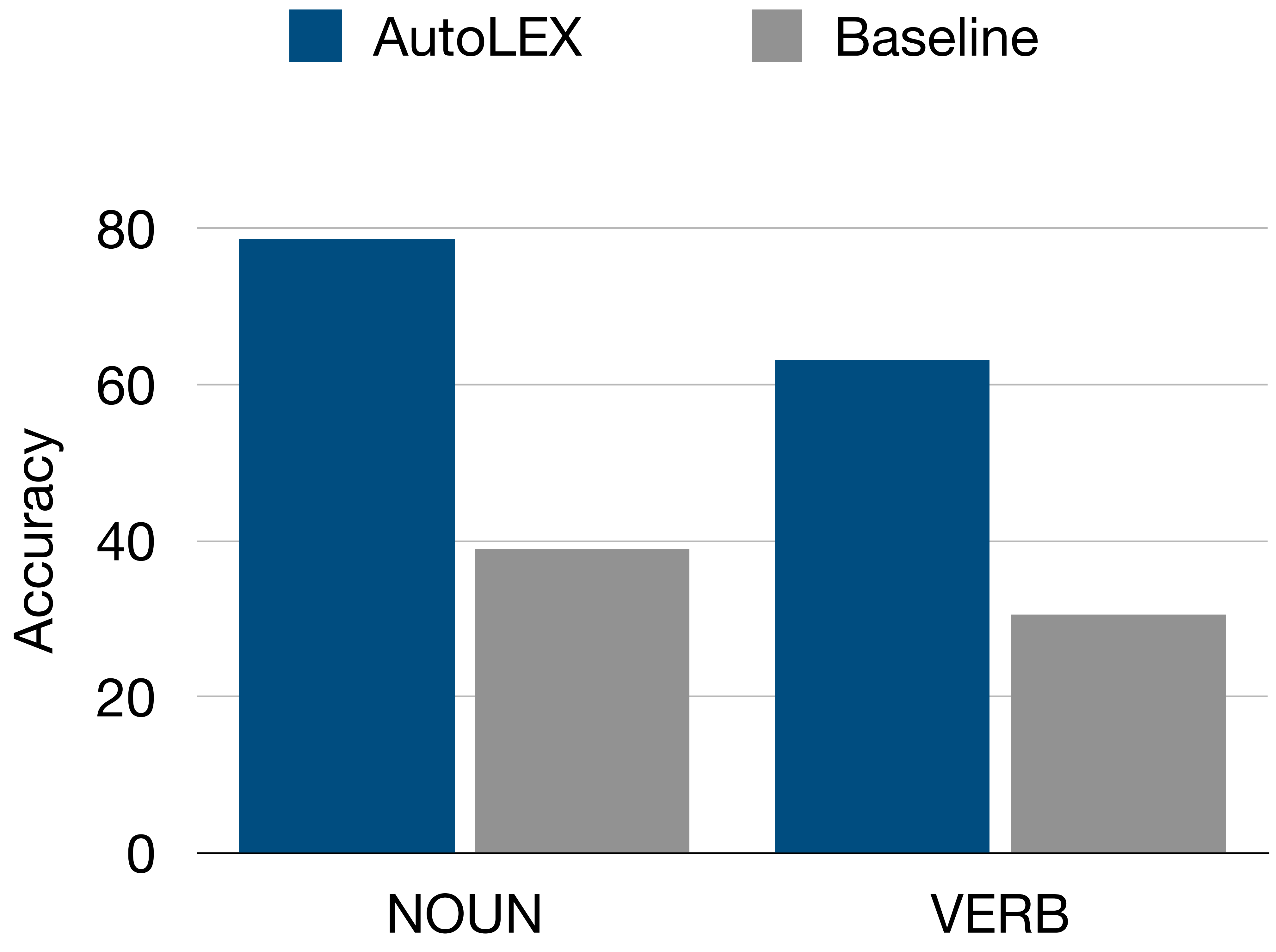
What are the common suffixes for **Kannada nouns**
and when is each used?

Affix Usage

AutoLEX: Quality Study

What are the common suffixes for **Kannada nouns** and when is each used?

Affix Usage



Automated Evaluation

AutoLEX: Quality Study

What are the common suffixes for Kannada nouns
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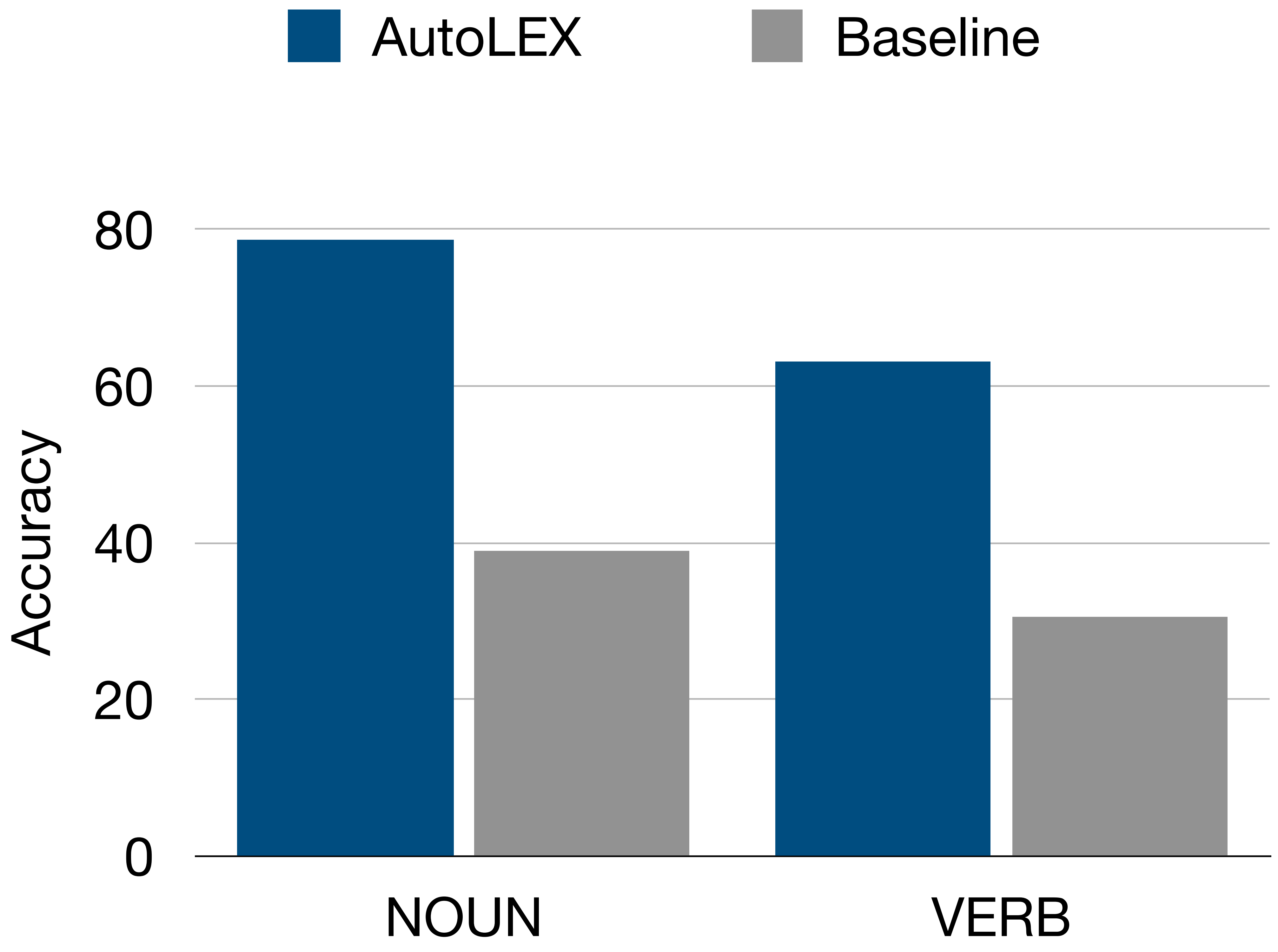
Affix Usage

NOUN: **9*/18 valid**

VERB: **7/13 valid**

Expert Evaluation



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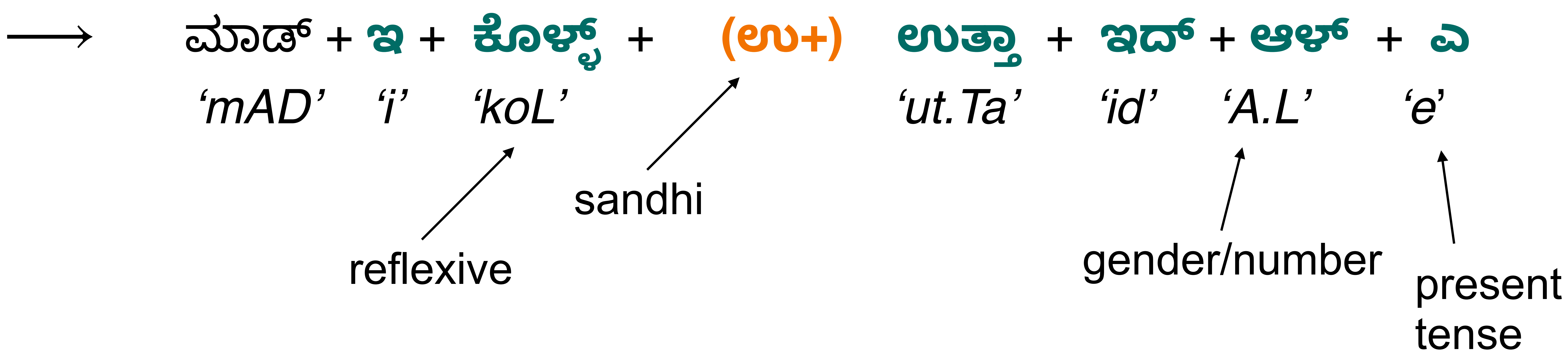

ಮಾಡಿಕೊಳ್ಳುತ್ತಿದ್ದಾಳೆ ⟶ ಮಾಡ್ + ಇ + ಕೊಳ್ಳ್ + (ಉ+) ಉತ್ತಾ + ಇದ್ + ಆಳ್ + ಎ

‘she’s doing it for herself’ *‘mAD’ ‘i’ ‘koL’ ‘ut.Ta’ ‘id’ ‘A.L’ ‘e’*

AutoLEX: Teacher Perception Study

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AutoLEX: Teacher Perception Study

- Evaluate the **relevance**, **utility**, and **presentation** of the materials

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AutoLEX: Teacher Perception Study

- Evaluate the **relevance**, **utility**, and **presentation** of the materials
- Recruited **12 Kannada teachers** and **5 Marathi teachers**

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Introduce **AutoLEX**
to teachers

AutoLEX: Teacher Perception Study

- Evaluate the **relevance**, **utility**, and **presentation** of the materials
- Recruited **12 Kannada teachers** and **5 Marathi teachers**

☎ →

Introduce **AutoLEX**
to teachers

🔍 →

1-2 weeks for
exploration of materials

AutoLEX: Teacher Perception Study

- Evaluate the **relevance**, **utility**, and **presentation** of the materials
- Recruited **12 Kannada teachers** and **5 Marathi teachers**

Introduce **AutoLEX** to teachers → 1-2 weeks for exploration of materials → Fill the questionnaire

Teacher Perception of Automatically Extracted Grammar Concepts for L2 Language Learning
Chaudhary**, Sampath, Sheshadri, Anastasopoulos, Neubig.* ***In Submission.

AutoLEX: Teacher Perception Study

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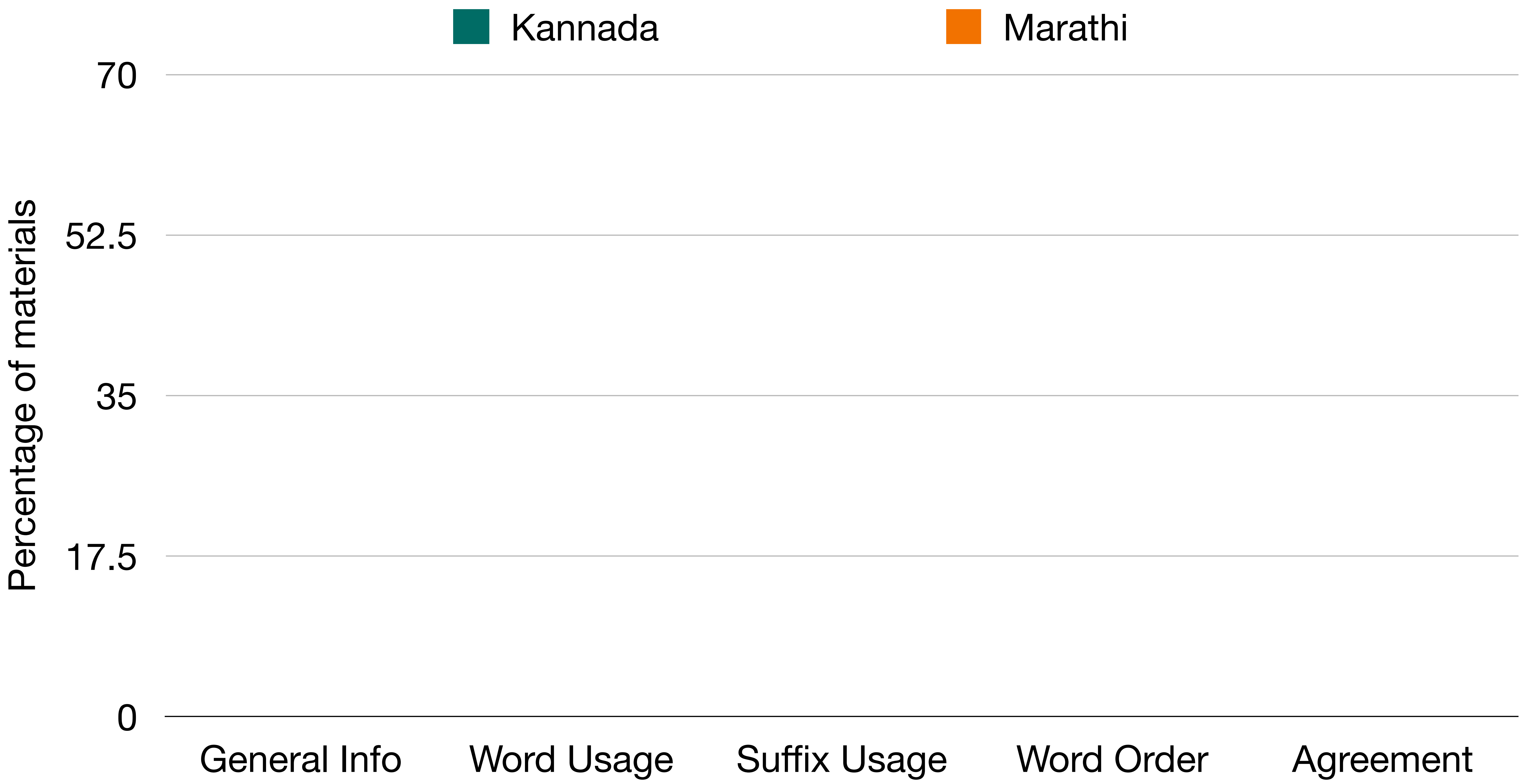

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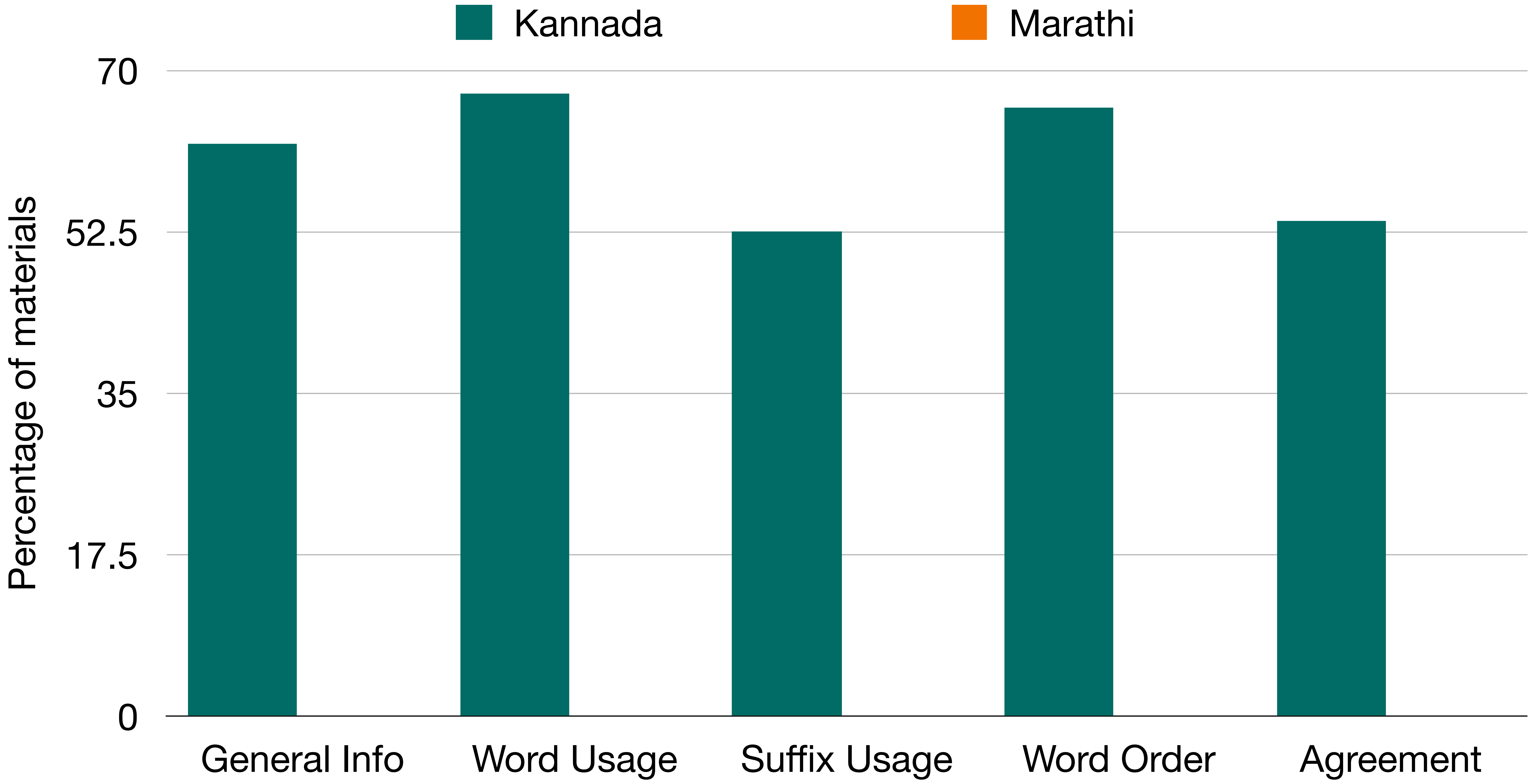

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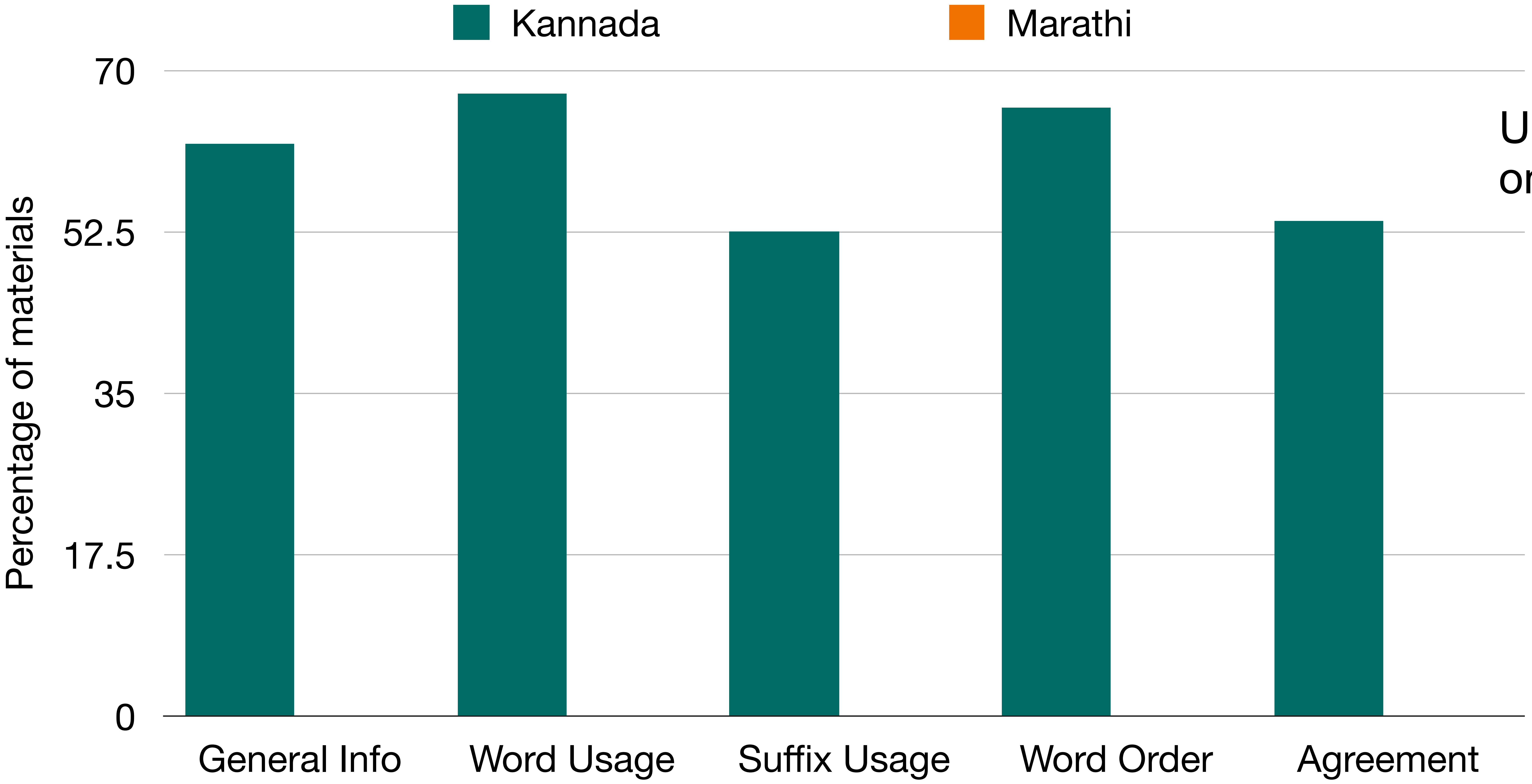

Underlying corpora based
on **formal and traditional usage**

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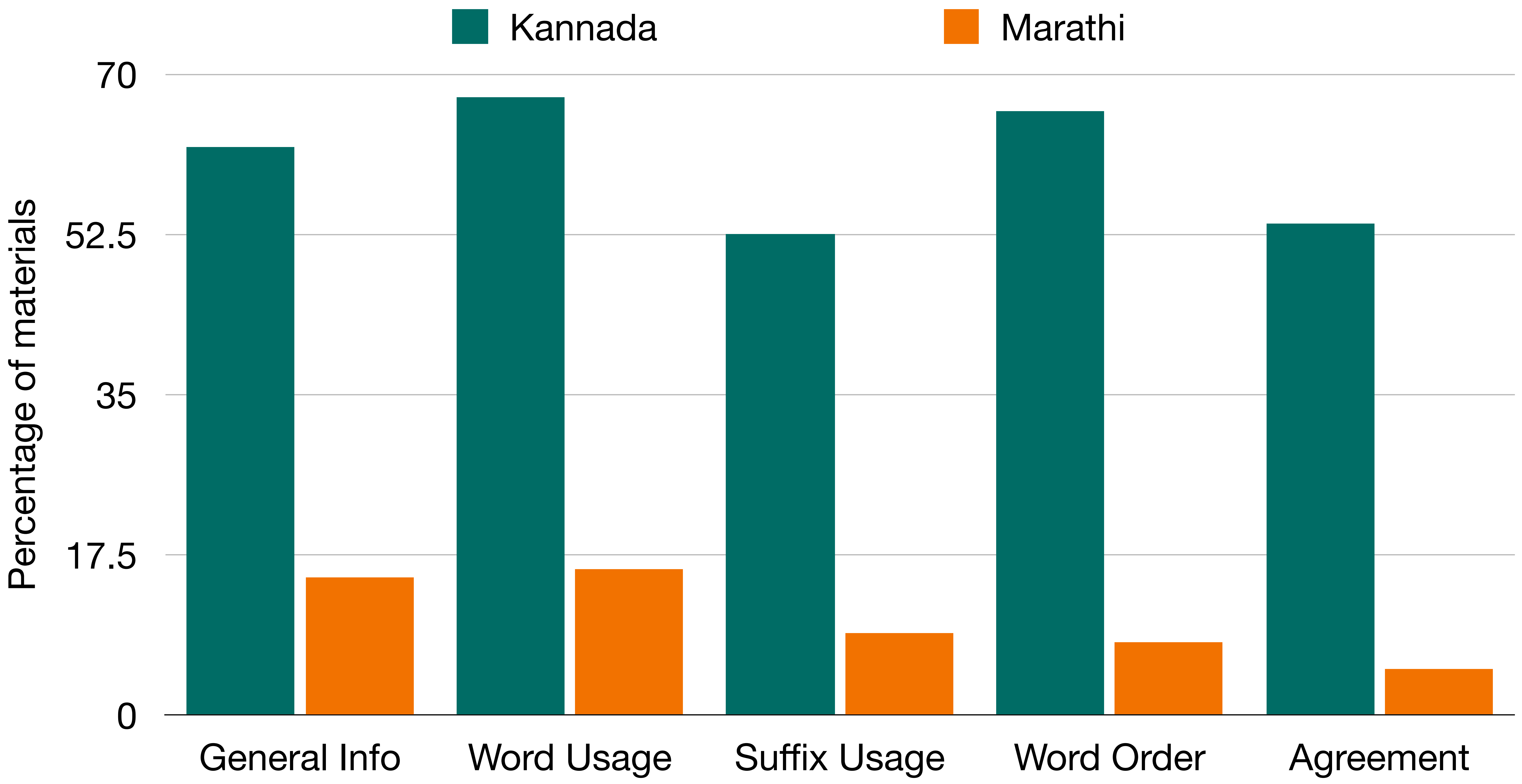

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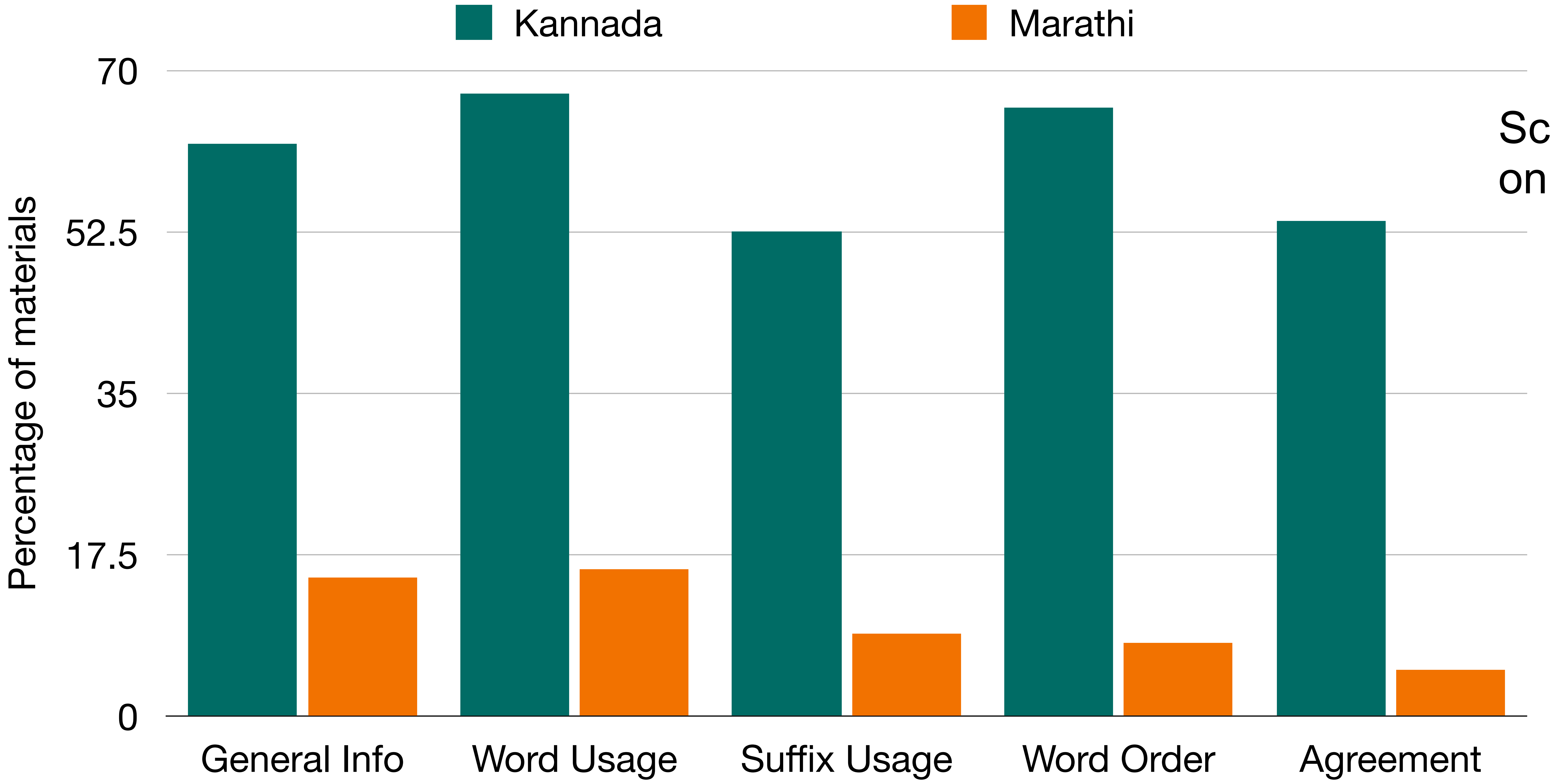

School's primary focus on **beginner-levels**

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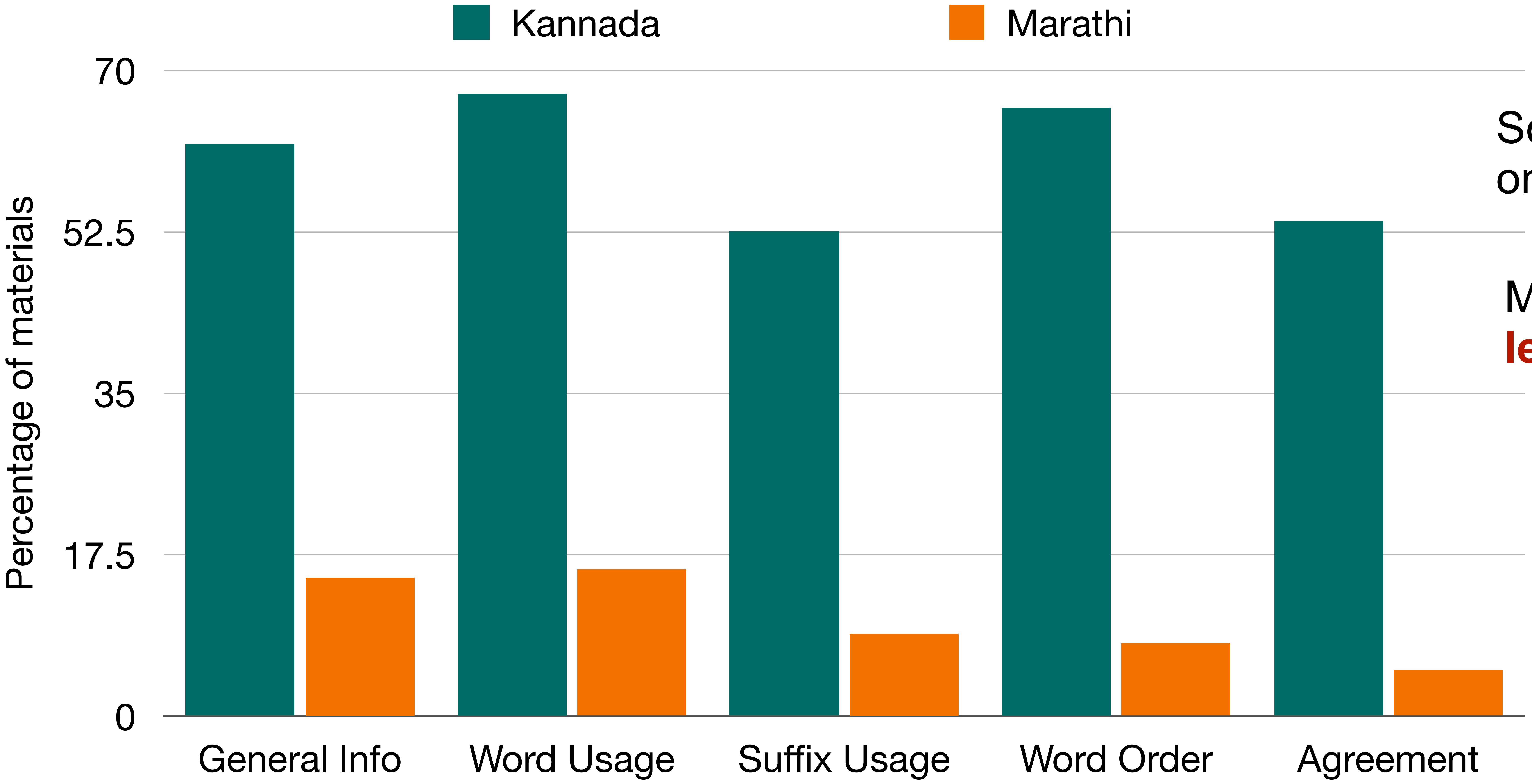

School's primary focus on **beginner-levels**

More beneficial for **advanced learners**

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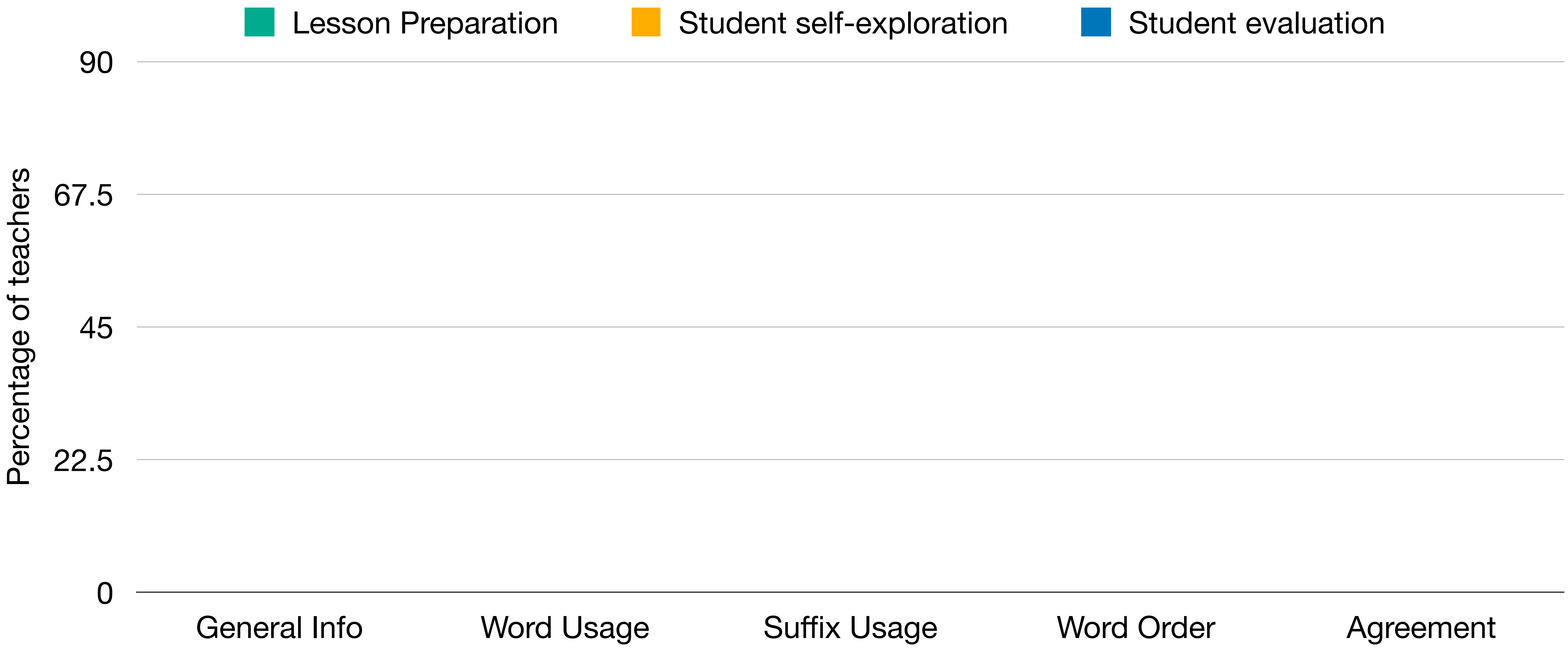

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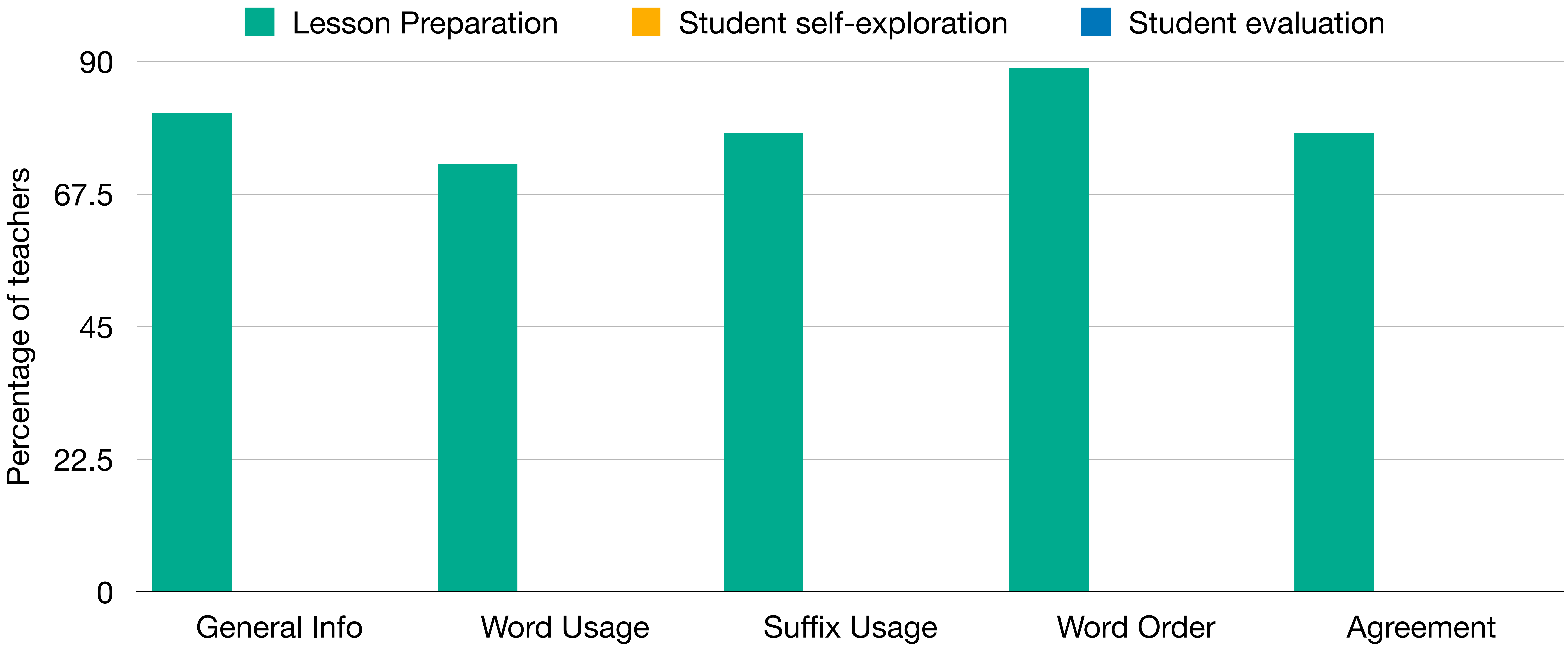

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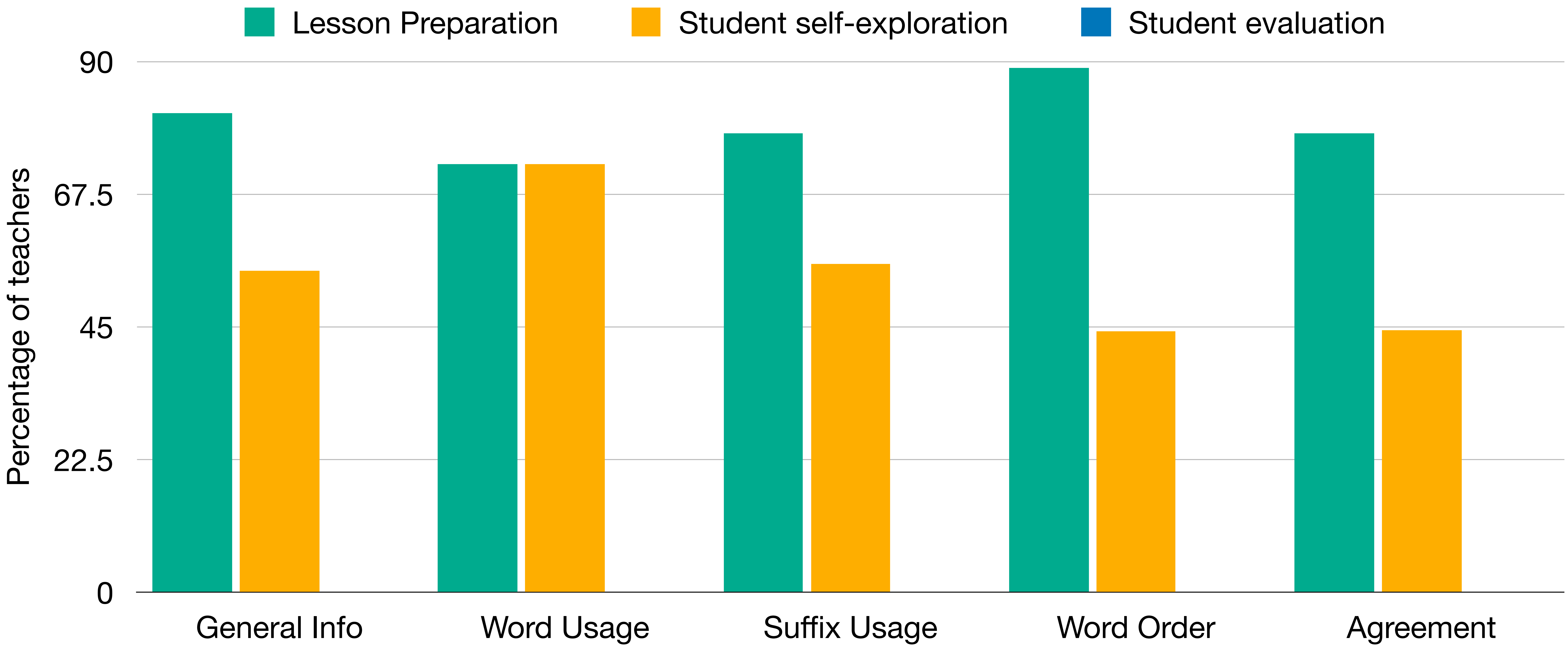

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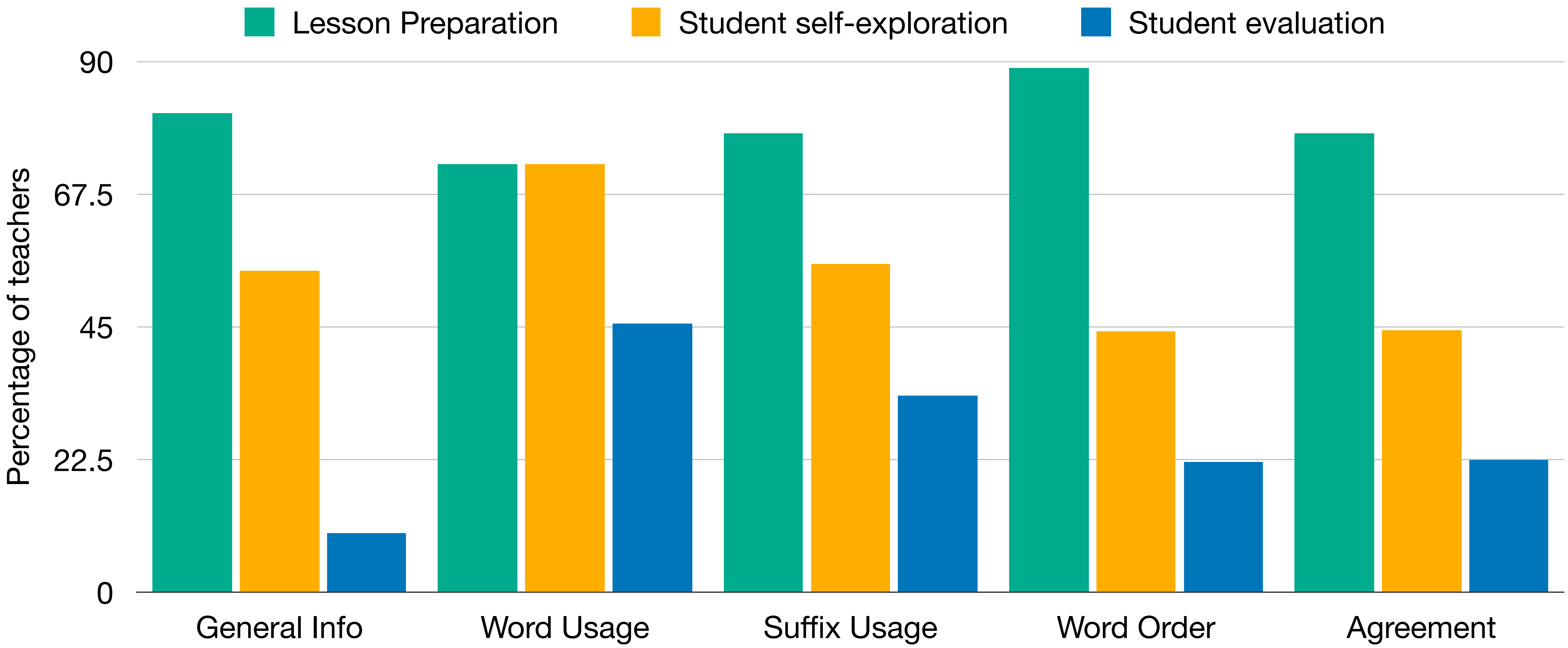

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AutoLEX: Teacher Testimonials

The illustrative examples, and the grouped synonyms. It does need some work on accuracy in some places, but this is a great start!

I used this tool to teach an American adult who takes private lessons, found this tool helpful in addressing her grammar questions.

given that these word pairs have been extracted from natural text, its interesting to see that there are certain word senses which are so frequently used in the real world which currently we haven't covered in our lesson but are we are now thinking of adding them.

If this tool could be used to target the older kids it would be very helpful. However, the past present and future tenses of the verbs are interesting and this tool managed to impress me with the vast database, Unfortunately, the words used are very technical, and make excellent tool to improve writing skills.

Providing teachers the ability to input a curated set of data (stories written in good and correct language) to prepare relevant examples from may be helpful. Working more collaboratively will help us a lot

Other Applications

Other Applications

Language
Descriptions

Other Applications

Automatic Multilingual Grammar Checker

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Descriptions →

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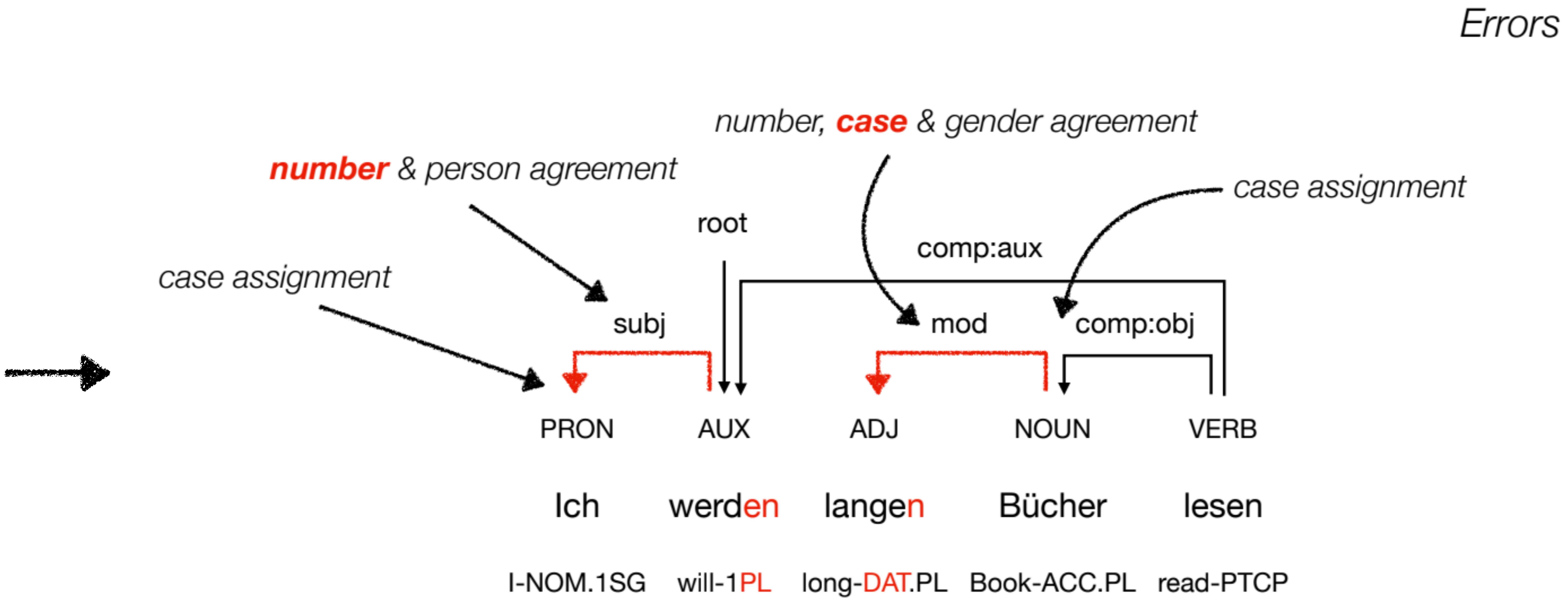

Errors

*number, **case** & gender agreement*

***number** & person agreement*

case assignment

root

comp:aux

case assignment

subj

mod

comp:obj

PRON AUX ADJ NOUN VERB

Ich werden langen Bücher lesen

I-NOM.1SG will-1PL long-DAT.PL Book-ACC.PL read-PTCP

Evaluating the Morphosyntactic Well-formedness of Generated Texts
*Pratapa, Anastasopoulos, RIjhwani, **Chaudhary,** Mortensen, Sheikh, Neubig, Tsvetkov.* ***EMNLP 2020***

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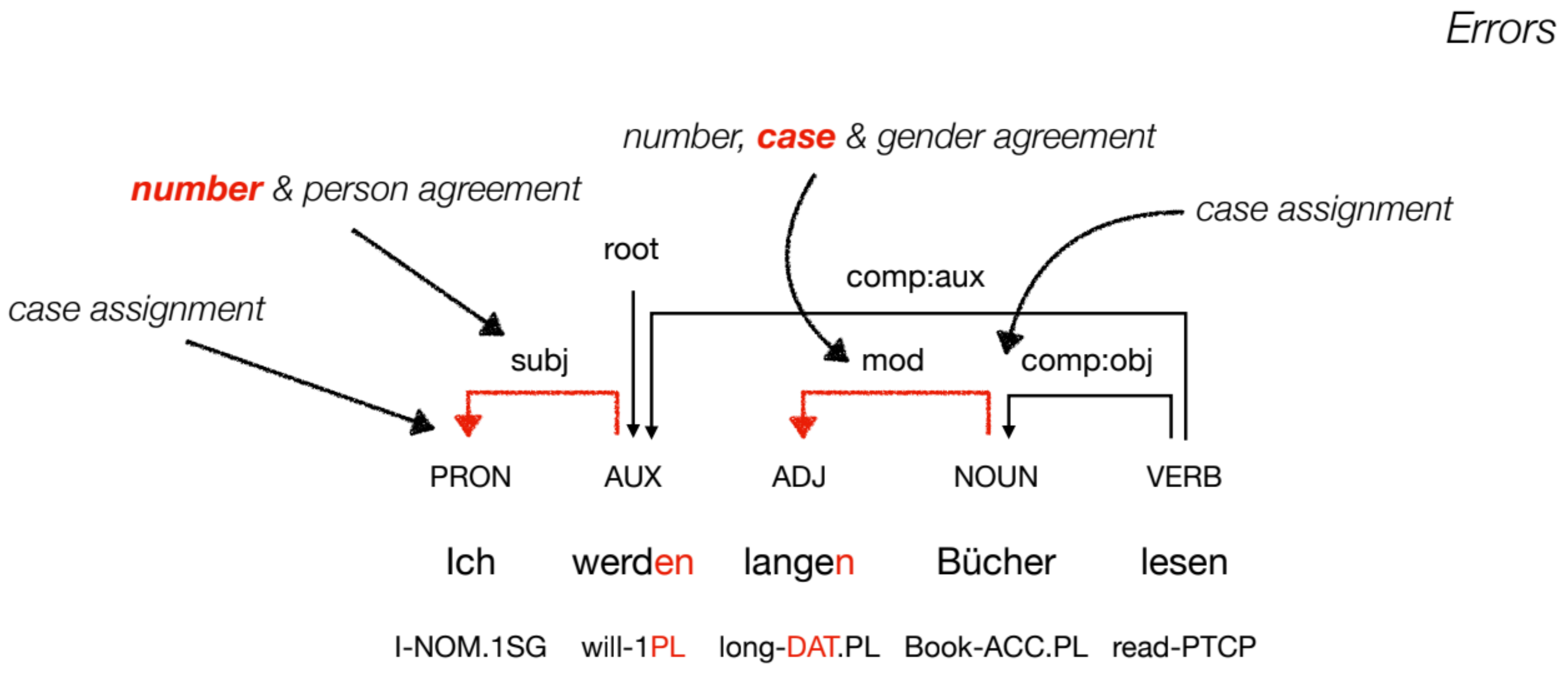

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Evaluating Context-Usage in MT models

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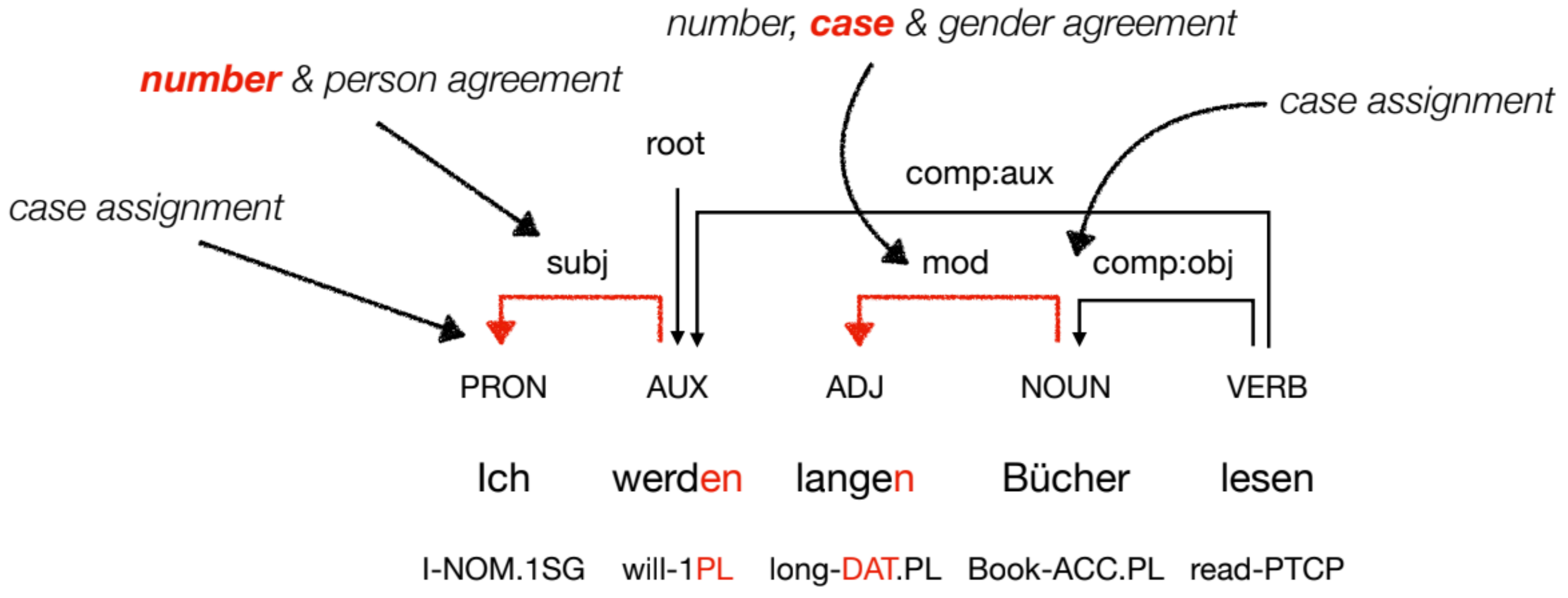

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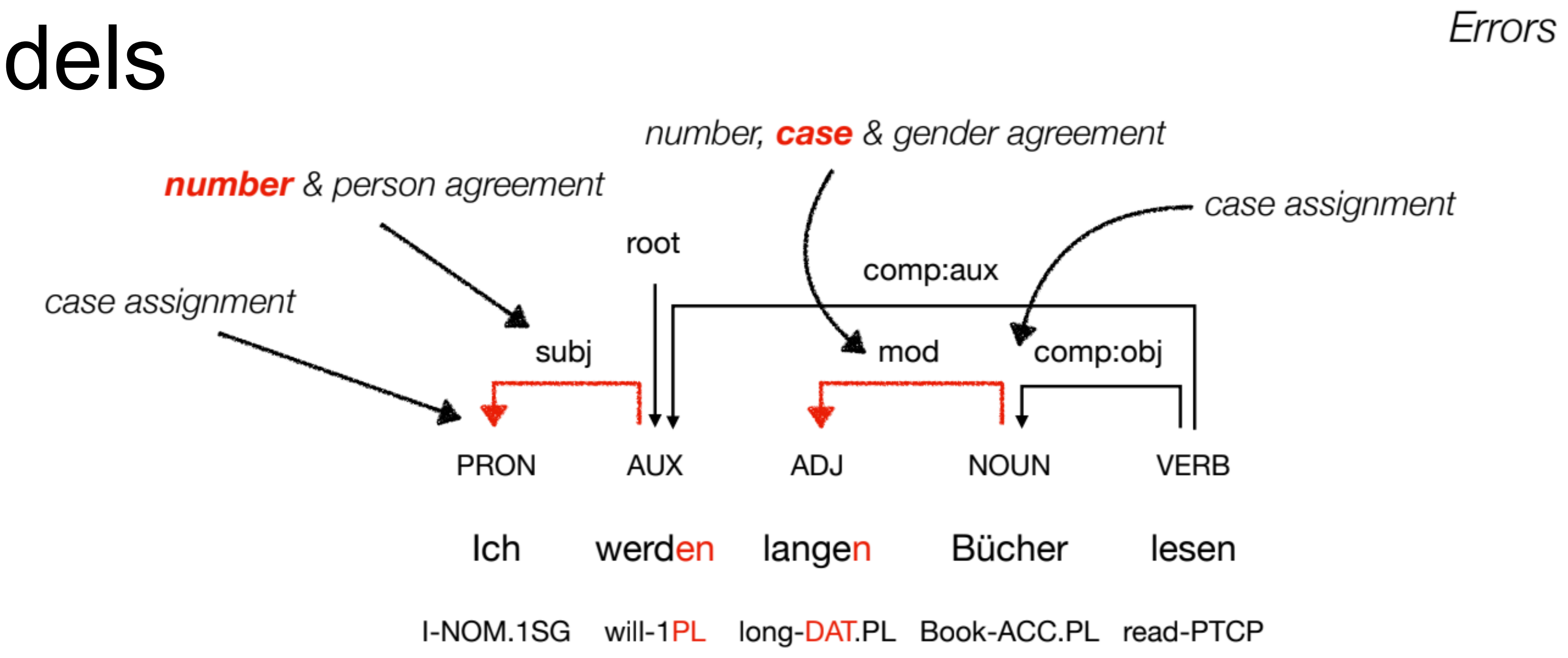
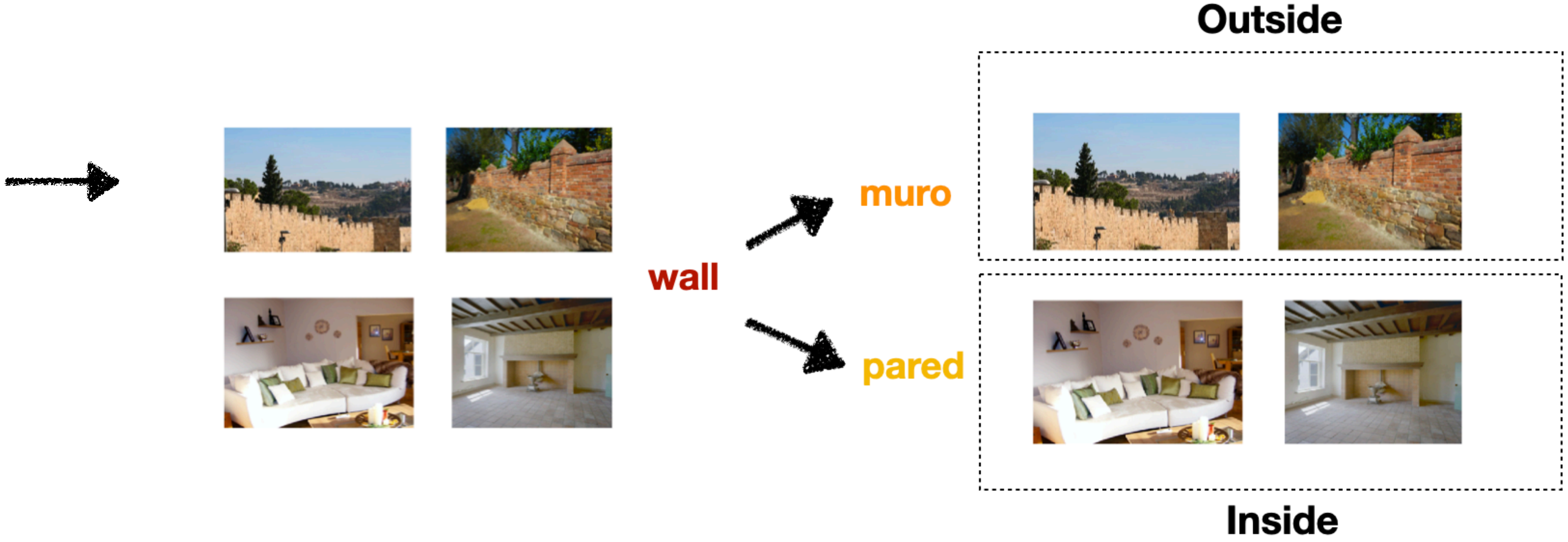


Evaluating the Morphosyntactic Well-formedness of Generated Texts

Language Descriptions



When is Wall a Pared and when a Muro? Extracting Rules Governing Lexical Selection
Chaudhary**, Yin, Anastasopoulos, Neubig.* ***EMNLP 2021

Other Applications

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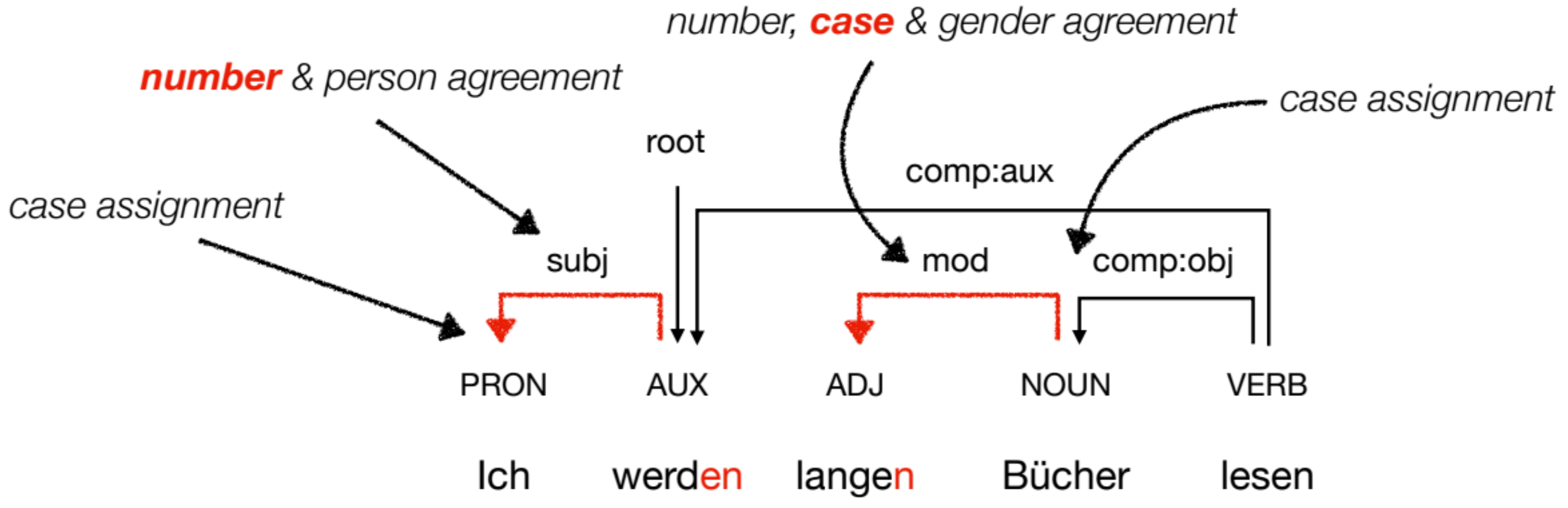

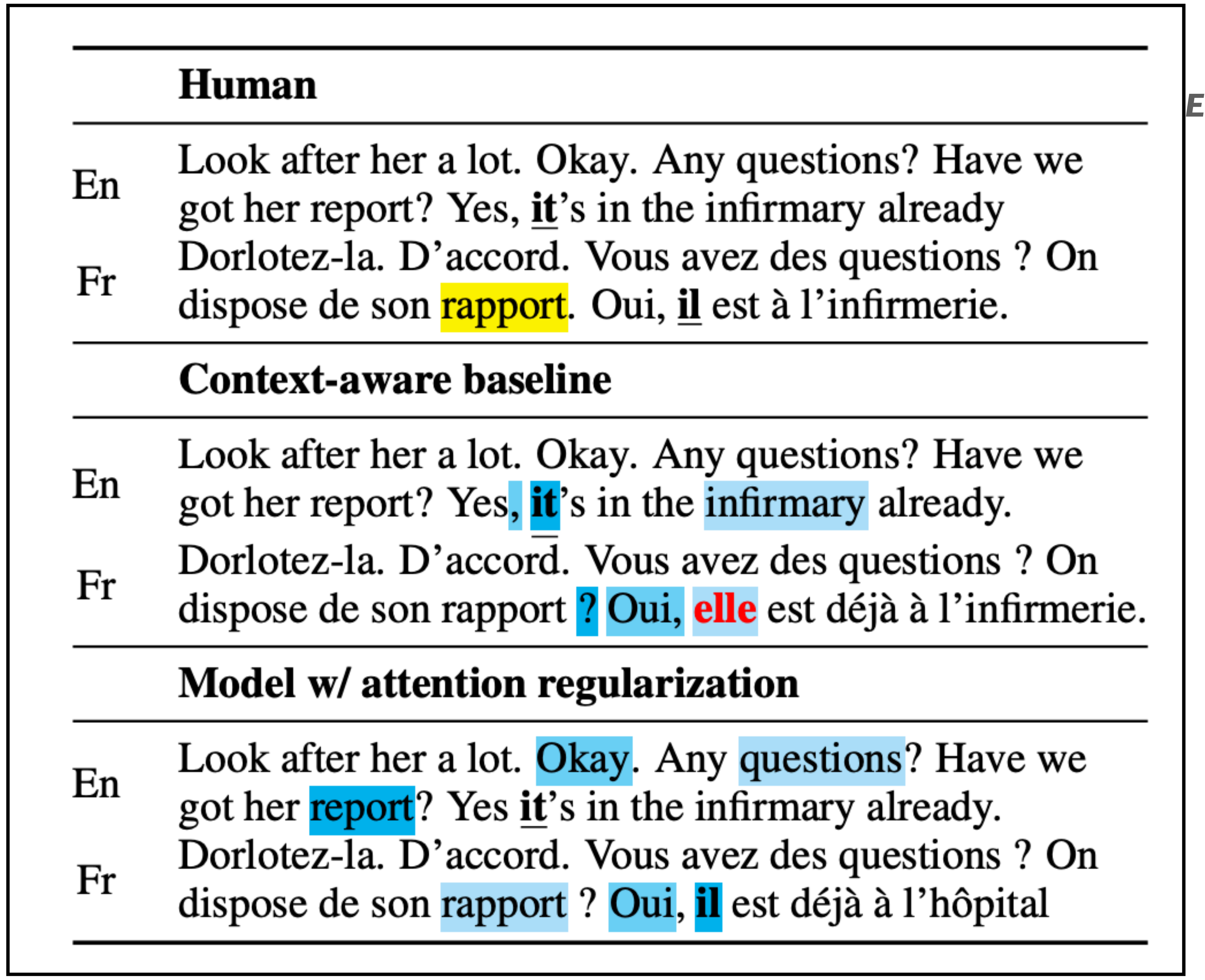

	Human
En	Look after her a lot. Okay. Any questions? Have we got her report? Yes, **it**'s in the infirmary already
Fr	Dorlotez-la. D'accord. Vous avez des questions ? On dispose de son rapport. Oui, **il** est à l'infirmerie.
	Context-aware baseline
En	Look after her a lot. Okay. Any questions? Have we got her report? Yes, **it**'s in the infirmary already.
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	Model w/ attention regularization
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EMNLP 2020

Language Descriptions →

Do Context-Aware Translation Models Pay the Right Attention?
*Yin, Fernandes, Pruthi, **Chaudhary**, Martins, Neubig.* ***ACL 2021***

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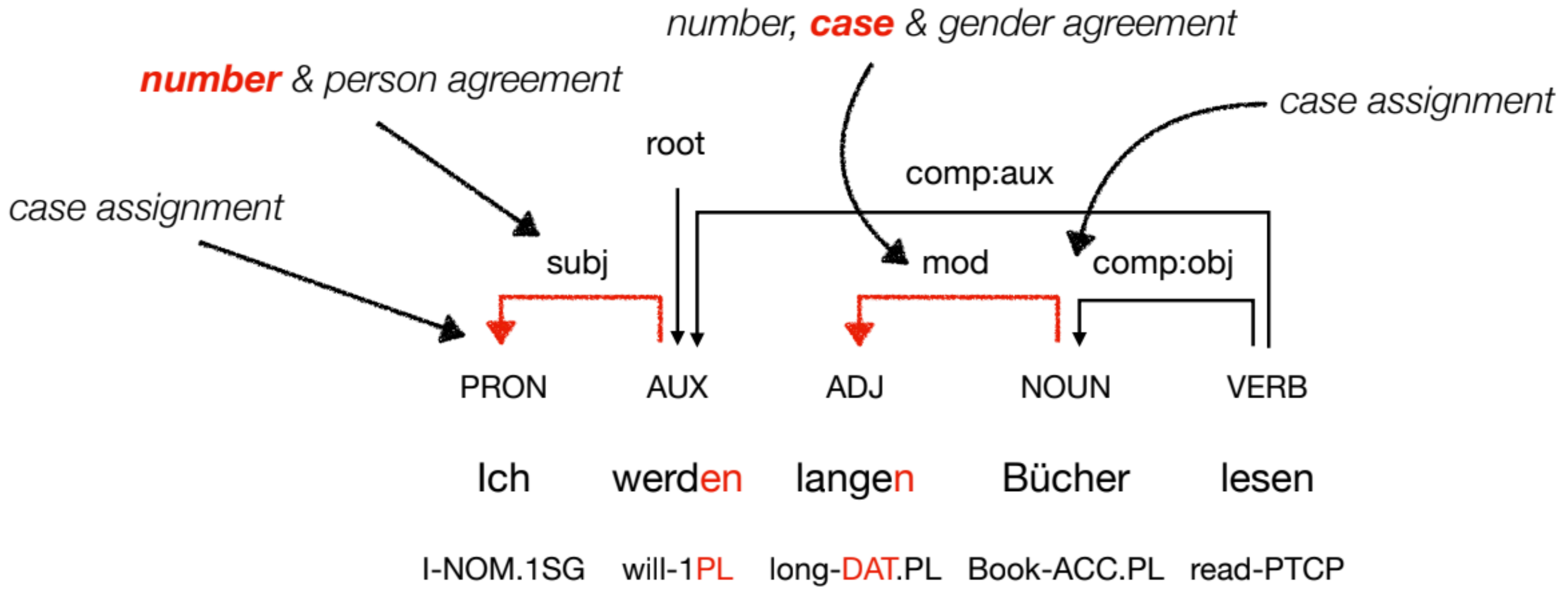

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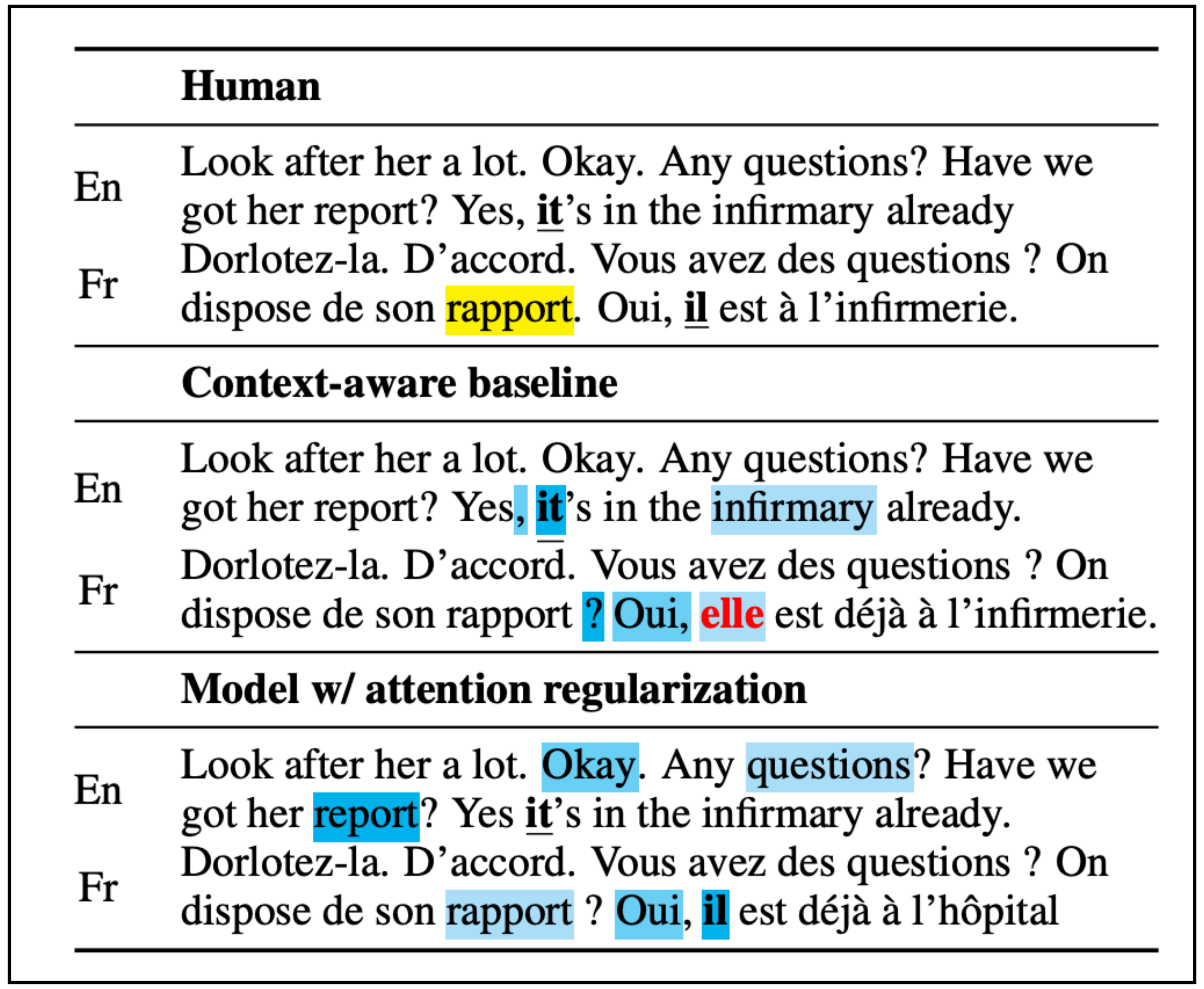

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Contributions

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- **AutoLEX: framework to extract and visualize language descriptions**

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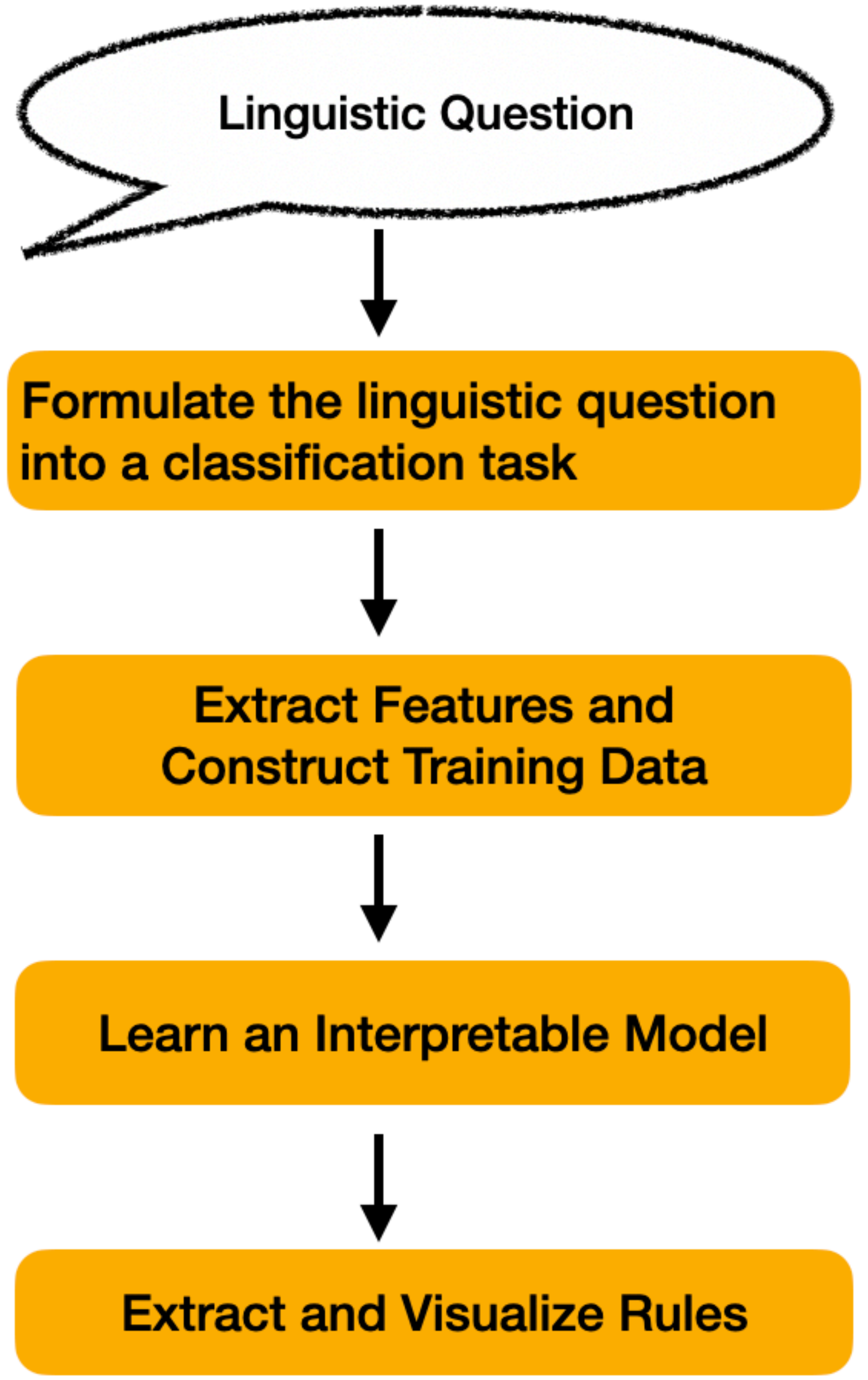


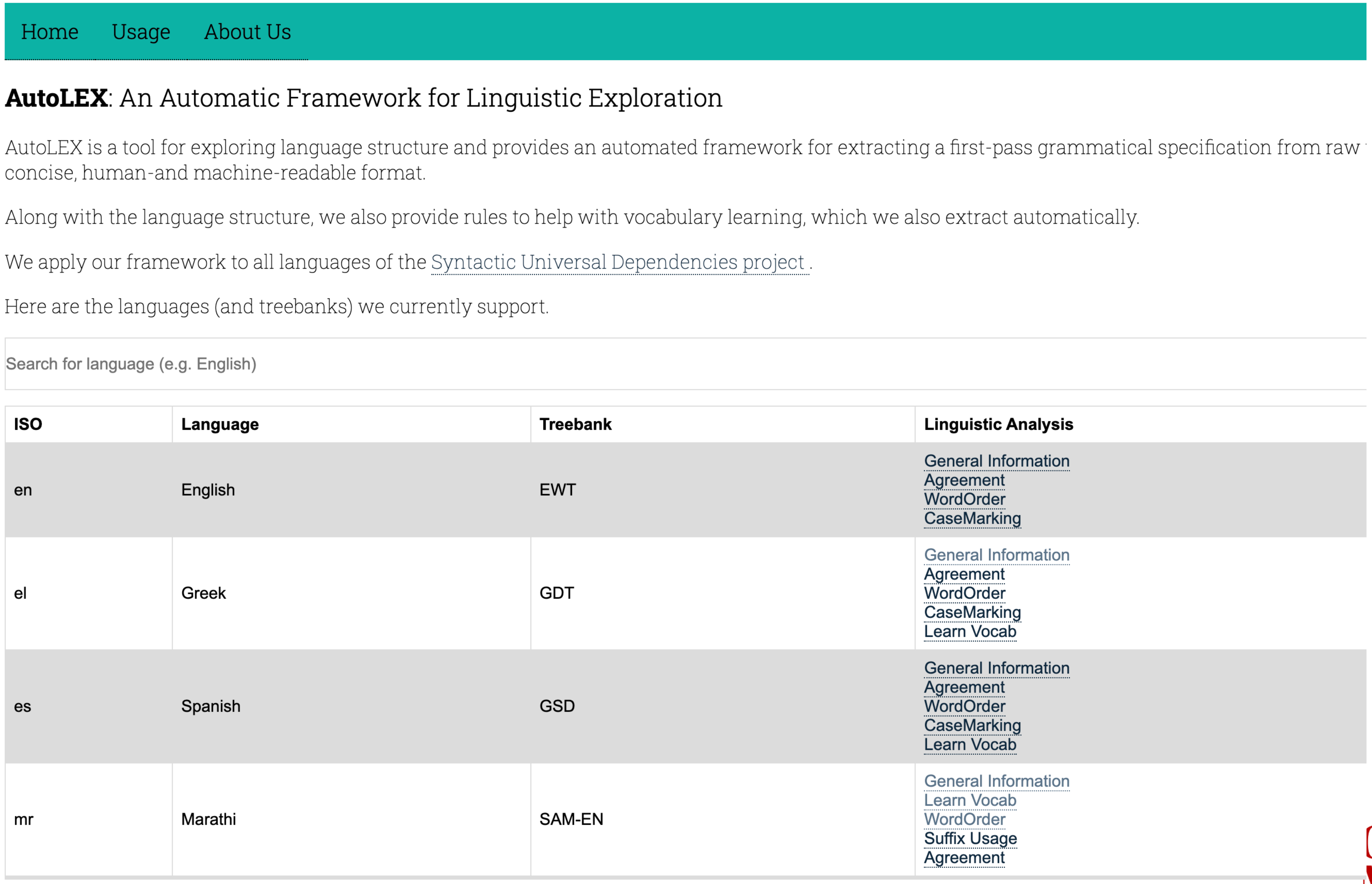
Linguistic Question

Formulate the linguistic question into a classification task

Extract Features and Construct Training Data

Learn an Interpretable Model

Extract and Visualize Rules



AutoLEX: An Automatic Framework for Linguistic Exploration

AutoLEX is a tool for exploring language structure and provides an automated framework for extracting a first-pass grammatical specification from raw concise, human-and machine-readable format.

Along with the language structure, we also provide rules to help with vocabulary learning, which we also extract automatically.

We apply our framework to all languages of the Syntactic Universal Dependencies project .

Here are the languages (and treebanks) we currently support.

ISO	Language	Treebank	Linguistic Analysis
en	English	EWT	General Information Agreement WordOrder CaseMarking
el	Greek	GDT	General Information Agreement WordOrder CaseMarking Learn Vocab
es	Spanish	GSD	General Information Agreement WordOrder CaseMarking Learn Vocab
mr	Marathi	SAM-EN	General Information Learn Vocab WordOrder Suffix Usage Agreement

Contributions

- **AutoLEX**: framework to extract and visualize language descriptions

http://www.autolex.co/interface/

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- **Real-World Utility**: established collaborations with teacher communities

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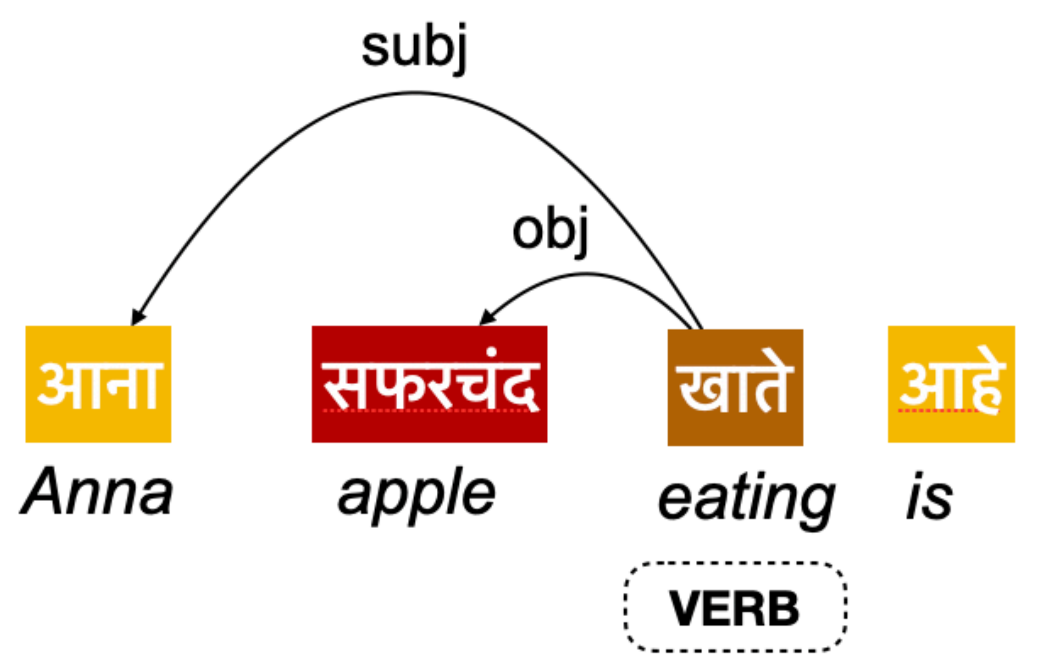
- **Real-World Utility**: established collaborations with teacher communities
- **Under-Resourced NLP**: effectively utilize existing data and collect new data

(Low-resource) Language Analysis



AutoLEX: Automatic Language Explorer

Subject **Object** **Verb**

तांदूळ	भात
/tandul/	/bhaat/
‘raw rice’	‘cooked rice’

Applications

Language Education and Documentation

https://www.autolex.co/

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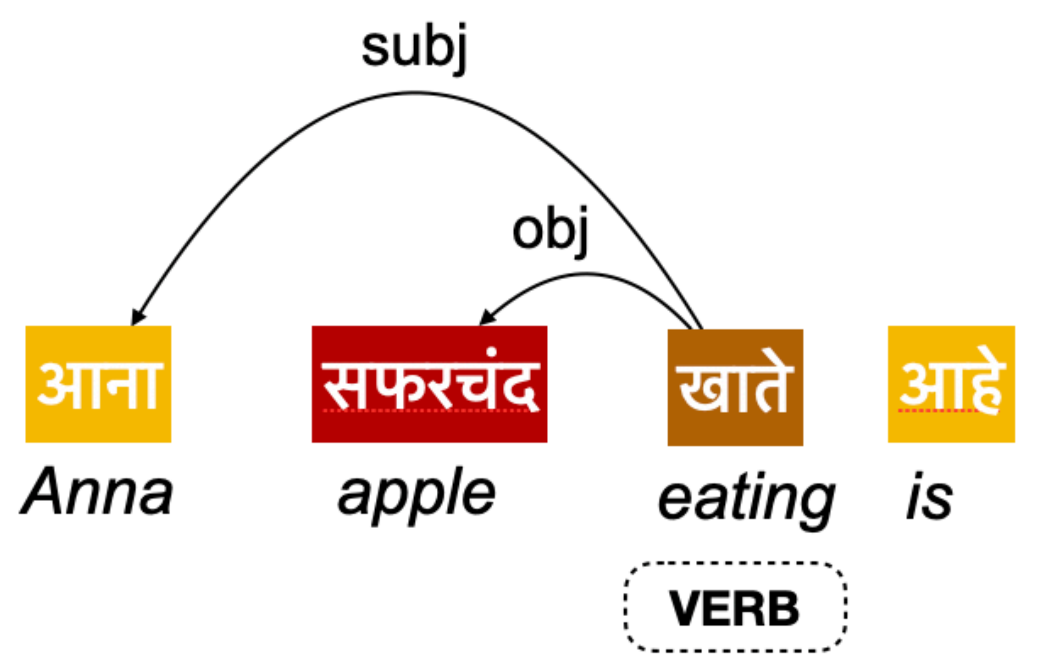

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What's Next?

(Low-resource) Language Analysis

AutoLEX: Automatic Language Explorer

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What's Next?

- We **demonstrated utility** on 4 languages, about 7,000 more to go

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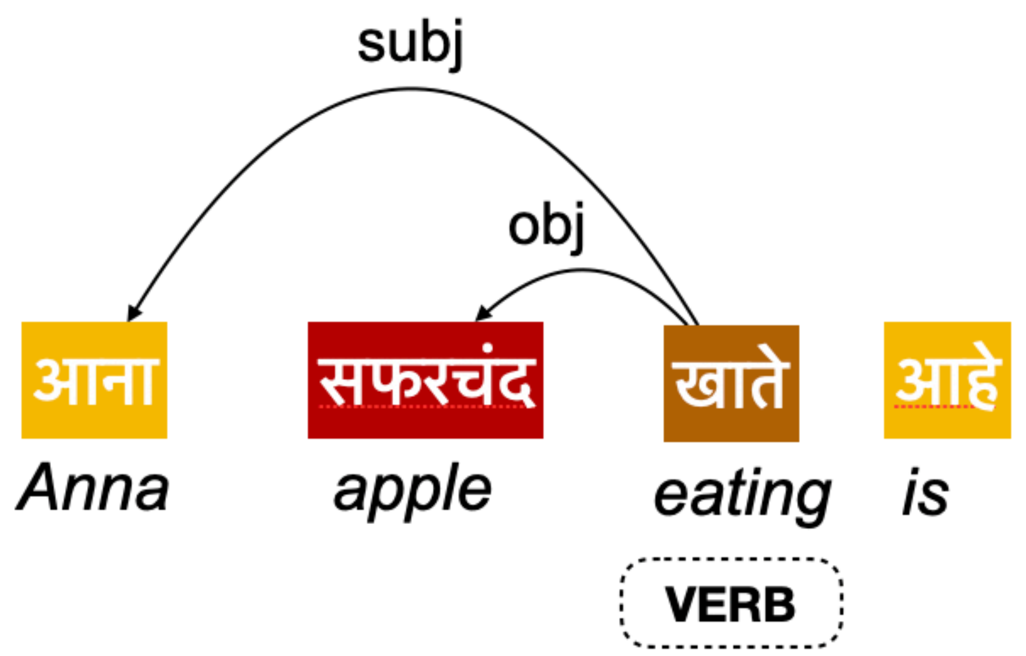

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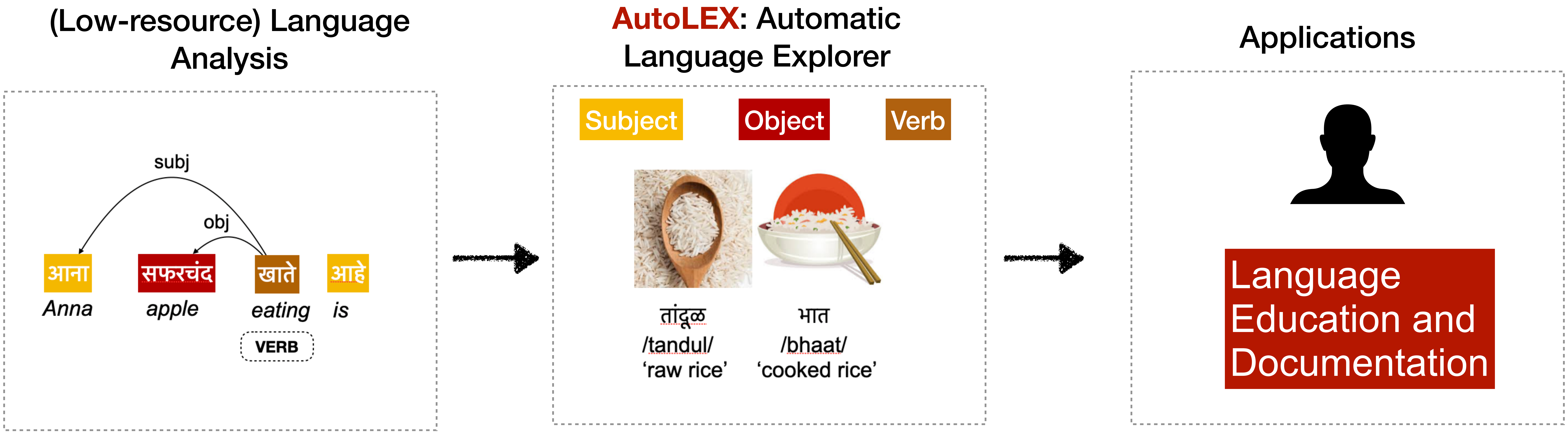
- **Low-resource language analysis** still doesn't work well enough



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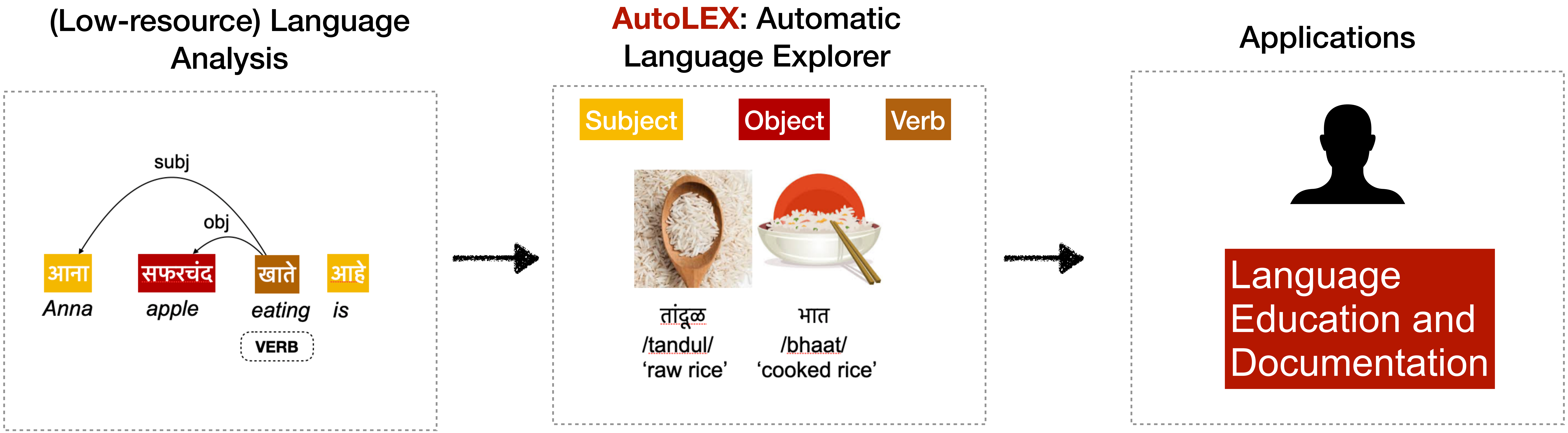
- Better **rule extraction methods**



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What’s Next?

- We **demonstrated utility** on 4 languages, about 7,000 more to go
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- Better **rule extraction methods**
- Close link w/ **data provenance** (conversational text >> legal text)