Scaling
Semantic Role Labeling and Semantic Parsing Across Languages

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Consolidator Grant
MOUSSE No. 726487

elexis european lexicographic infrastructure
ELEXIS project No. 731015

SAPIENZA NLP

Joint work with

Simone Conia

Andrea Di Fabio

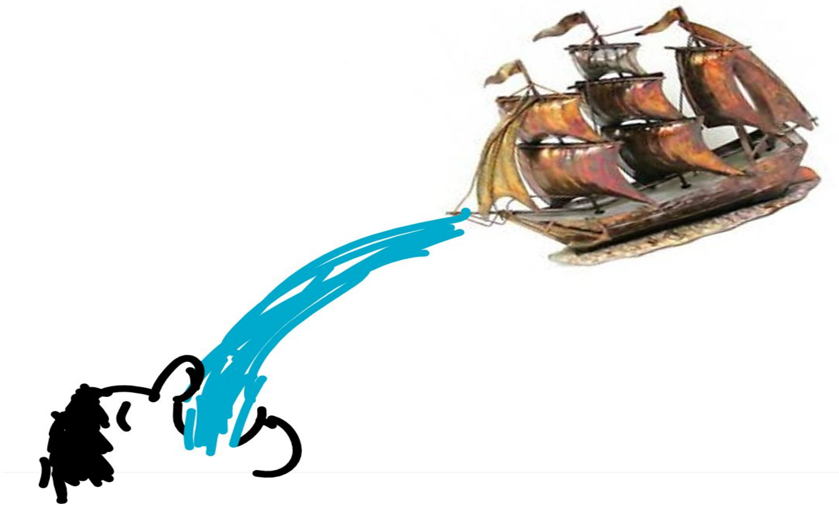
Rexhina Blloshmi

Rocco Tripodi

(with thanks for many slides/pictures)

Machine Translation «does not understand»

- **EN** Is it healthy to drink from a copper vessel?
- **IT** È salutare bere da una nave di rame?
- **EN** Is it healthy to drink from a copper ship?



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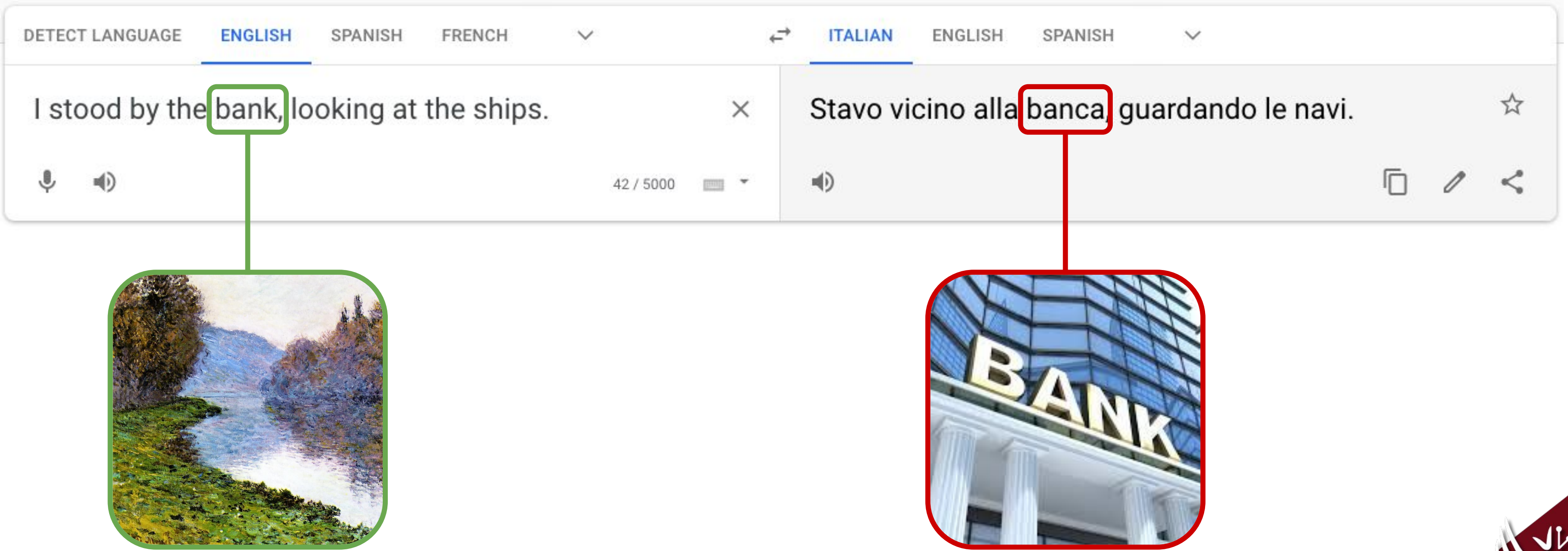
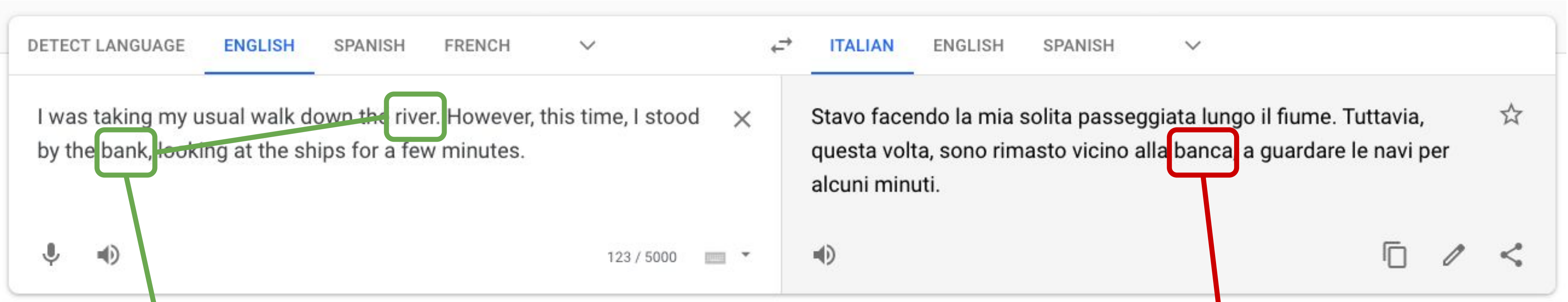


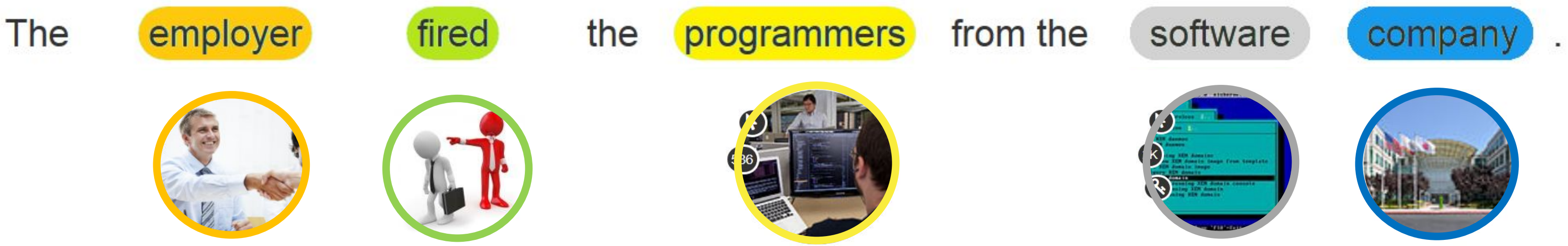
Machine Translation «does not understand»

More context does NOT help...



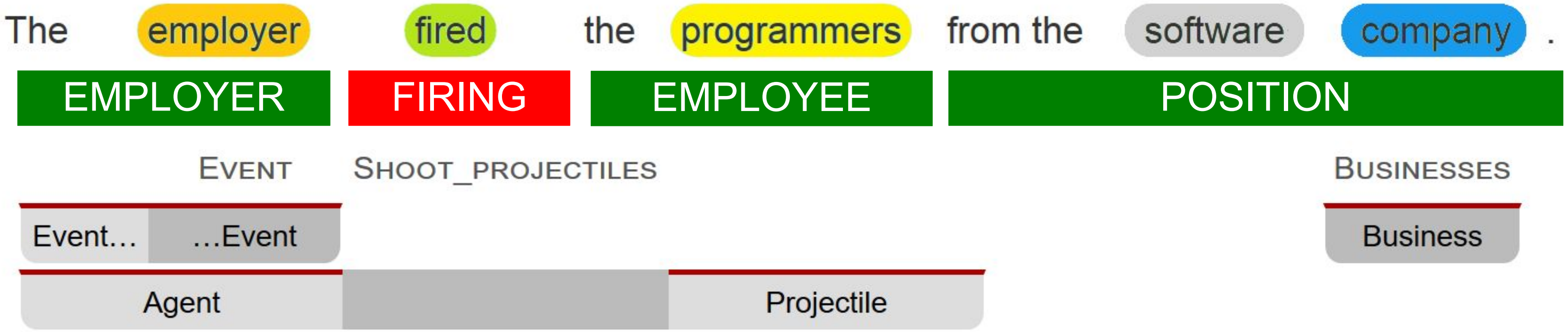
3 tasks to enable Natural Language Understanding

- **Word Sense Disambiguation**
  - Associating meaning with words occurring in context



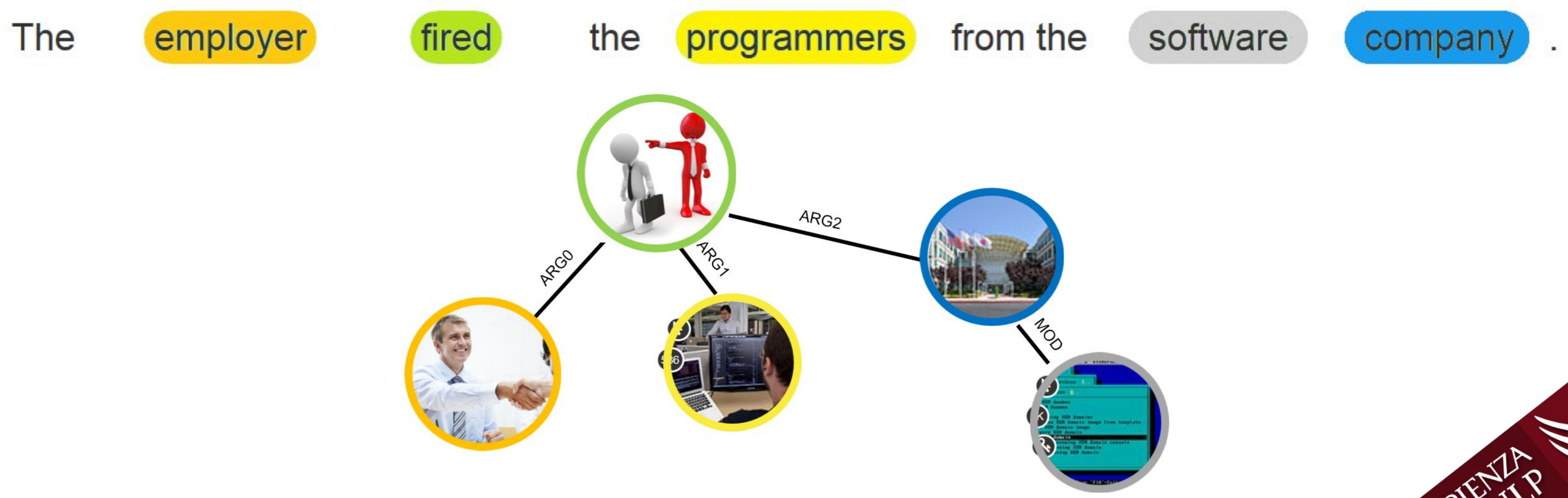
3 tasks to enable Natural Language Understanding

- Word Sense Disambiguation
- **Semantic Role Labeling**
  - «Shallow semantic parsing» which performs predicate-argument annotations



3 tasks to enable Natural Language Understanding

- Word Sense Disambiguation
- Semantic Role Labeling
- **Semantic Parsing**
    - Transforming the text into a structured semantic representation



Issues in Natural Language Understanding

- Paucity of resources and training data in most languages
  - Resulting in a big performance gap
- Lack of shared semantics across languages

- We will **address these issues** in this talk
  - We will be focusing on SRL and Semantic Parsing, but we also have work on scaling WSD multilingually (**MuLaN @ IJCAI 2020**; **XL-WSD @ AAAI 2021**)

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Issues in Natural Language Understanding

- Semantic Role Labeling
  - Good but inconsistent results across languages. ⟹ **OUR WORK** Bridging the multilingual gap in SRL. **(Conia and Navigli, COLING 2020)**
- Semantic Parsing
  - Unimpressive performance across languages. ⟹ **OUR WORK** Enabling cross-lingual Semantic Parsing. **(Blloshmi et al., EMNLP 2020)**
- Semantic Role Labeling + Semantic Parsing
  - Language-specific inventories (e.g. PropBank). ⟹ **OUR WORK** VerbAtlas: a novel semantic resource. **(Di Fabio et al., EMNLP 2019)**

Semantic Role Labeling

An overview

Semantic Role Labeling (SRL)

An overview

SRL is the task of automatically addressing:

"Who did What to Whom, Where, When and How?"

(Gildea and Jurafsky, 2000; Màrquez et al., 2008)

Semantic Role Labeling (SRL)

An overview

The quick brown fox jumps over the lazy dog

Semantic Role Labeling (SRL)

An overview

The quick brown fox **jumps** over the lazy dog

1 Predicate identification

Find all the predicates in a sentence.

Semantic Role Labeling (SRL)

An overview

The quick brown fox **jumps** over the lazy dog

`jump.03`

1. **Predicate identification** — Find all the predicates in a sentence.
2. **Predicate disambiguation** — Choose the most appropriate sense for each predicate.

Semantic Role Labeling (SRL)

An overview

The quick brown fox **jumps** over the lazy dog

jump.03

1. **Predicate identification** — Find all the predicates in a sentence.
2. **Predicate disambiguation** — Choose the most appropriate sense for each predicate.
3. **Argument identification** — Find the arguments of each predicate.

Semantic Role Labeling (SRL)

An overview

The quick brown fox	jumps	over the lazy dog
ARG0 (Who?)	jump.03	ARG2 (Over what?)

1. **Predicate identification** — Find all the predicates in a sentence.
2. **Predicate disambiguation** — Choose the most appropriate sense for each predicate.
3. **Argument identification** — Find the arguments of each predicate.
4. **Argument classification** — Assign a semantic role to each argument.

Syntax in Semantic Role Labeling

Advantages and Disadvantages

Syntax in SRL

Advantages

ADVANTAGE: syntax can be a strong indicator for many subtasks

1. Predicate identification
2. Predicate disambiguation
3. Argument identification
4. Argument classification

Syntax in SRL

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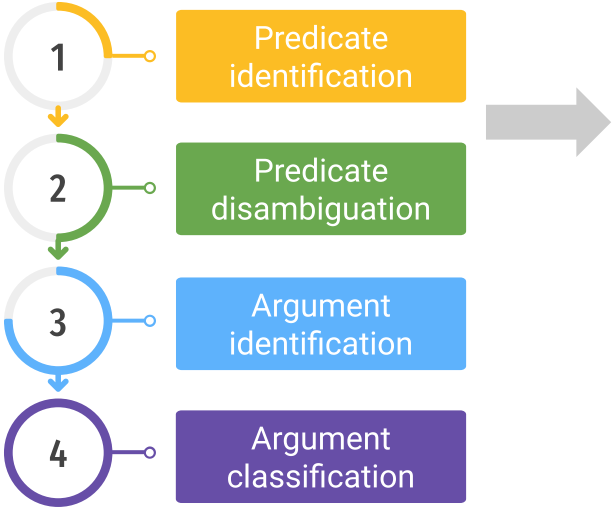

Part-of-speech (POS) tagging and lemmatization

Syntax in SRL

Advantages

ADVANTAGE: syntax can be a strong indicator for many subtasks

1. Predicate identification
2. Predicate disambiguation
3. Argument identification
4. Argument classification

Predicate identification, Predicate disambiguation → Part-of-speech (POS) tagging and lemmatization

Argument identification, Argument classification → Syntax-based rules, dependency neighbors and syntactic relations

Syntax in SRL

Disadvantages

DISADVANTAGE: syntactic annotations are sometimes <u>expensive and scarce</u>

1. Predicate identification
2. Predicate disambiguation

→ Part-of-speech (POS) tagging and lemmatization

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Syntax in SRL

Disadvantages

Especially in low-resource languages!

DISADVANTAGE: syntactic annotations are sometimes expensive and scarce

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Syntax in SRL

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Part-of-speech (POS) tagging and lemmatization

Syntax-based rules, dependency neighbors and syntactic relations

POS tagging*		
EN	> 95%	Great!
ZH	< 90%	Good

*Results of Stanza NLP in the CoNLL-2018 shared task on syntactic parsing.

Syntax in SRL

Disadvantages

Especially in low-resource languages!

DISADVANTAGE: syntactic annotations are sometimes expensive and scarce

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Part-of-speech (POS) tagging and lemmatization

POS tagging*		
EN	> 95%	Great!
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Syntax-based rules, dependency neighbors and syntactic relations

MLAS*		
EN	~ 77%	So so
ZH	< 66%	Is it reliable?

*Morphology-aware Label Attachment Score - Results of Stanza NLP in the CoNLL-2018 shared task on syntactic parsing.

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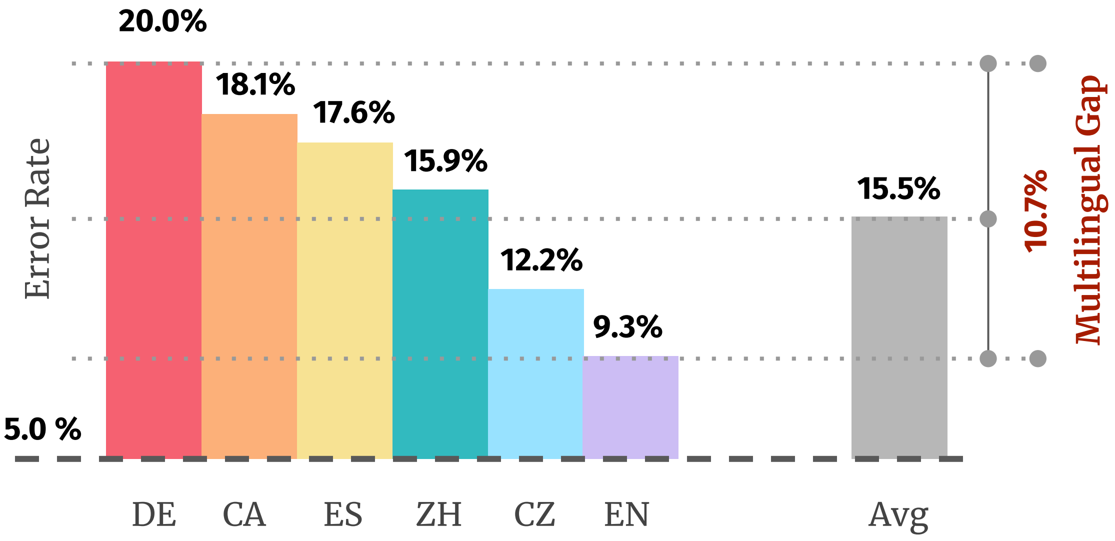
The Multilingual Gap
in Semantic Role Labeling

The Multilingual Gap
in Semantic Role Labeling

Recent progress has left a wide gap between high- and low-resource languages

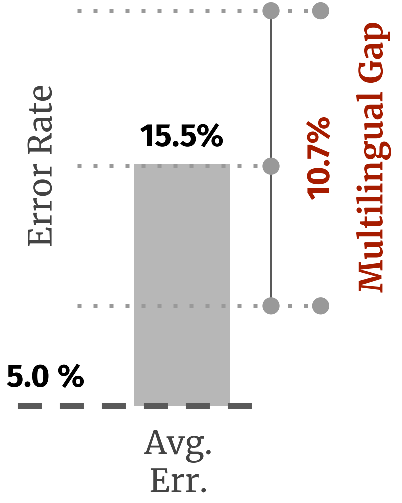


Average error rates (% F1) of state-of-the-art SRL systems presented in 2019 and evaluated on CoNLL-2009.

Bridging the Gap in Multilingual SRL

Conia and Navigli, COLING 2020

Recent progress has left a wide gap between high- and low-resource languages



Q: Is it possible to significantly close this gap?

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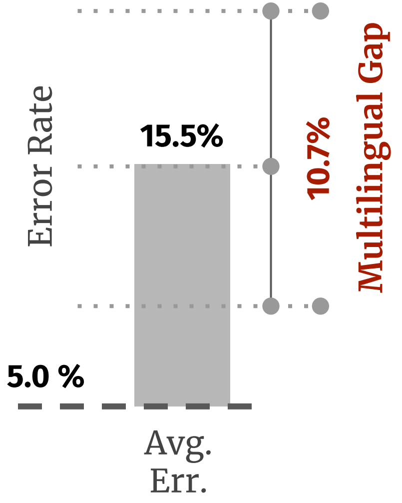

Q: Is it possible to significantly close this gap?

A: Yes!

The Multilingual Gap

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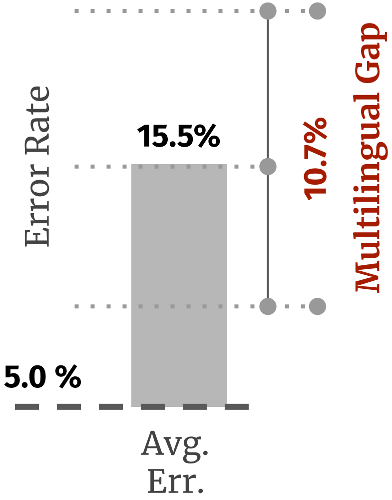

Q: Is it possible to significantly close this gap?

A: Yes! And we don't need syntax!

Bridging the Gap in Multilingual SRL

Conia and Navigli, COLING 2020

Bridging the Gap in Multilingual SRL

a Language-Agnostic Approach (Conia and Navigli, COLING 2020)

OBJECTIVE

Bridging the gap in **multilingual Semantic Role Labeling**

Bridging the Gap in Multilingual SRL

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Bridging the gap in **multilingual Semantic Role Labeling**

without relying on any **language-specific features** (lemma, POS, syntax)

Bridging the Gap in Multilingual SRL

a Language-Agnostic Approach (Conia and Navigli, COLING 2020)

OBJECTIVE

Bridging the gap in **multilingual Semantic Role Labeling**

without relying on any **language-specific features** (lemma, POS, syntax)

and setting a **strong and robust baseline** for future innovations

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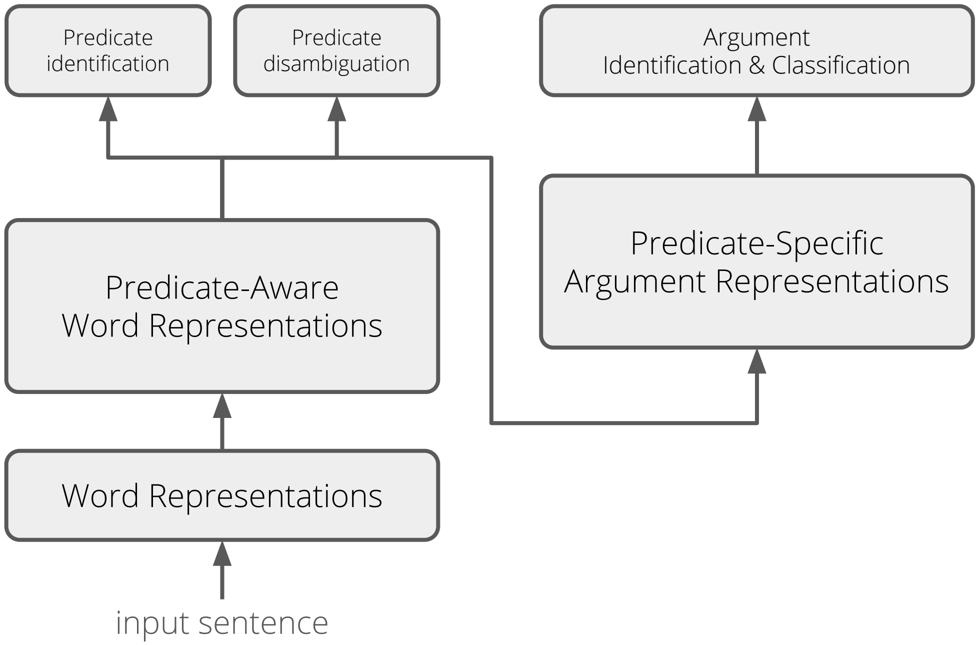
Method

A language-agnostic SRL model

Model Architecture

Overview



Model Architecture

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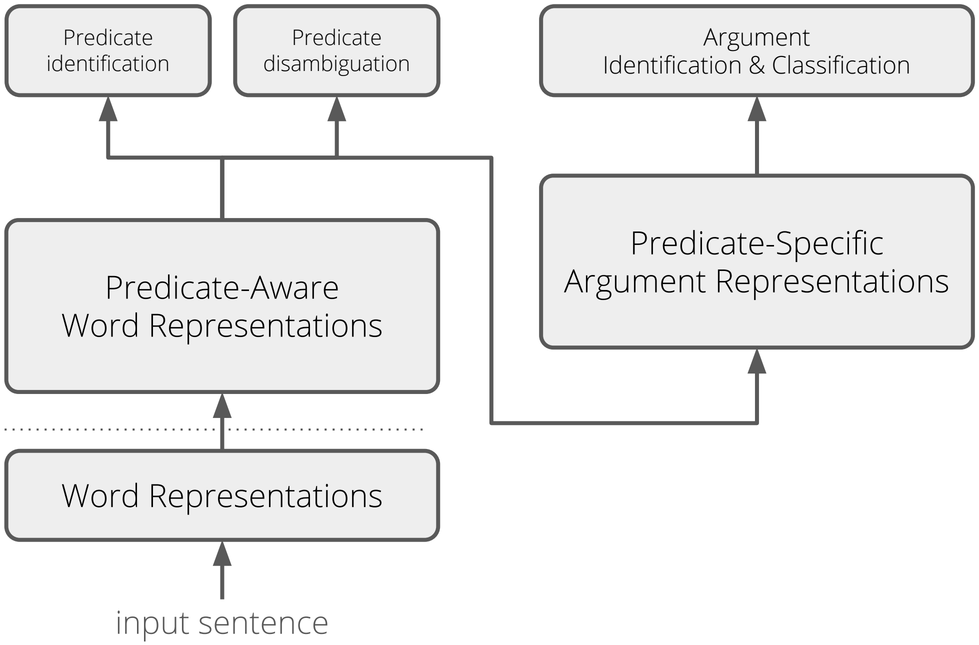

Just the input sentence:

- No predicate indicator flags
- No predicate embeddings
- No predicate appended
- No syntactic features

Model Architecture

Overview

Sentence-level info:

- ALL predicate positions
- ALL predicate senses

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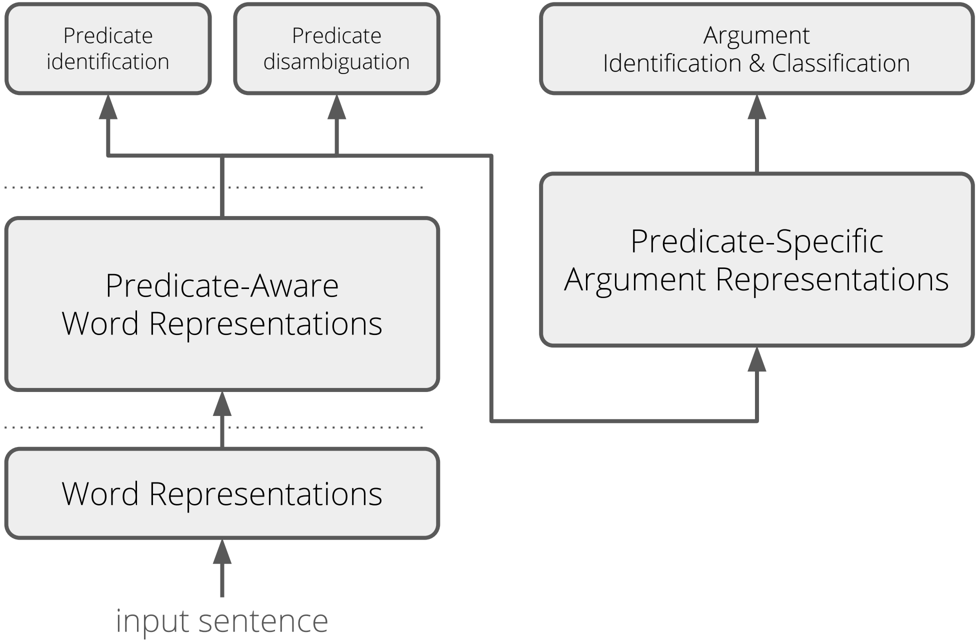

Model Architecture

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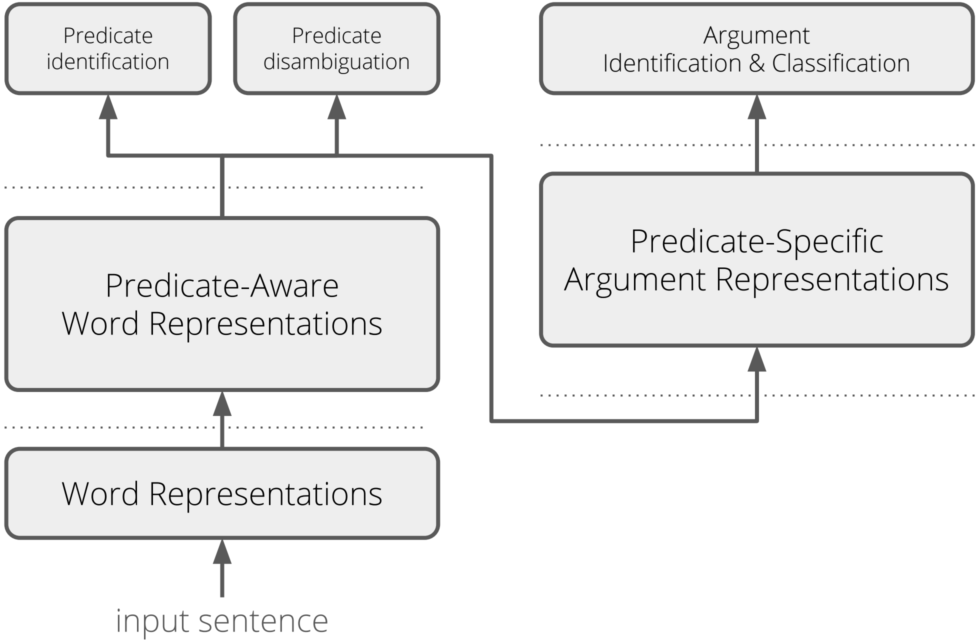
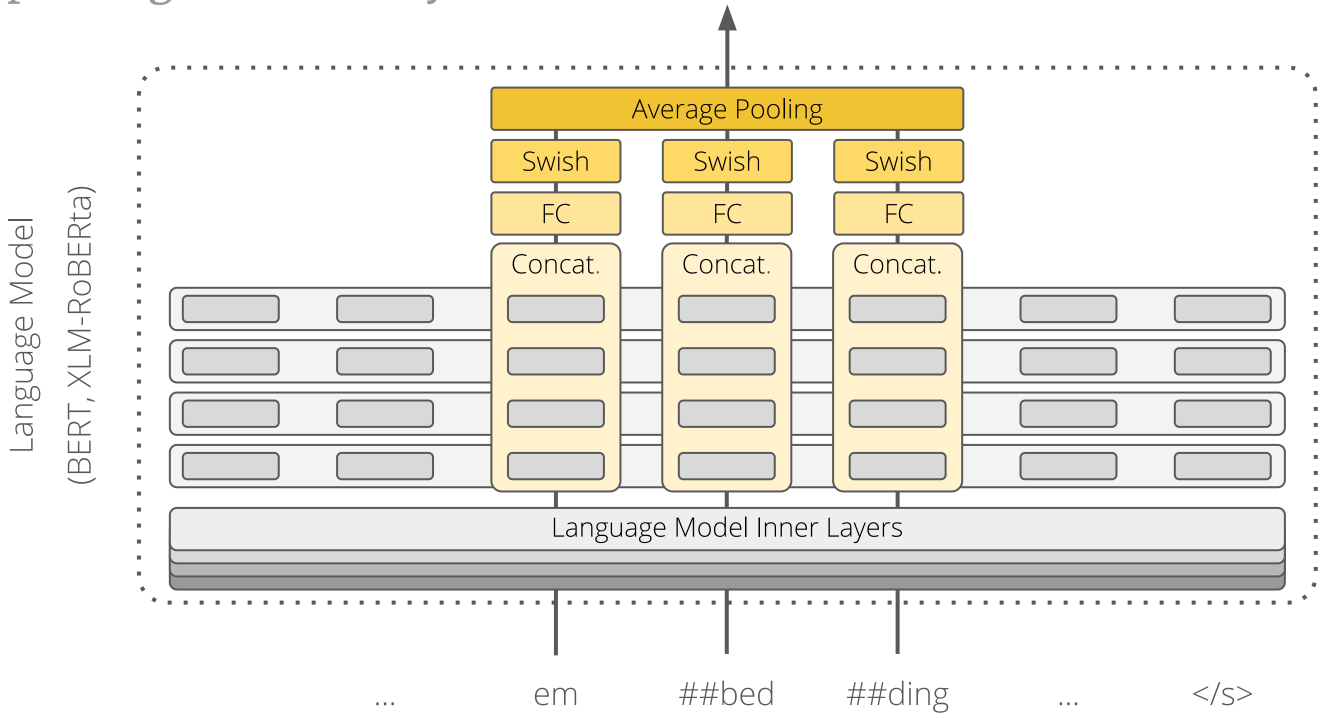


Predicate-specific info:

- Predicate-argument relations

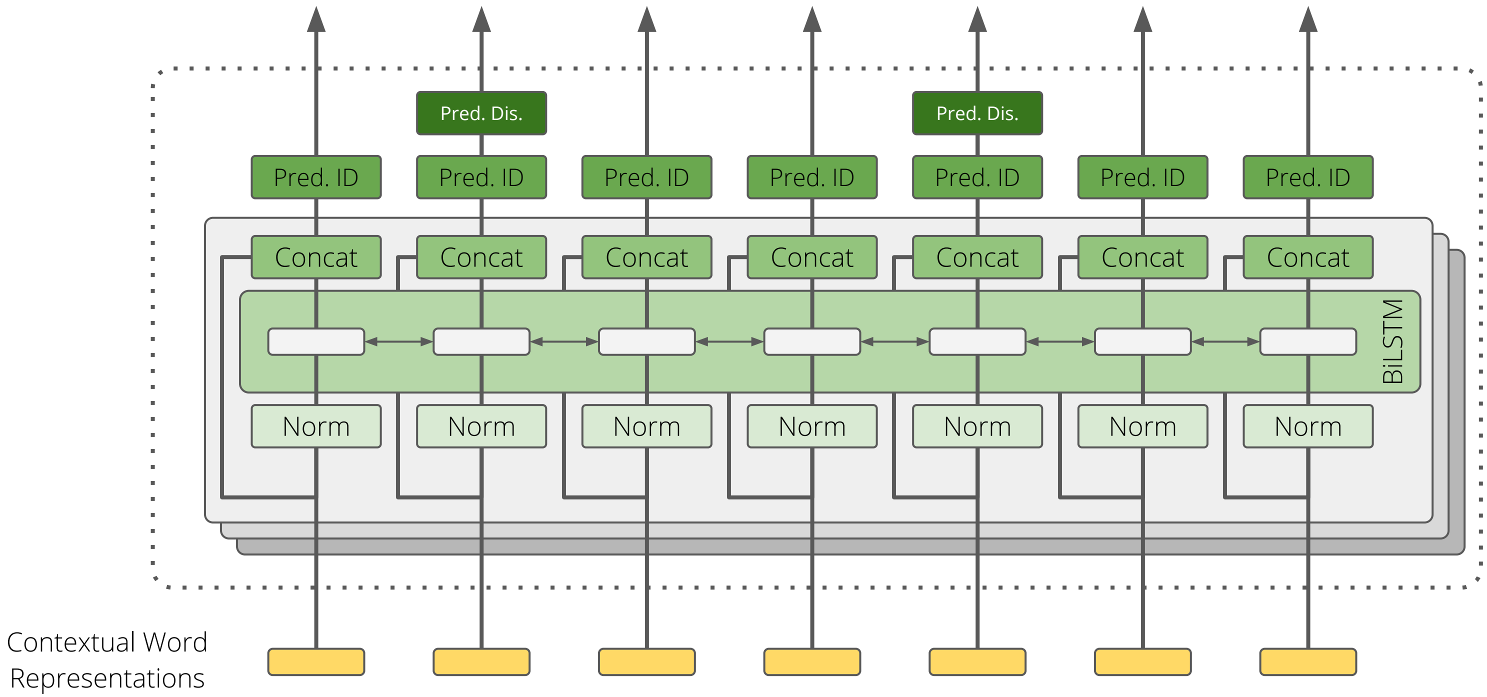
Contextualized Word Representations

Exploiting the inner layers



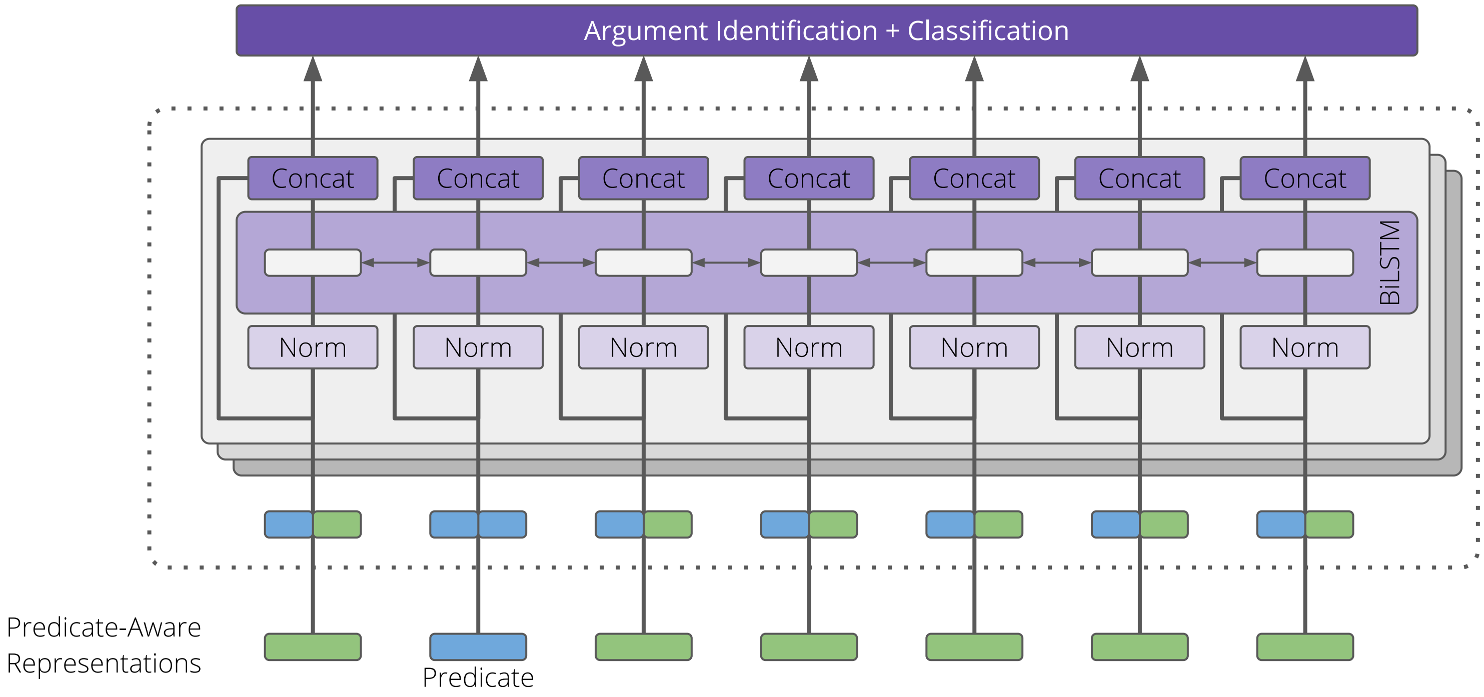
Predicate-Aware Word Representations

Recontextualizing the representations with respect to ALL the predicates



Predicate-Specific Argument Representations

Specializing word representations with respect to a SINGLE predicate



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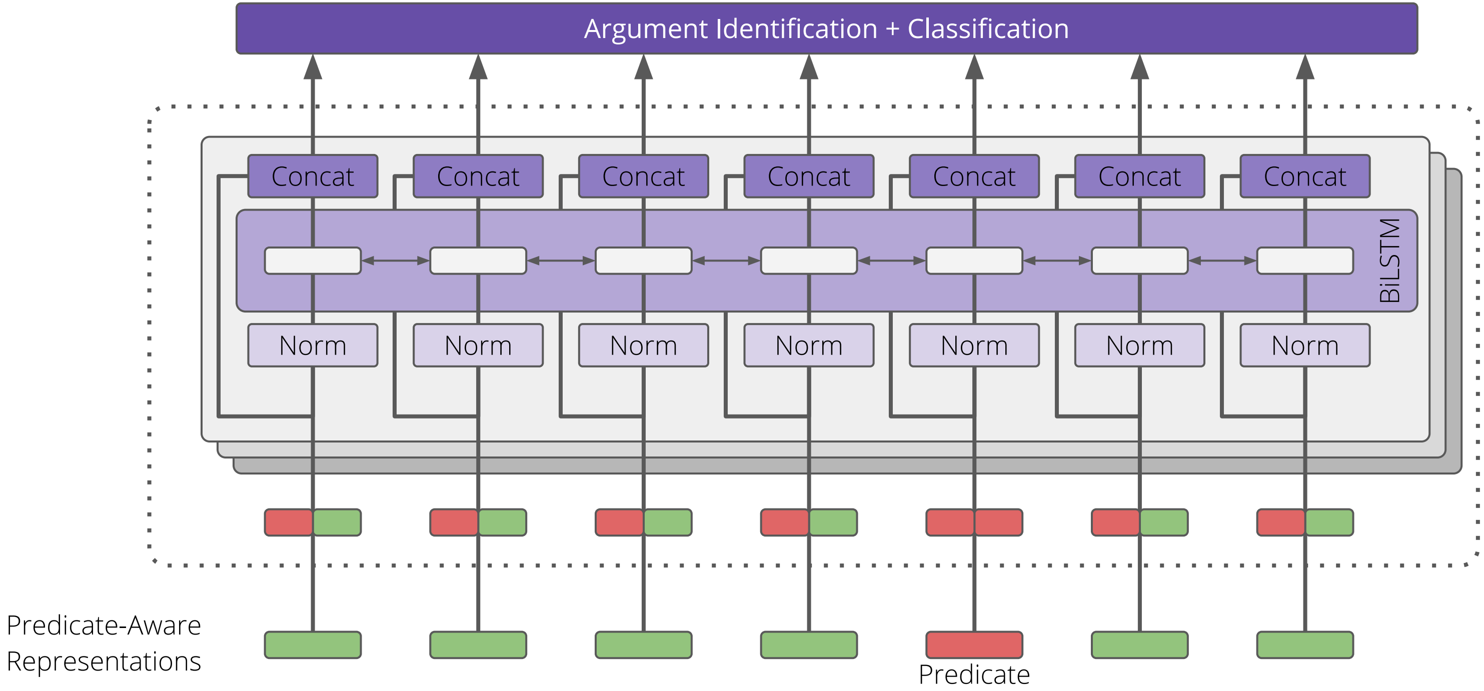
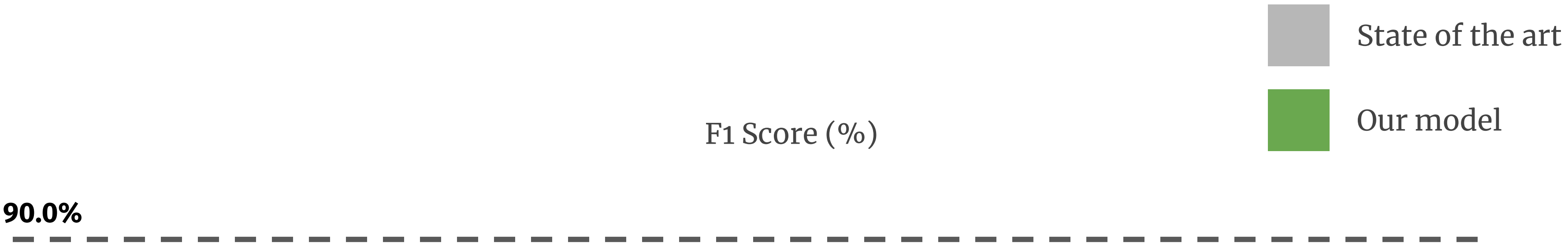


Evaluation

Dependency-based English SRL

English SRL

Dependency-based SRL on CoNLL-2009



English SRL

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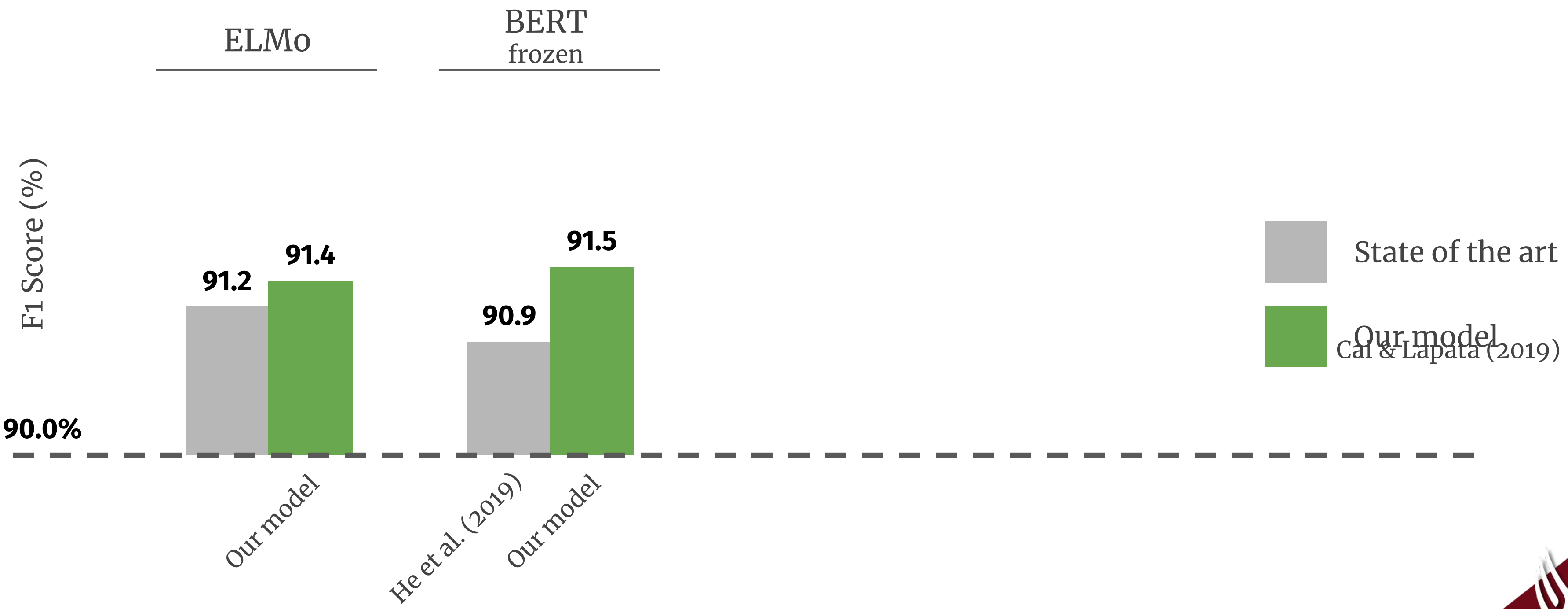

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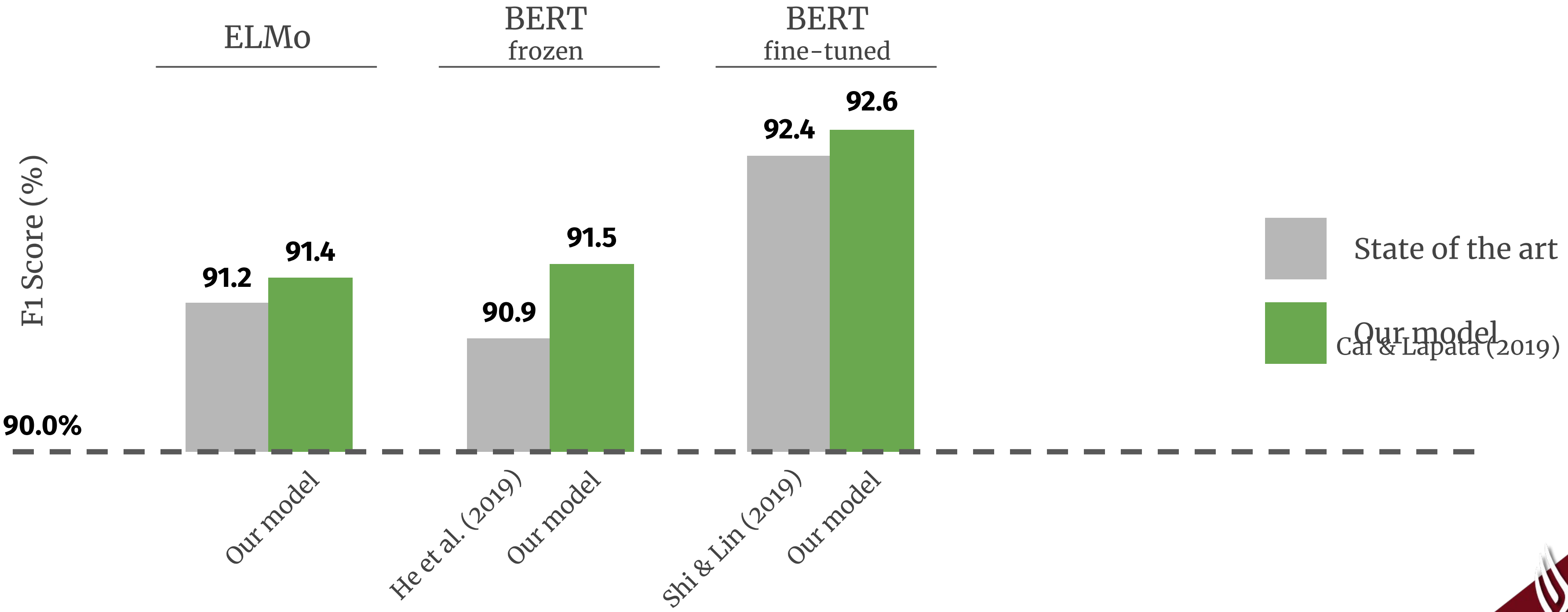

English SRL

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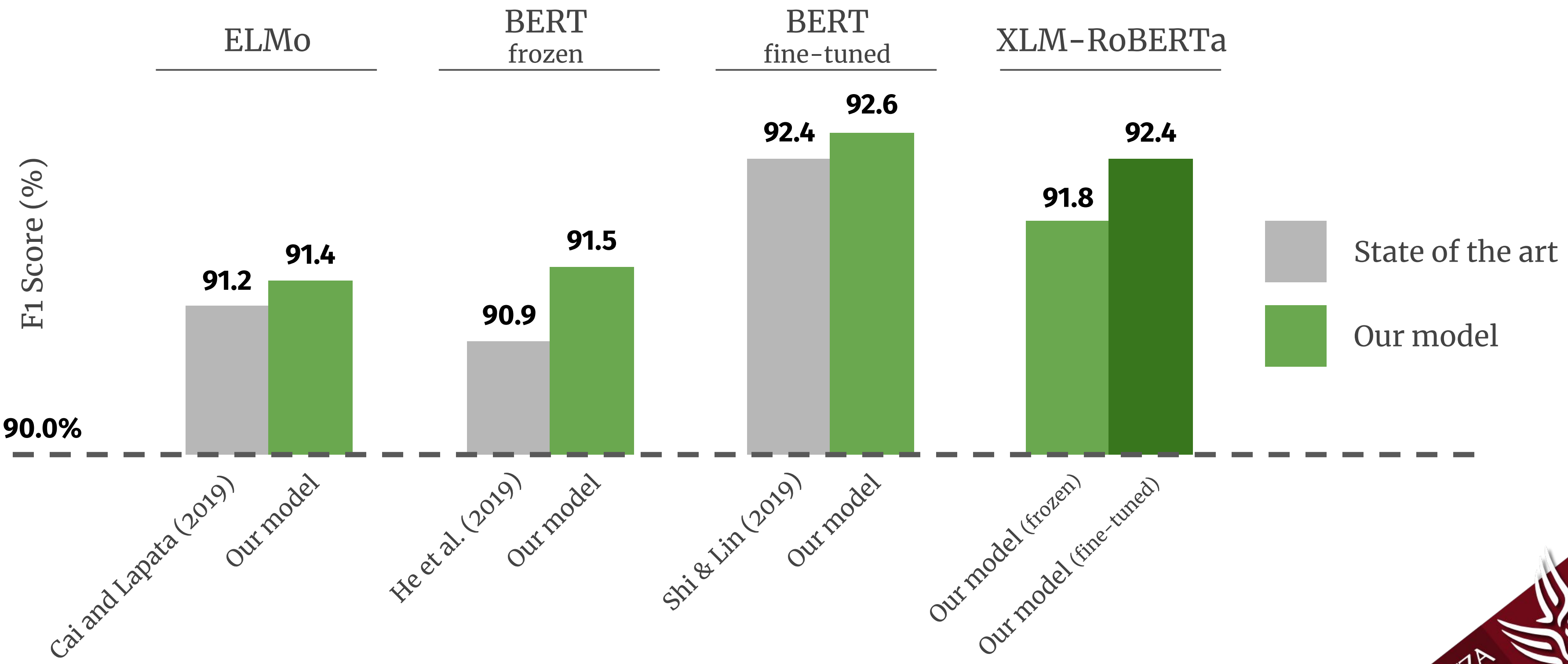
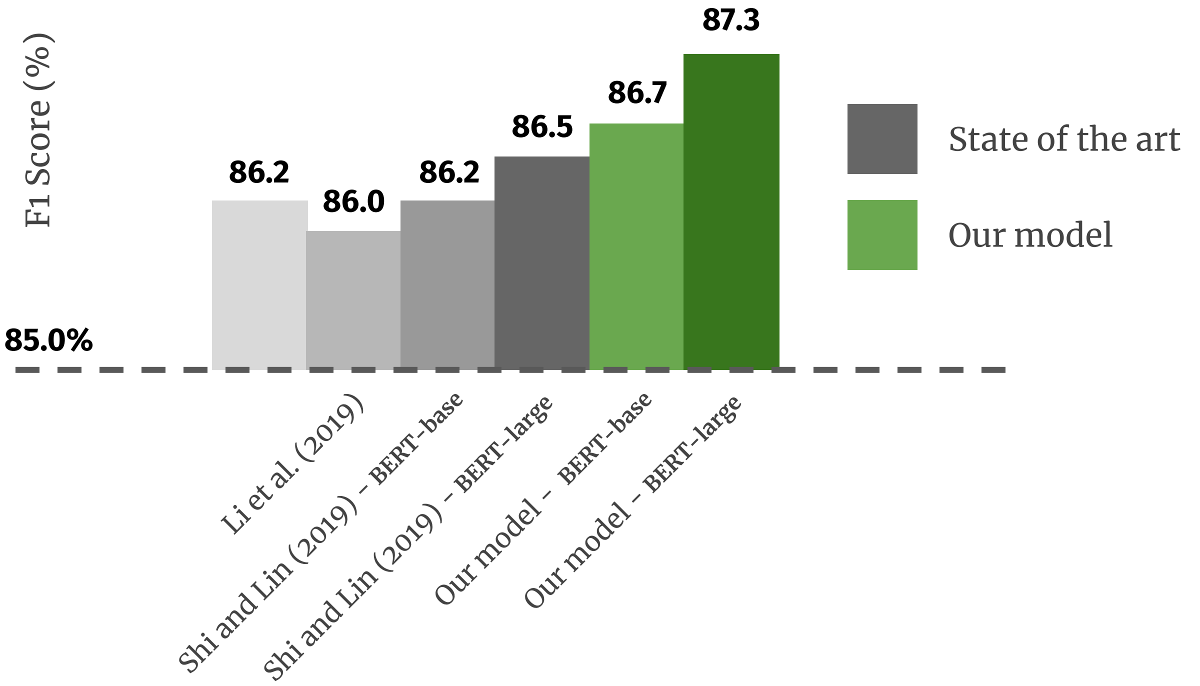


English SRL

Span-based SRL on CoNLL-2012



Ouchi et al. (2018)

Evaluation

Multilingual and Cross-Lingual SRL

Multilingual SRL

on CoNLL-2009

He et al. 2019
syntax-aware SOTA

Our model
BERT (frozen)

Our model
XLM-R (frozen)

Our model
BERT (fine-tuned)

Our model
XLM-R (fine-tuned)

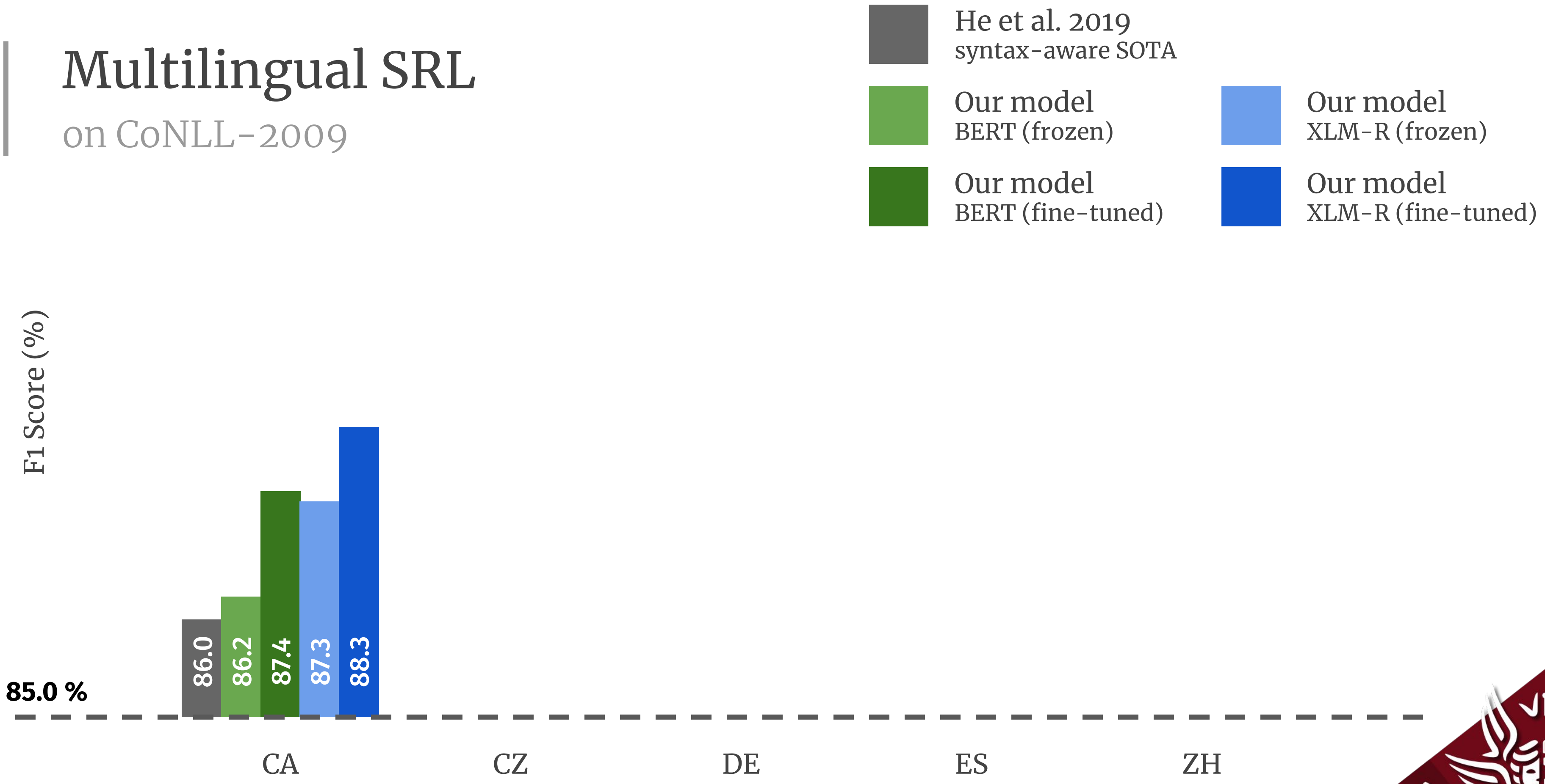
F1 Score (%)

85.0 %

CA CZ DE ES ZH

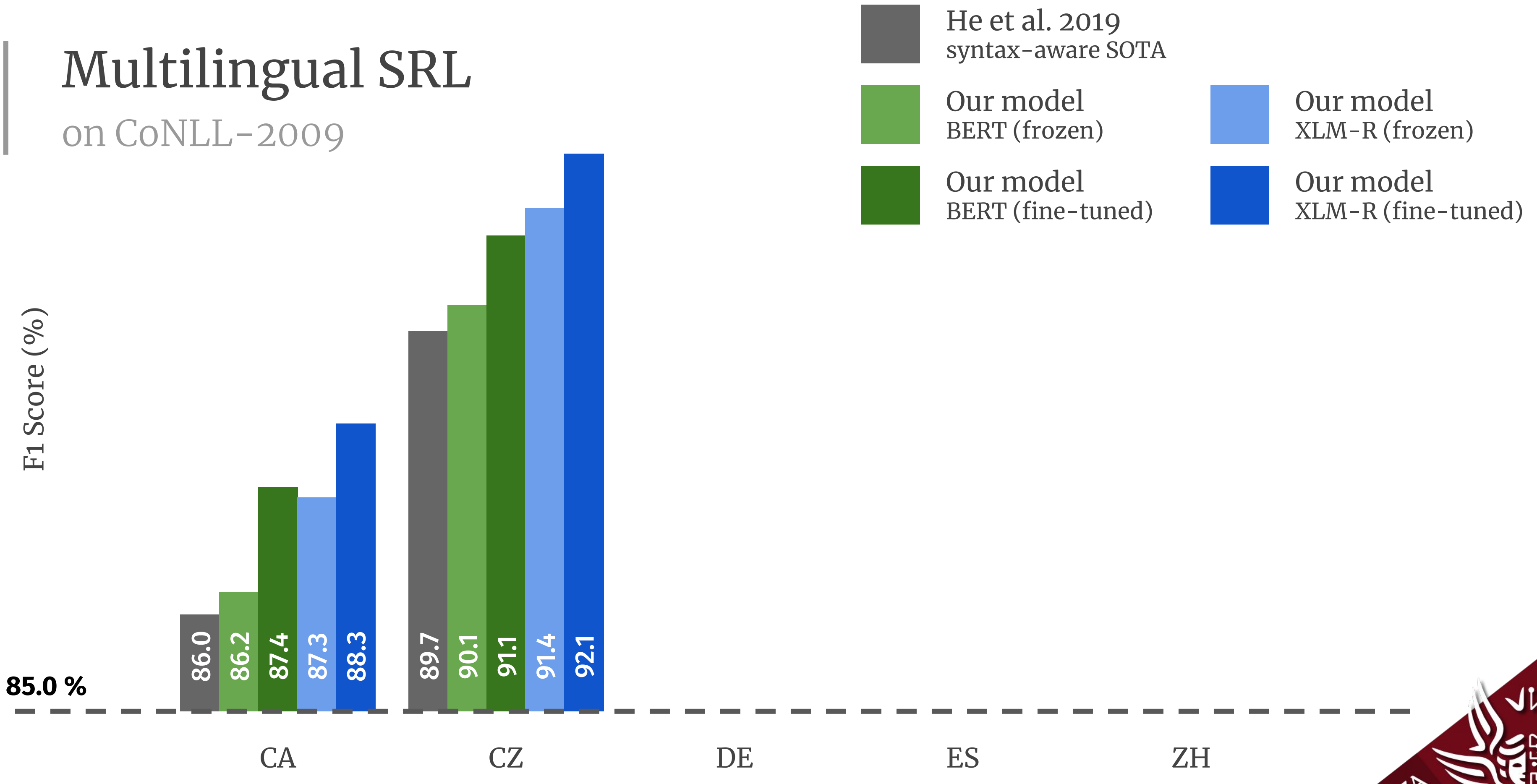
Multilingual SRL

on CoNLL-2009



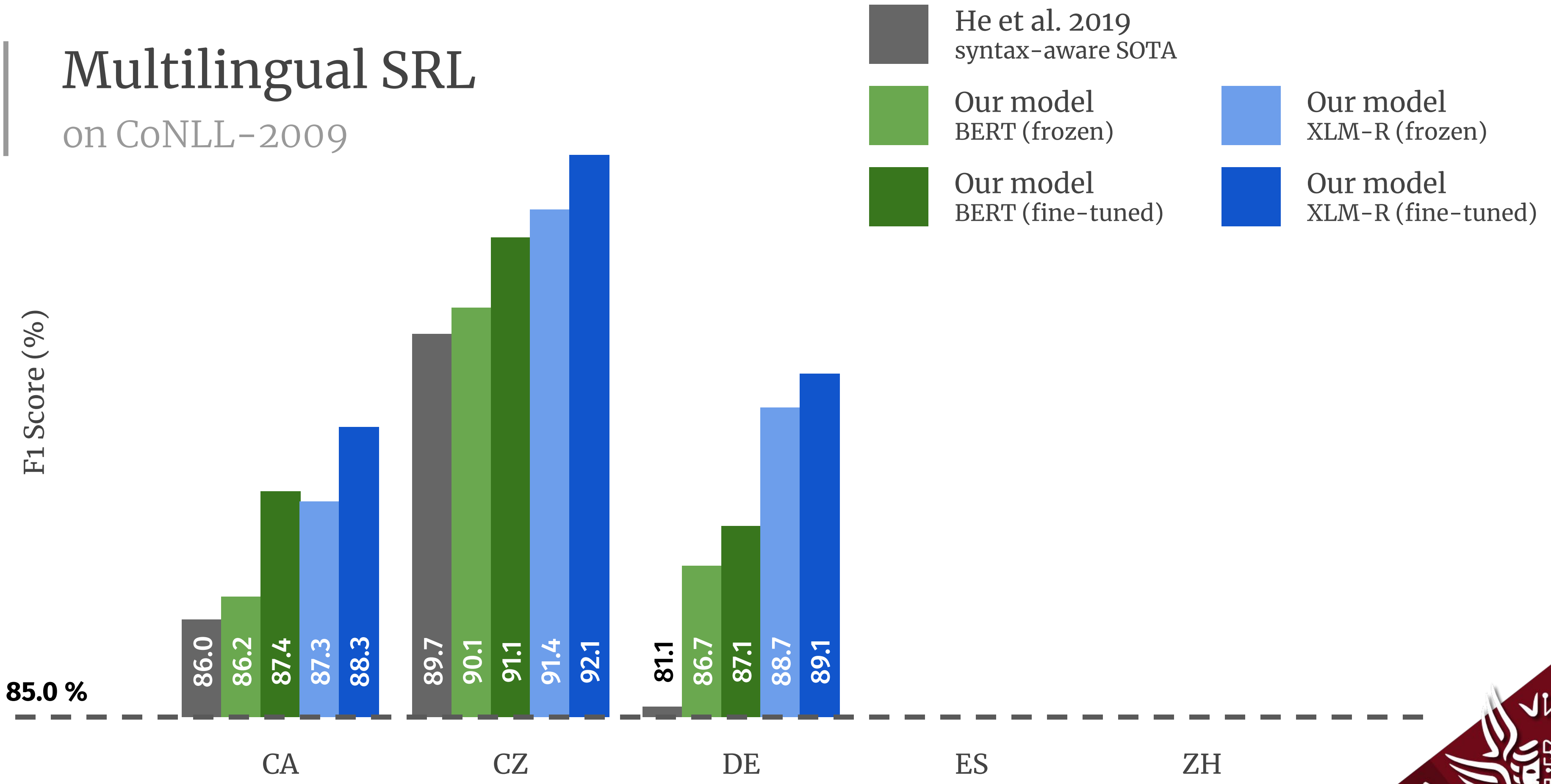
Multilingual SRL

on CoNLL-2009



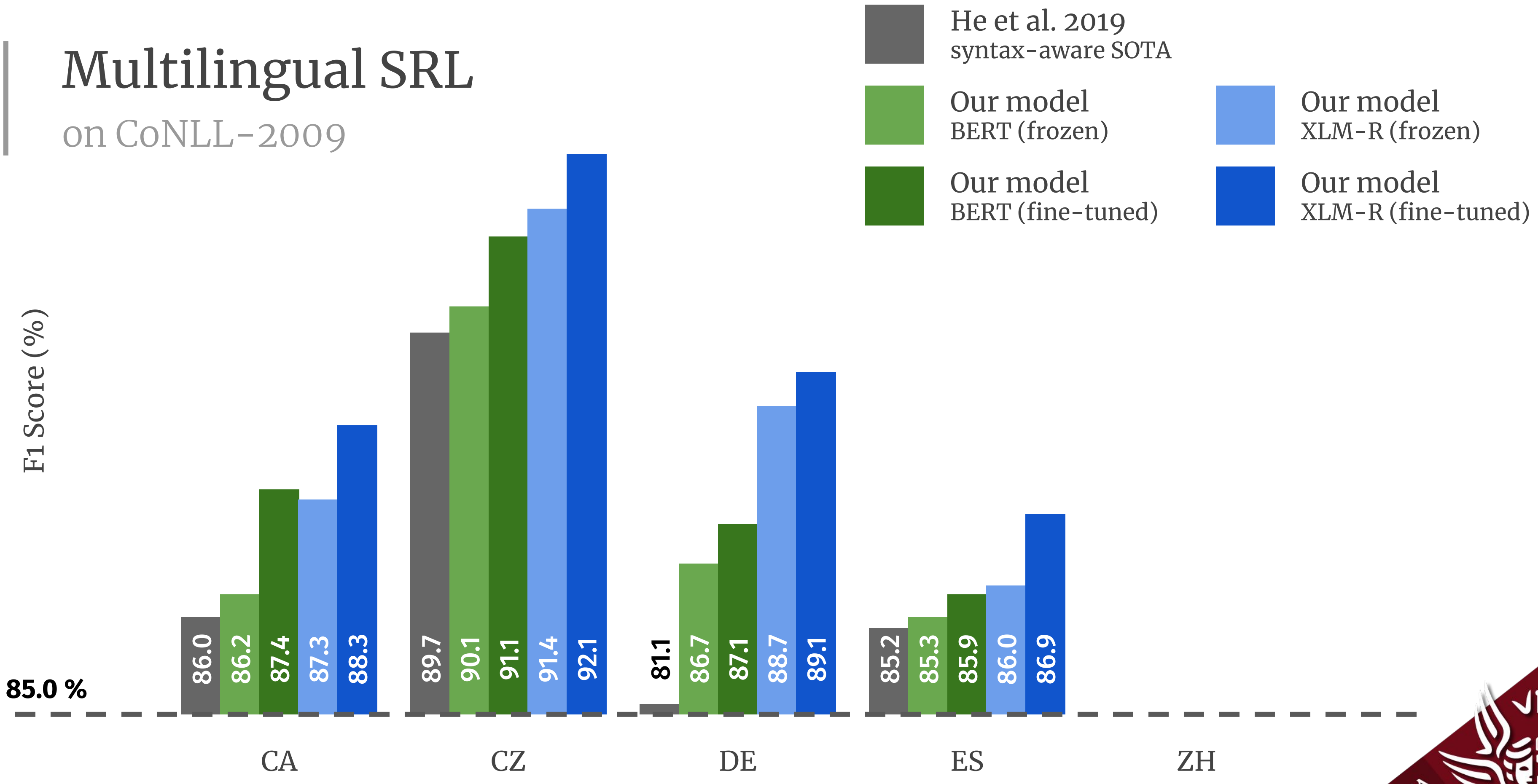
Multilingual SRL

on CoNLL-2009



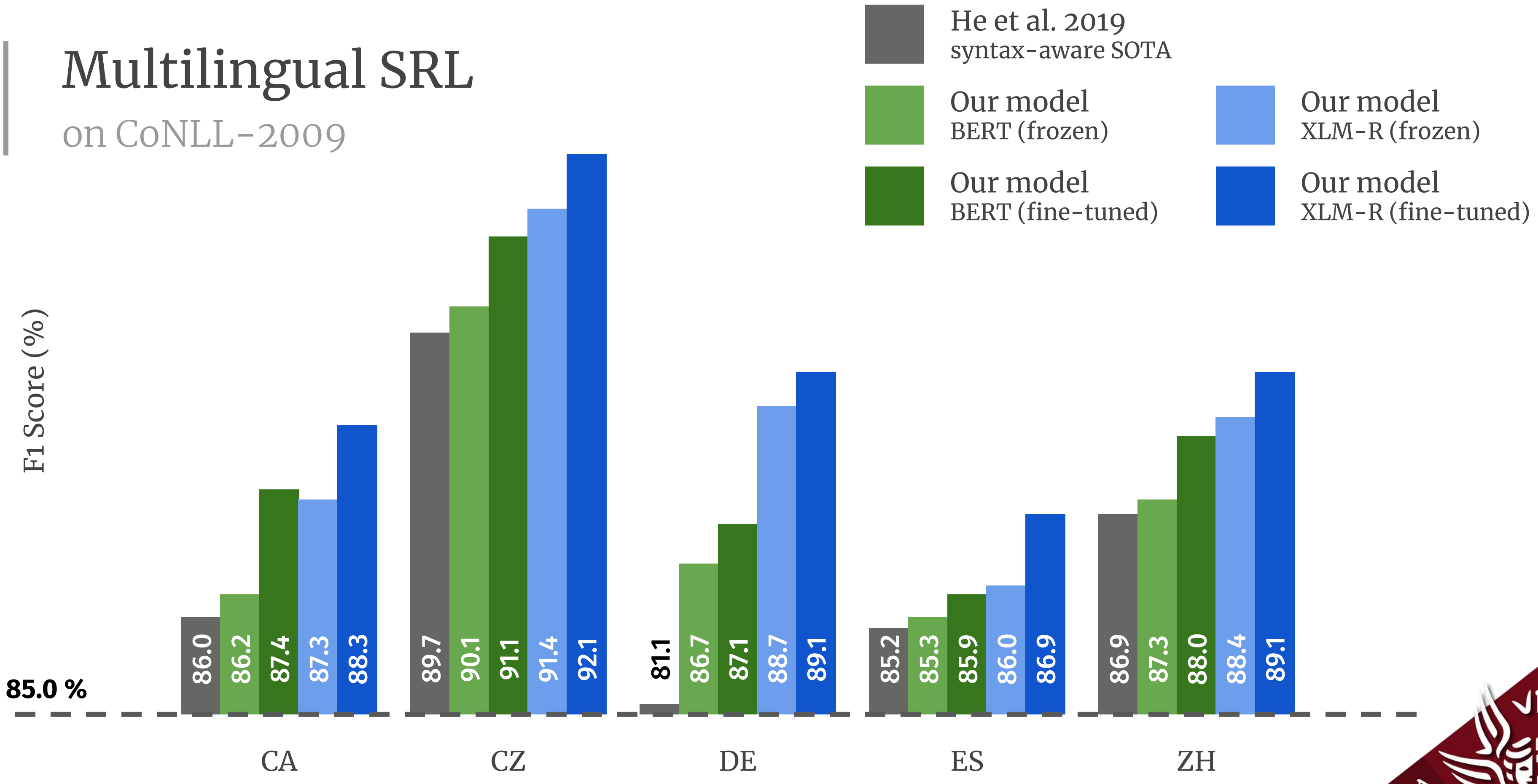
Multilingual SRL

on CoNLL-2009



Multilingual SRL

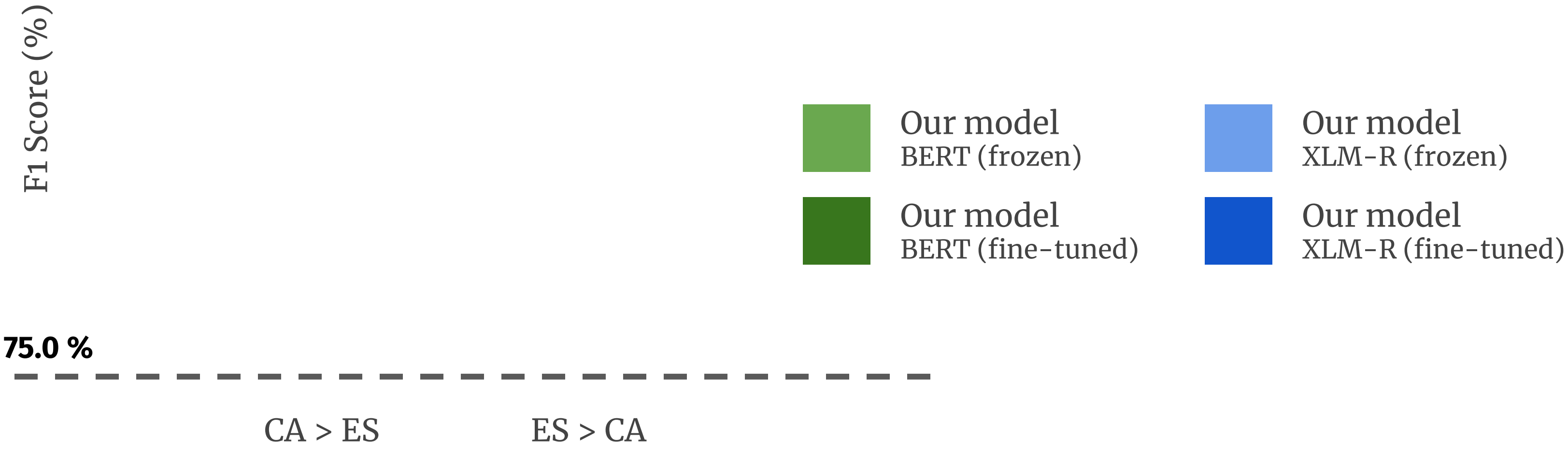
on CoNLL-2009



Zero-Shot Cross-Lingual SRL

on CoNLL-2009

Our approach shows promising results in zero-shot cross-lingual SRL*.



* Spanish and Catalan are the only languages annotated with the same predicate-argument structure inventory in CoNLL-2009.

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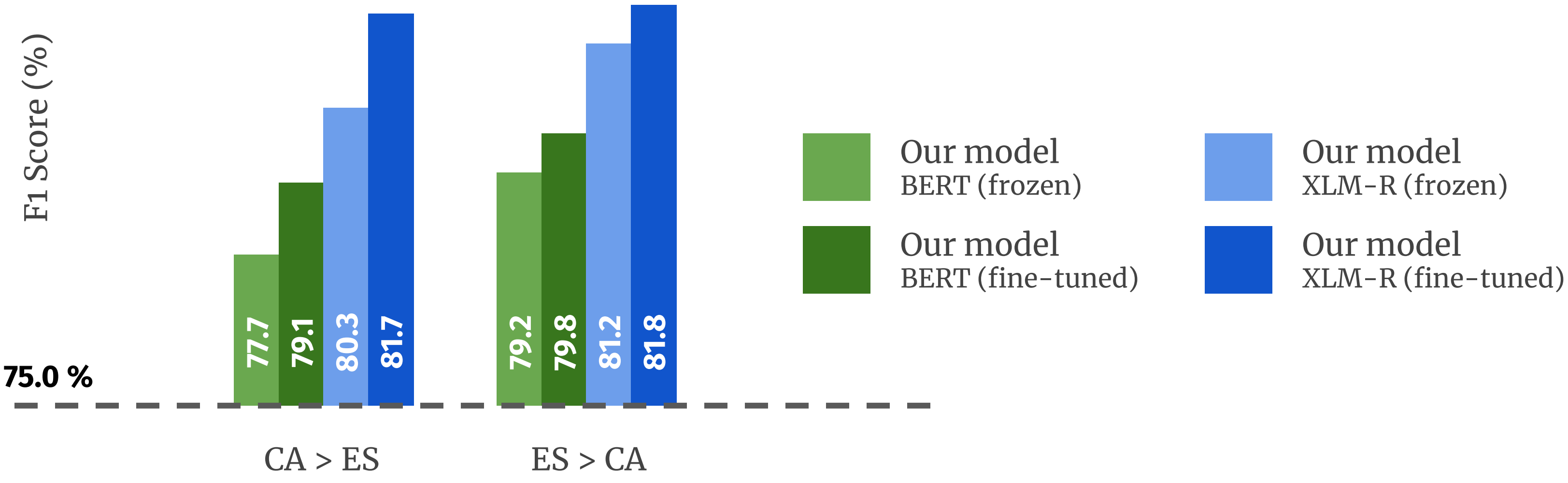

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Robust SRL in Low-Resource Settings

Learning curves

There are **only 17K predicates in German** (vs 37K in Catalan and 180K in English).

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Learning curves

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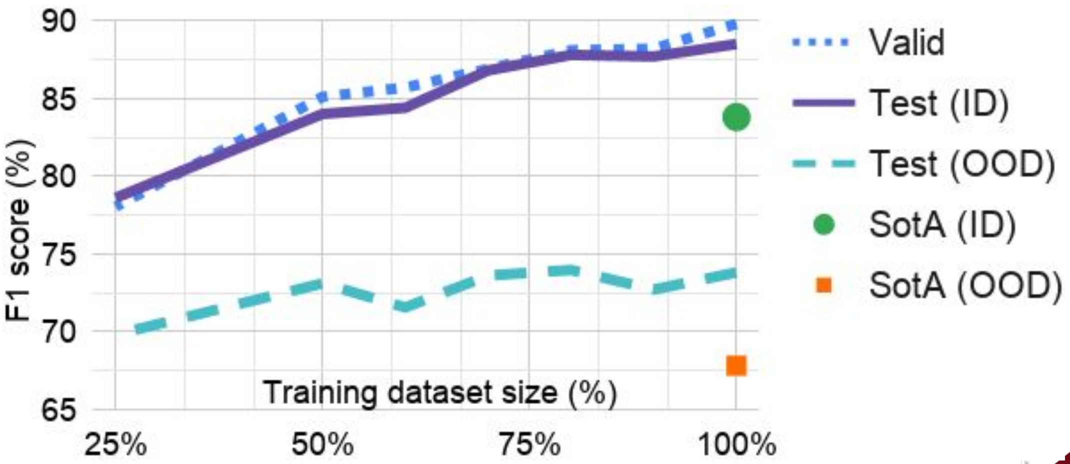
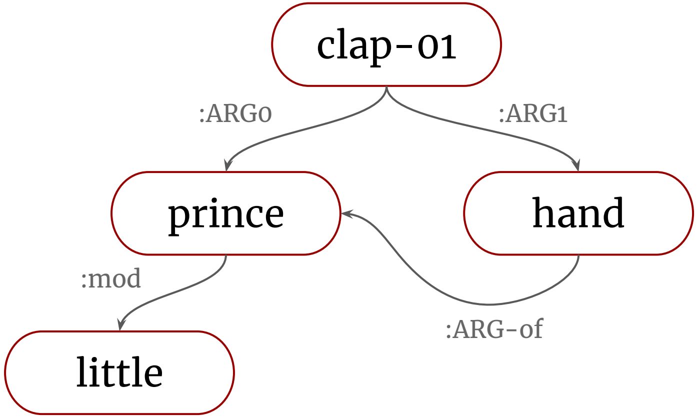
SOTA results with
just 50% of the training data!



Cross-Lingual Semantic Parsing

An overview

Abstract Meaning Representation



EN

The little prince clapped his hands.

Can we use AMR across languages?

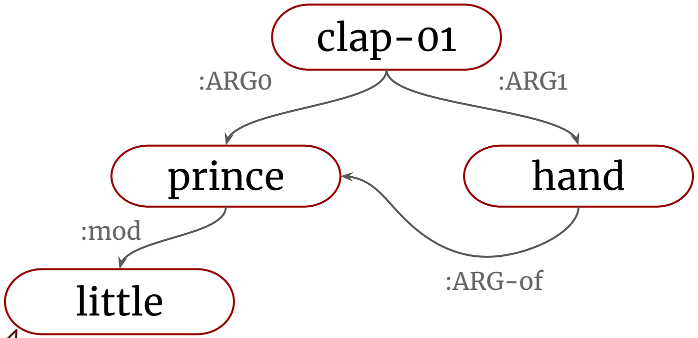
AMR Slogans

- AMR is **not an interlingua**.
- AMR is heavily biased towards **English.**
- AMR makes extensive use of **PropBank** framesets.

AMR Slogans

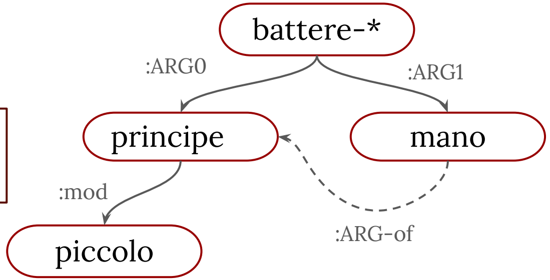
- AMR aims to **abstract away** from syntactic idiosyncrasies.
- AMR is **agnostic** about how to derive meanings from strings.
- Xue et al. (2014), Migueles-Abraira et al. (2018):
  "Non an interlingua, but close";
  "Adjustable AMR guidelines to cover the cross-lingual aspects".
  - English - PropBank
  - Spanish - AncoraNet
  - Chinese - Chinese PropBank
  - Czech - PDT-Vallex
  - ....

AMR in languages other than English

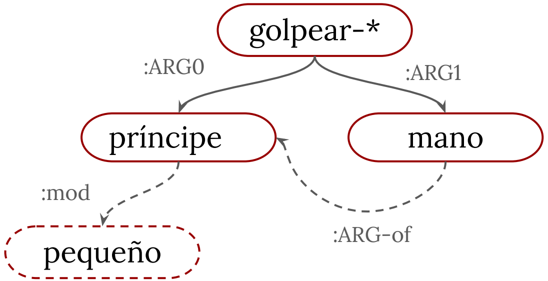


EN The little prince clapped his hands.

IT Il piccolo principe batteva le (sue) mani.



ES El principito golpeó las (sus) manos.



Cross-Lingual AMR

Damonte and Cohen (2018): “Although not an interlingua, AMR can act as one”.

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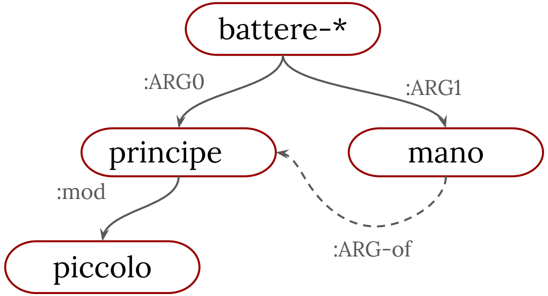

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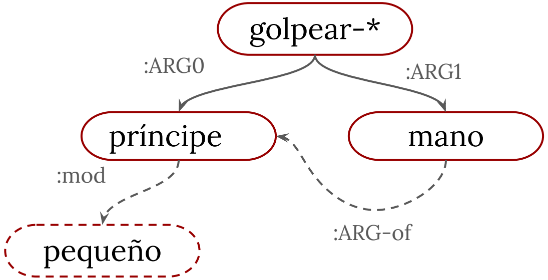
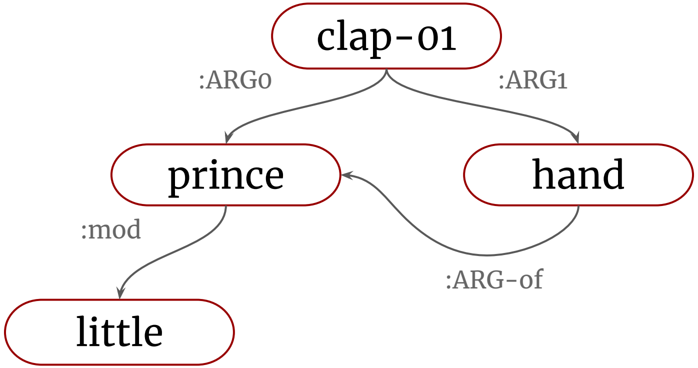
El principito golpeó las (sus) manos.





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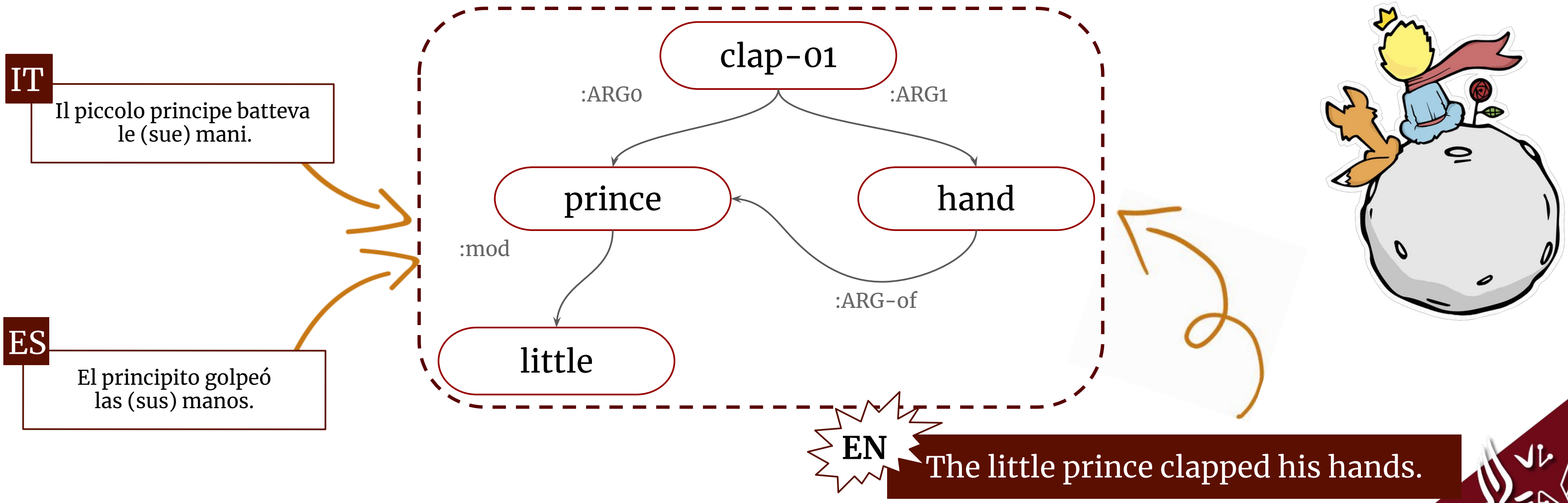


Cross-Lingual AMR Challenges

I. Explicit/implicit **word-to-node AMR alignments** in English AMR parsers:
   A. based on English
   B. hard to be projected across languages through English

II. No available **cross-lingual AMR data.**

Enabling Cross-Lingual AMR Parsing

Blloshmi, Tripodi and Navigli, EMNLP 2020

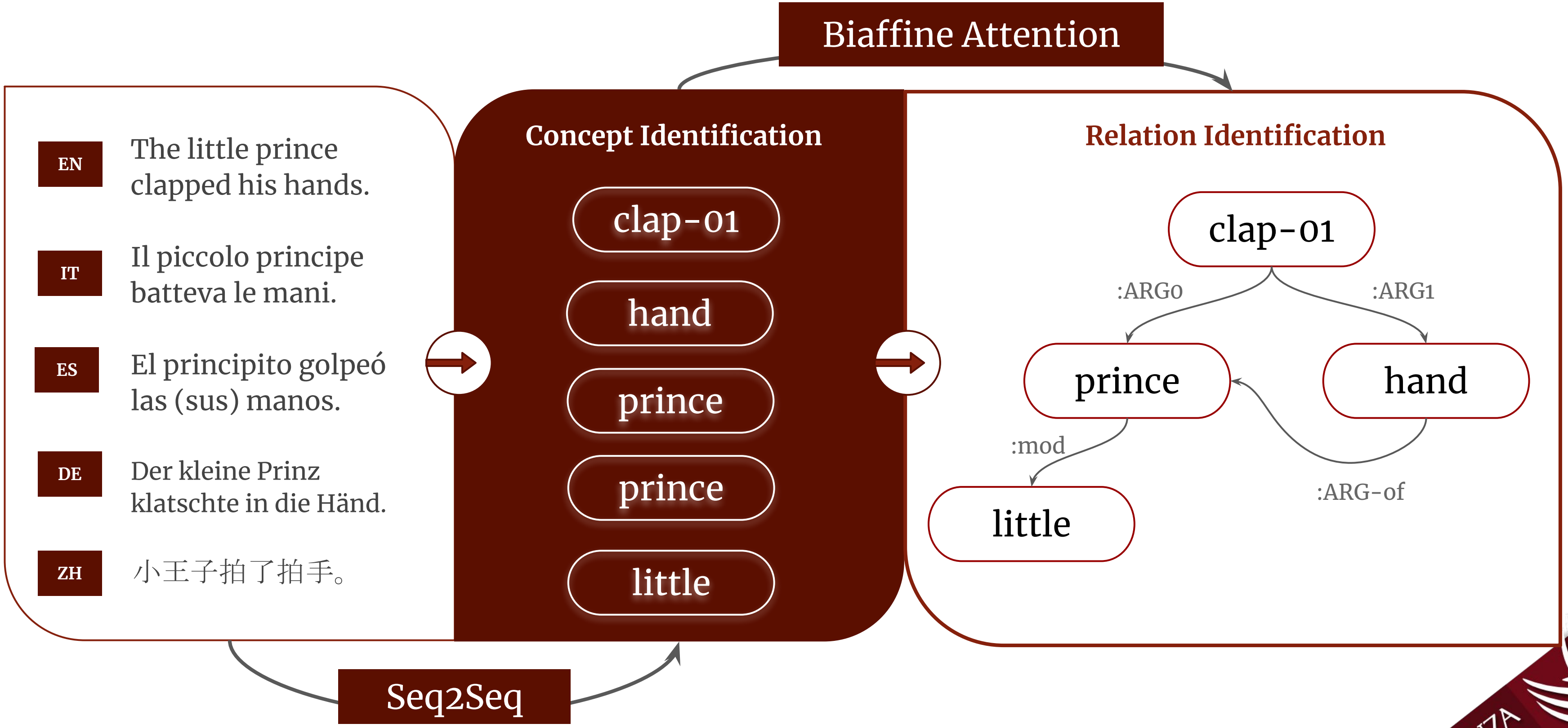
In this work ...

XL-AMR
a cross-lingual AMR parser that disposes of AMR alignments

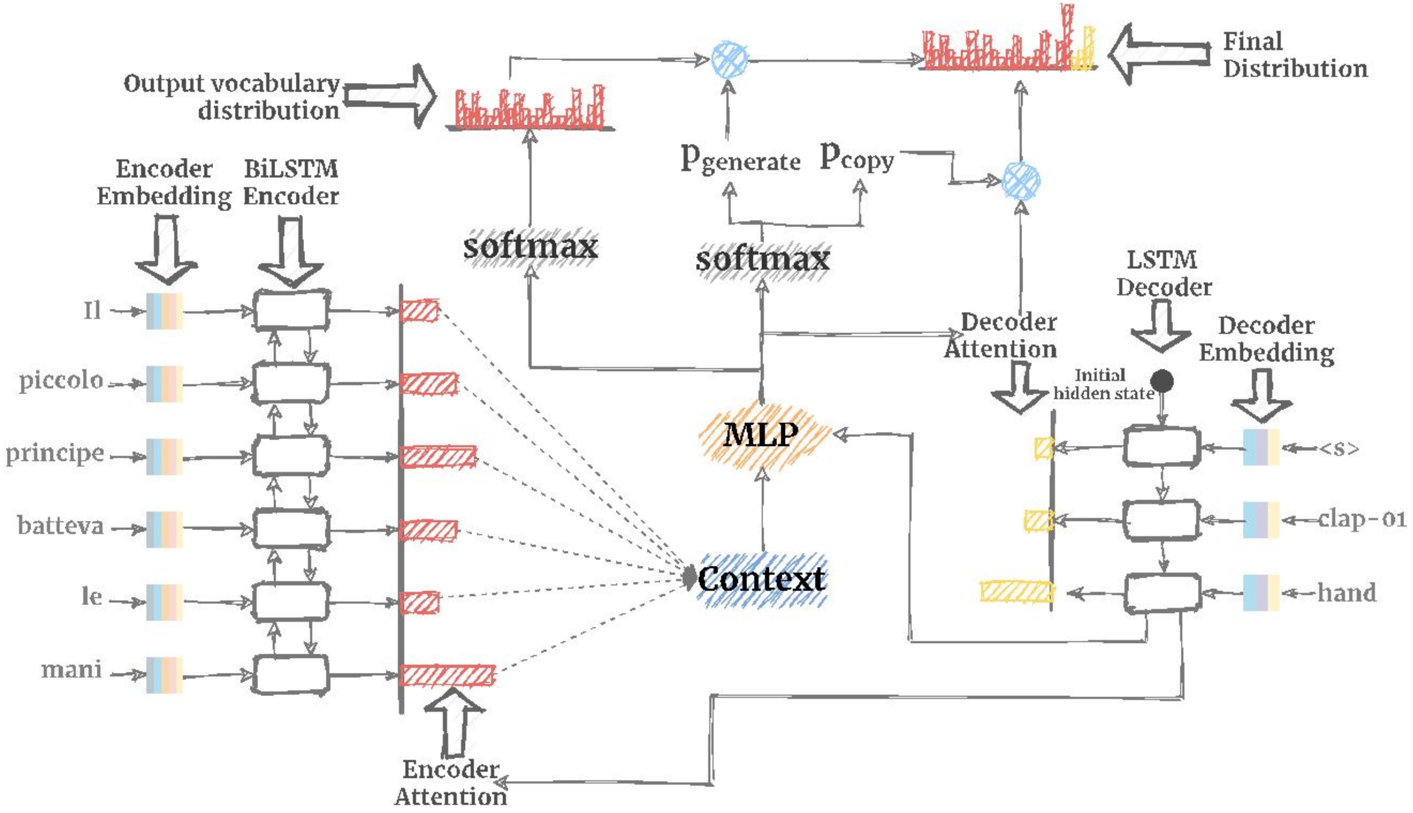
Silver data
for cross-lingual AMR of diverse quality on which we train XL-AMR

Qualitative insights on XL-AMR handling language divergences

XL-AMR: Model Overview



XL-AMR: Concept Identification



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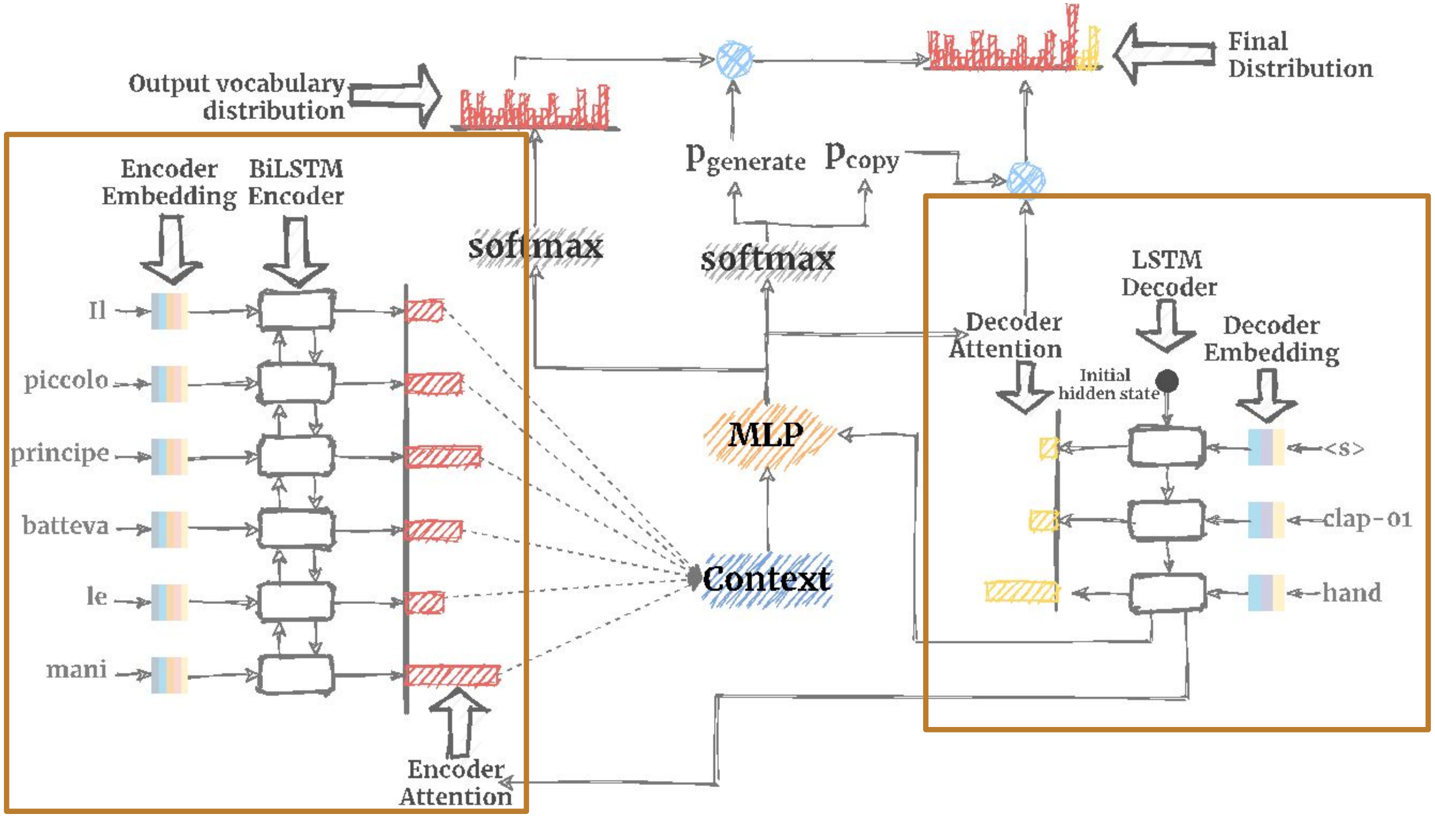

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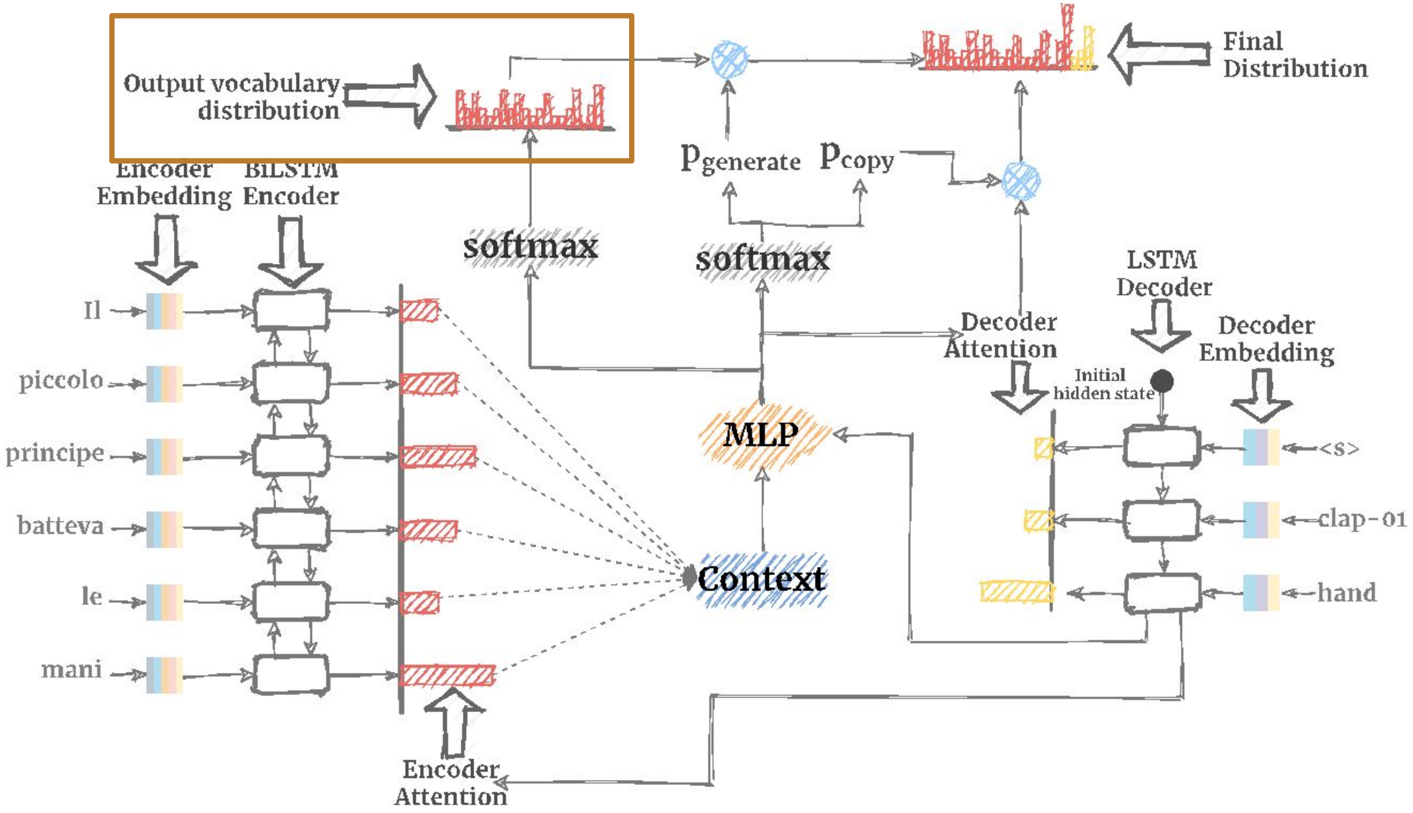
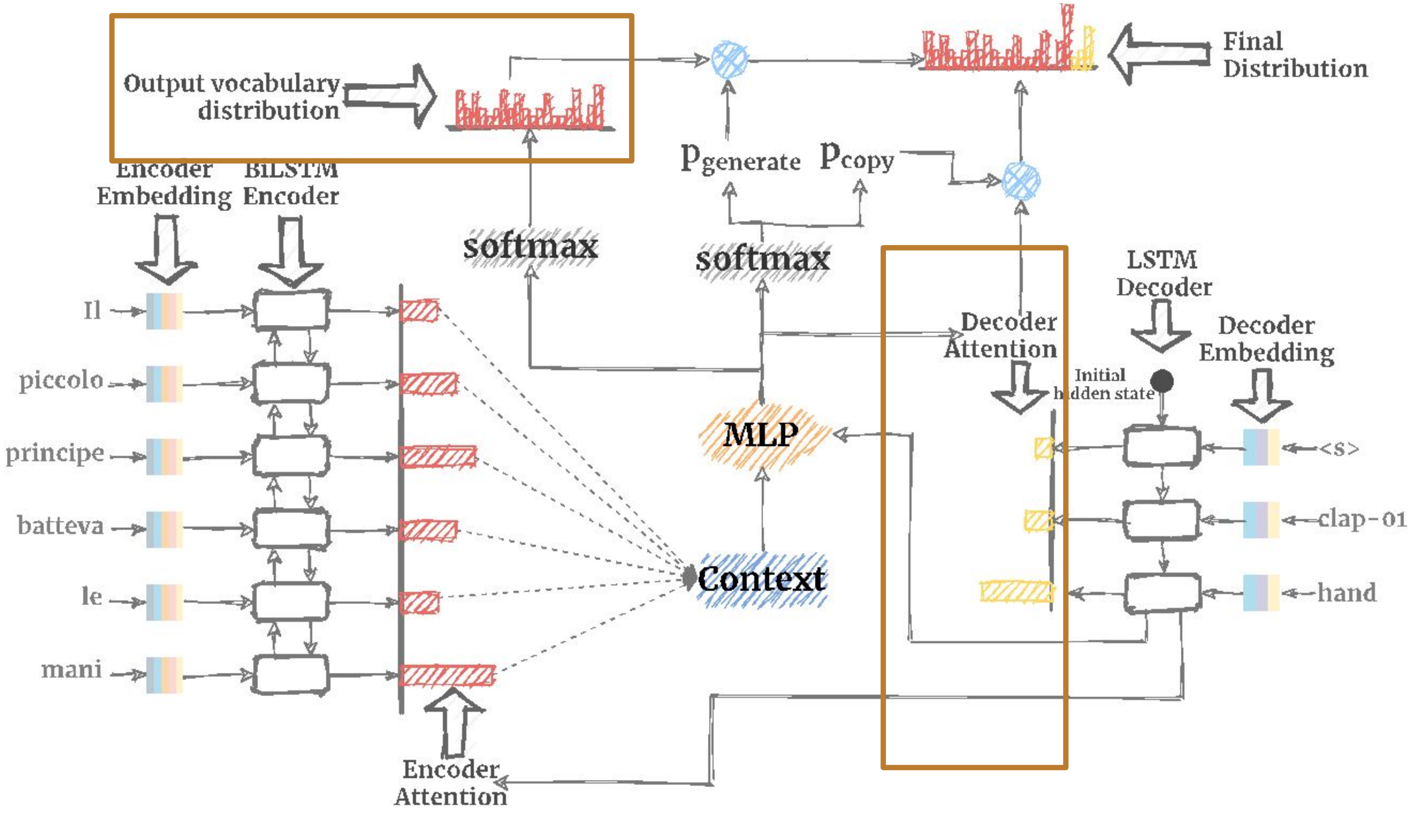


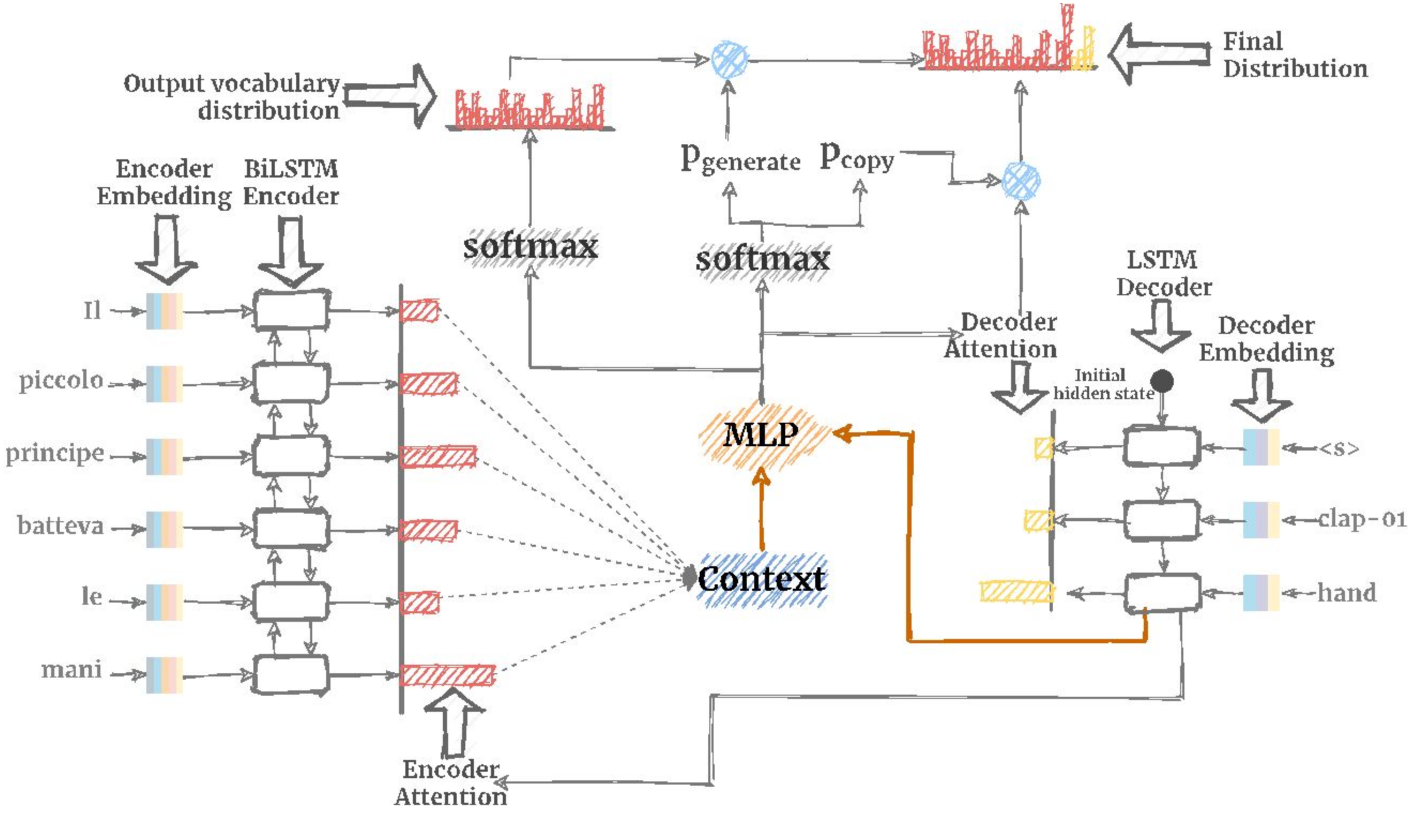
SAPIENZA NLP

XL-AMR: Concept Identification



SAPIENZA NLP

XL-AMR: Concept Identification



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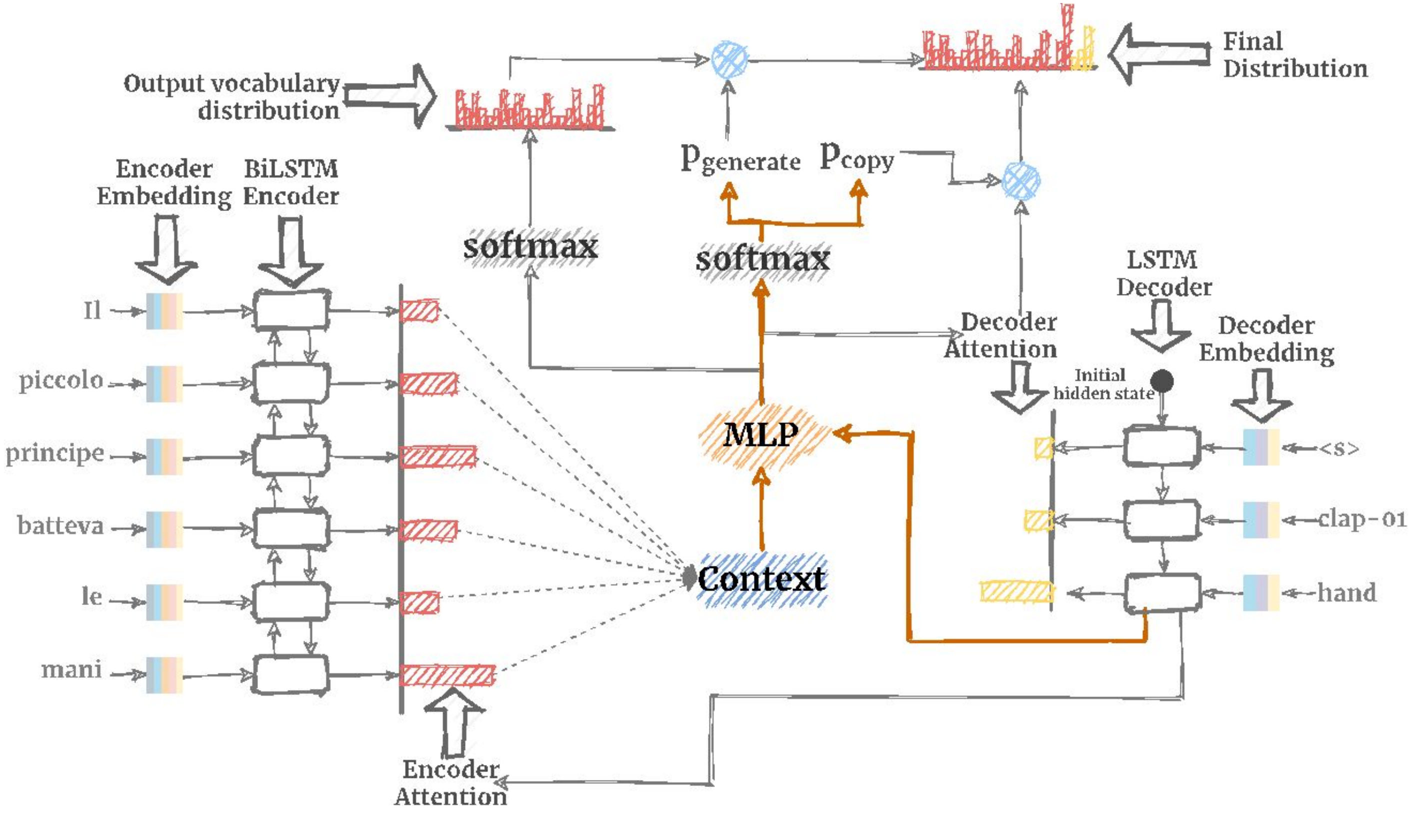

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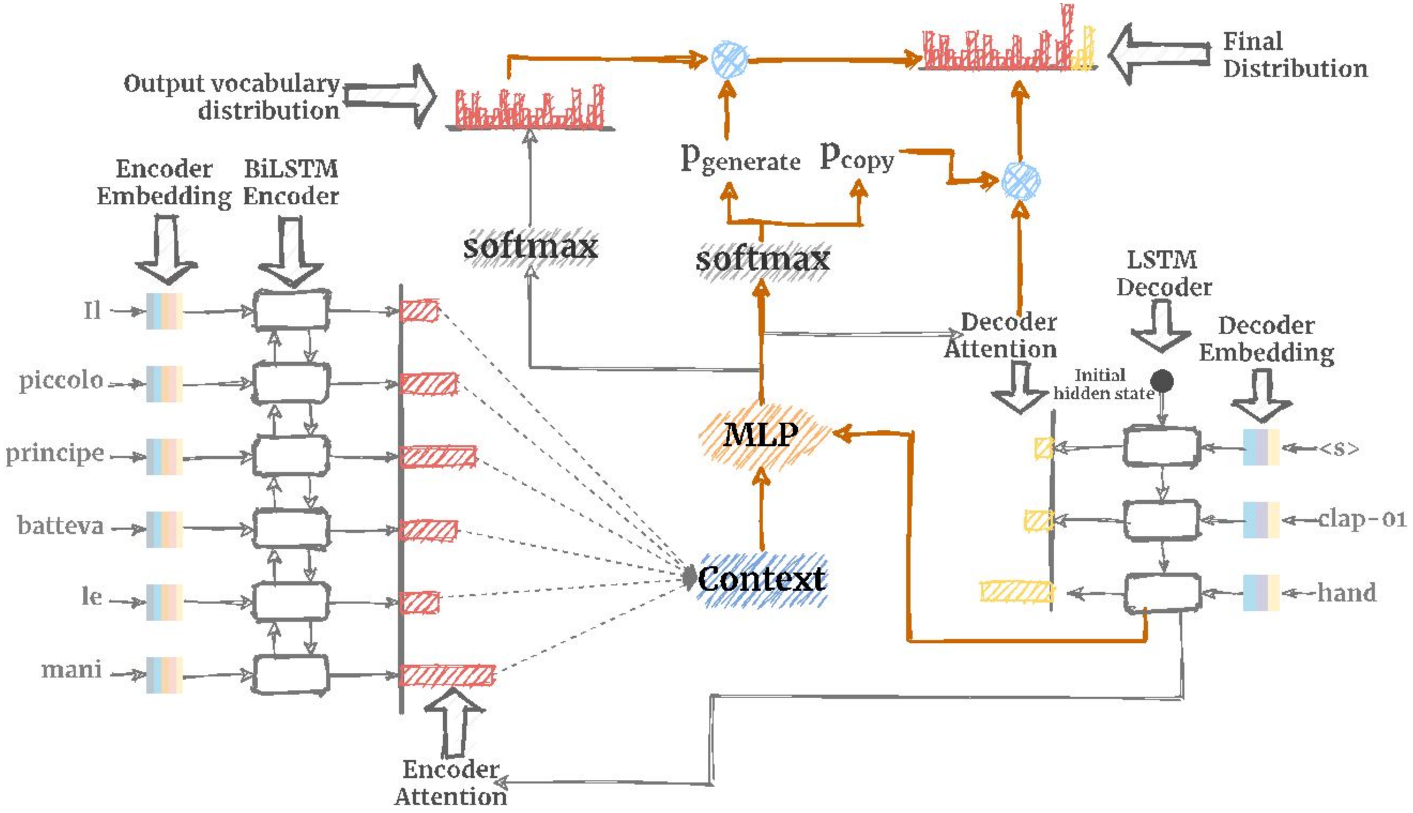

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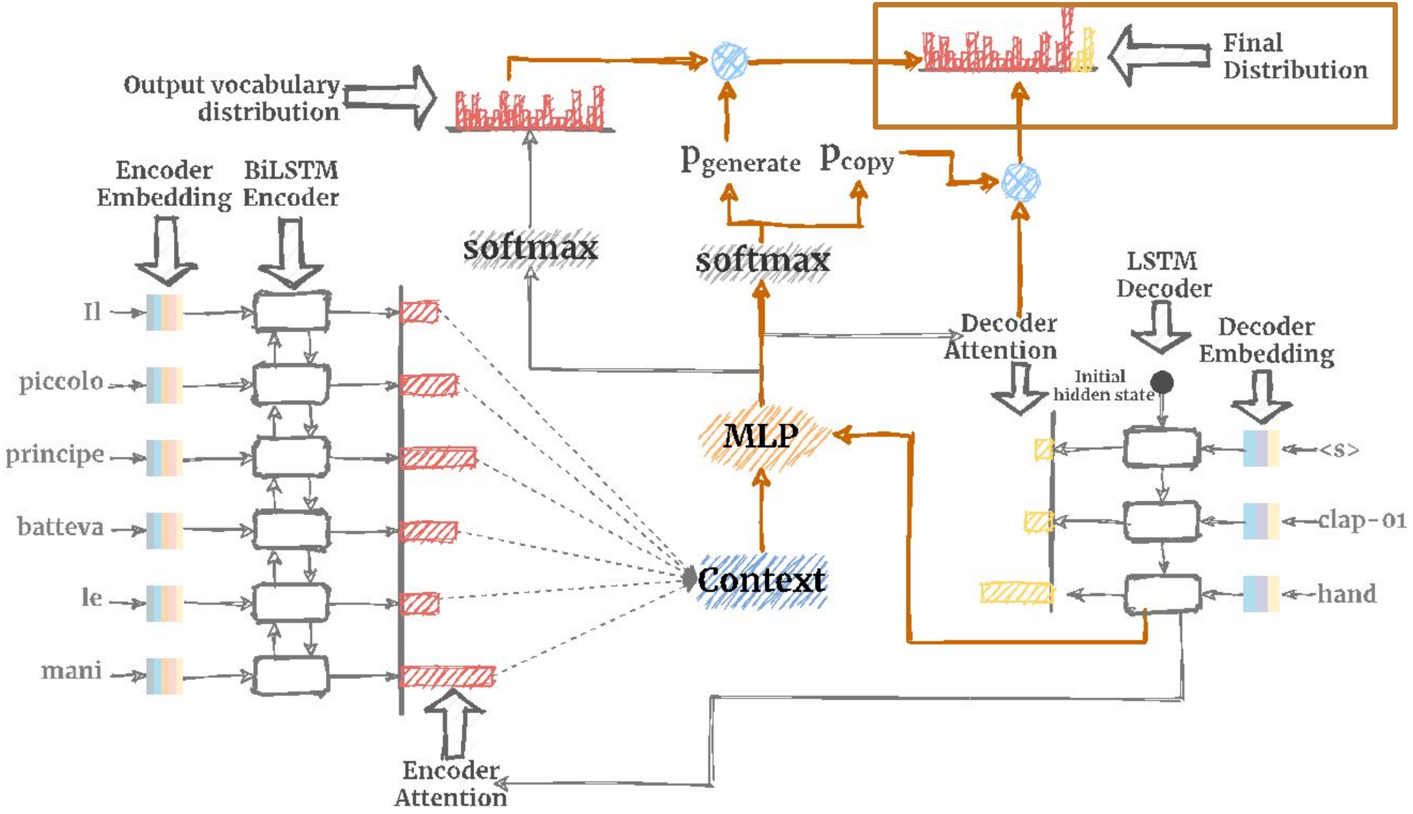

Silver Data Creation via Annotation Projection

I. through Parallel Sentences

II. through Machine Translated Sentences

Silver Data Creation via Annotation Projection

I. through Parallel Sentences

- Advantage: **Gold translated** sentences
- Disadvantage: **Silver parsed** AMR graphs

ParallelSents-SilverAMR

II. through Machine Translated Sentences

Silver Data Creation via Annotation Projection

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- Advantage: **Gold translated** sentences
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PARALLELSENTS-SILVERAMR

II. through Machine Translated Sentences

- Advantage: **Gold parsed** AMR graphs
- Disadvantage: **Silver translated** sentences

GOLDAMR-SILVERTRANSLATIONS

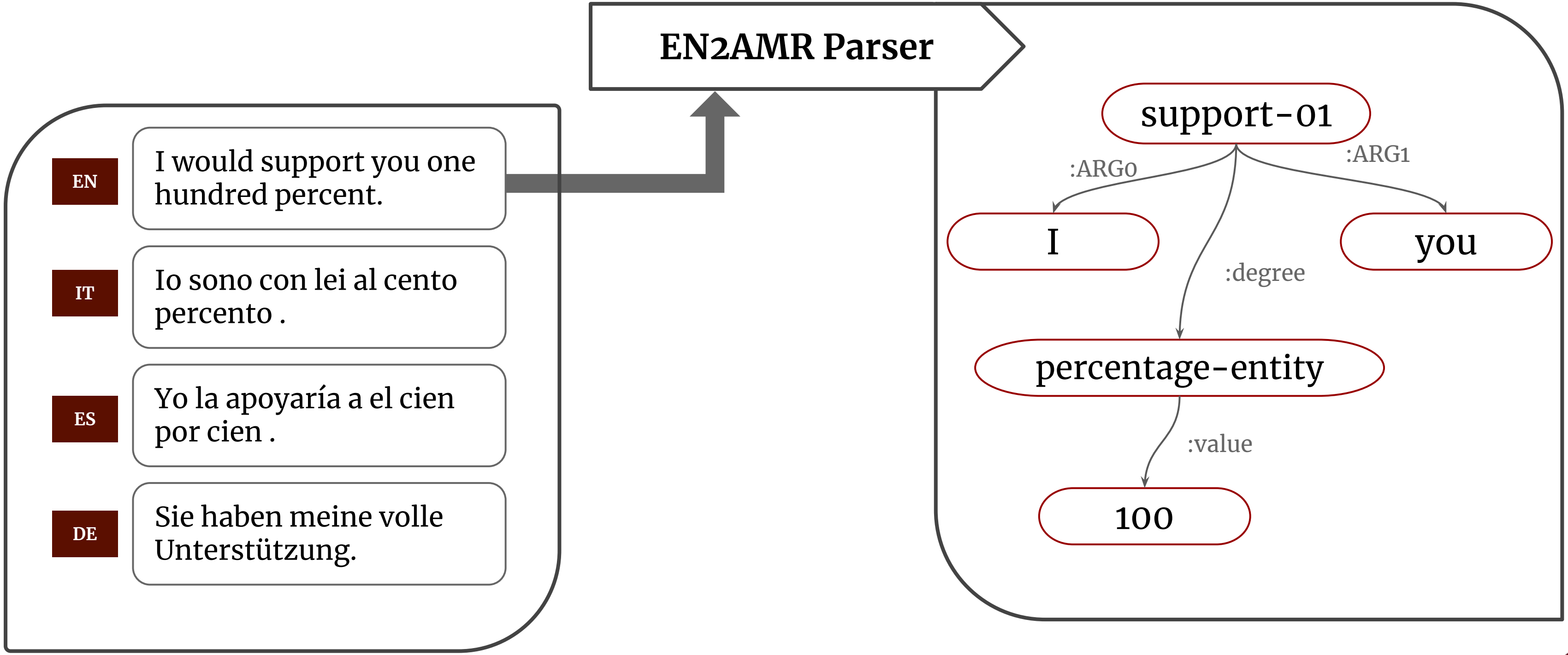
SAPIENZA NLP

ParallelSents–SilverAMR

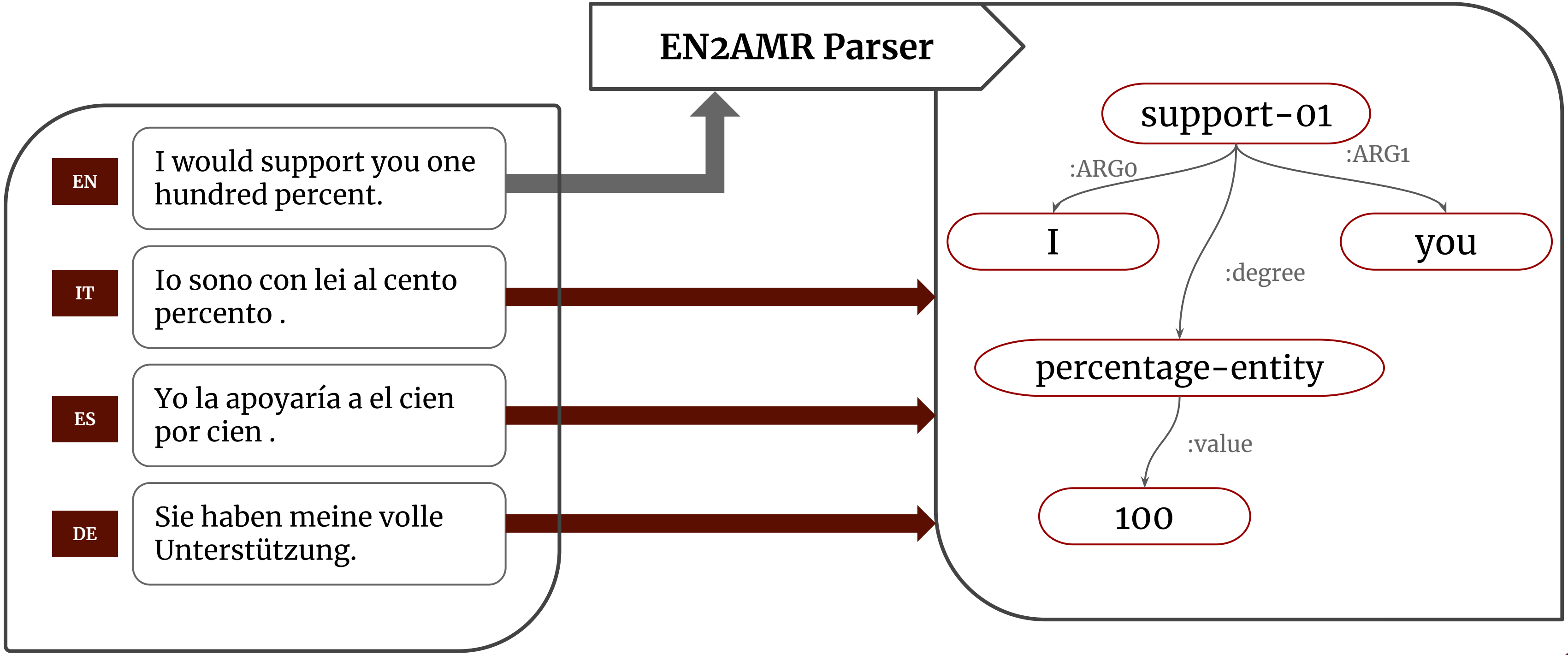
EN2AMR Parser

EN	I would support you one hundred percent.
IT	Io sono con lei al cento percento .
ES	Yo la apoyaría a el cien por cien .
DE	Sie haben meine volle Unterstützung.

ParallelSents–SilverAMR



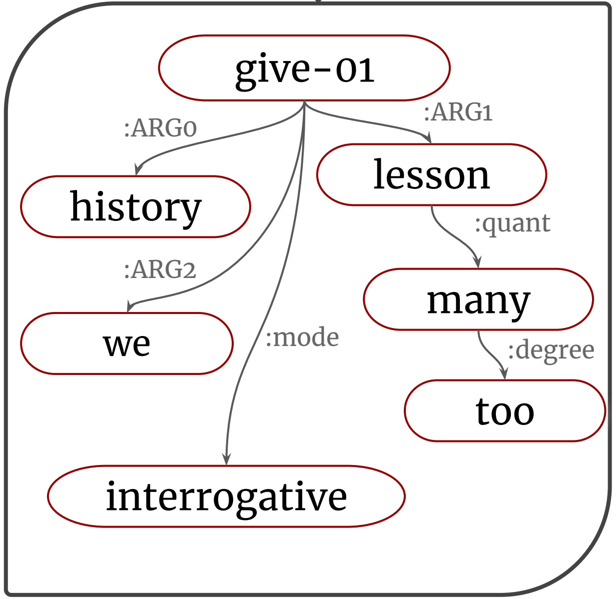
ParallelSents-SilverAMR



GoldAMR–SilverTranslations

EN

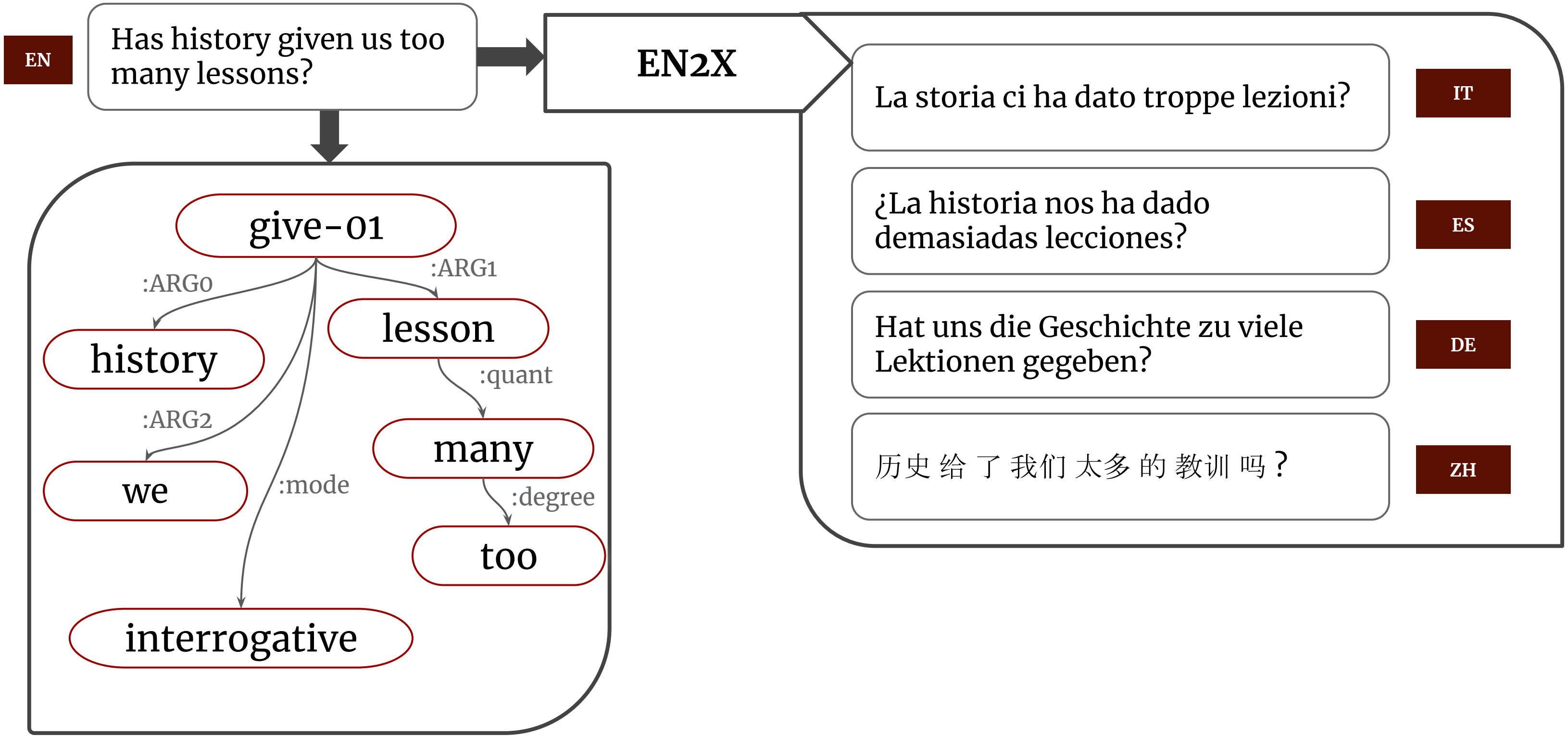
Has history given us too many lessons?



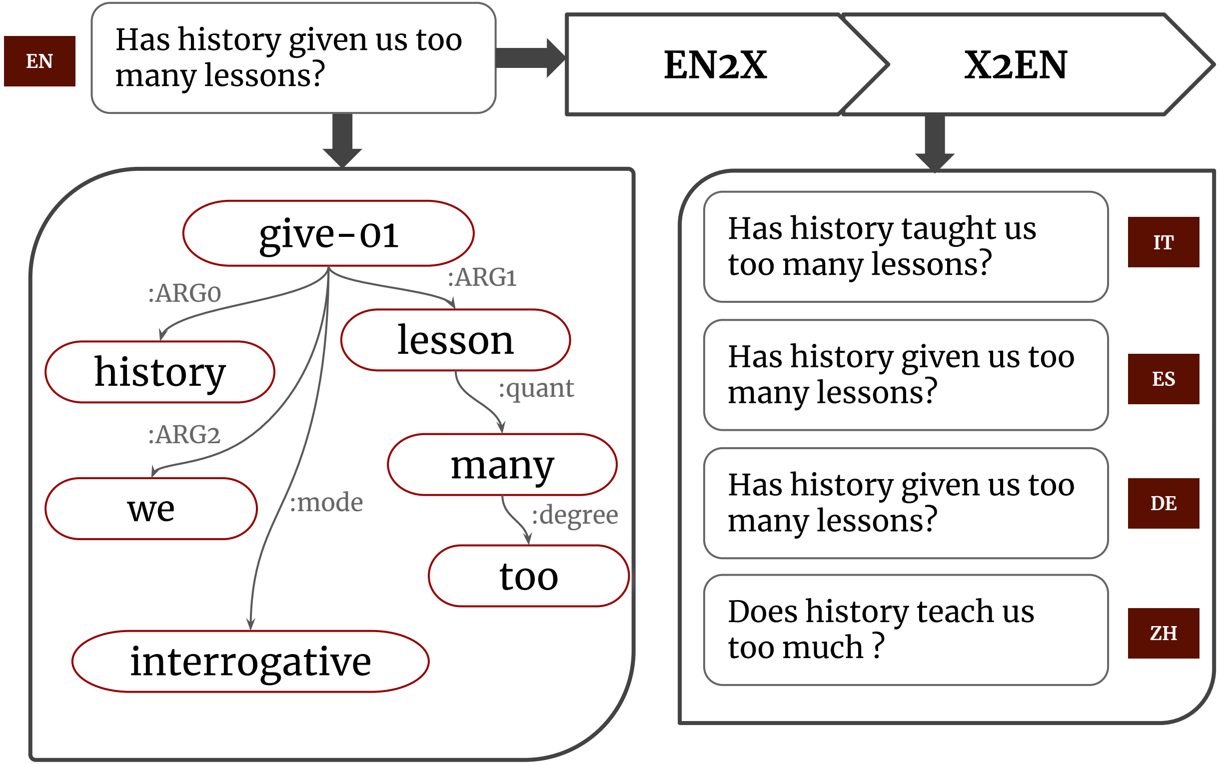
EN2X

X2EN

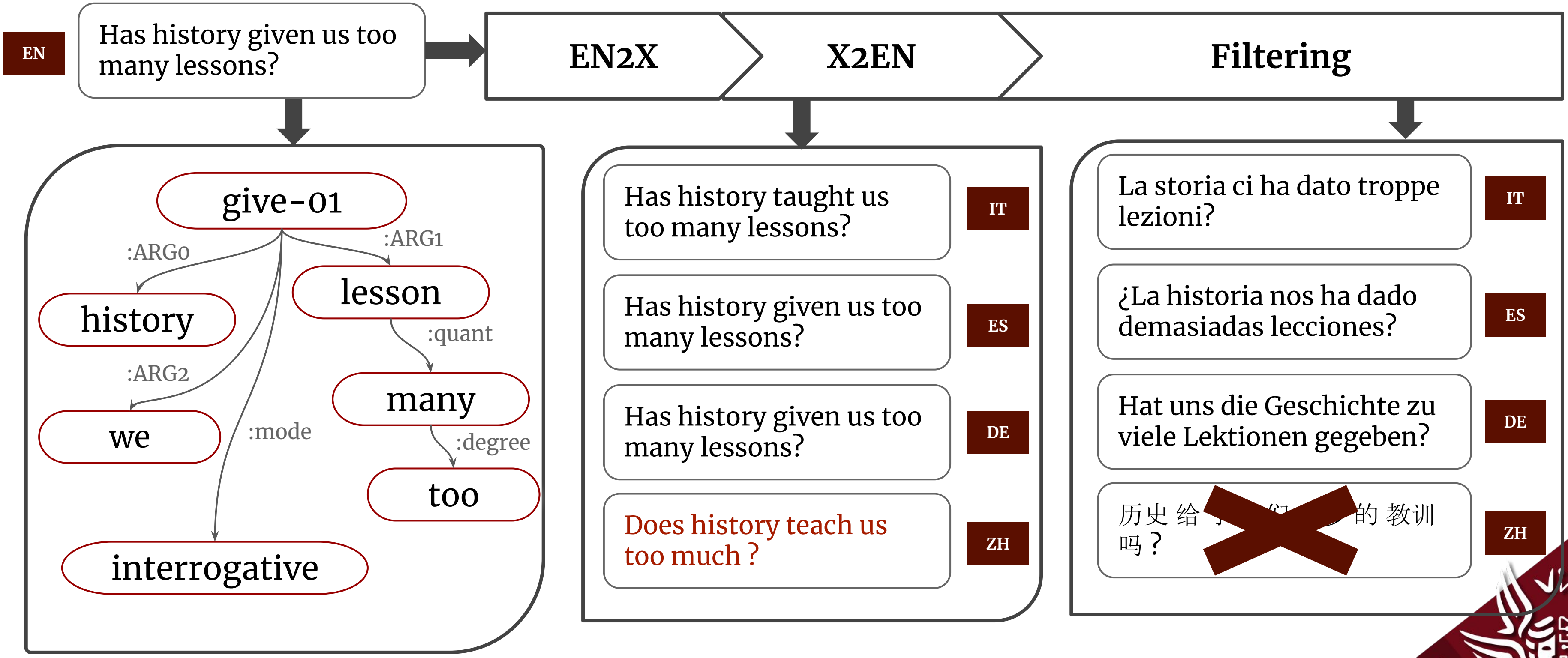
GoldAMR-SilverTranslations



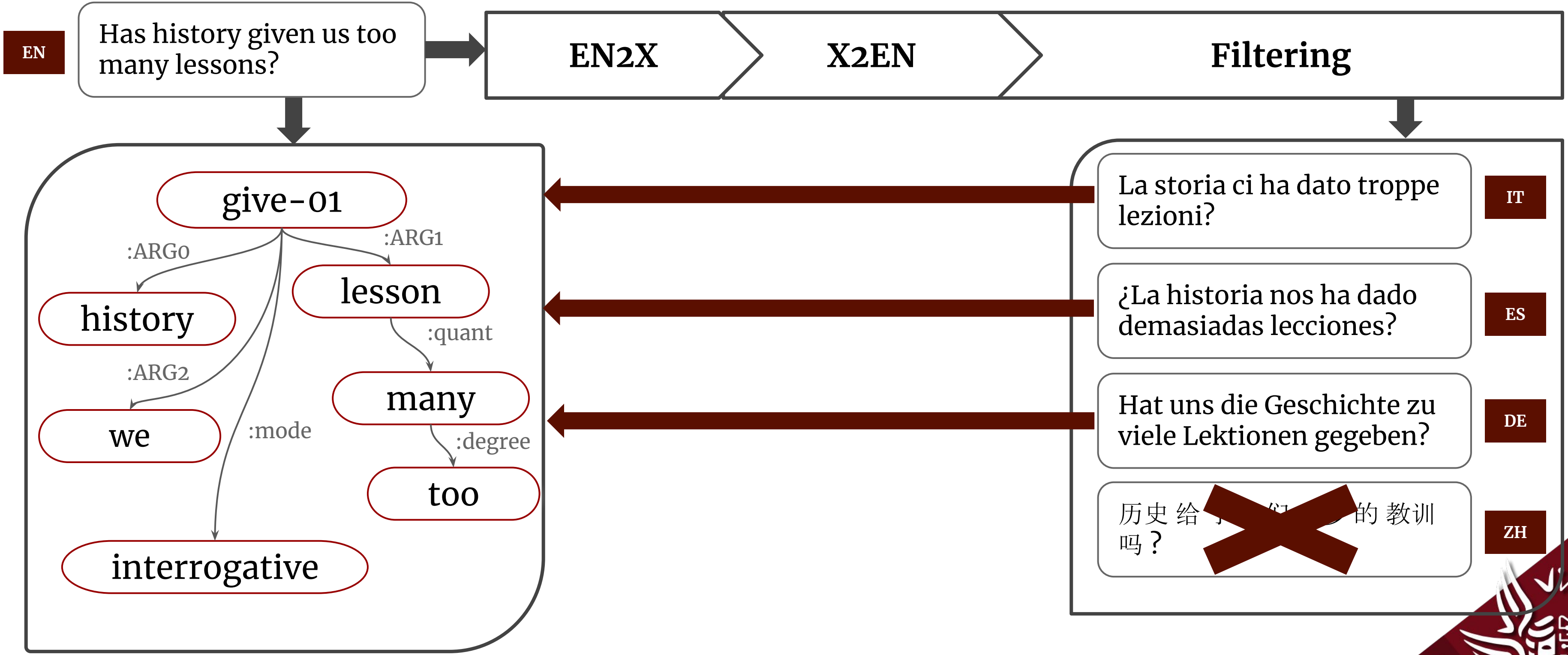
GoldAMR–SilverTranslations



GoldAMR-SilverTranslations



GOLDAMR-SILVERTRANSLATIONS



SAPIENZA NLP

Experimental Setup

Configuration

Evaluation

- **AMR2.0 - Four Translations (Damonte and Cohen, 2020):**
  A. Chinese
  B. German
  C. Italian
  D. Spanish

- **Smatch F1**

Annotation Projection

I. **Europarl**, as the parallel sentences corpus

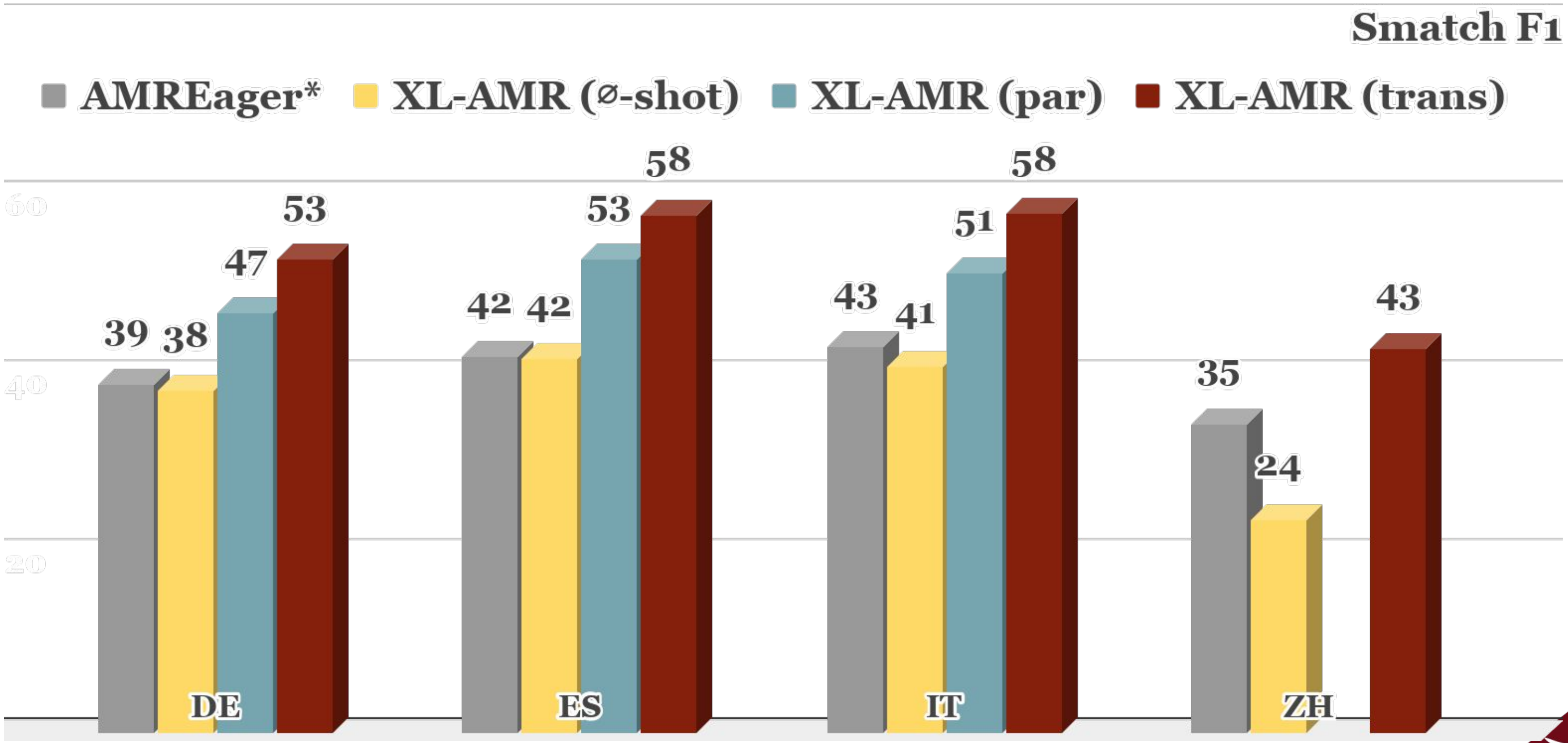
II. **AMR 2.0**, as gold annotated dataset

XL-AMR Variants

I. ∅-shot (EN to lang)
II. Language-Specific (lang to lang)
III. Multilingual (all)
IV. Bilingual (EN+lang)

SAPIENZA NLP

Results



*AMREager (Damonte and Cohen, 2018) is the only cross-lingual AMR parser from the literature.

Results

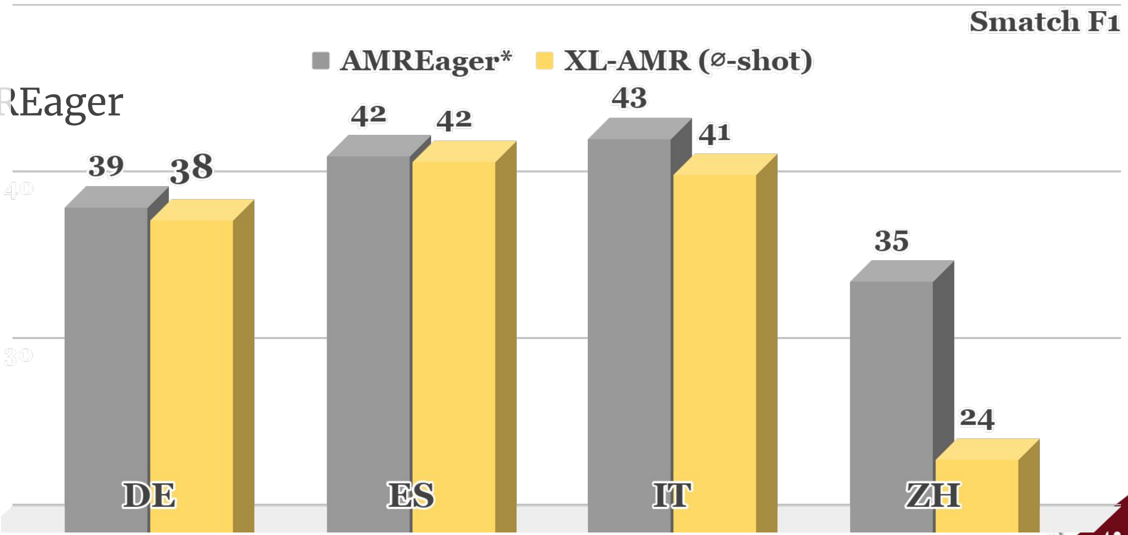
I. ∅-shot XL-AMR performs on par with AMREager or worse.

II. XL-AMR (par) outperforms AMREager by ~8 points.

-disposal of AMR alignments.

III. XL-AMR (trans) outperforms XL-AMR (par) by 5-7 points and AMREager by 8-16 points.

-disposal of AMR alignments
-better quality corpus



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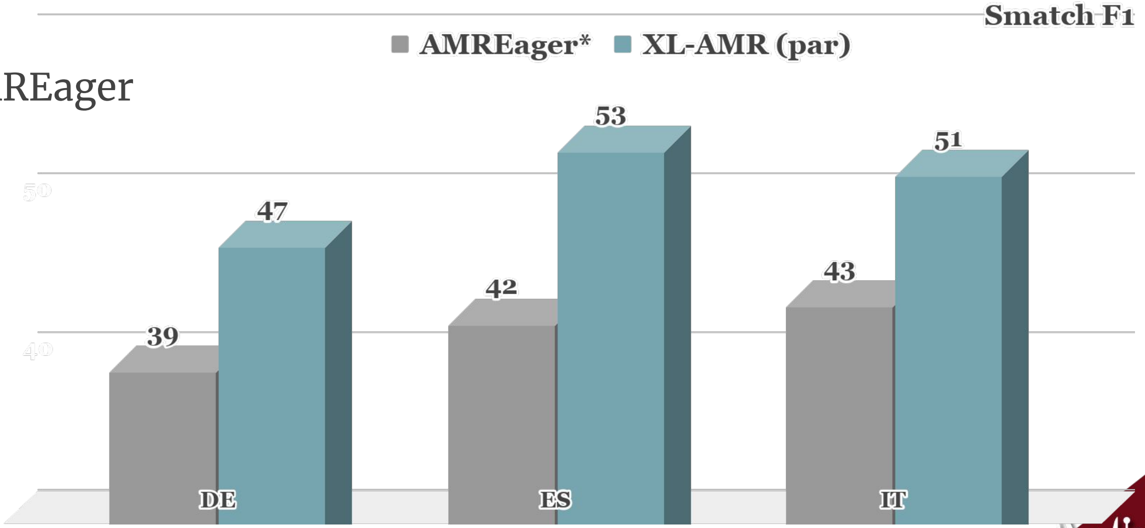

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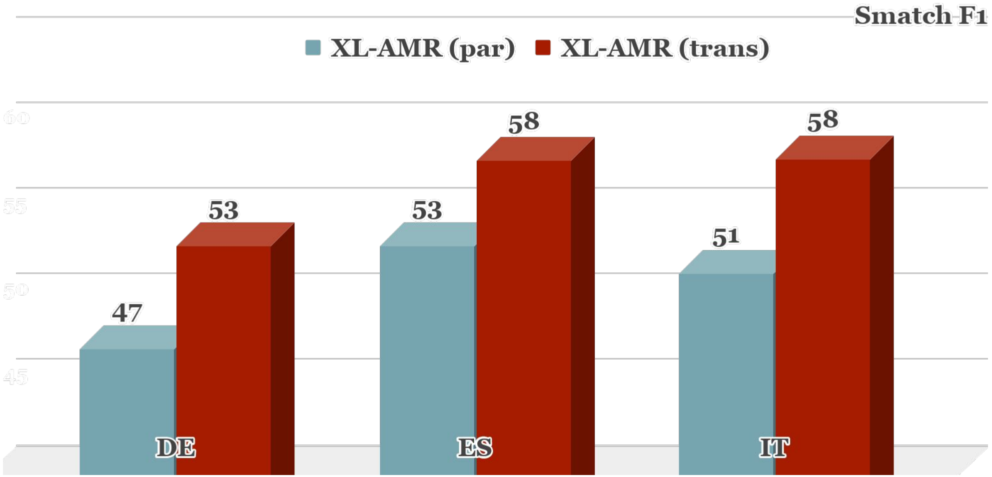
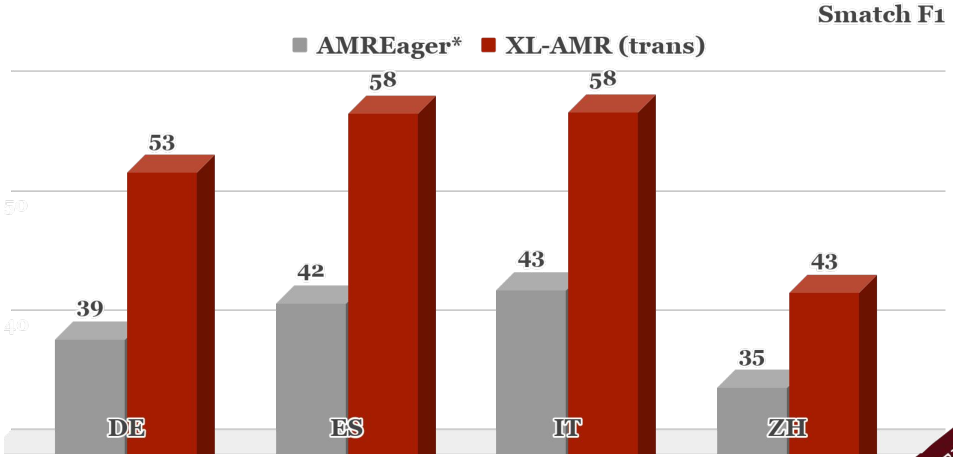


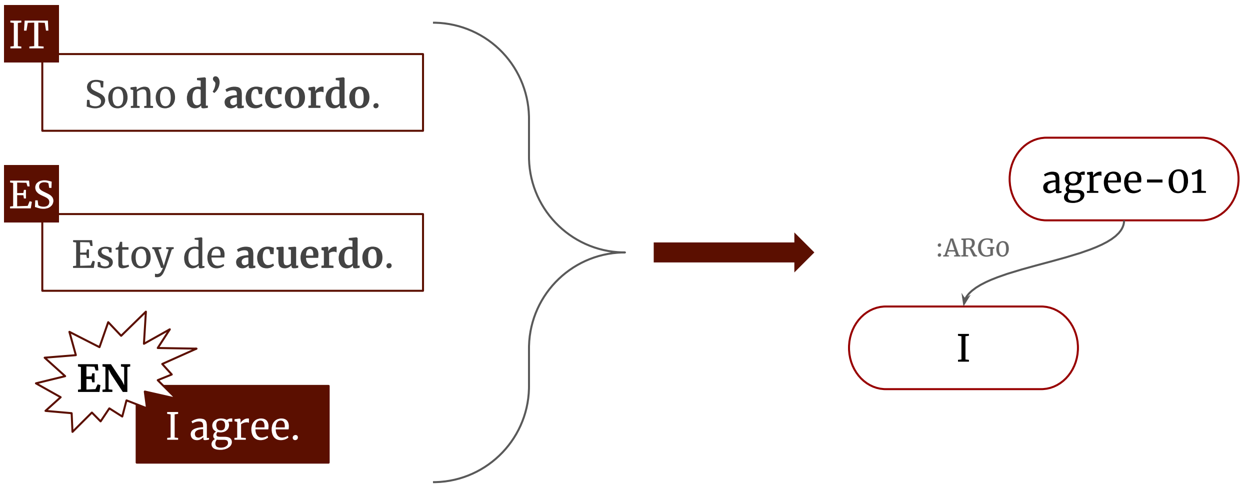


Qualitative Analysis

Handling translation divergences of Dorr (1994)

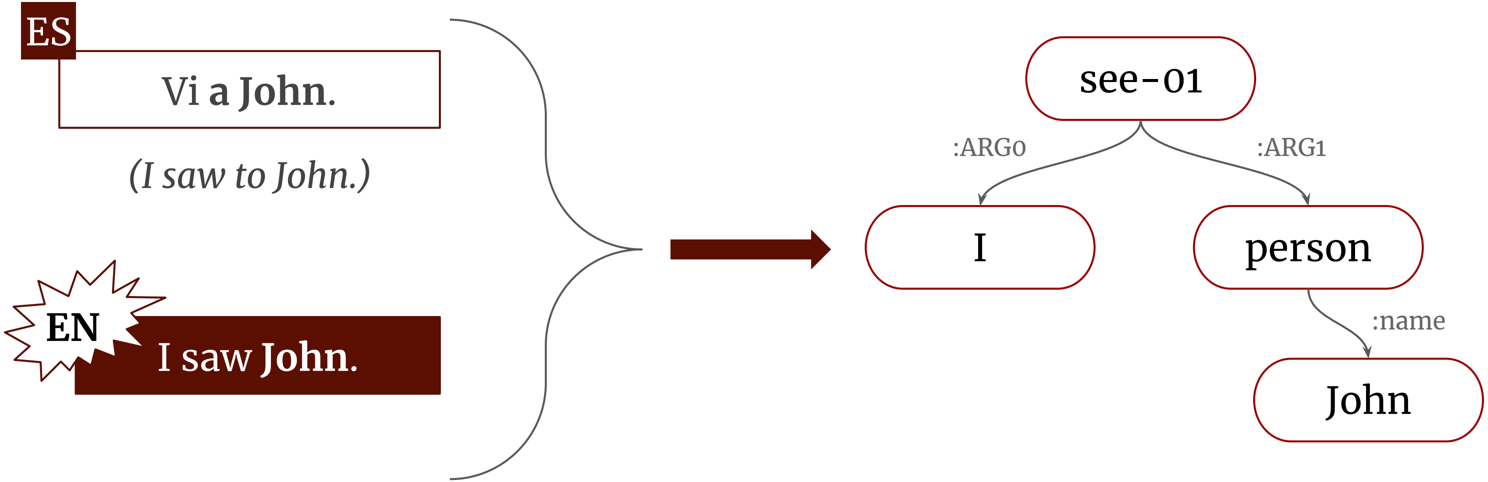
Translation Divergences

Categorical – the same meaning is expressed by different syntactic categories across languages, e.g., POS-tags.



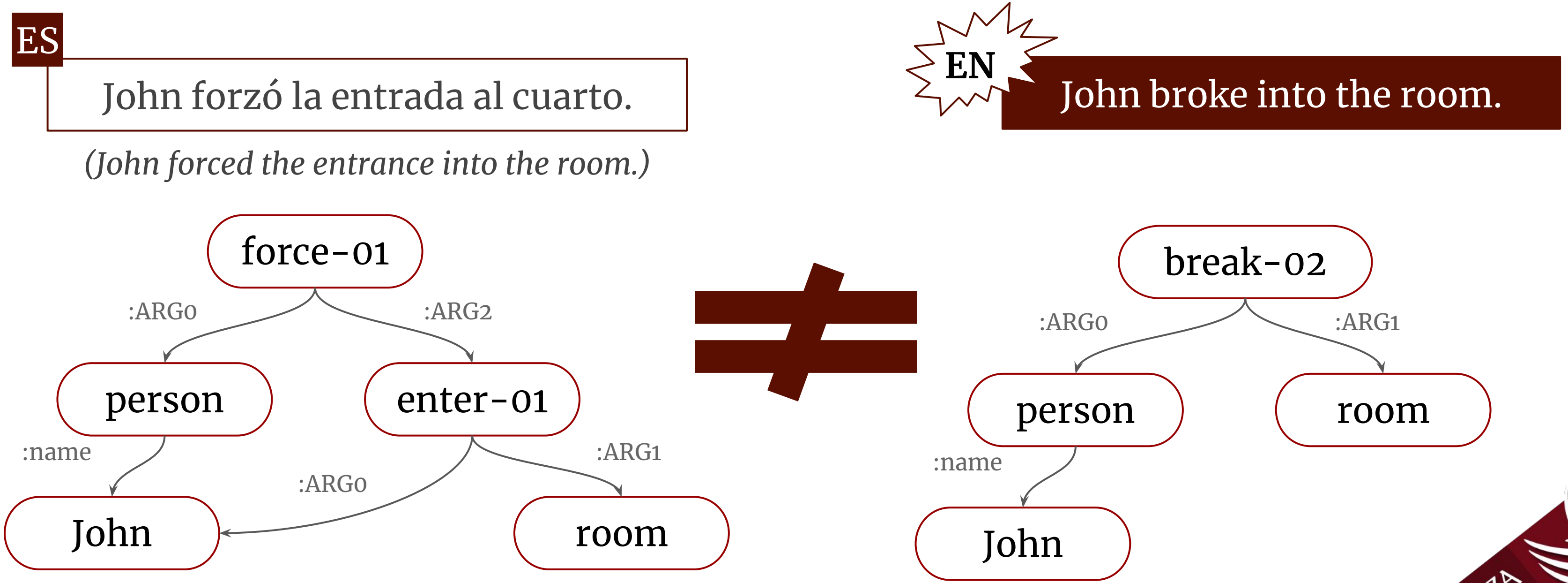
Translation Divergences

Structural – A verbal object is realized as a noun phrase in one language and as prepositional phrase in the other.



Translation Divergences

Lexical - A verb is translated with a different lexical verb across languages.



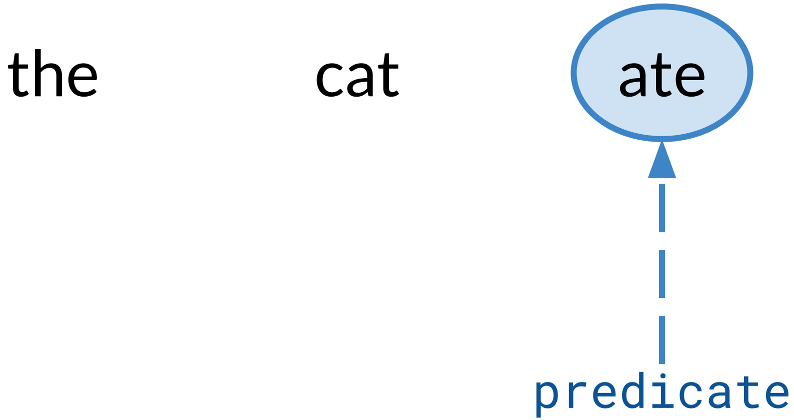
Semantic Role Labeling (SRL)

Who did what to whom?

the cat ate the fish

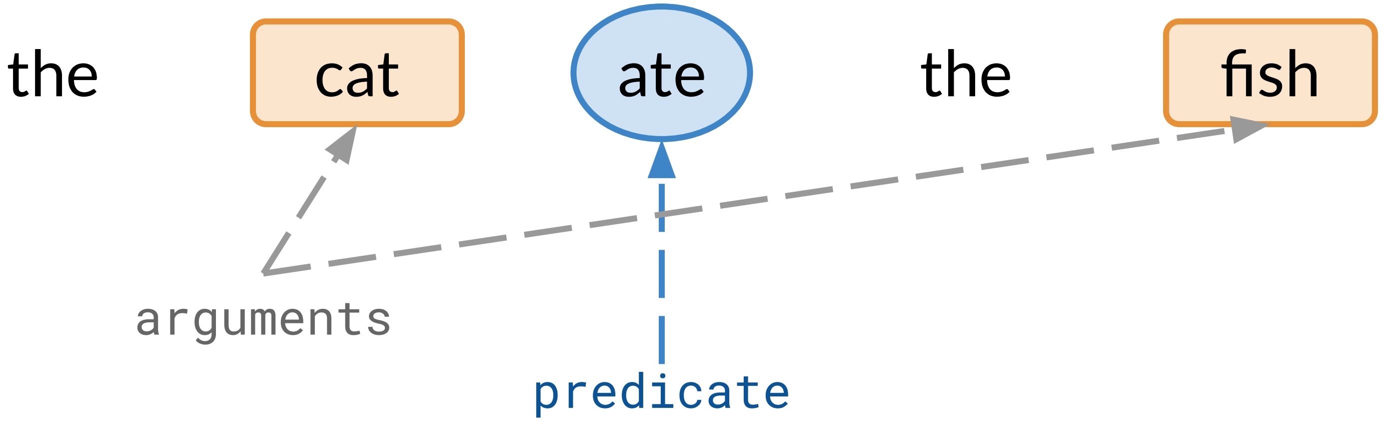
Semantic Role Labeling (SRL)

Who did what to whom?



Semantic Role Labeling (SRL)

Who did what to whom?



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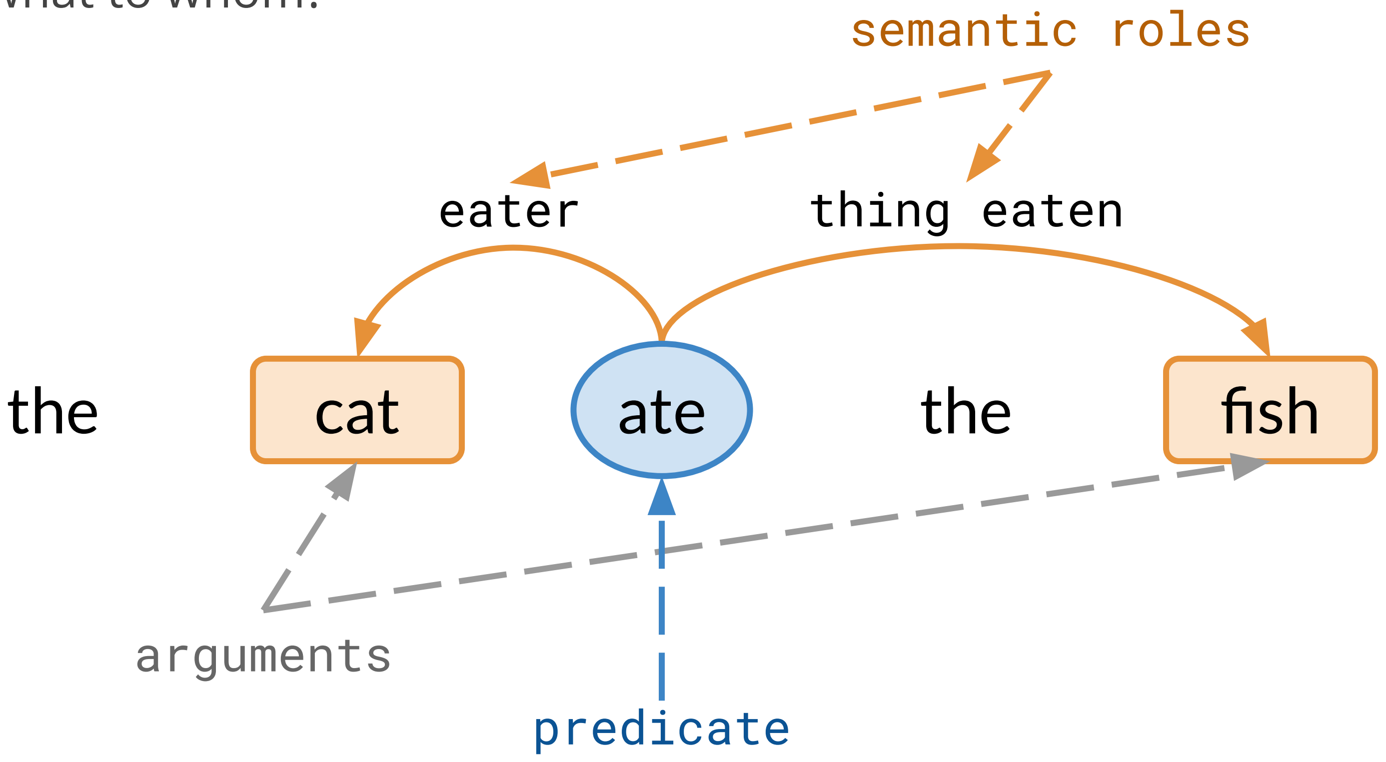


A unified representation for all languages

Key goal of **sentence-level semantics**:

- Providing a semantic representation that is **independent** (or as independent as possible) **from the language**

However:

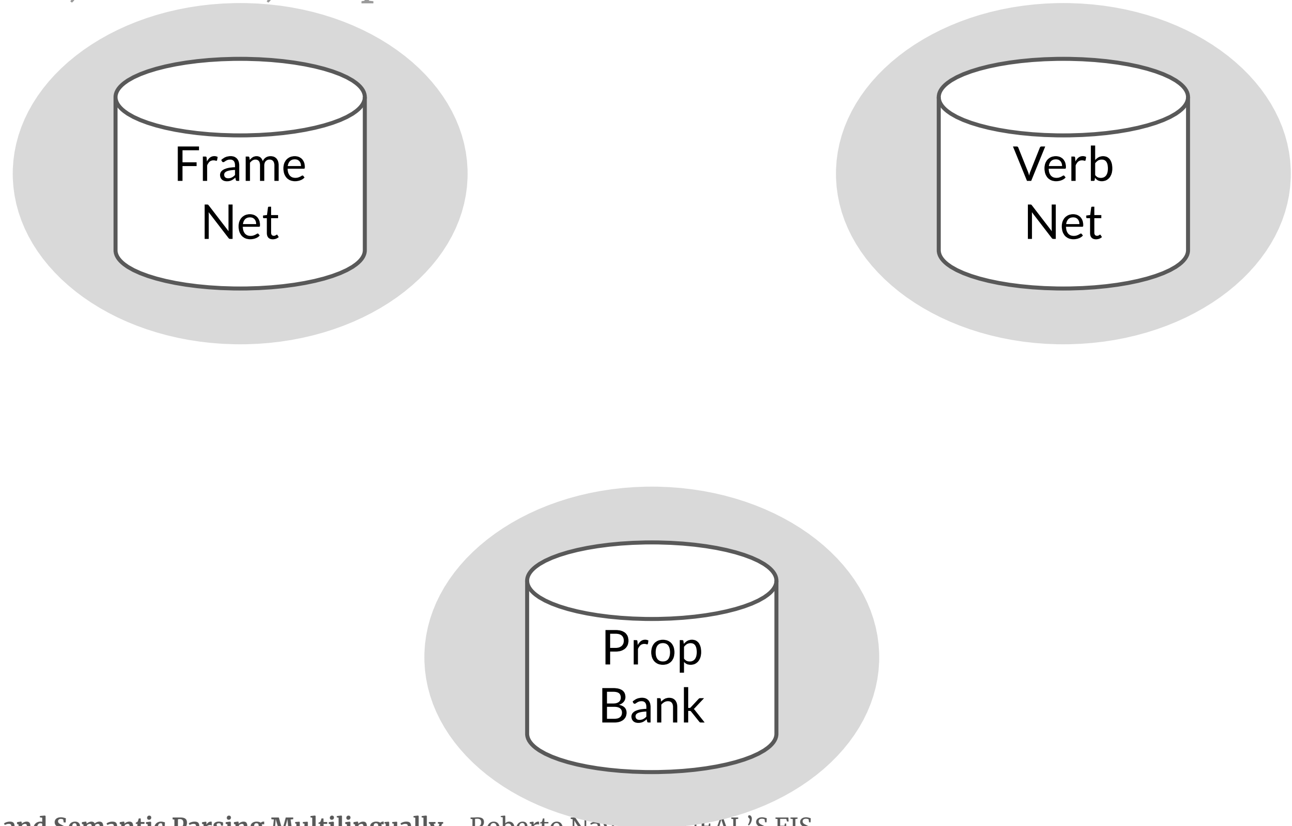
- In SRL, we are using **different predicate inventories** for **different languages**
- In AMR parsing, we are hampered by the **lack of multilingual data** and the use of PropBank with **English-specific predicate senses**

Resources for SRL

An overview

SRL: Limitations of Current Resources

FrameNet, VerbNet, PropBank



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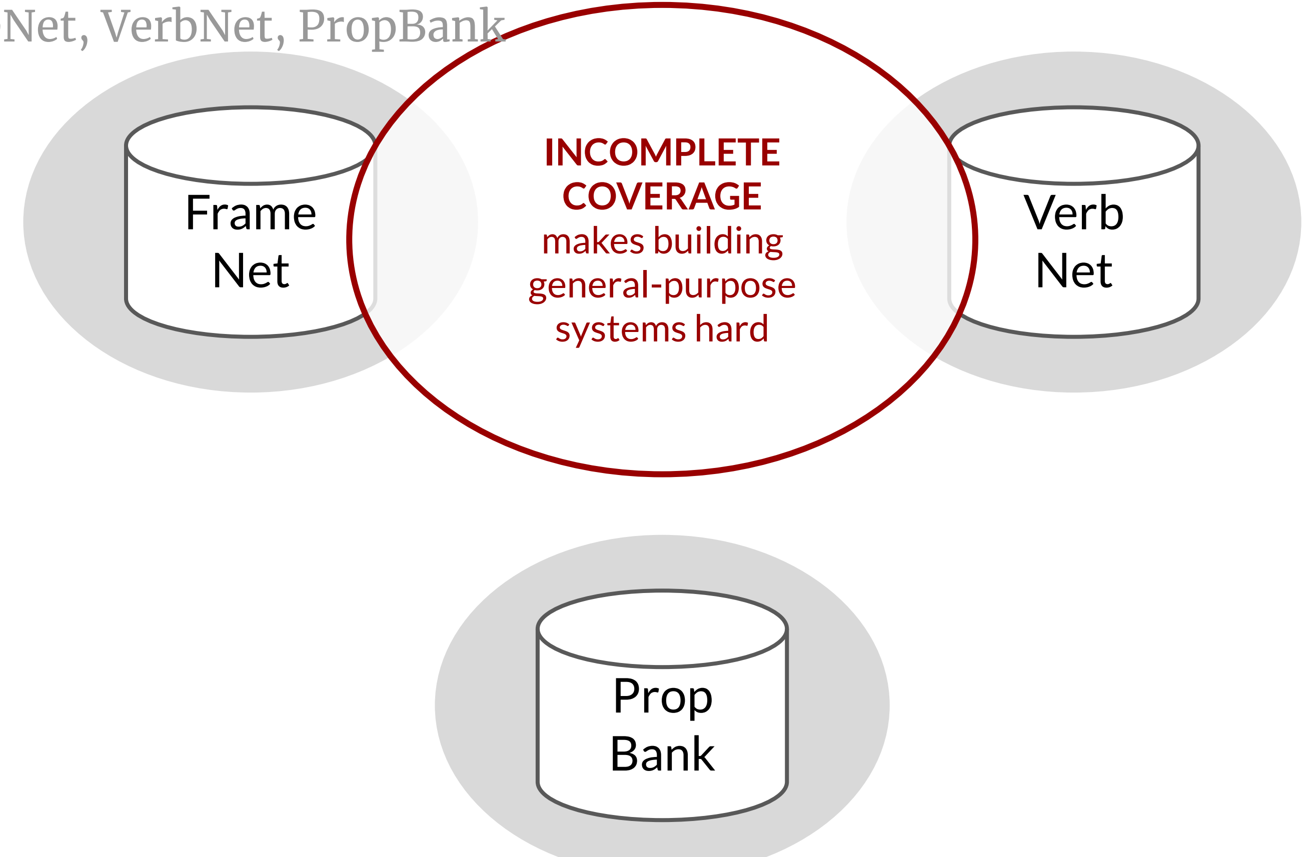

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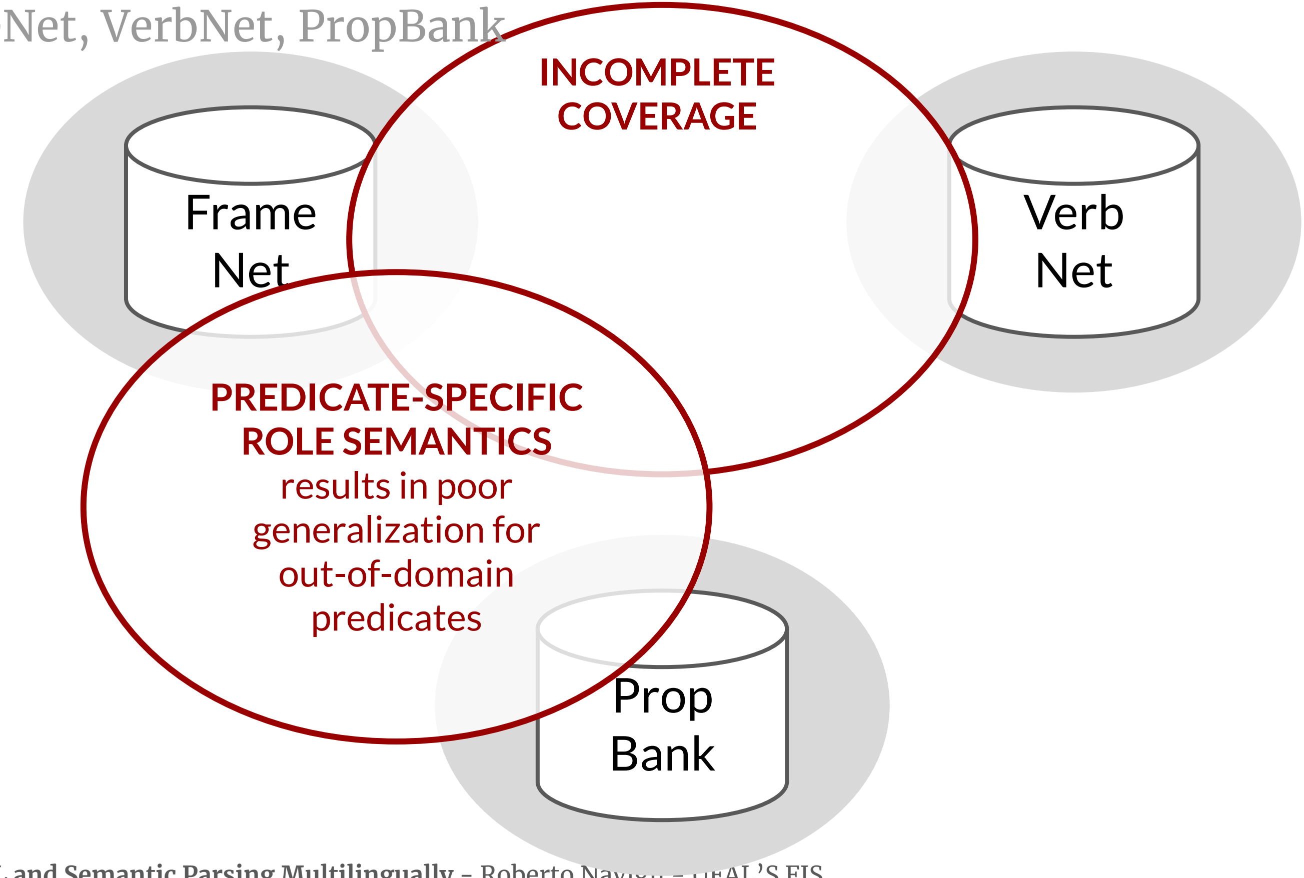

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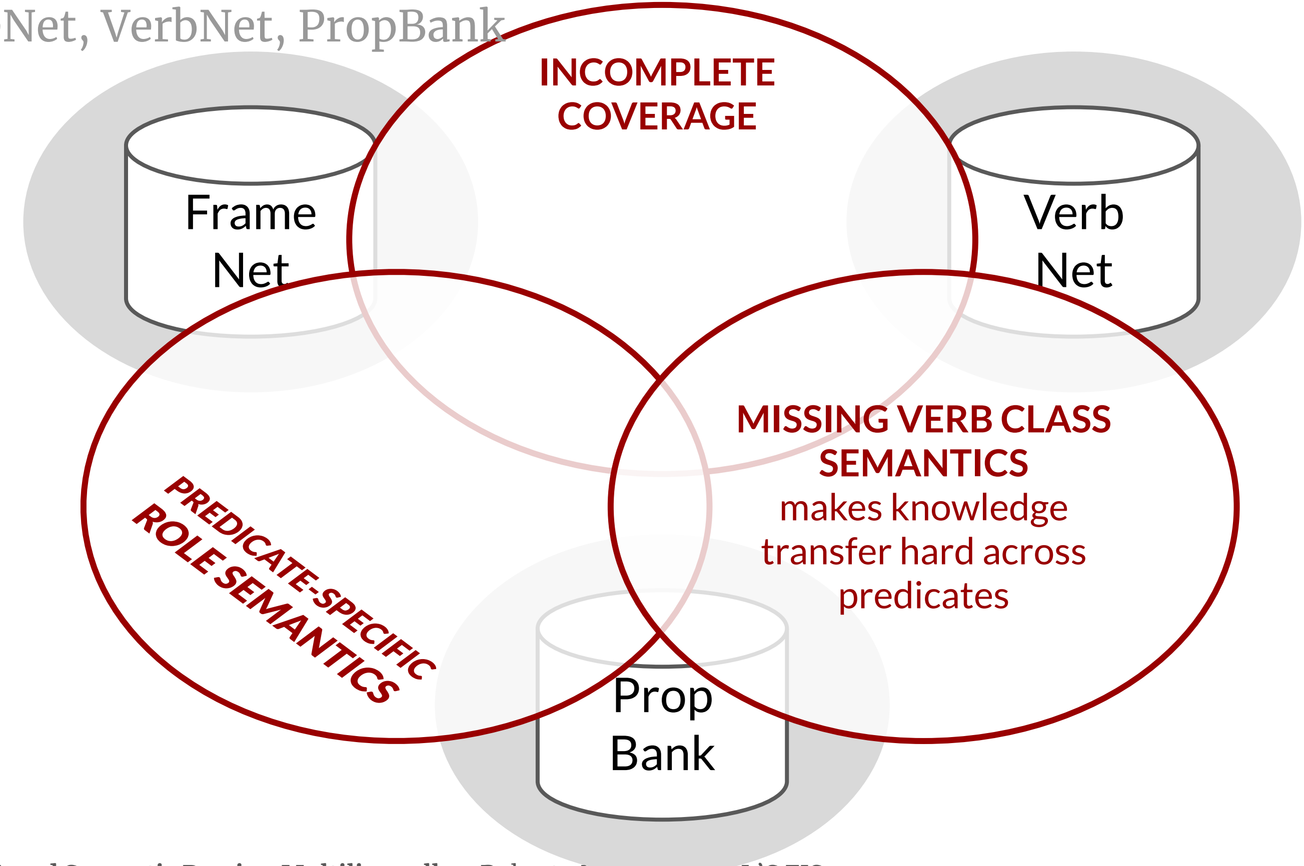

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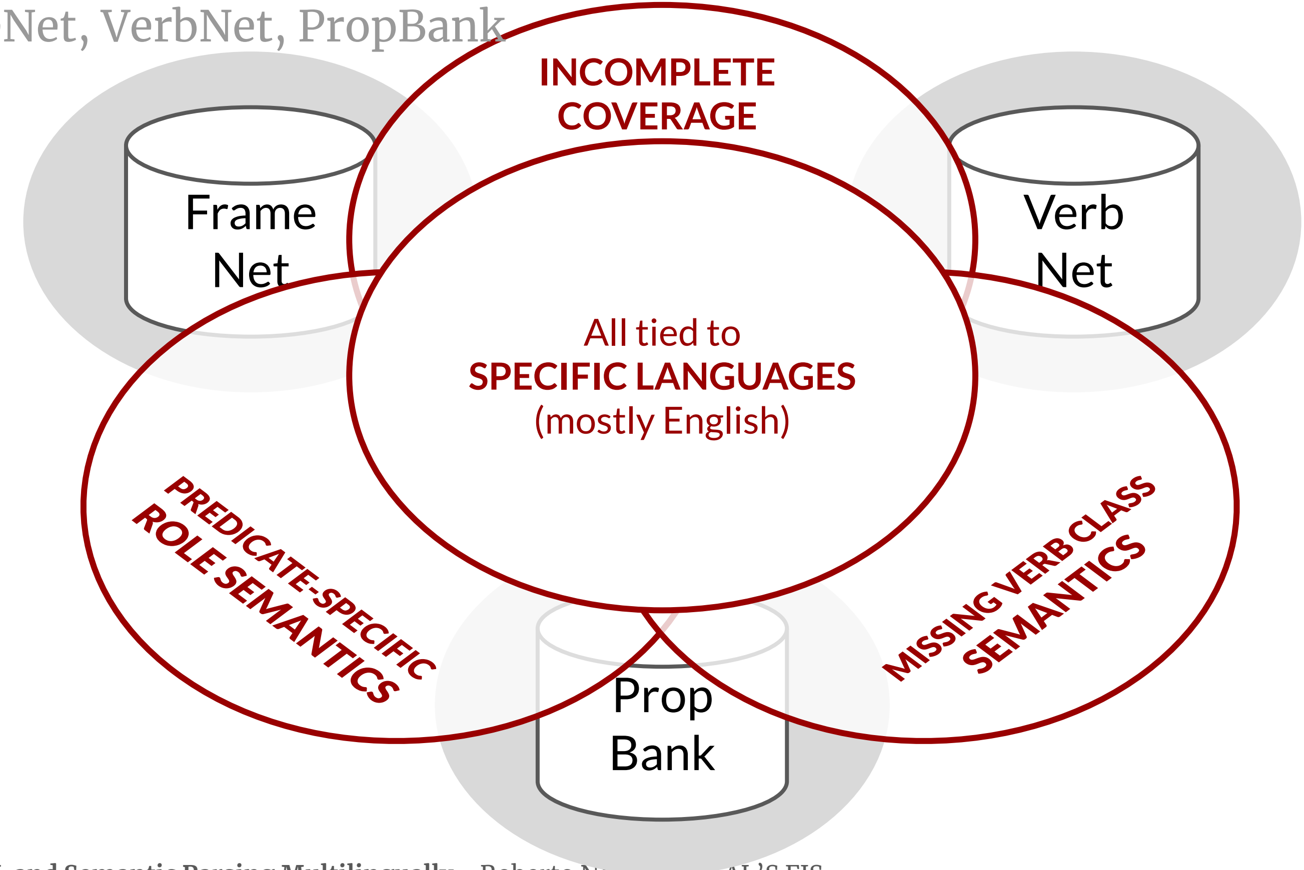


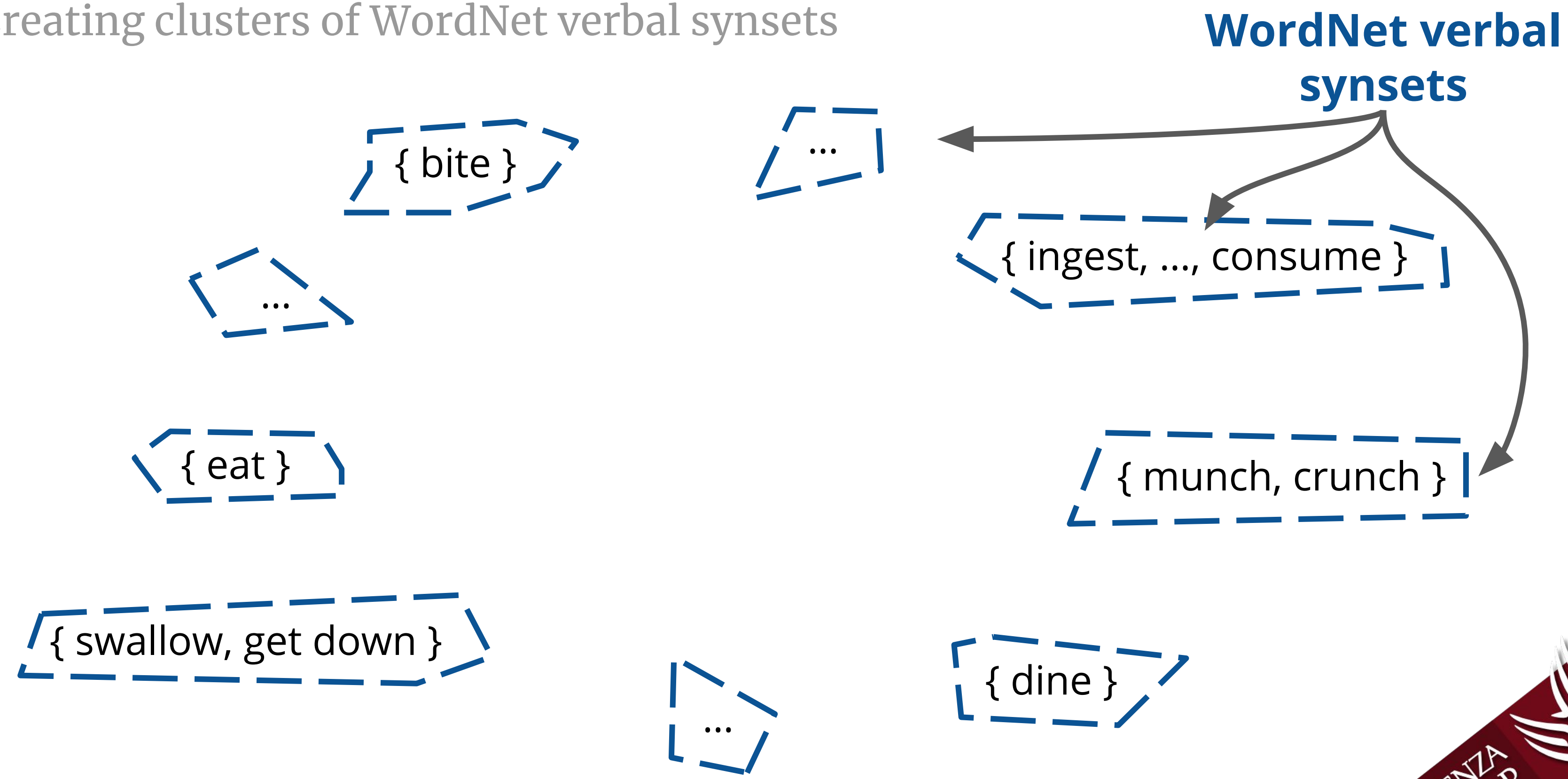
Introducing

VerbAtlas

Di Fabio, Conia and Navigli - EMNLP 2019

Manually clustering predicates into frames

Creating clusters of WordNet verbal synsets



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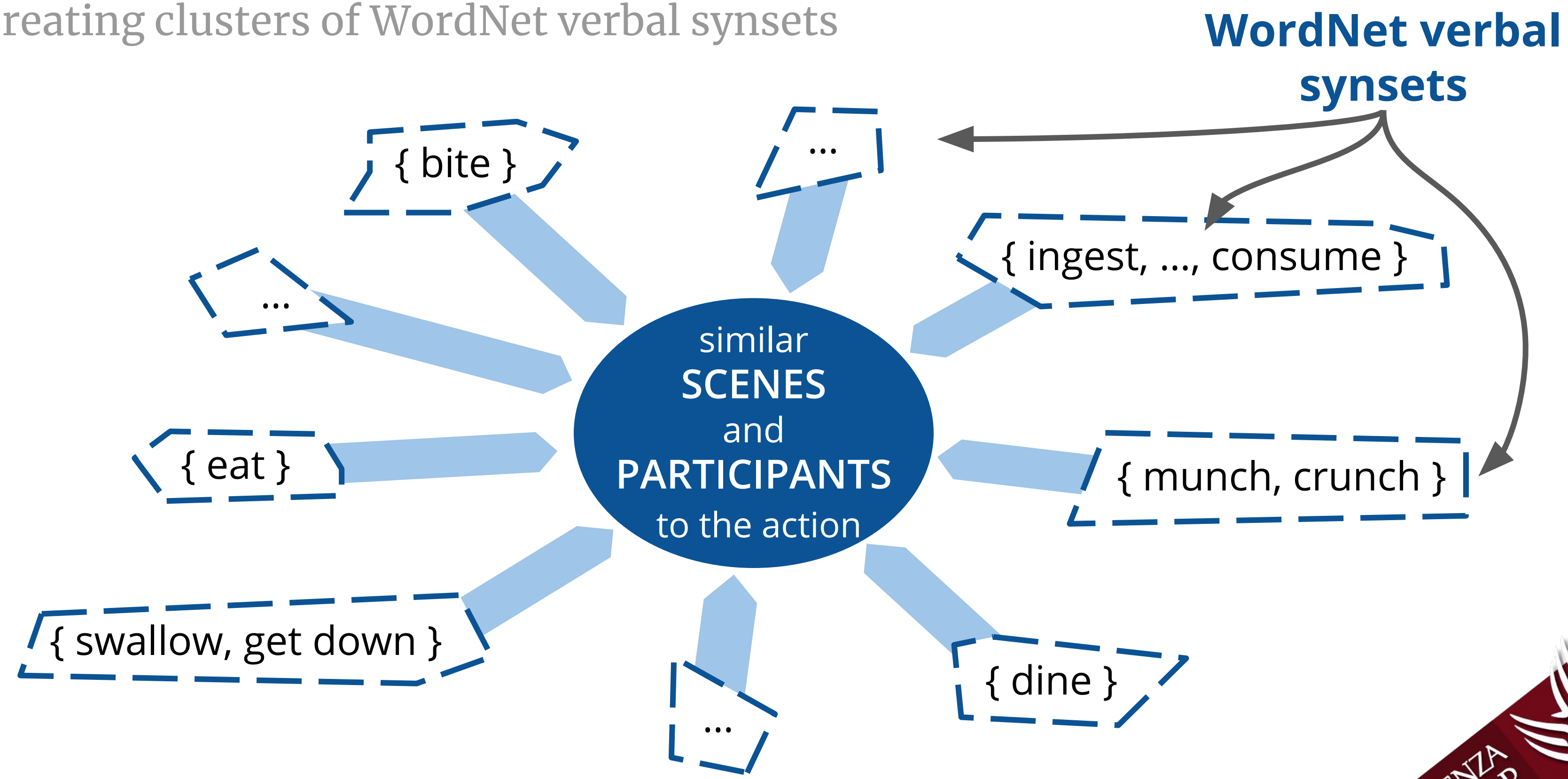

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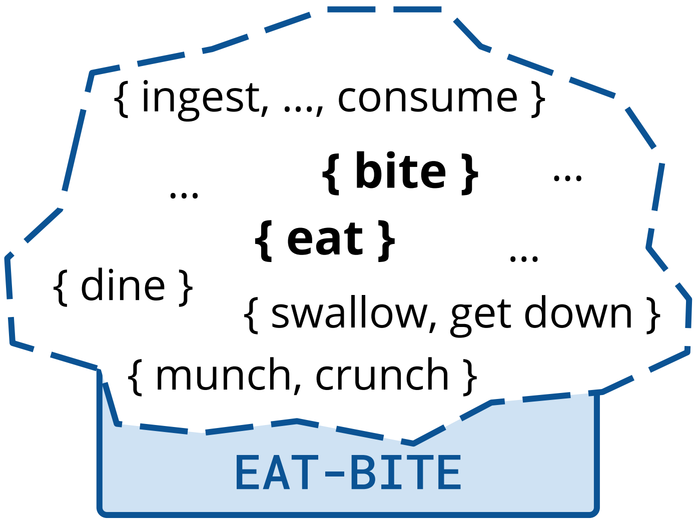
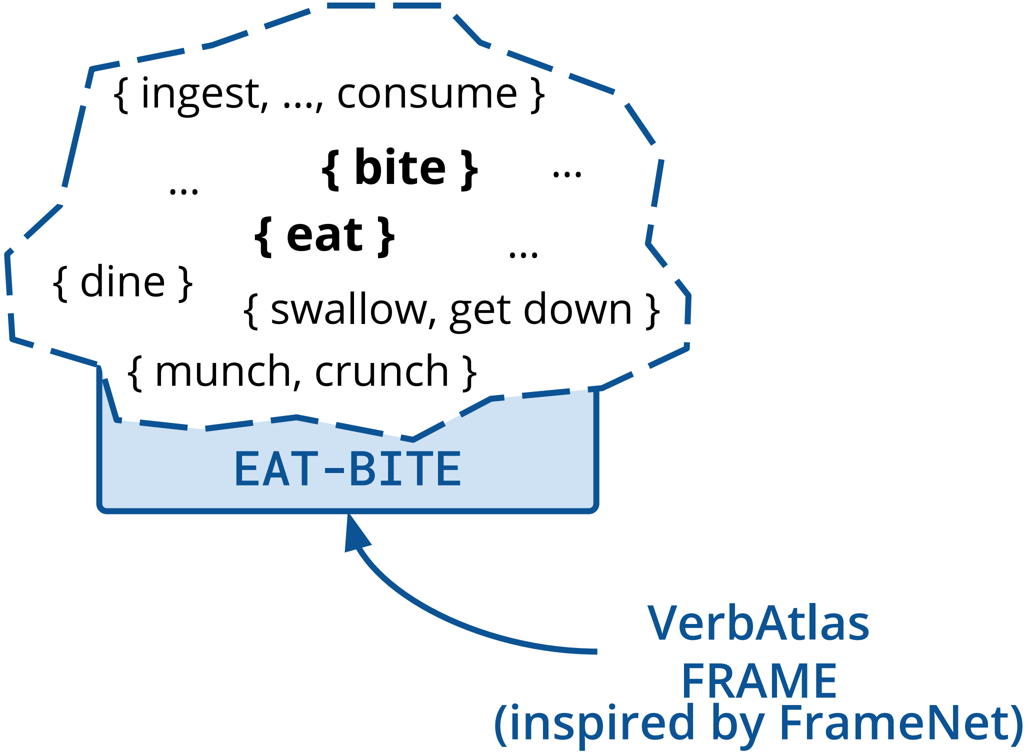


Frames in VerbAtlas

All WordNet verbal synsets organized into semantic frames



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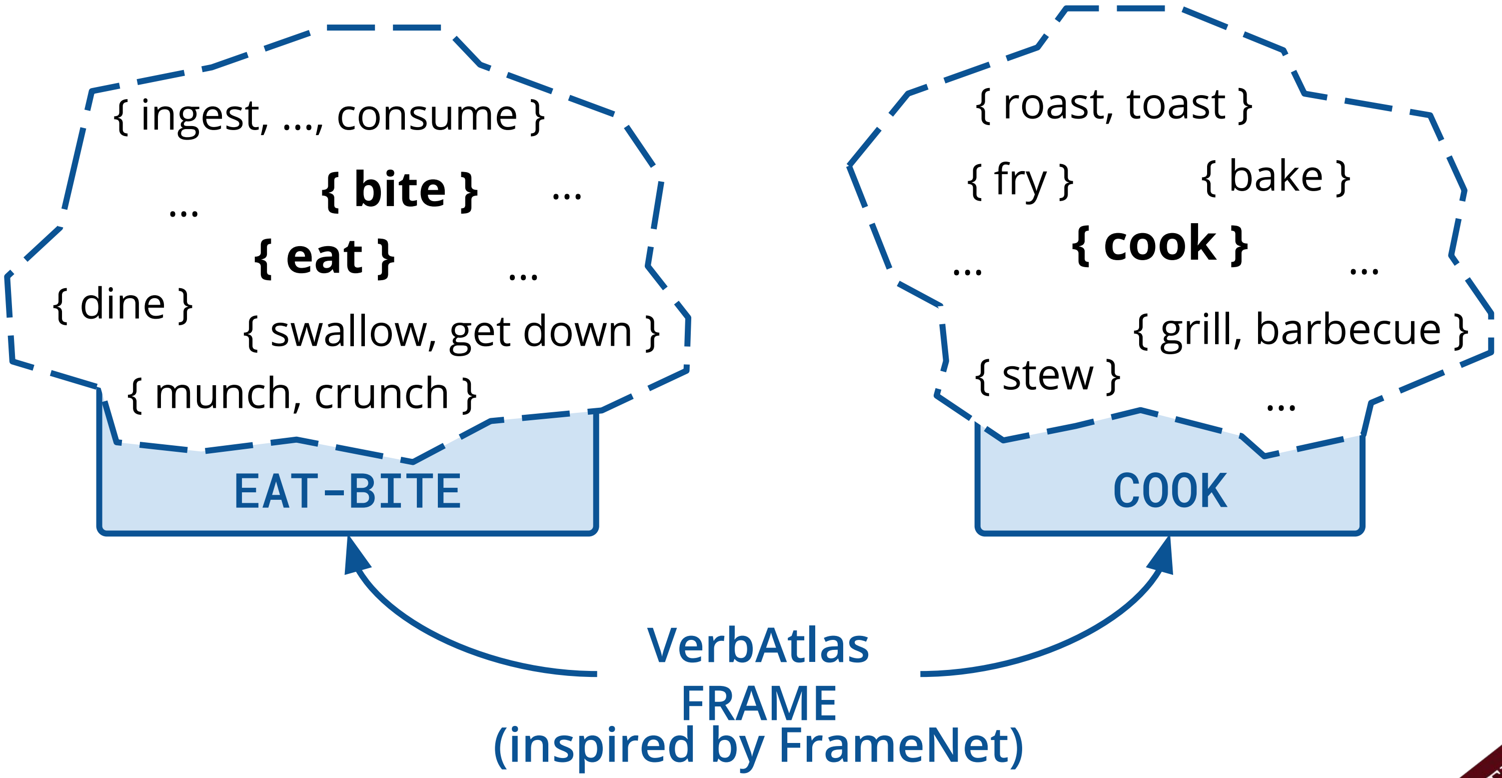

Semantic Roles: from VerbNet to VerbAtlas

From VerbNet roles...

Goal Value Time Product Stimulus Precondition

Final_Time Pivot Manner Co-Agent Source

Patient Location

Agent Instrument Predicate Material

Source

Extent Reflexive Experiencer

Affector Result

Path Axis

Co-Patient Asset Destination Duration

Result Attribute

Initial_Location Beneficiary Cause Topic

Recipient

Trajectory Co-Theme Initial_state Context

Semantic Roles: from VerbNet to VerbAtlas

... to VerbAtlas roles

Stimulus
Goal
Time
Product
Value
Precondition
Co-Agent
Pivot
Final_Time
Source
Manner
Patient
Location
Agent
Instrument
Predicate
Material
Source
Reflexive
Extent
Affector
Result
Experiencer
Path
Axis
Co-Patient
Asset
Destination
Duration
Result
Attribute
Beneficiary
Cause
Topic
Initial_Location
Recipient
Co-Theme
Initial_state
Trajectory
Context

Prototypical Argument Structures in VerbAtlas

Frame-level organization for Semantic Roles

VerbAtlas Semantic Role Set - inspired by VerbNet

`Agent`	`Patient`	`Instrument`	`Result`	`Location`	`...`	`Source`

Prototypical Argument Structures in VerbAtlas

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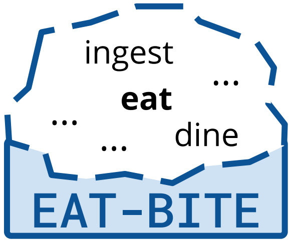


PROTOTYPICAL ARGUMENT STRUCTURE of **EAT-BITE**

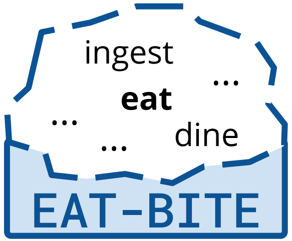
`Agent` `Patient` `Instrument` `Result` `Location` `...` `Source`

Prototypical Argument Structures in VerbAtlas

Frame-level organization for Semantic Roles

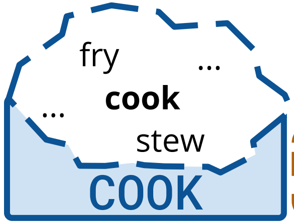
VerbAtlas Semantic Role Set - inspired by VerbNet

Agent	Patient	Instrument	Result	Location	...	Source



PROTOTYPICAL ARGUMENT STRUCTURE of **EAT-BITE**

Agent	Patient	Instrument	Result	Location	...	Source



PROTOTYPICAL ARGUMENT STRUCTURE of **COOK**

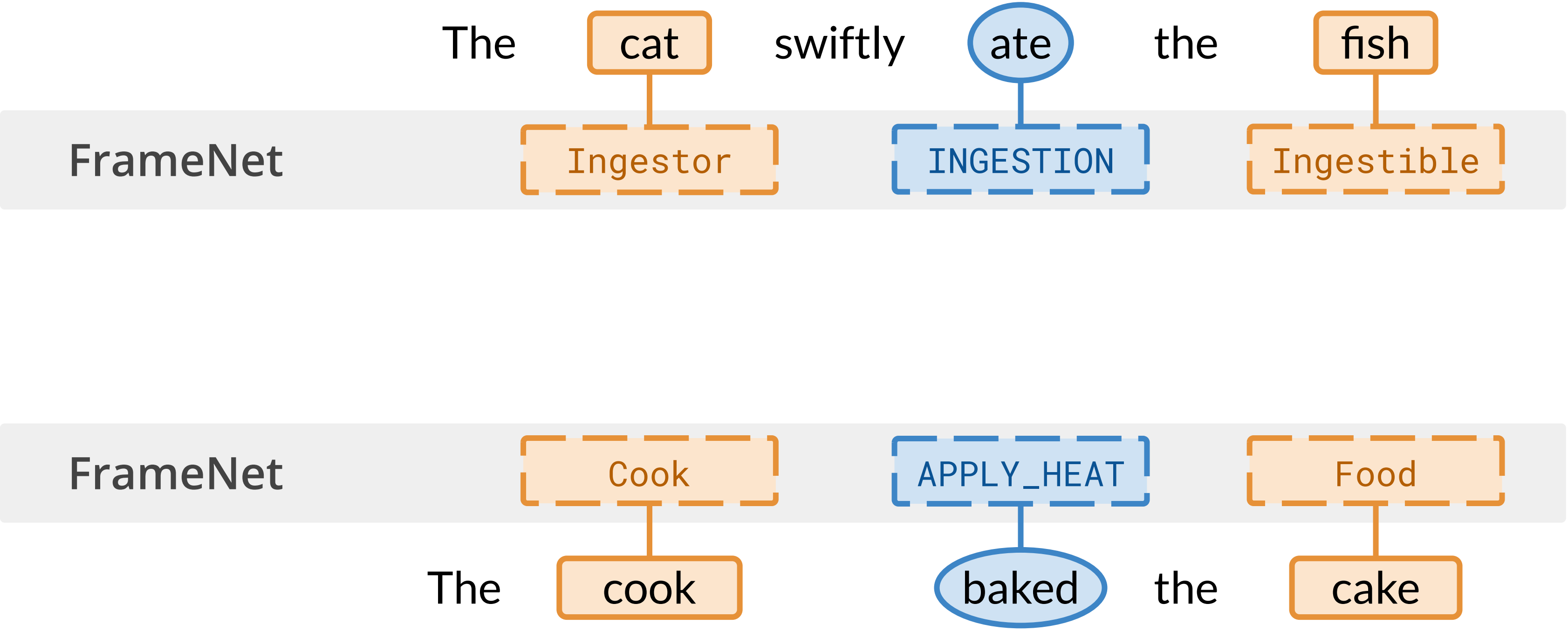
Agent	Patient	Instrument	Result	Location	...	Source

Comparing VerbAtlas

to FrameNet, VerbNet and PropBank

FrameNet vs VerbAtlas

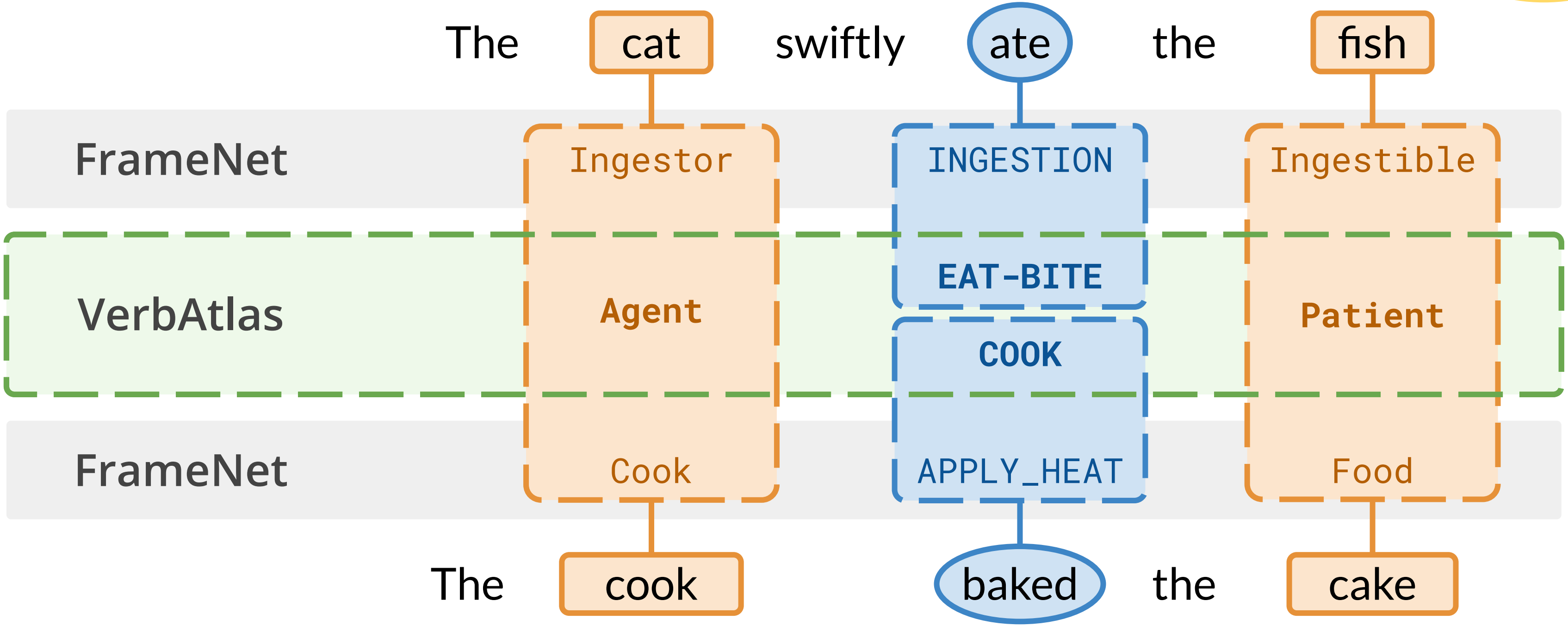
Comparing semantic roles



FrameNet vs VerbAtlas

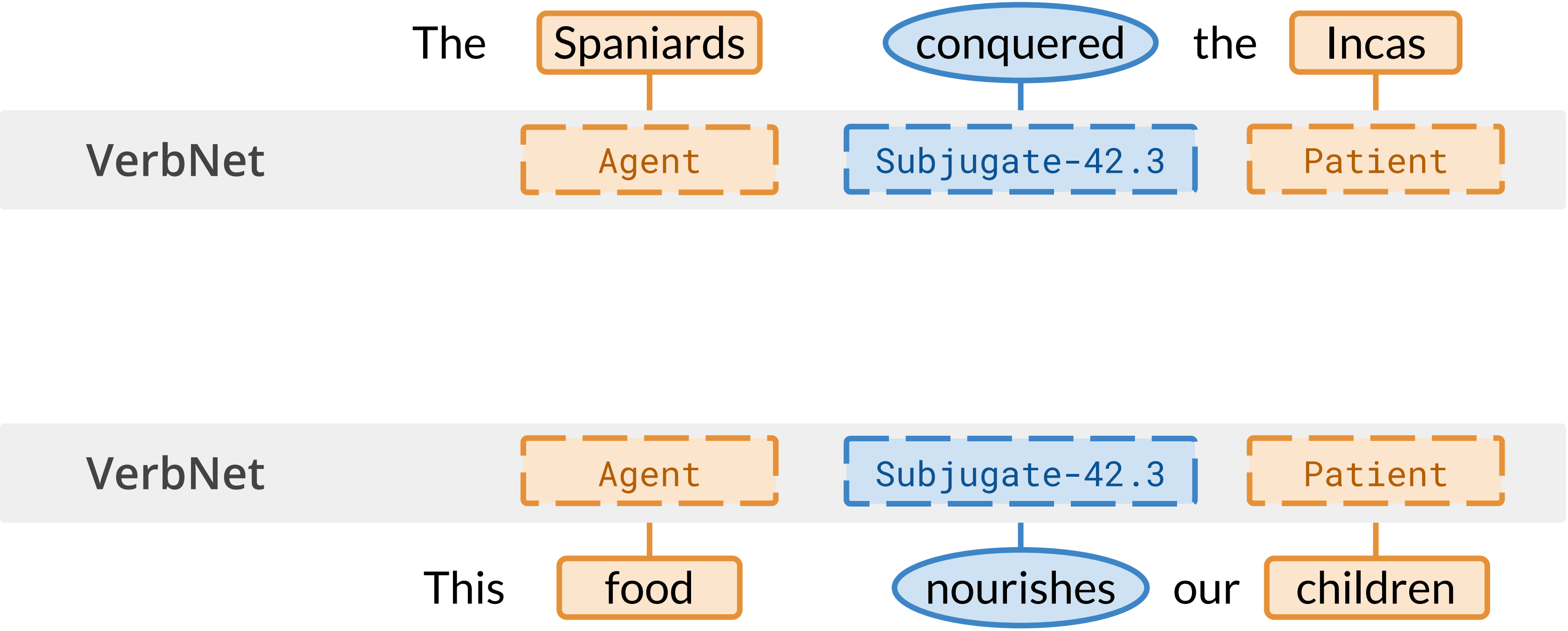
Comparing semantic roles

CROSS-DOMAIN ROLES



VerbNet vs VerbAtlas

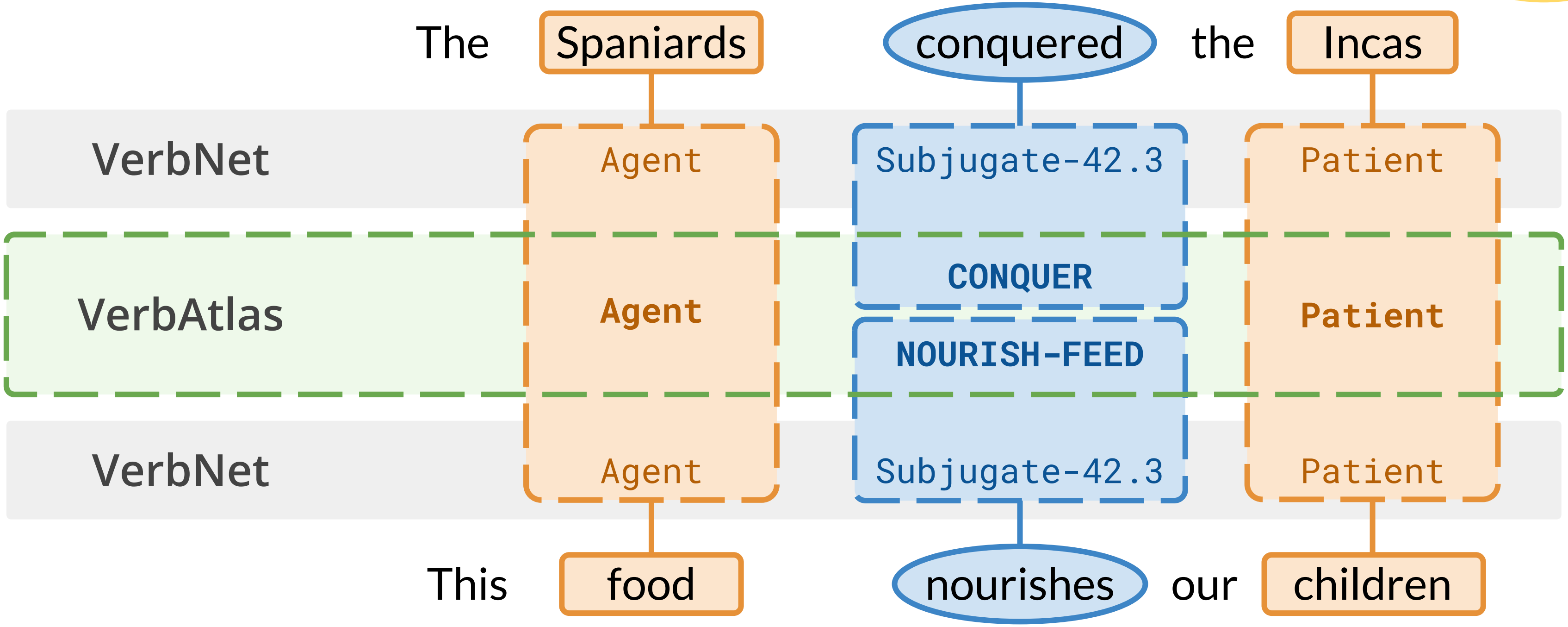
Comparing predicate classes



VerbNet vs VerbAtlas

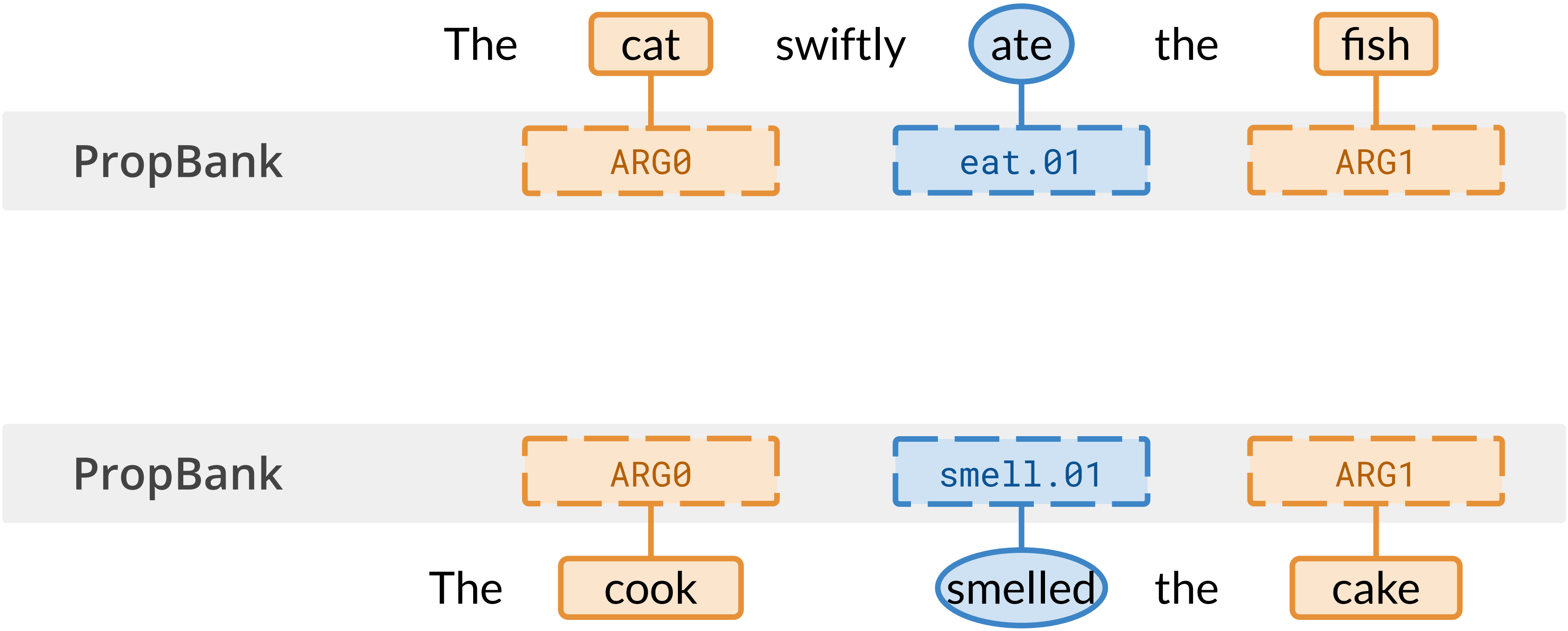
Comparing predicate classes

Semantically-CONSISTENT FRAMES



PropBank vs VerbAtlas

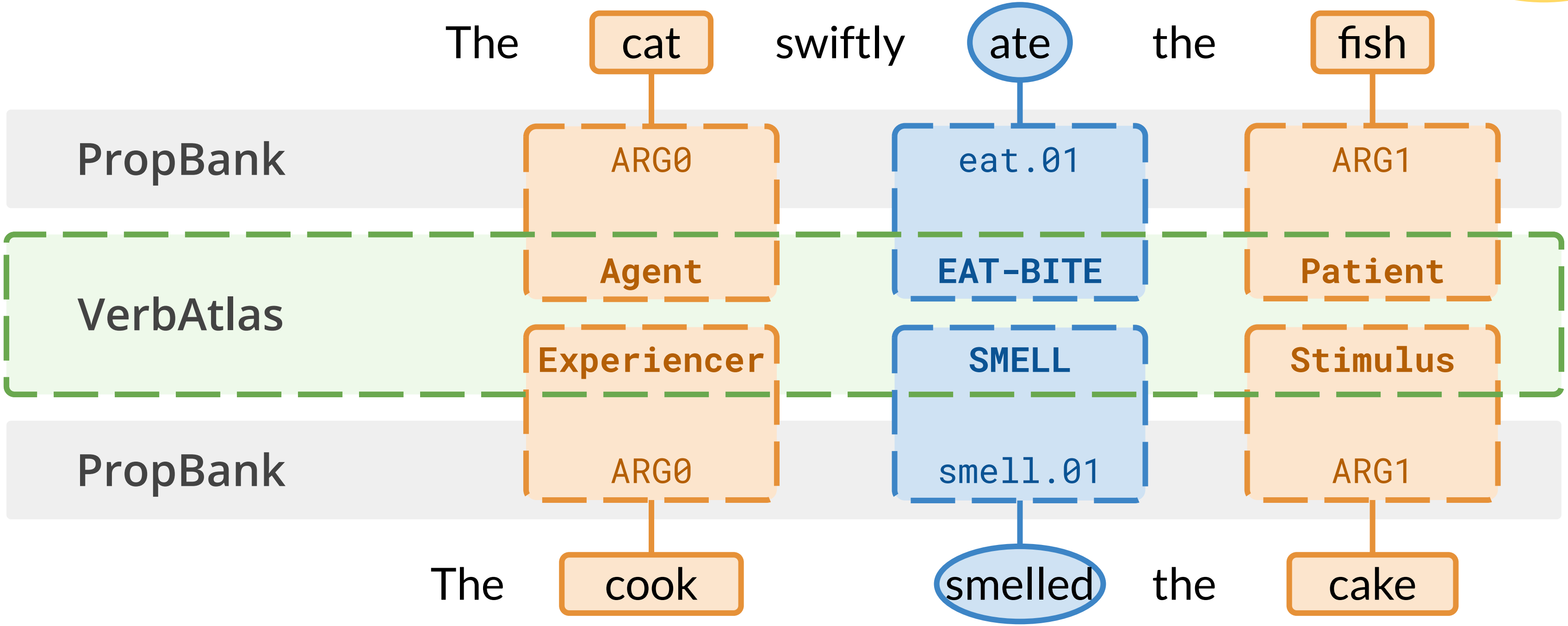
Comparing predicate and roles



PropBank vs VerbAtlas

Comparing predicate and roles

INFORMATIVE ROLE LABELS



VerbAtlas

Statistics & Multilingual Scalability

Some Statistics

FrameNet vs VerbNet vs PropBank vs VerbAtlas

	Meaning units	#
FrameNet	Lexical units	5,200
VerbNet	Senses	6,791
PropBank	Framesets	10,687
VerbAtlas	Synsets	**13,767**

FULL COVERAGE of verbal meanings

Some Statistics

FrameNet vs VerbNet vs PropBank vs VerbAtlas

	Meaning units	#	Cluster type	#
FrameNet	Lexical units	5,200	Frames	1,224
VerbNet	Senses	6,791	Levin's classes	329
PropBank	Framesets	10,687	Verbs	5,649
VerbAtlas	Synsets	**13,767**	Frames	**466**

FULL COVERAGE of verbal meanings

COARSE FRAMES reduce data sparsity

Some Statistics

FrameNet vs VerbNet vs PropBank vs VerbAtlas

	Meaning units	#	Cluster type	#	Argument Roles	#
FrameNet	Lexical units	5,200	Frames	1,224	Frame elements	10,542
VerbNet	Senses	6,791	Levin's classes	329	Thematic roles	39
PropBank	Framesets	10,687	Verbs	5,649	Proto-roles	6
VerbAtlas	Synsets	**13,767**	Frames	**466**	Semantic roles	**25**

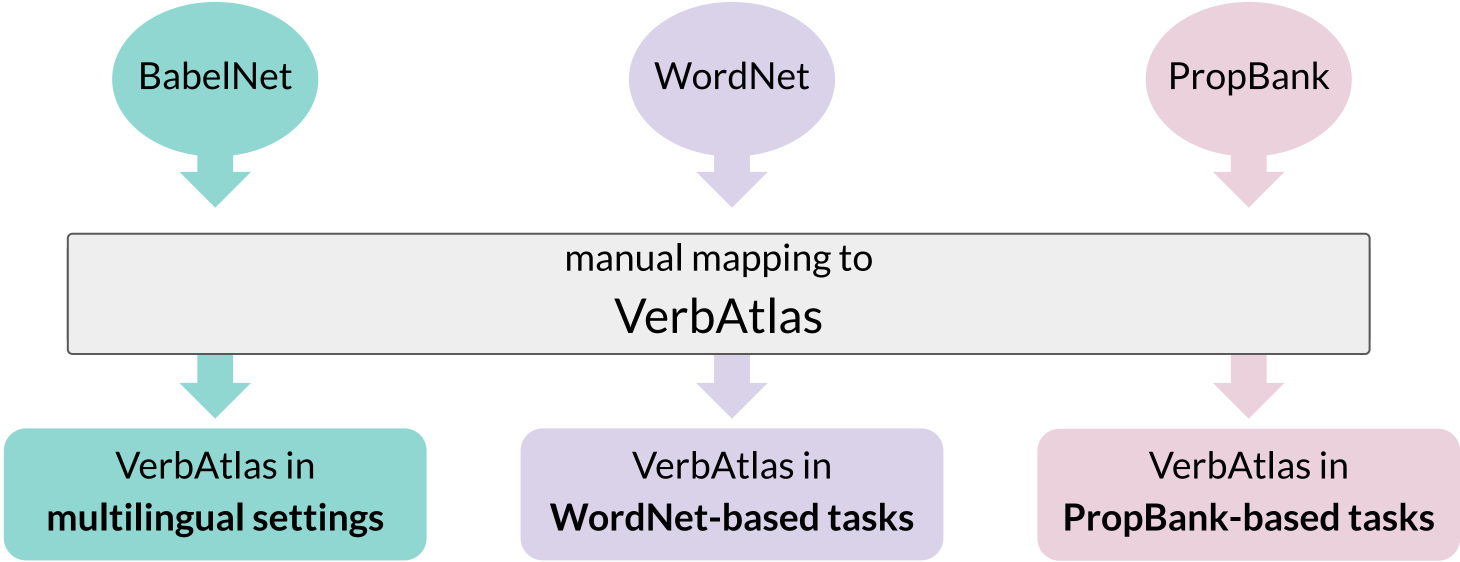
FULL COVERAGE of verbal meanings

COARSE FRAMES reduce data sparsity

FEW & EXPLICIT semantic roles

Linkage to Existing Resources

Multiple tasks and multiple languages



Easy Multilinguality with VerbAtlas and BabelNet
An example

The	cook	smelled	the	cake
Il	cuoco	ha annusato	la	torta
Le	cuisinier	a senti	le	gâteau
_	厨师	闻到了	_	蛋糕的味道

Easy Multilinguality with VerbAtlas and BabelNet

An example

SMELL

The	cook	smelled bn:00093929v	the	cake
Il	cuoco	ha annusato bn:00093929v	la	torta
Le	cuisinier	a senti bn:00093929v	le	gâteau
_	厨师	闻到了 bn:00093929v	_	蛋糕的味道

(NEAR) SYNONYMS across languages

SAME BabelNet synset

SAME VerbAtlas Frame!

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Easy Multilinguality with VerbAtlas and BabelNet

An example

	Experiencer	SMELL		Stimulus
The	cook	smelled bn:00093929v	the	cake
Il	cuoco	ha annusato bn:00093929v	la	torta
Le	cuisinier	a senti bn:00093929v	le	gâteau
_	厨师	闻到了 bn:00093929v	_	蛋糕的味道

SAME VerbAtlas Roles!

(NEAR) SYNONYMS across languages

SAME BabelNet synset

SAME VerbAtlas Frame!

SAME VerbAtlas Roles!

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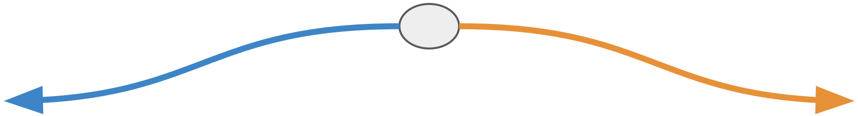
VerbAtlas and SRL

Experimental Validation

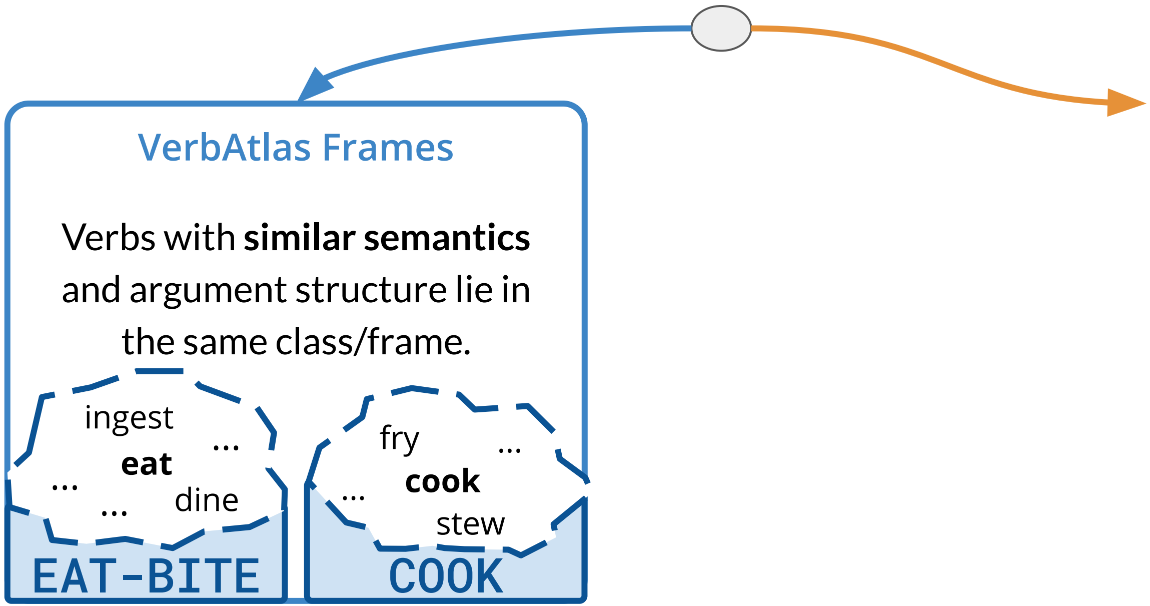
VerbAtlas and SRL

VerbAtlas abstractions for SRL



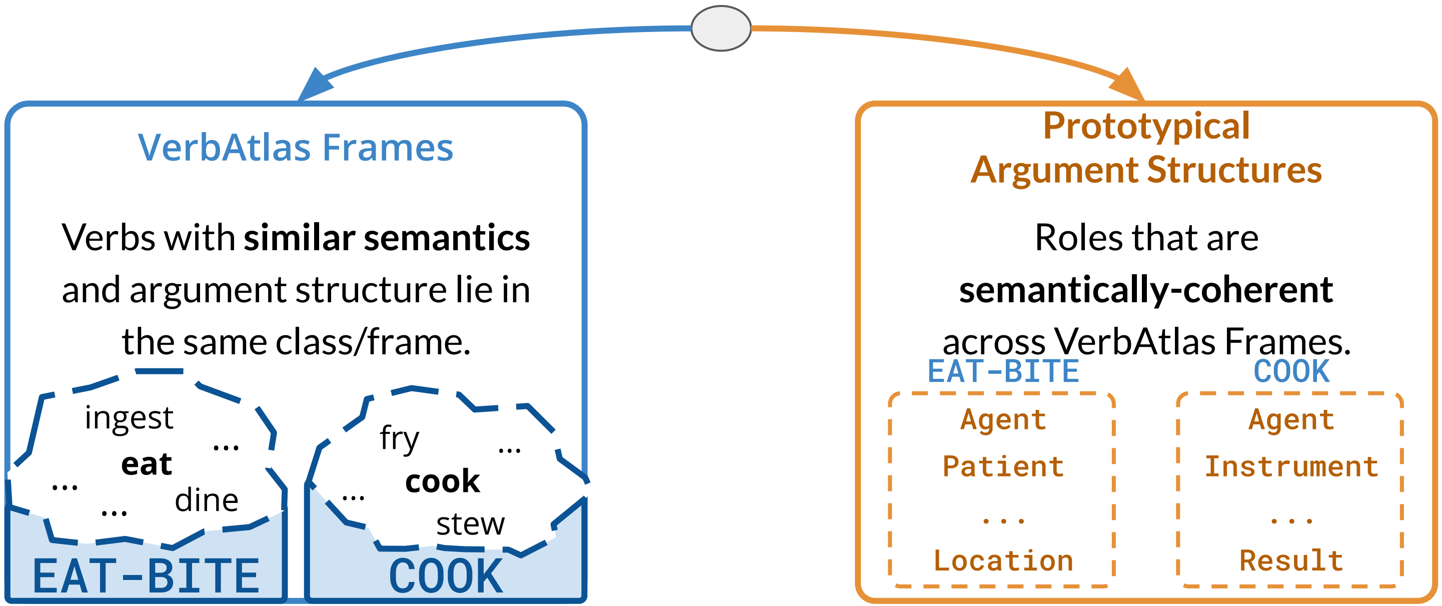
VerbAtlas and SRL

VerbAtlas abstractions for SRL



VerbAtlas and SRL

VerbAtlas abstractions for SRL



VerbAtlas and SRL

VerbAtlas abstractions for SRL

VerbAtlas Frames

Verbs with **similar semantics** and argument structure lie in the same class/frame.

ingest … **eat** … dine …

EAT-BITE

fry … **cook** … stew

COOK

Prototypical Argument Structures

Roles that are **semantically-coherent** across VerbAtlas Frames.

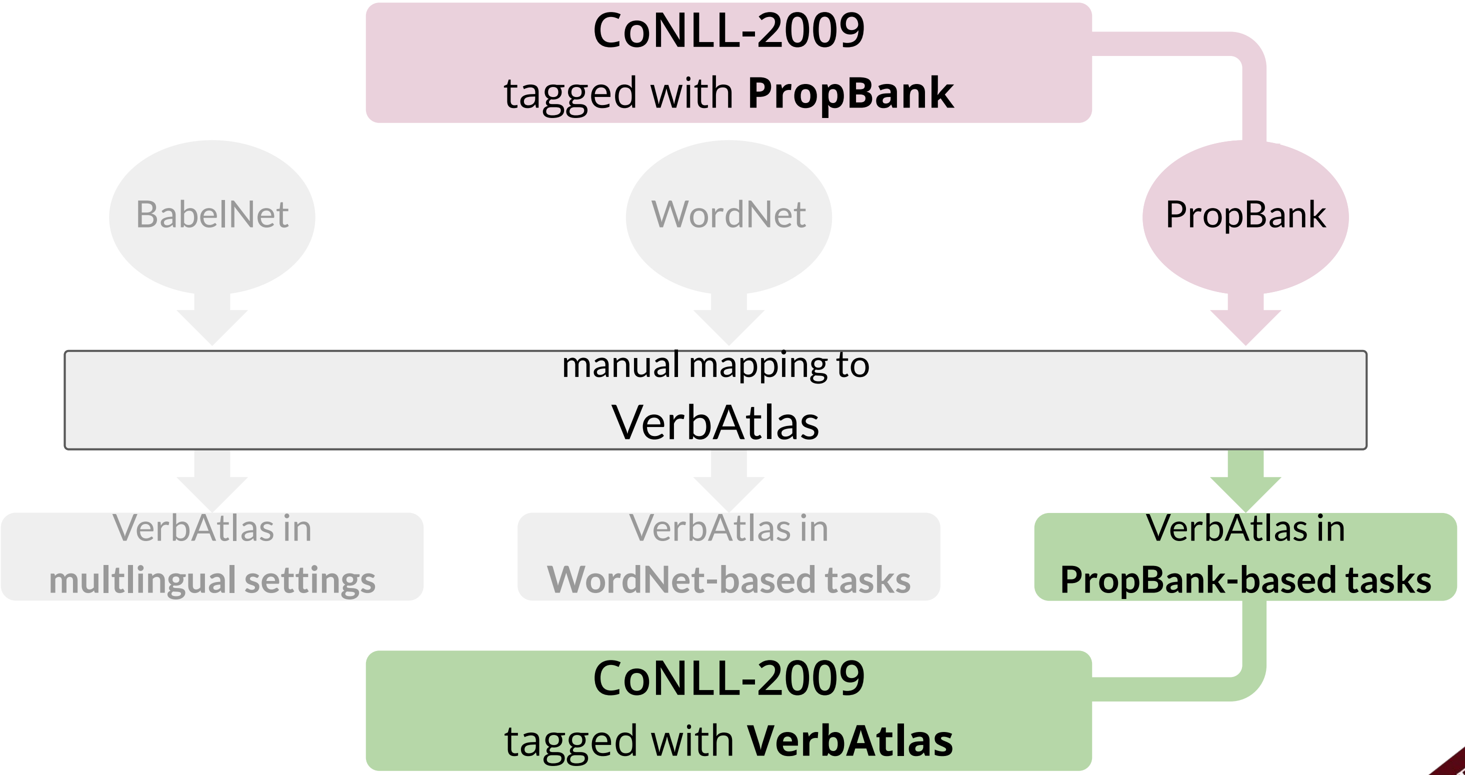
EAT-BITE: Agent, Patient, ..., Location

COOK: Agent, Instrument, ..., Result

Hypothesis: VerbAtlas Frames and Roles lead to better SRL performance

Dataset: CoNLL-2009

Retagging the dataset with VerbAtlas



Model architecture

1 An existing SRL system, from Cai et al. (2018)

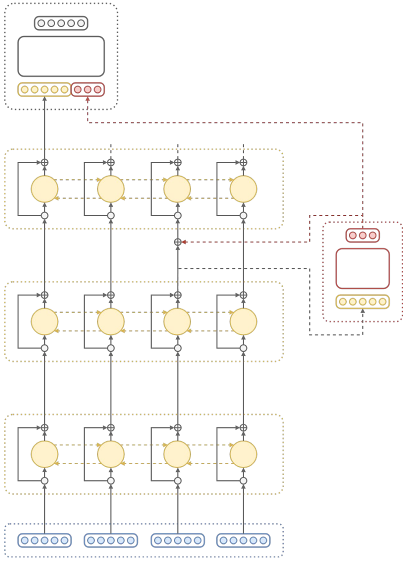
2

3

PropBank/NomBank role scorer

BiLSTM layers

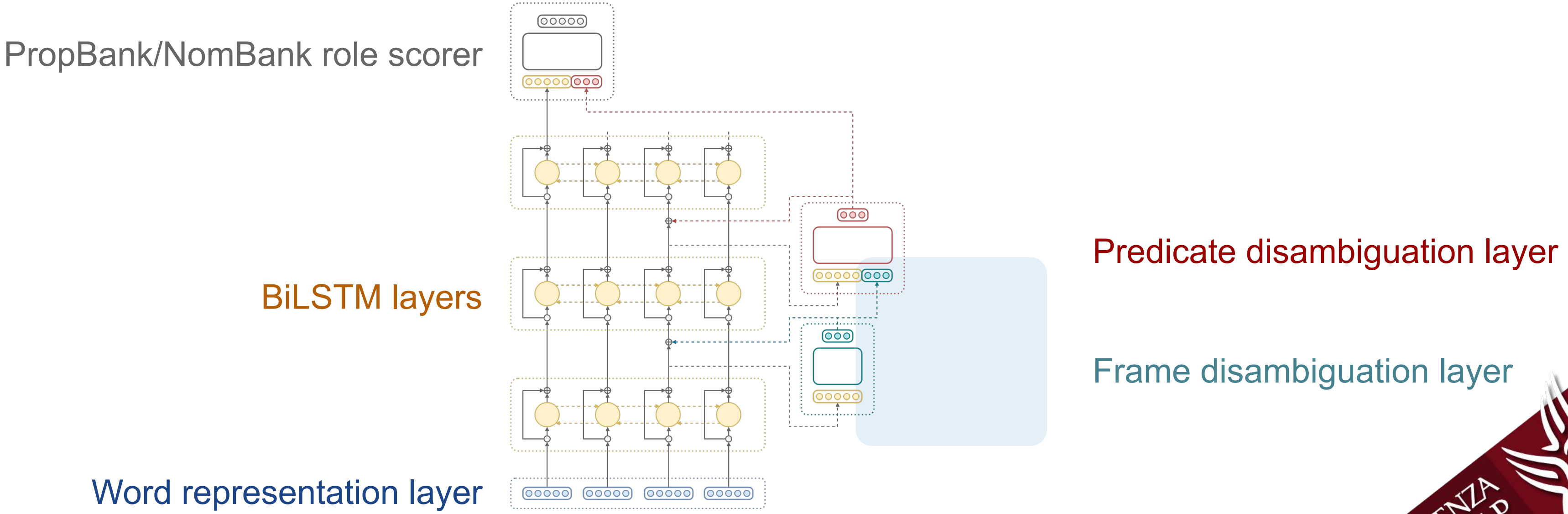
Word representation layer



Predicate disambiguation layer

Model architecture

1. An existing SRL system, from Cai et al. (2018)
2. Aiding predicate disambiguation with frame disambiguation
3.



Model architecture

1 An existing SRL system, from Cai et al. (2018)

2 Aiding predicate disambiguation with frame disambiguation

3 Achieving a deeper understanding thanks to finer-grained semantically-coherent roles

PropBank/NomBank role scorer

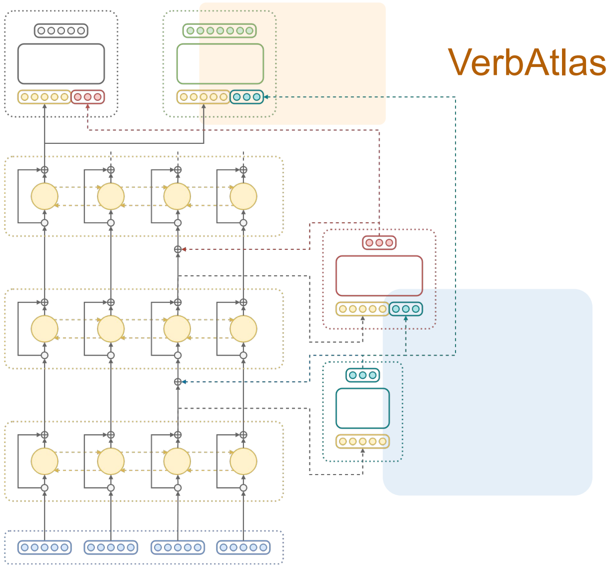
VerbAtlas role scorer

BiLSTM layers

Predicate disambiguation layer

Frame disambiguation layer

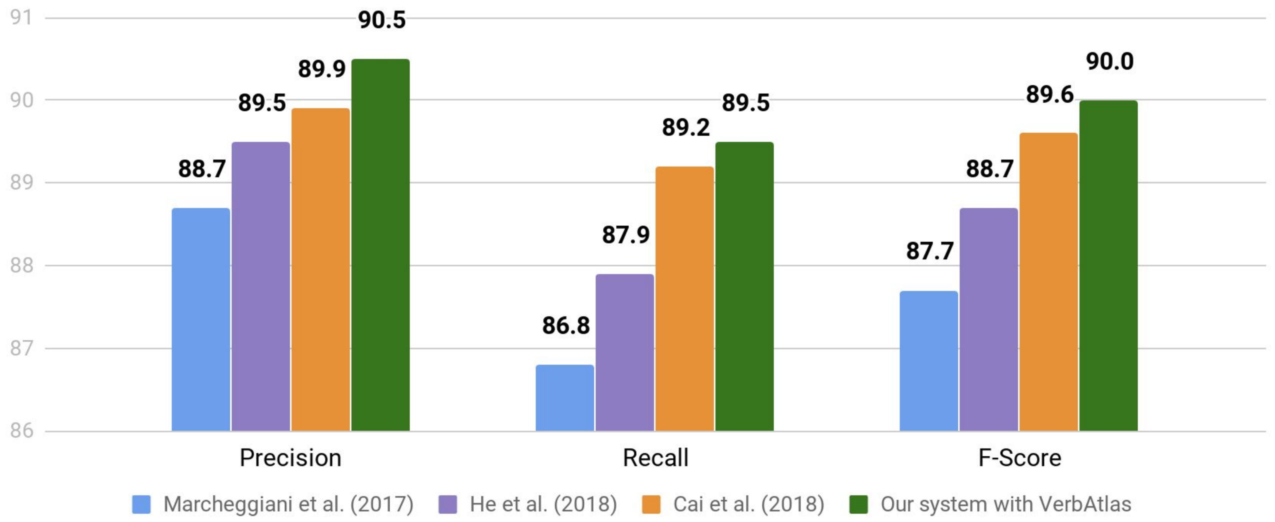
Word representation layer



Results in CoNLL-2009 (1)

In-domain evaluation

VerbAtlas
+
PropBank
>
PropBank



The integration of VerbAtlas leads to significant improvements in the in-domain test set...

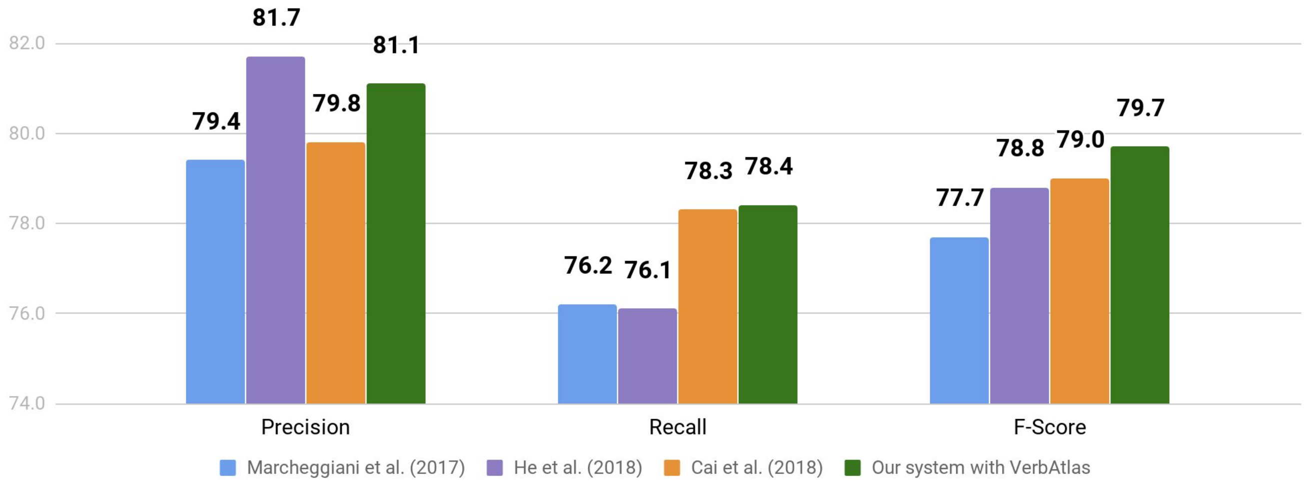
*improvements are statistically significant ($p < 0.05$)

SAPIENZA NLP

Results in CoNLL-2009 (2)

Out-of-domain evaluation

GENERALIZES BETTER ACROSS DOMAINS



… showing improvements in the out-of-domain test set as well.

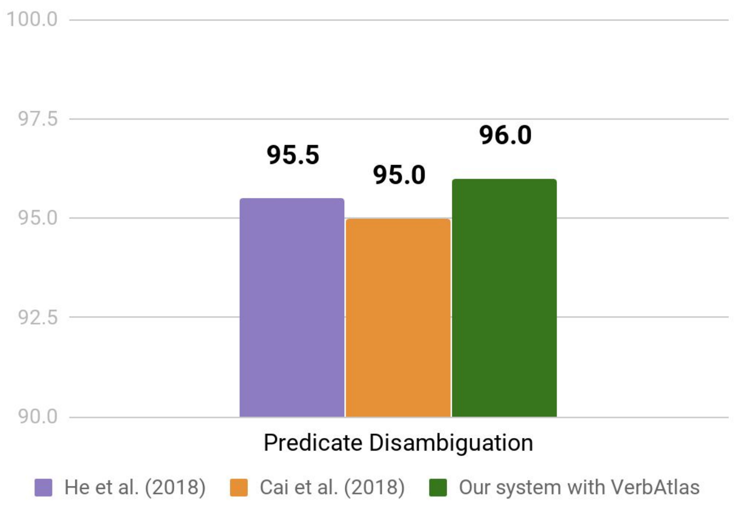
*improvements are statistically significant ($p < 0.05$)

SAPIENZA NLP

Results in CoNLL-2009 (3)

Predicate sense disambiguation

VERBATLAS FRAMES HELP DISAMBIGUA-TION



Bonus point

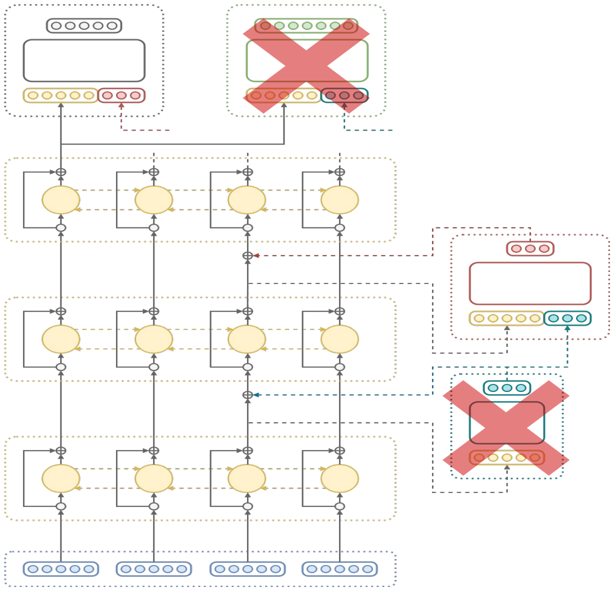
Outperforming the (pre-BERT) state-of-the-art in predicate disambiguation.

improvements are statistically significant ($p < 0.05$*)

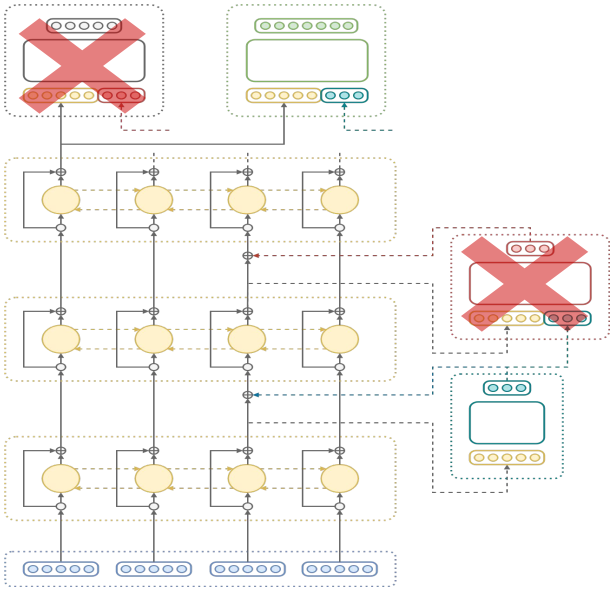
Contribution of VerbAtlas to the Results

An Ablation Study

NO VerbAtlas



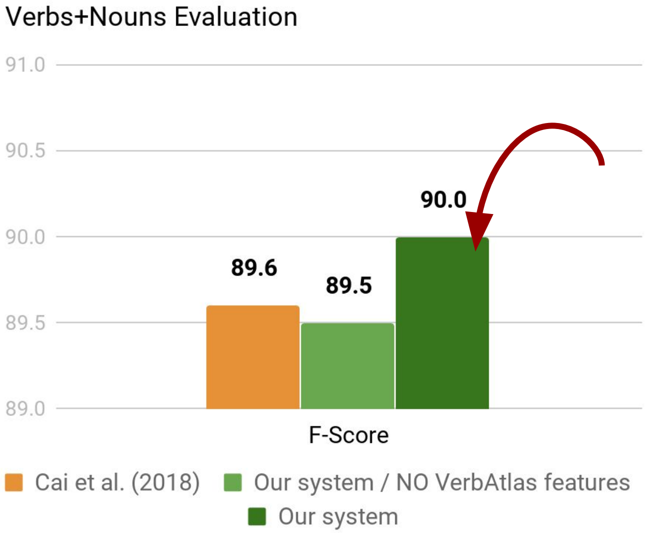
vs



NO PropBank/NomBank

Contribution of VerbAtlas to the Results

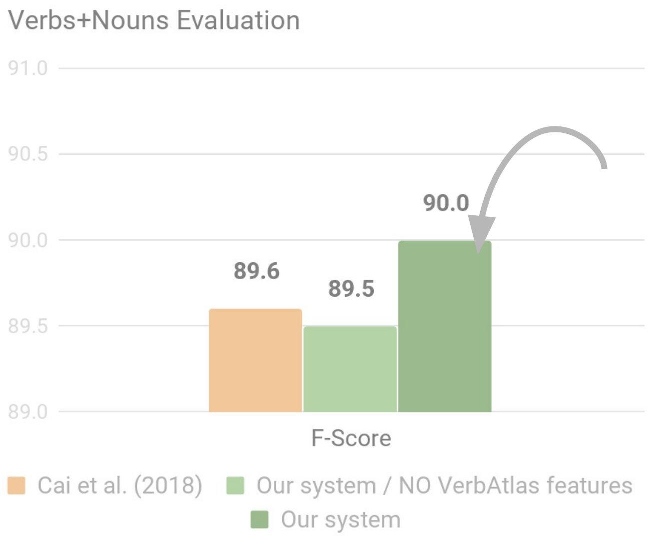
An Ablation Study

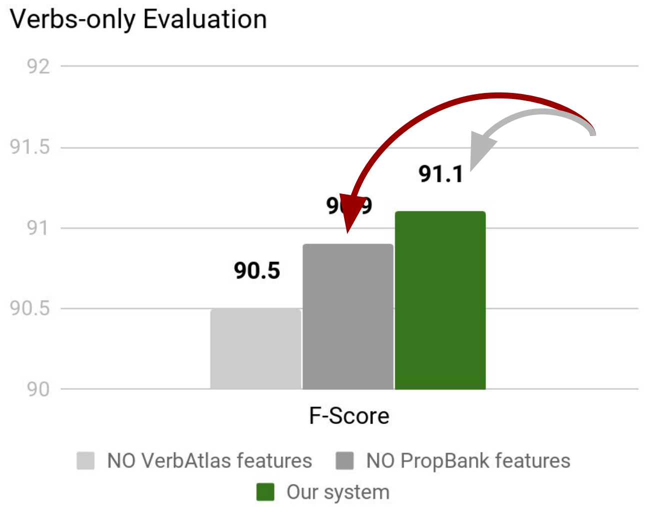


When VerbAtlas is **removed**, our system falls in line with Cai et al. (2018).

Contribution of VerbAtlas to the Results

An Ablation Study





When VerbAtlas is **removed**, our system falls in line with Cai et al. (2018).

Removing VerbAtlas causes a larger drop in performance.

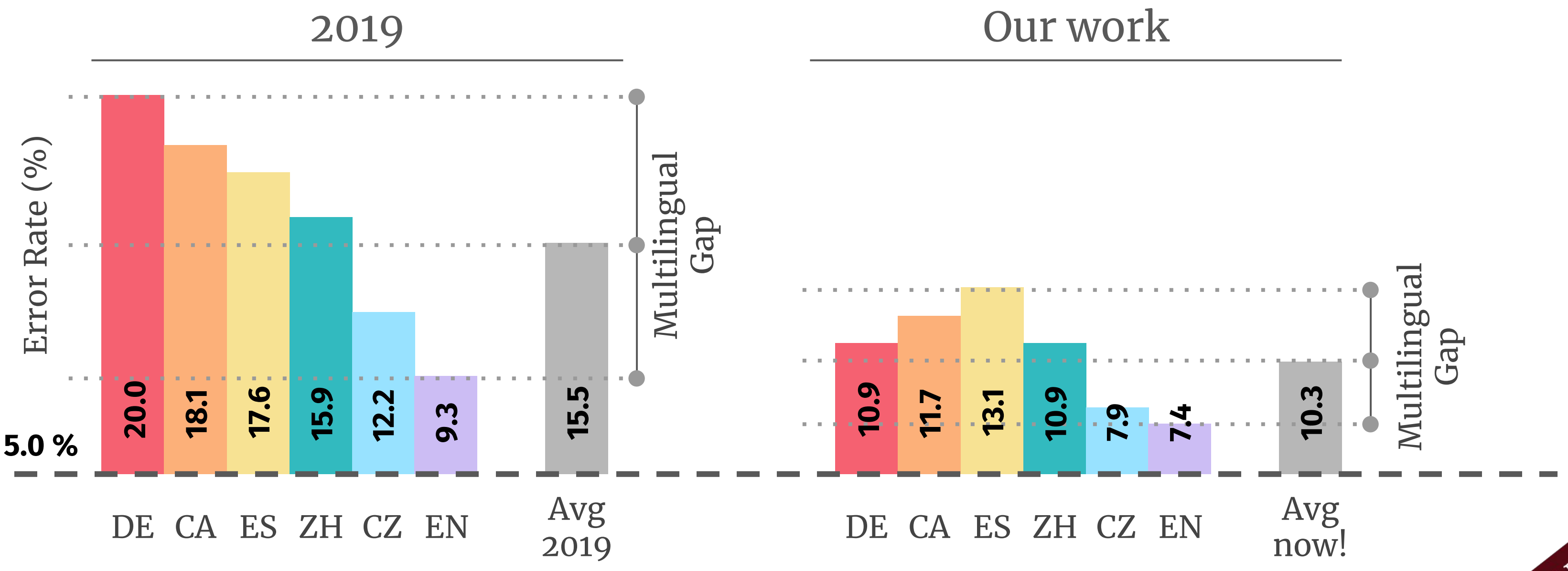
Conclusion (& Future Work)

- **Multilinguality** in Semantic Role Labeling
- Towards an **interlingua** with Semantic Parsing
- **VerbAtlas**: a cross-lingual semantic inventory

SRL - Conclusion

Bridging the multilingual gap in multilingual SRL (Conia and Navigli, 2020)

Yes, it is possible to narrow the gap between high- and low-resource languages!



SRL - Conclusion & Future Work

Bridging the multilingual gap in multilingual SRL (Conia and Navigli, 2020)

Our study shows that a language-agnostic approach can:

- Significantly **narrow the multilingual gap**
- Advance the **state of the art** in 6 languages
- Be **robust** in low-resource settings
- Provide promising results in **zero-shot cross-lingual SRL**

We hope that our work will:

- Provide a **strong multilingual baseline** for syntax-based innovations
- Prompt further work in **cross-lingual SRL**
- Encourage the use of SRL in **cross-lingual downstream tasks**

Conclusion

Bridging the multilingual gap in multilingual SRL (Conia and Navigli, 2020)

Bridging the gap in **multilingual Semantic Role Labeling**

without relying on any **language-specific features** (lemma, POS, syntax)

and setting a **strong and robust baseline** for future innovations

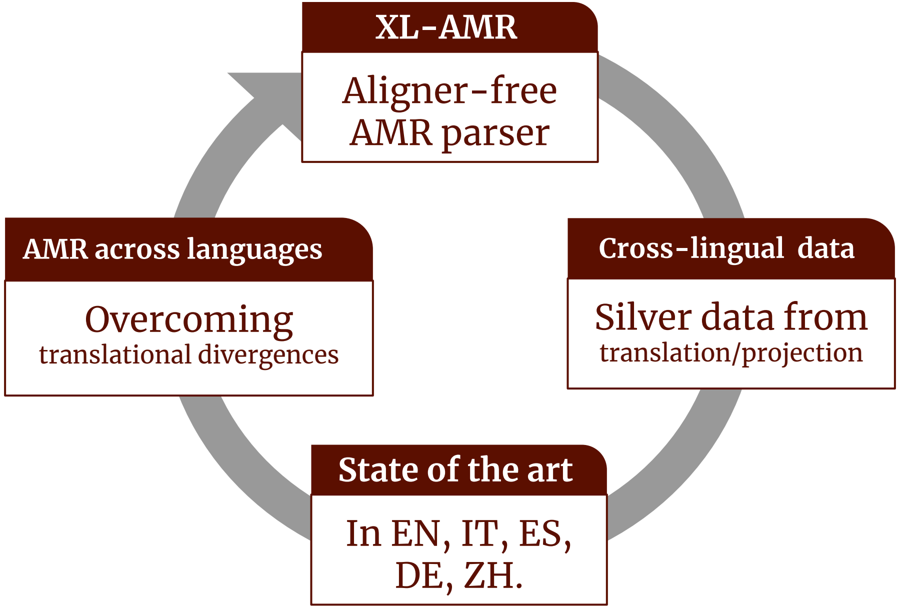
Our language-agnostic approach:

- Significantly **narrows the multilingual gap**
- Advances the **state of the art** in 6 languages
- Is **robust** in low-resource settings

Semantic Parsing - Conclusion

Enabling cross-lingual Semantic Parsing (Blloshmi, Tripodi and Navigli, 2020)

AMR can act as an interlingua and cross-lingual data (even silver) is useful!



Conclusions

XL-AMR

An aligner-free cross-lingual AMR parser

Cross-lingual AMR data

Silver data of diverse quality using different techniques

State of the art

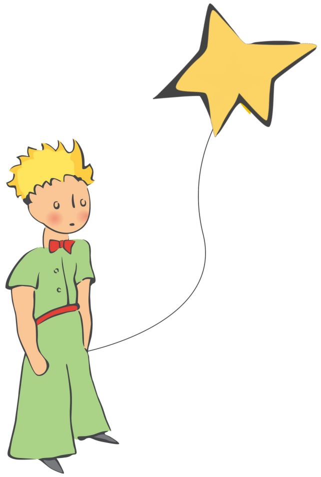
XL-AMR sets the state of the art in all the tested languages

AMR across languages

XL-AMR overcomes most of the translational divergences

Semantic Parsing – Future Work

Enabling cross-lingual Semantic Parsing (Blloshmi, Tripodi and Navigli, 2020)



Integration of unified lexical resources for handling lexical divergences

Cross-lingual AMR structures into downstream tasks

VerbAtlas - Conclusion

A novel large-scale verbal semantic resource (Di Fabio, Conia and Navigli, 2019)

FRAMES
to organize verbs into semantic clusters

ROLES
that generalize across verbs and frames

LINKING
to WordNet, BabelNet and PropBank

MORE!
e.g. additional synset-level information, ...

Conclusions…

VerbAtlas: a novel large-scale verbal semantic resource, featuring:

FRAMES
to organize verbs into semantic clusters

ROLES
that generalize across verbs and frames

LINKING
to WordNet, BabelNet and PropBank

MORE!
e.g. additional synset-level information, ...

…and Future Work

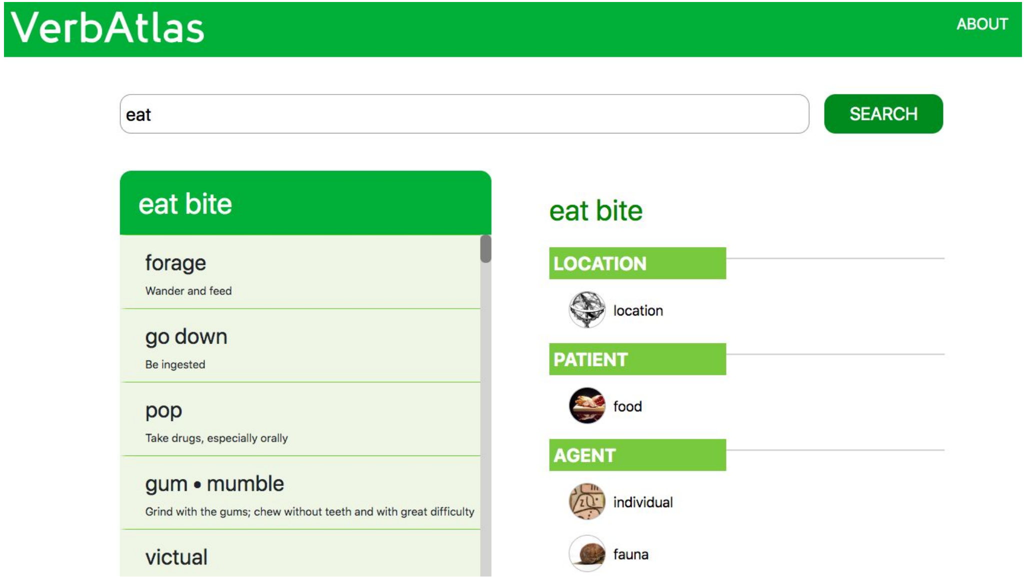
GOING MULTILINGUAL
with BabelNet

LANGUAGE MODELS
+ VerbAtlas

SYNTAGNET
+ VerbAtlas

VerbAtlas is online! Check it out at:

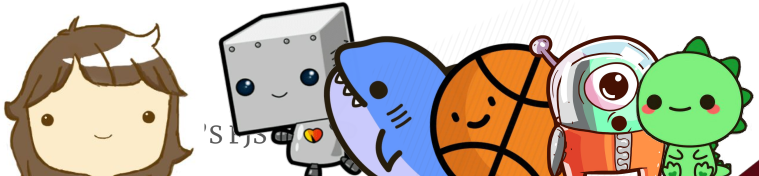
http://verbatlas.org



Thank you!

Wrapping up, Generationary…

- ★ handles DM with a pure, simple **SEQ2SEQ FORMULATION**
- ★ exploits **PRIOR KNOWLEDGE** through pre-training
- ★ performs **STATE-OF-THE-ART DEFINITION MODELING**
- ★ is able to **TACKLE DISCRIMINATIVE TASKS** such as WSD, matching state-of-the-art approaches with **NO FURTHER TRAINING**
- ★ is not bound to any sense inventory and benefits from **MULTIPLE RESOURCES**
- ★ can both disambiguate and generalize to **UNSEEN EXPRESSIONS**.



Current/future directions

- Going **MULTILINGUAL** (e.g. use BabelNet definitions)
    - **Spoiler: BabelNet 5.0** announced soon with 20 millions synsets and 500 languages!
- Going more **SEMANTIC**
    - Both in SRL and Semantic Parsing
- Much more!

BabelNet

Thank you for your attention!

Check out our work!

- BabelNet: https://babelnet.org/
- VerbAtlas: http://verbatlas.org/
- InVeRo: http://nlp.uniroma1.it/invero/
- Our group: http://nlp.uniroma1.it/

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