NLP:
Neural Language Priming

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What are effective language processing representations?

We can explore the space using priming

Images by @iamr, @clutchdown on Unsplash

What is priming?

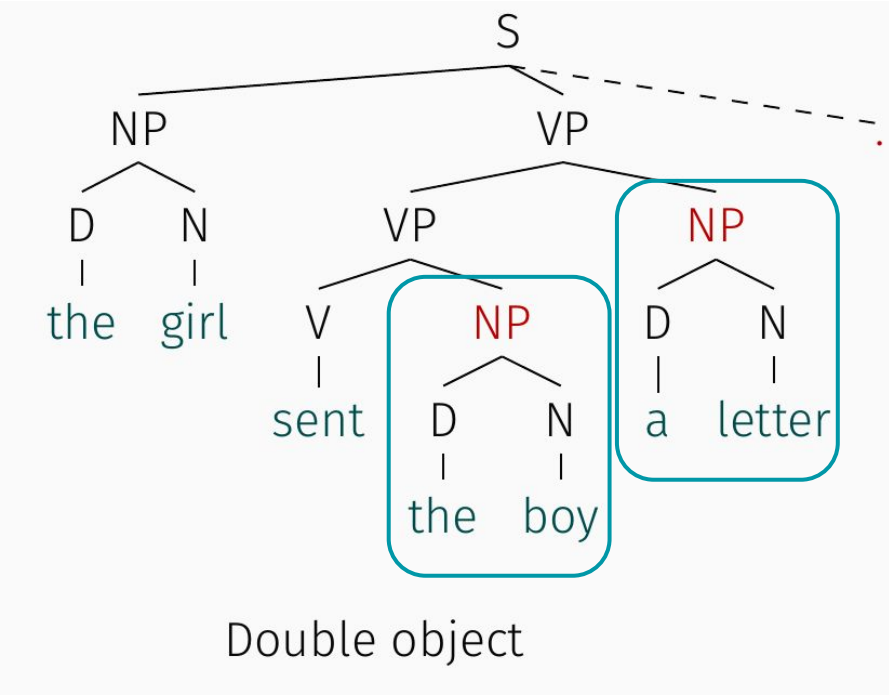
… cassowary …

Cassowaries …

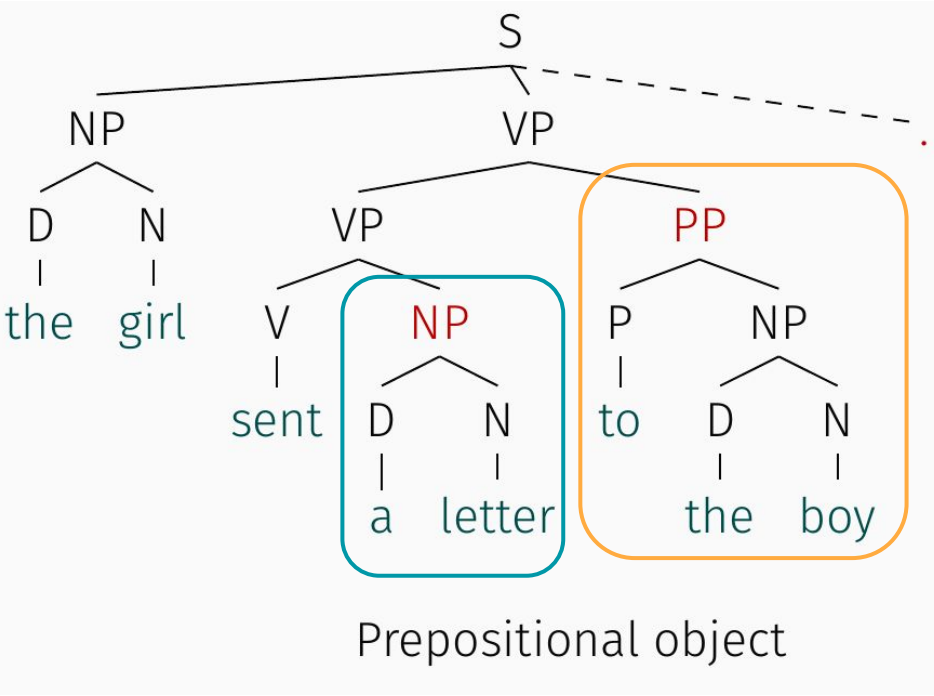
… Just like a cassowary!

… cassowary …

What is structural priming?



Double object



Prepositional object

What is structural priming?

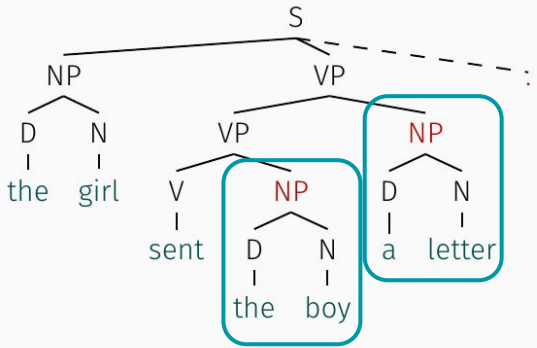
A rockstar sold some cocaine to the undercover agent.

…

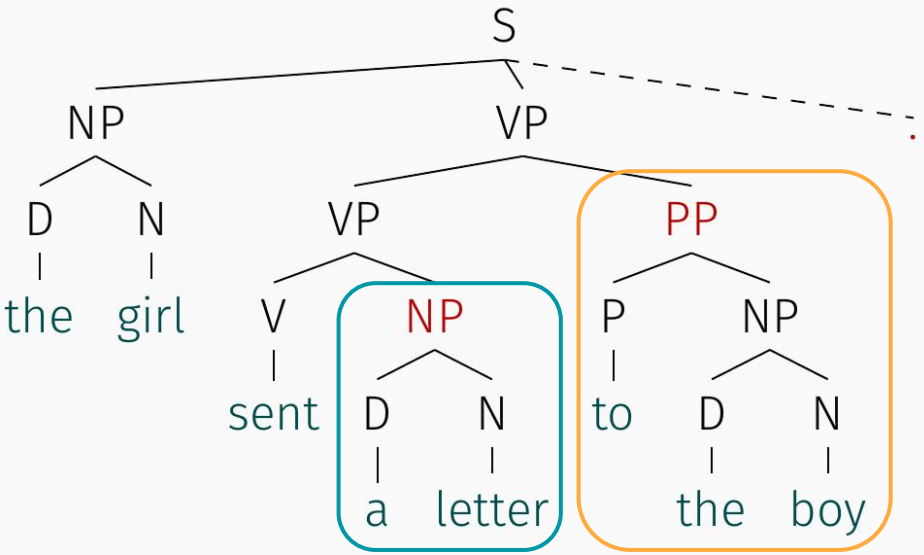
The girl sent a letter to the boy.

(Bock, 1986)

What is structural priming?



Double object



Prepositional object

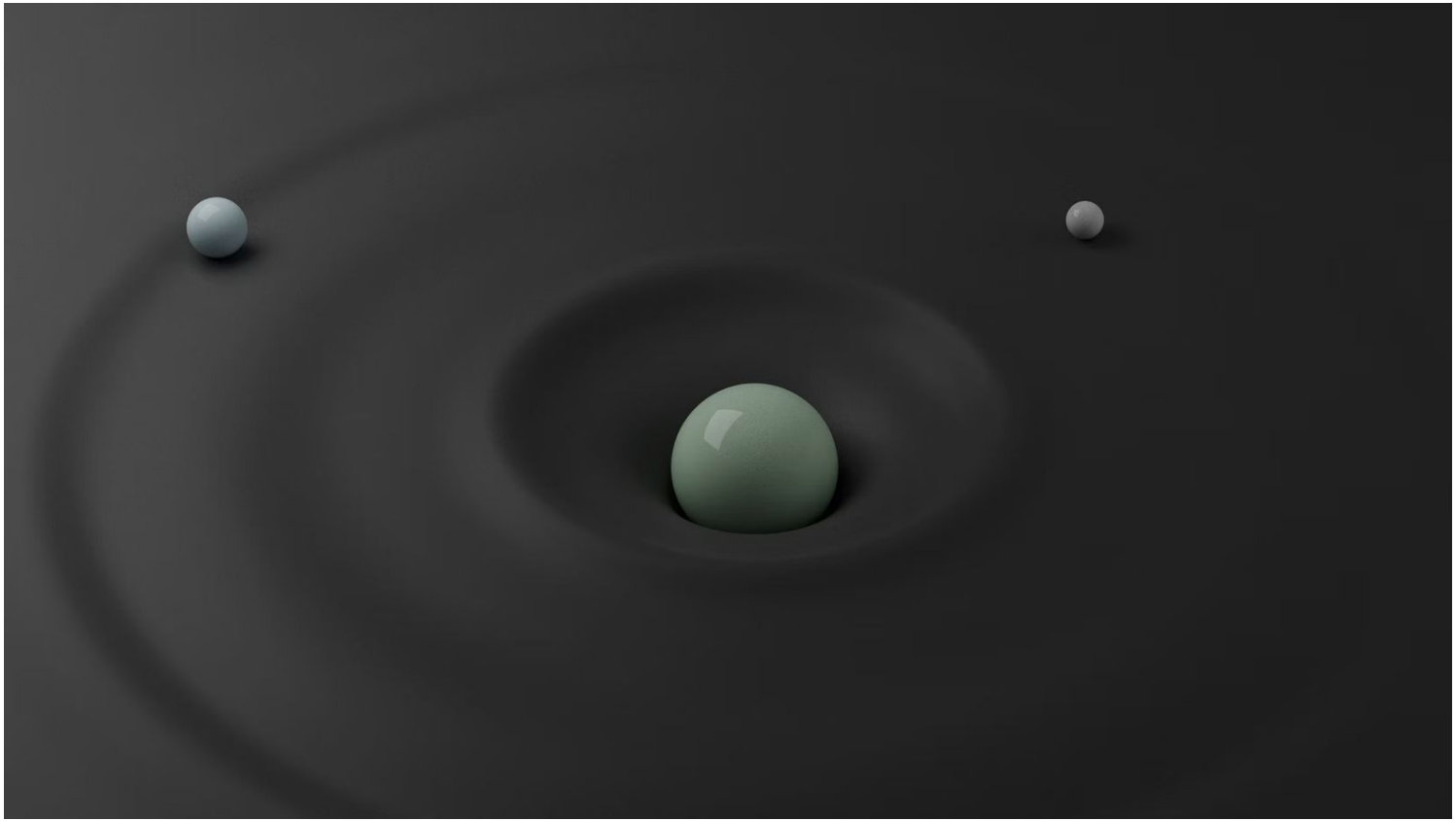


Image by @hassaanhere on Unsplash

Why expect this to work with NNs?

Neural networks operate over probability spaces

NNs require large amounts of data to train

Small amounts of training data should skew distributions according to sensitivity without wholly retraining them

Neural language models can be primed

Tal Linzen

A Neural Model of Adaptation in Reading

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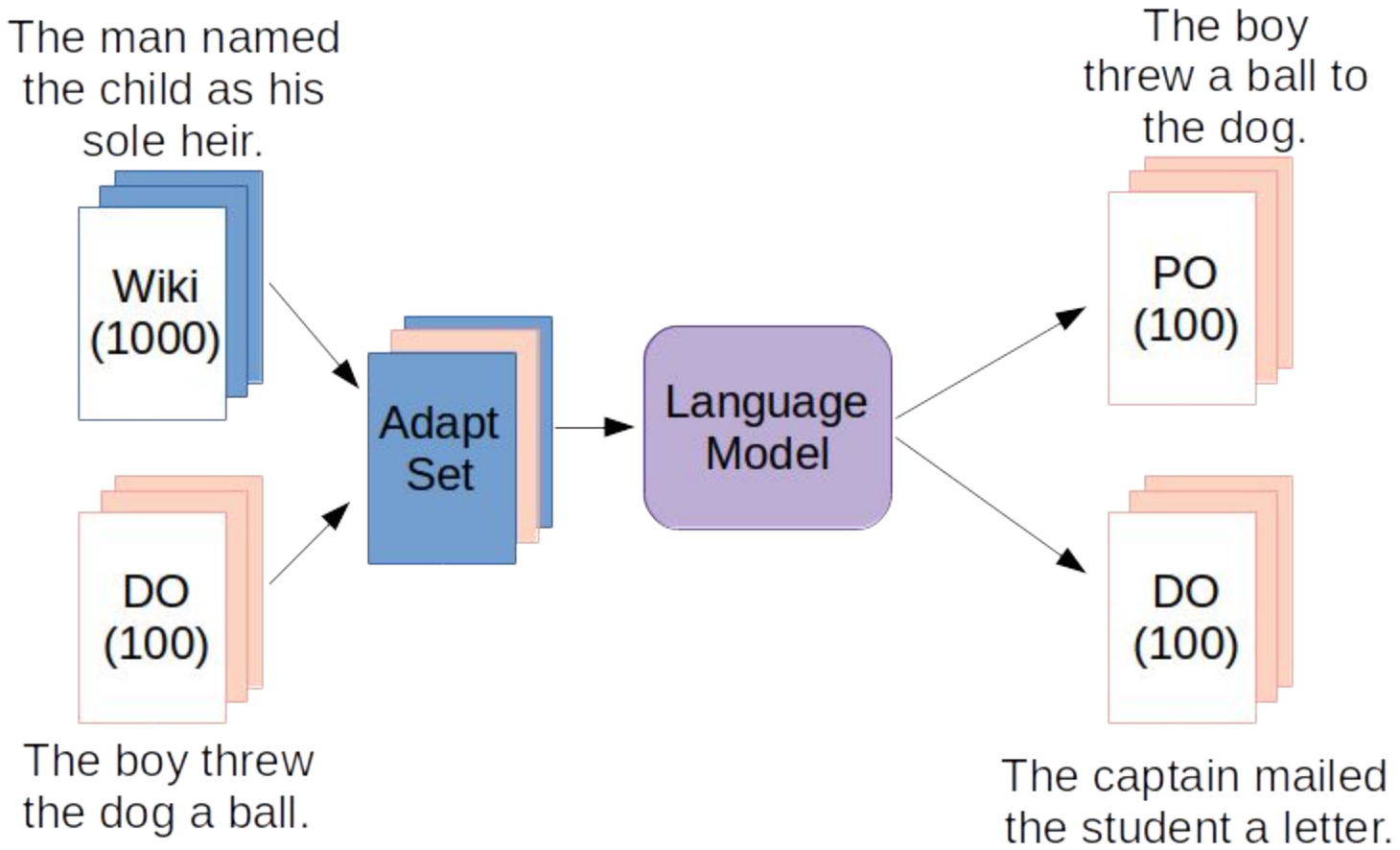
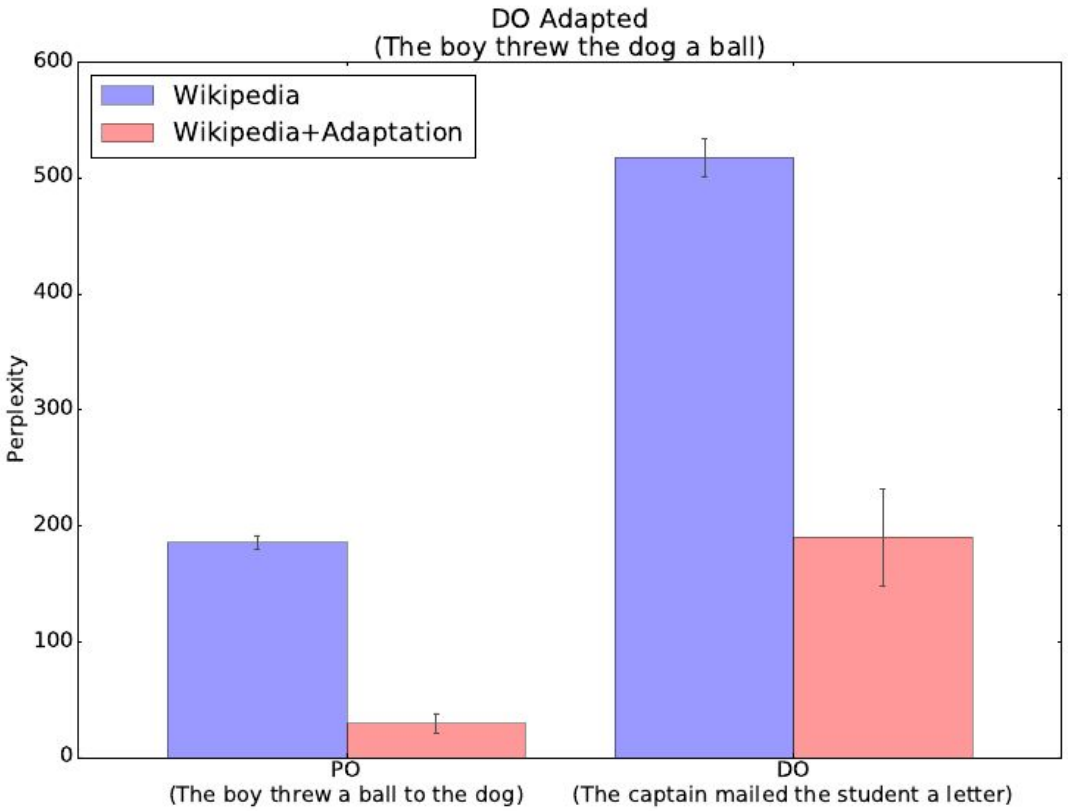
Proceedings of EMNLP 2018

Adaptation priming algorithm

1) Test on a sentence
2) Update weights by fine-tuning on that sentence
3) Repeat on remaining sentences


The man named the child as his sole heir.
Wiki (1000)
DO (100)
The boy threw the dog a ball.
Adapt Set
Language Model
The boy threw a ball to the dog.
PO (100)
DO (100)
The captain mailed the student a letter.


DO Adapted
(The boy threw the dog a ball)
Wikipedia
Wikipedia+Adaptation
Perplexity
600
500
400
300
200
100
0
PO
(The boy threw a ball to the dog)
DO
(The captain mailed the student a letter)

Cumulative priming reveals underlying structure

Grusha Prasad

Tal Linzen

Using Priming to Uncover the Organization of Syntactic Representations in Neural Language Models

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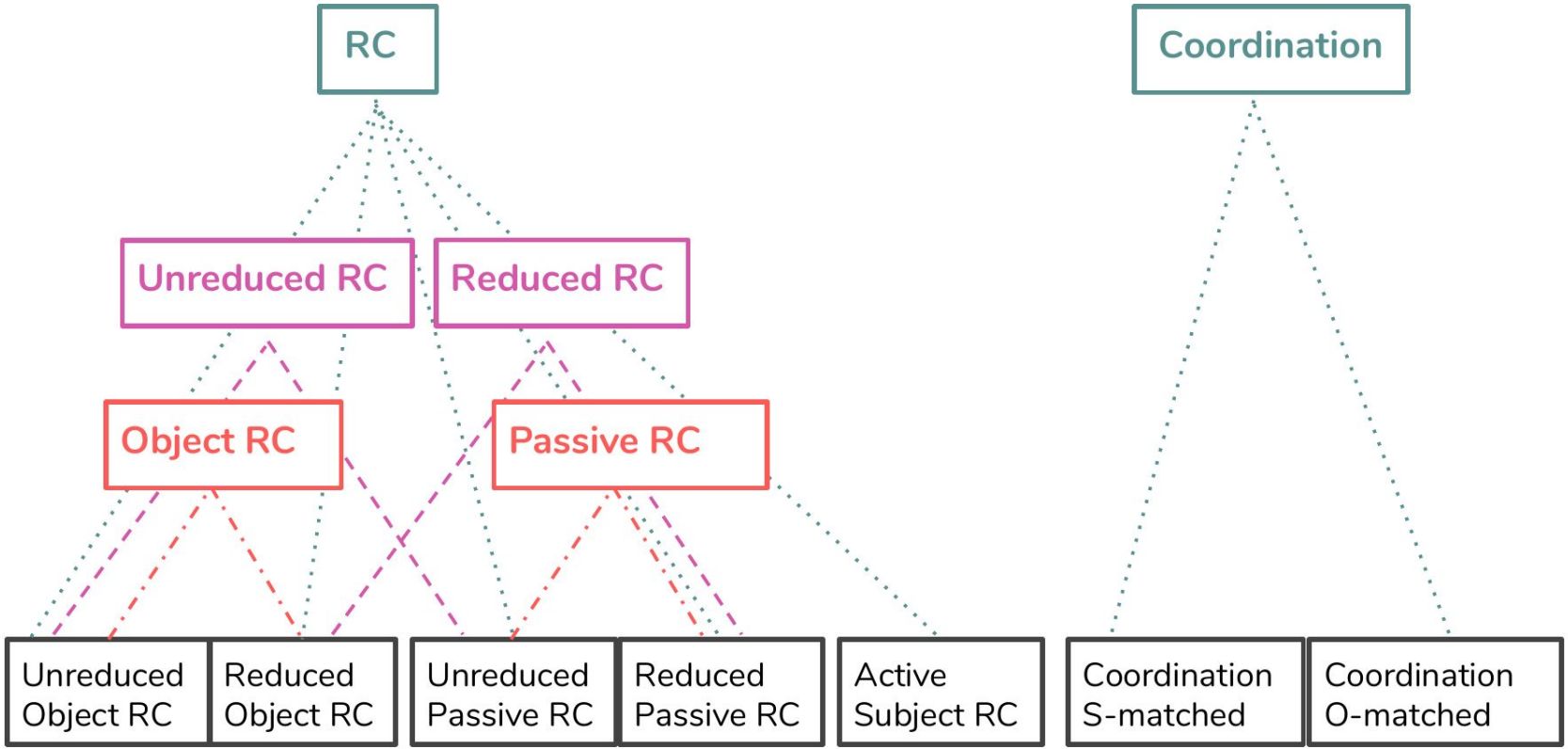
Proceedings of CoNLL 2019

Cumulative priming reveals underlying structure

Abstract structure	Example
Unreduced Object RC	The conspiracy that the employee welcomed divided the beautiful country.
Reduced Object RC	The conspiracy the employee welcomed divided the beautiful country.
Unreduced Passive RC	The conspiracy that was welcomed by the employee divided the beautiful country.
Reduced Passive RC	The conspiracy welcomed by the employee divided the beautiful country.
Active Subject RC	The employee that welcomed the conspiracy quickly searched the buildings.
PS/ORC-matched Coordination	The conspiracy welcomed the employee and divided the beautiful country.
ASRC-matched Coordination	The employee welcomed the conspiracy and quickly searched the buildings.


RC
Coordination
Unreduced RC
Reduced RC
Object RC
Passive RC
Unreduced Object RC
Reduced Object RC
Unreduced Passive RC
Reduced Passive RC
Active Subject RC
Coordination S-matched
Coordination O-matched

Priming reveals abstraction depth

Deb Bhattacharya

Filler-gaps that neural networks fail to generalize

Debasmita Bhattacharya and **Marten van Schijndel**
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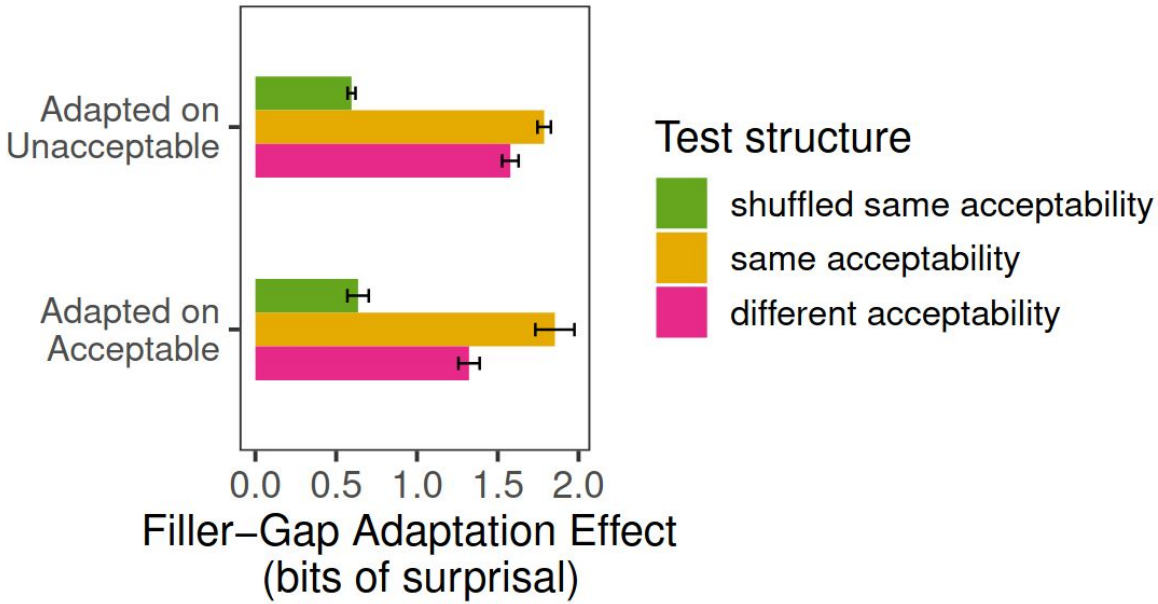
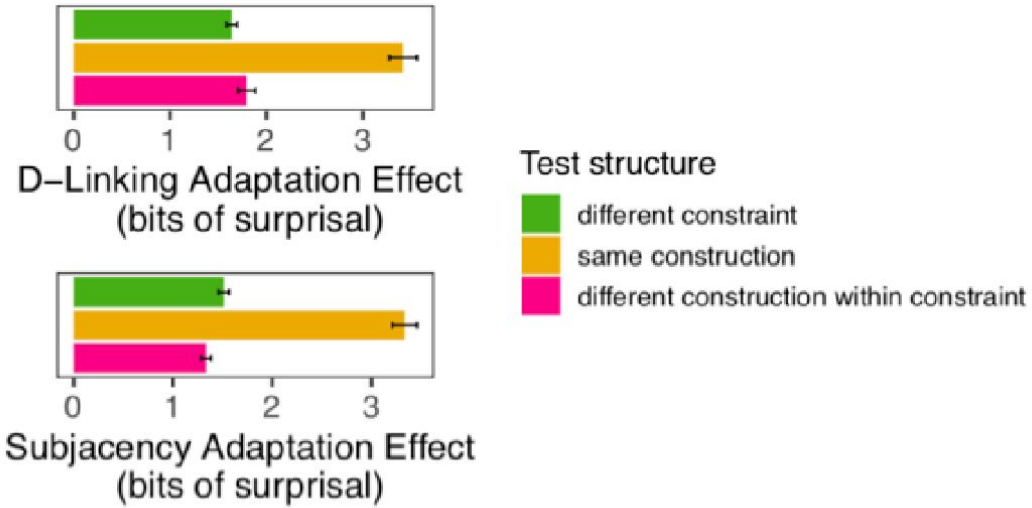
Proceedings of CoNLL 2020

Construction	Examples	L	S	E	D
Adjunct island	*What did you go home because you needed to do __?	-		-	
Wh- island	*Whom did Susan ask why Sam was waiting for __?		-		(+)
Subject island	*Who is that __ went home likely?	-	-	-	
Left branch island	*Whose does Susan like __ account?		-		(+)
Coordinate structure island	*What did Sam eat __ and broccoli?			+	
Complex NP island	*What did you hear the claim that Fred solved __?		-		
Object extraction	Who is it probable that Bill likes __?	+		+	(+)
Non-bridge verb island	*How did she whisper that he had died __?	?	?		

Networks encode broad FG existence



Networks do not encode abstract FG constraints



Priming reveals constraint-like rankings

Forrest Davis

Uncovering Constraint-Based Behavior in Neural Models via Targeted Fine-Tuning

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Proceedings of ACL 2021

(a) Sally frightened Mary because **she** was so terrifying.

Who is terrifying?

(a) Sally frightened Mary because **she** was so terrifying.

(a) Sally frightened Mary because **she** was so terrifying.

(a) Sally frightened Mary because **she** was so terrifying.

Who is terrifying?

Sally

(b) Sally **feared** Mary because **she** was so terrifying.

Who is terrifying?

(b) Sally **feared** Mary because **she** was so terrifying.

Who is terrifying?

Mary

Implicit Causality

- Some verbs are **subject-biased**
  - *frightened, amused, astonished, enraged*

- Others are **object-biased**
  - *feared, admired, loved, hated*

(Garvey and Caramazza, 1974)

Is it attested cross-linguistically?

Yes

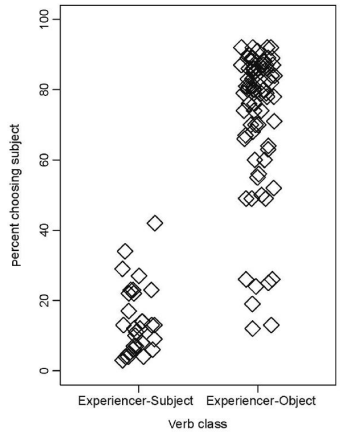


Figure 6. Degree of subject-bias for English emotion verbs reported in Ferstl, Granham, Manouilidou (in press).

English

Dutch

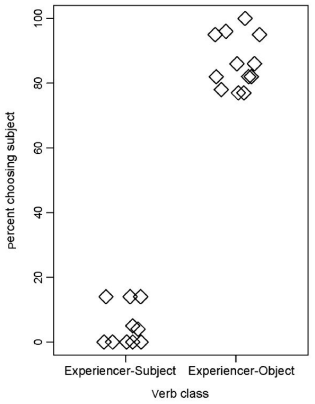


Figure 8. Degree of subject-bias for Dutch emotion verbs reported by Koornneef and van Berkum (2006).

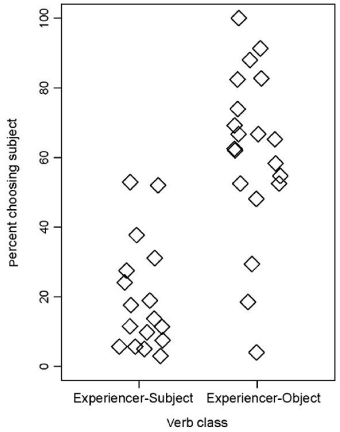


Figure 7. Degree of subject-bias for emotion verbs in Spanish as reported by Goikoetxea et al. (2008).

Spanish

Italian

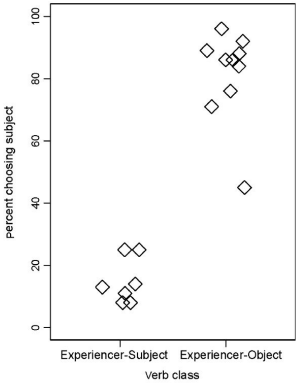


Figure 9. Degree of subject-bias for emotion verbs in Italian as reported by Mannetti and de Grada (1991).

from Hartshorne et al. (2013)

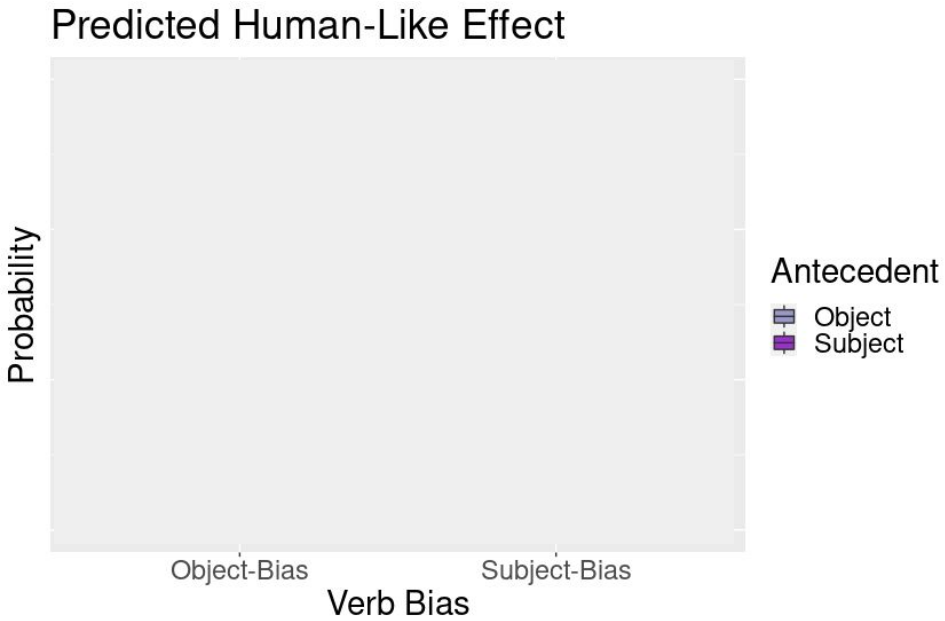
English

Evaluating English BERT for IC behavior

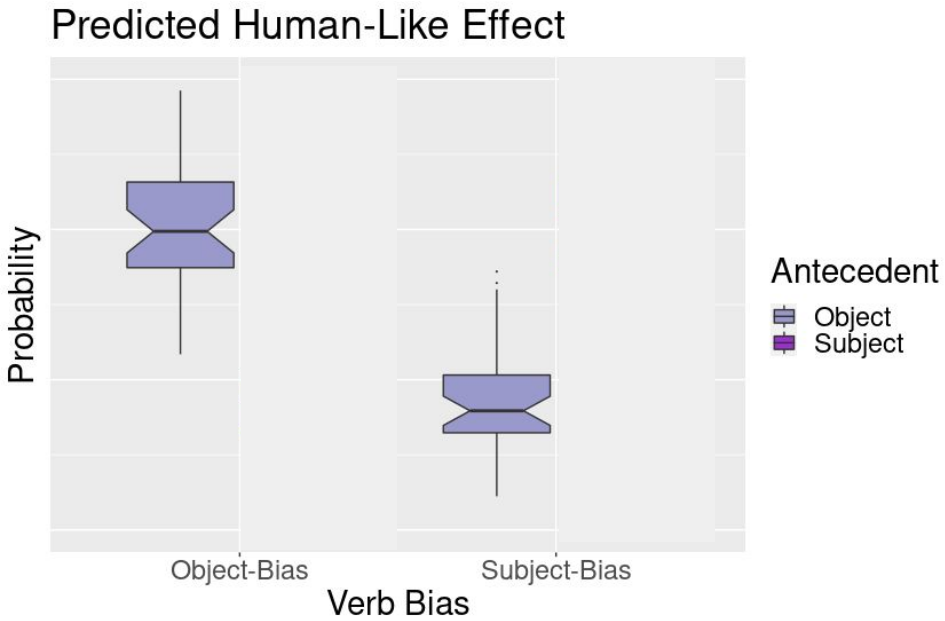
the man admired the woman because [MASK] was there.

- ~300 IC verbs from Ferstl et al. (2011)
- 14 pairs of stereotypical masculine and feminine nouns (e.g., king-queen) substituted in for subject and object (balanced for gender and position)
- bert-base-uncased (HuggingFace)
- Expect higher probability for pronouns agreeing with the bias (admire = object-biased)
    - P(she) > P(he)

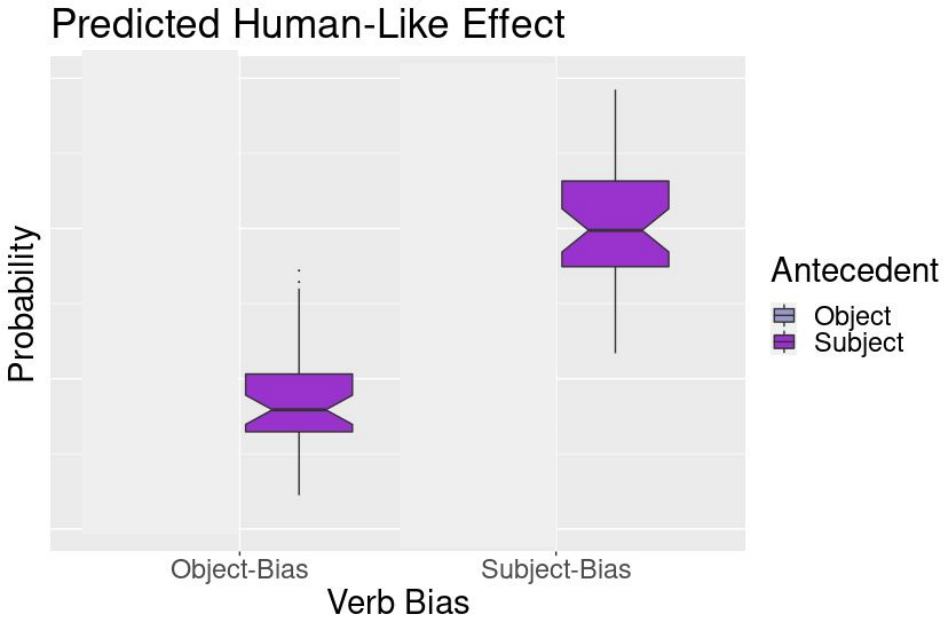
Evaluating English BERT for IC behavior



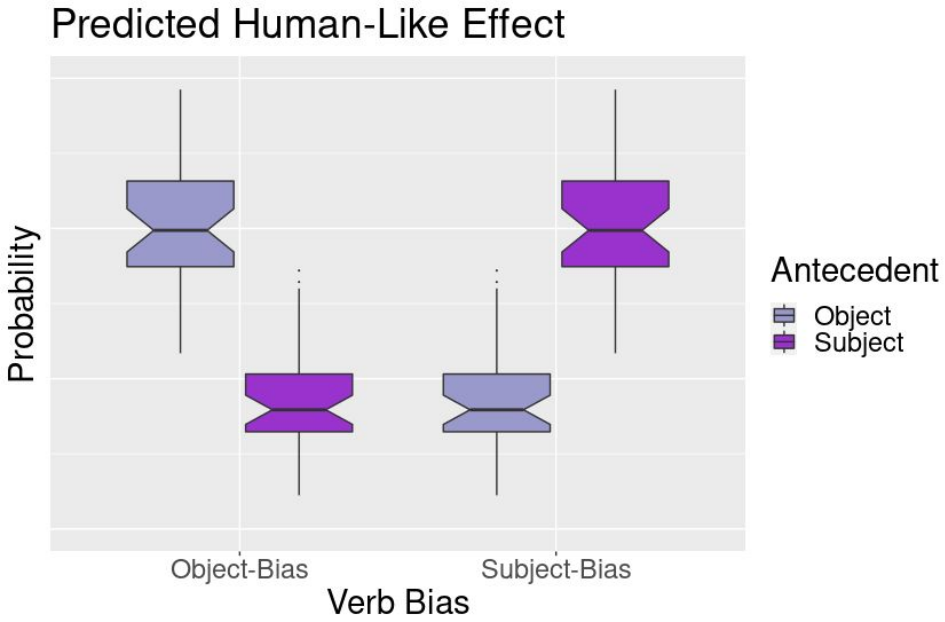
Evaluating English BERT for IC behavior



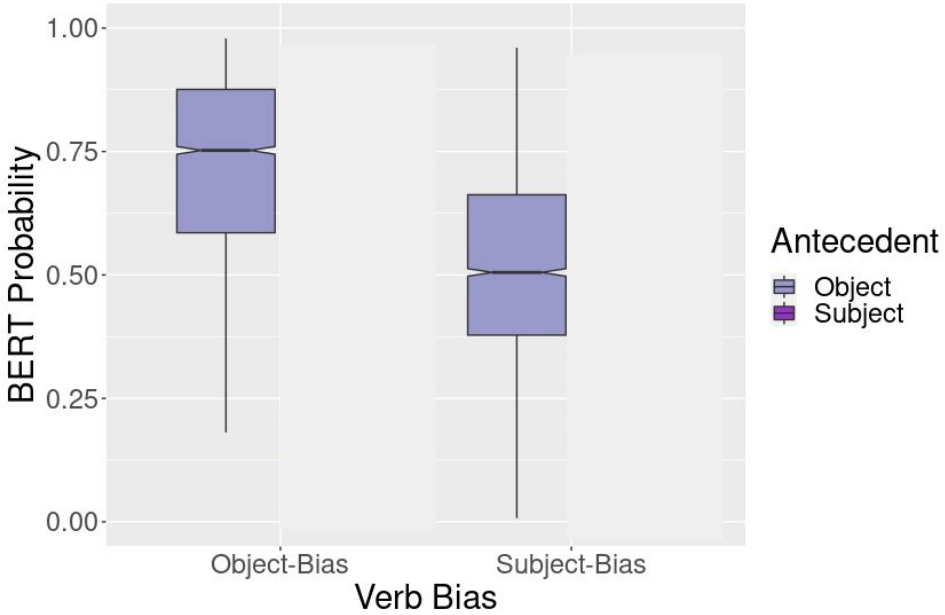
Evaluating English BERT for IC behavior



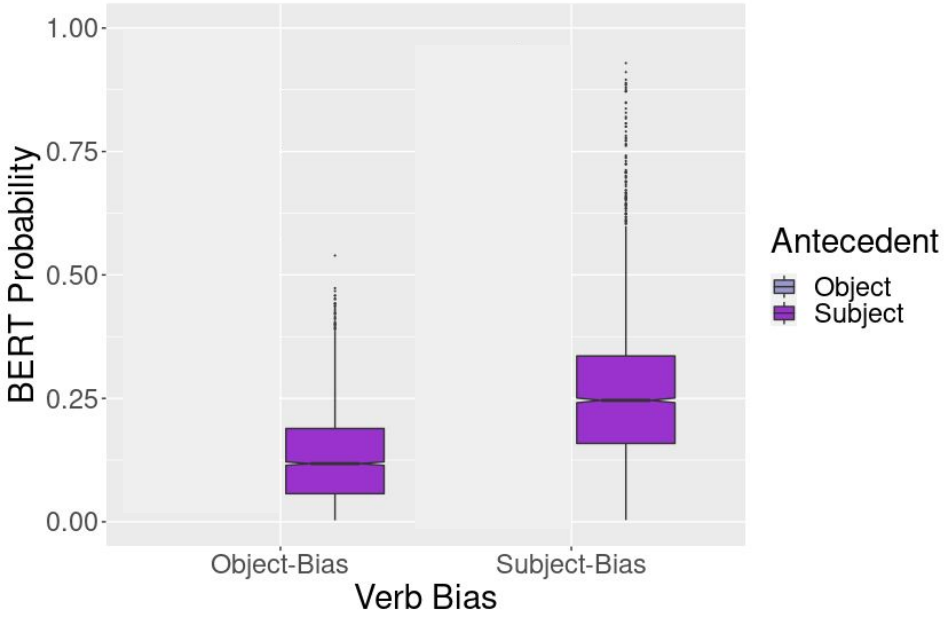
Evaluating English BERT for IC behavior



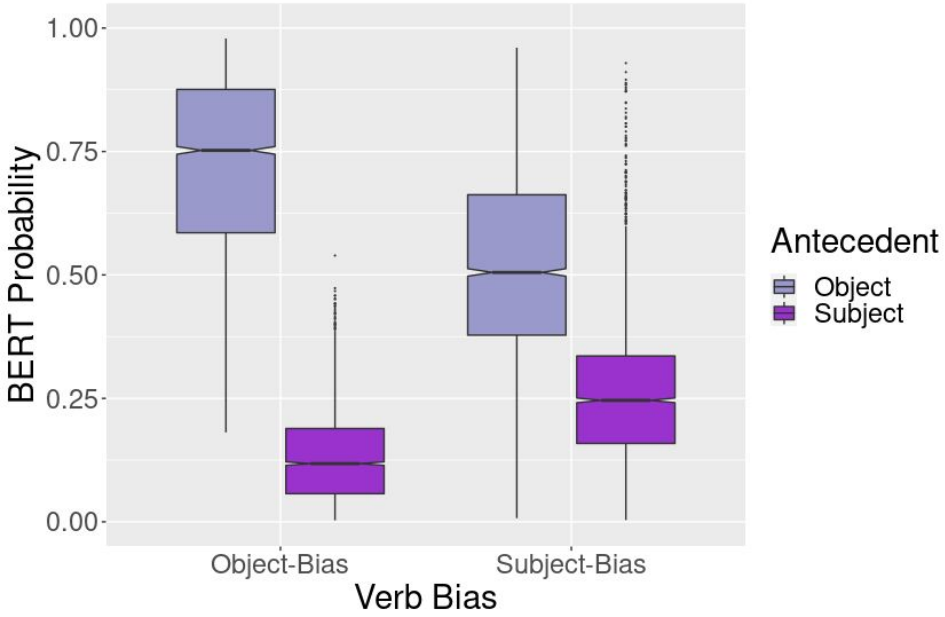
English BERT shows IC behavior



English BERT shows IC behavior



English BERT shows IC behavior



Spanish & Italian

Evaluating Spanish BERT for IC behavior

el hombre admiró a la mujer porque [MASK] estaba allí.

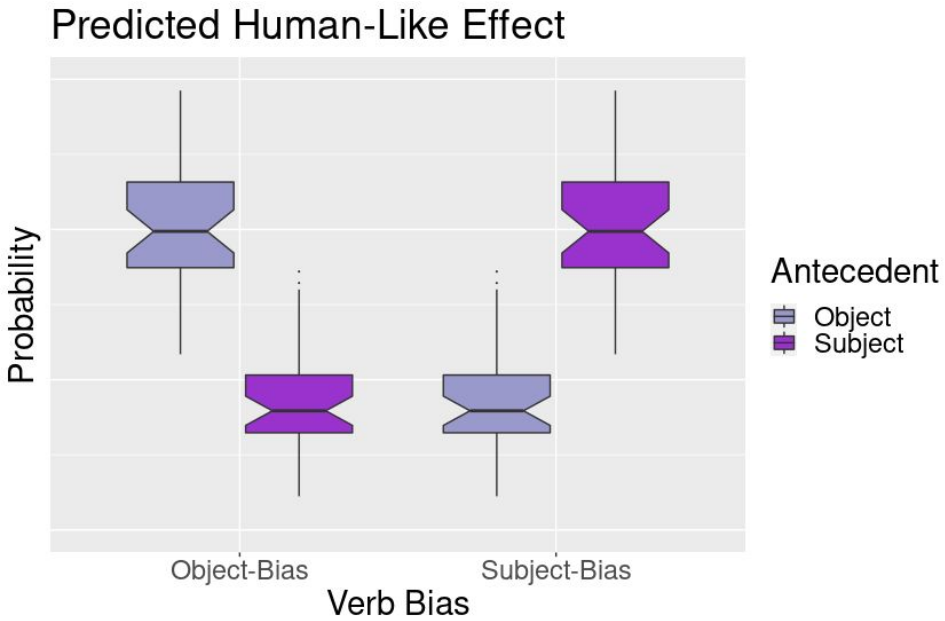
- 100 IC verbs from Goikoetxea et al. (2008)
- 14 pairs of stereotypical m and f nouns subbed for subject and object (balanced for gender, position)
- dccuchile/bert-base-spanish-wwm-uncased (aka BETO; HuggingFace)
- Expect higher probability for pronouns agreeing with the bias (admiró = object-biased)
    - P(ella) > P(él)

Evaluating Italian BERT for IC behavior

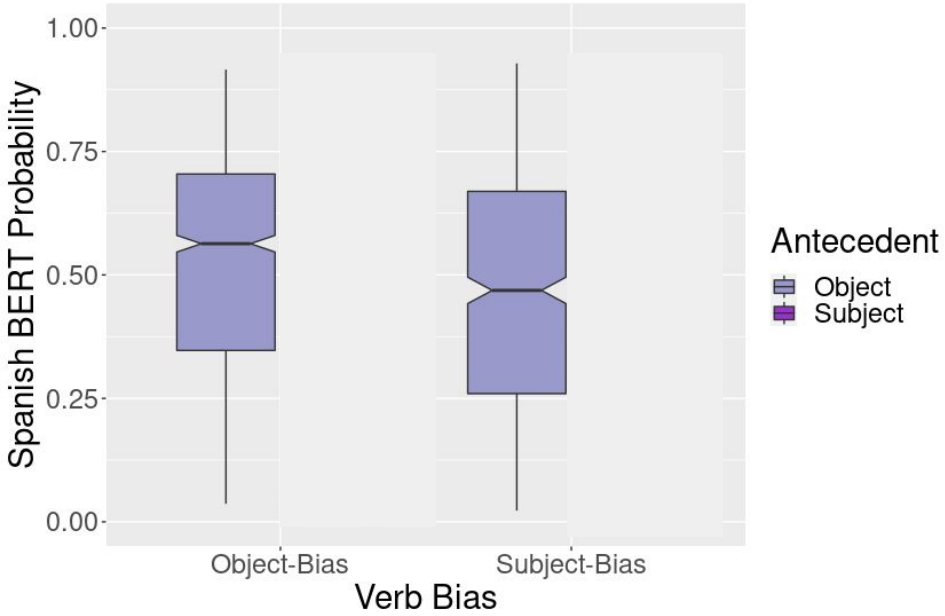
l'uomo lusinga la donna a causa del tipo di persona che [MASK] è.

- 40 IC verbs from Mannetti and de Grada (1991)
- 14 pairs of stereotypical m and f nouns subbed for subject and object (balanced for gender, position)
- dbmdz/bert-base-italian-uncased (HuggingFace)
- Expect higher probability for pronouns agreeing with the bias (lusinga = object-biased)
    - P(lei) > P(lui)

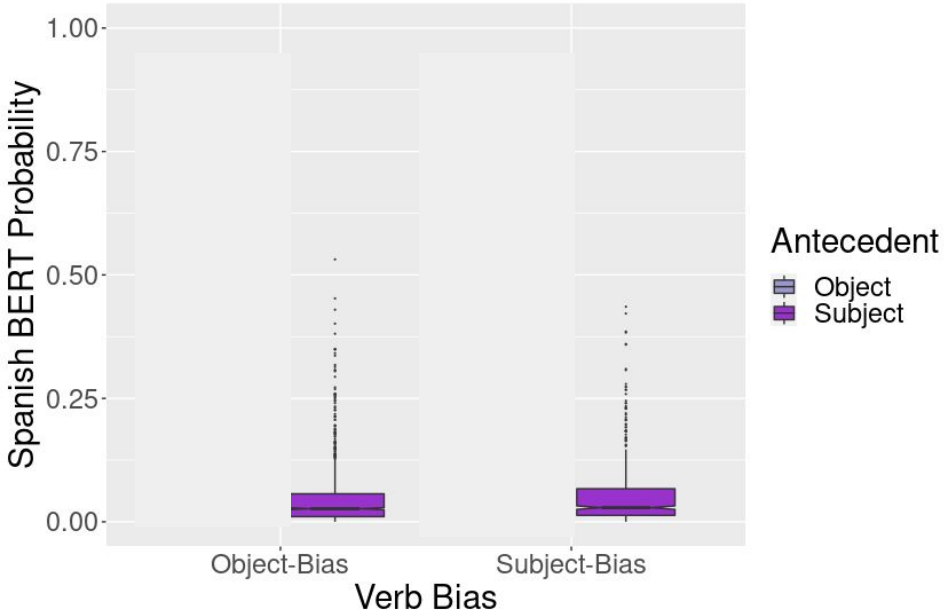
Recall what we want to see



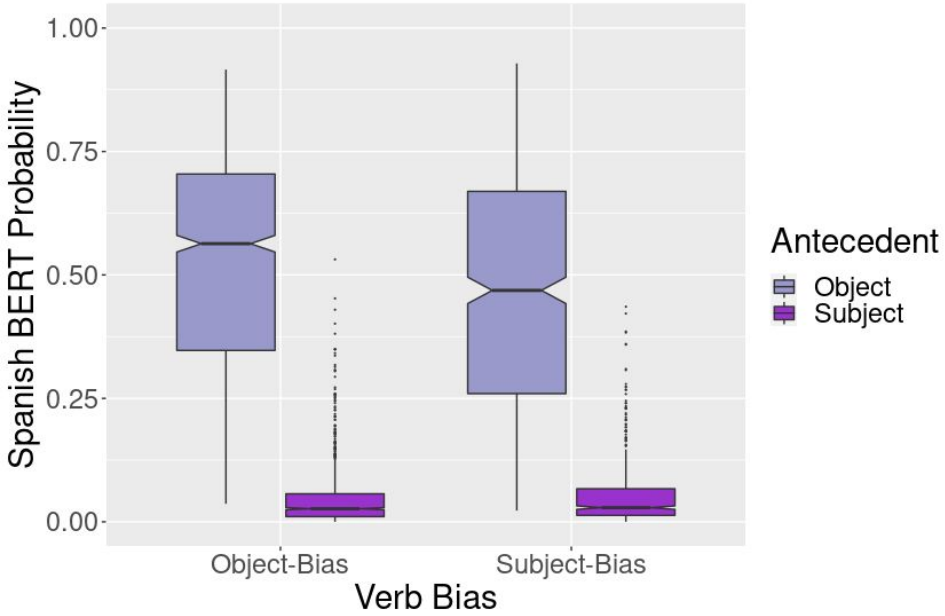
Spanish BERT partial? IC behavior



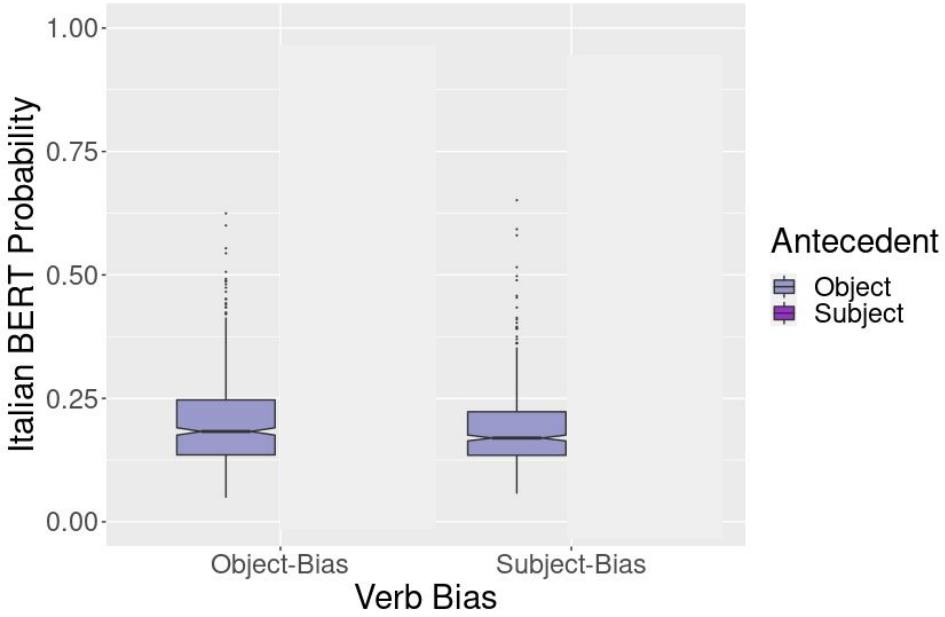
Spanish BERT partial? IC behavior



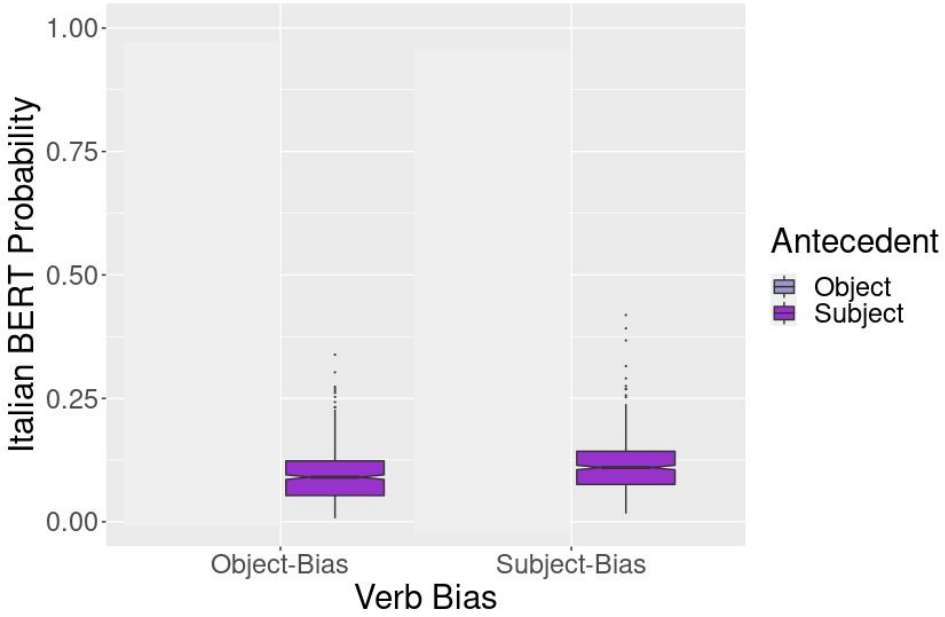
Spanish BERT partial? IC behavior



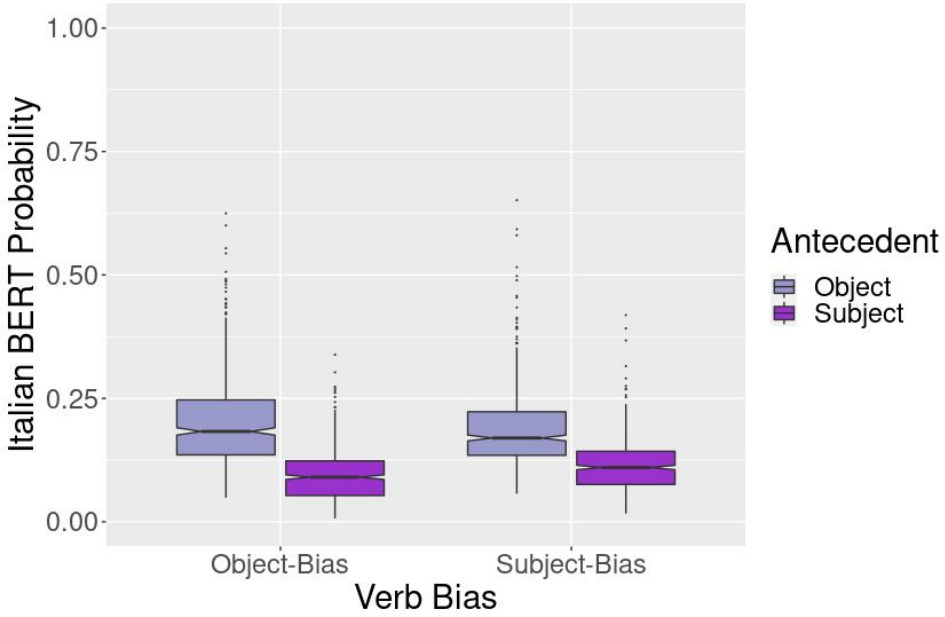
Italian BERT no IC behavior



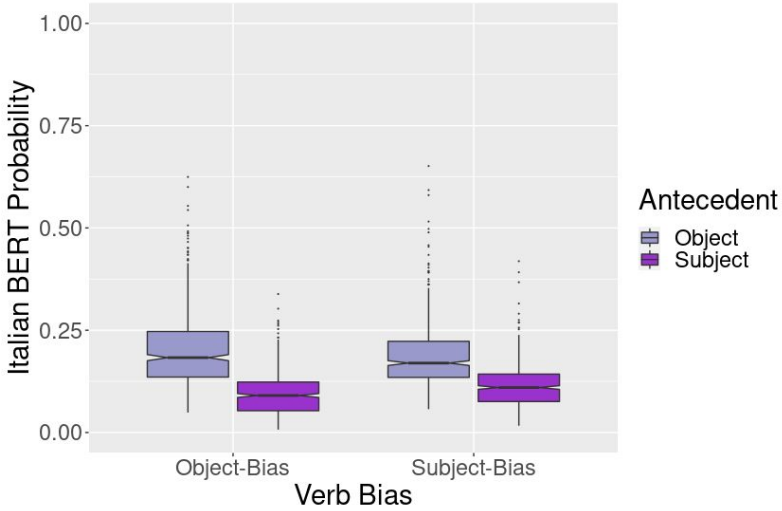
Italian BERT no IC behavior



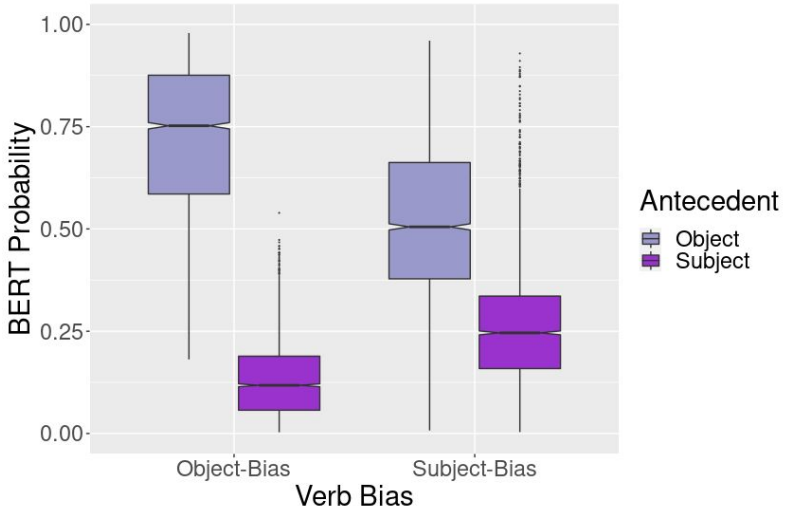
Italian BERT no IC behavior



Italian BERT no IC behavior



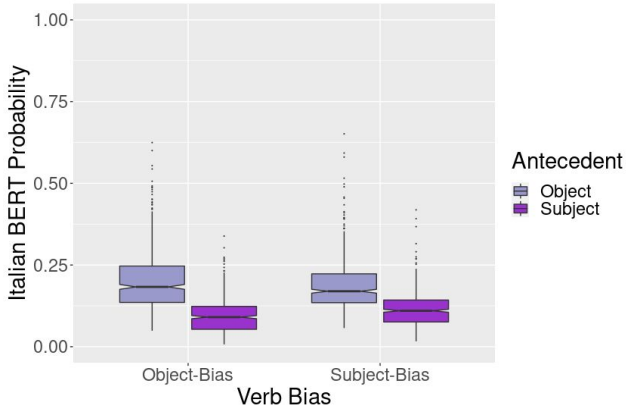
Italian



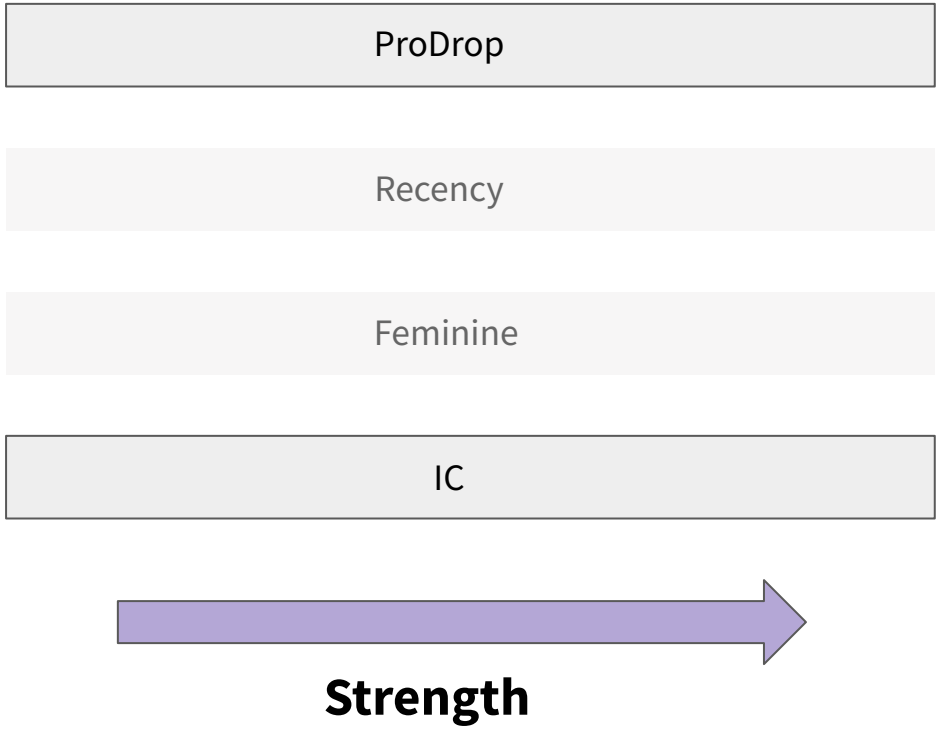
English

Why aren’t we learning IC in Spanish & Italian

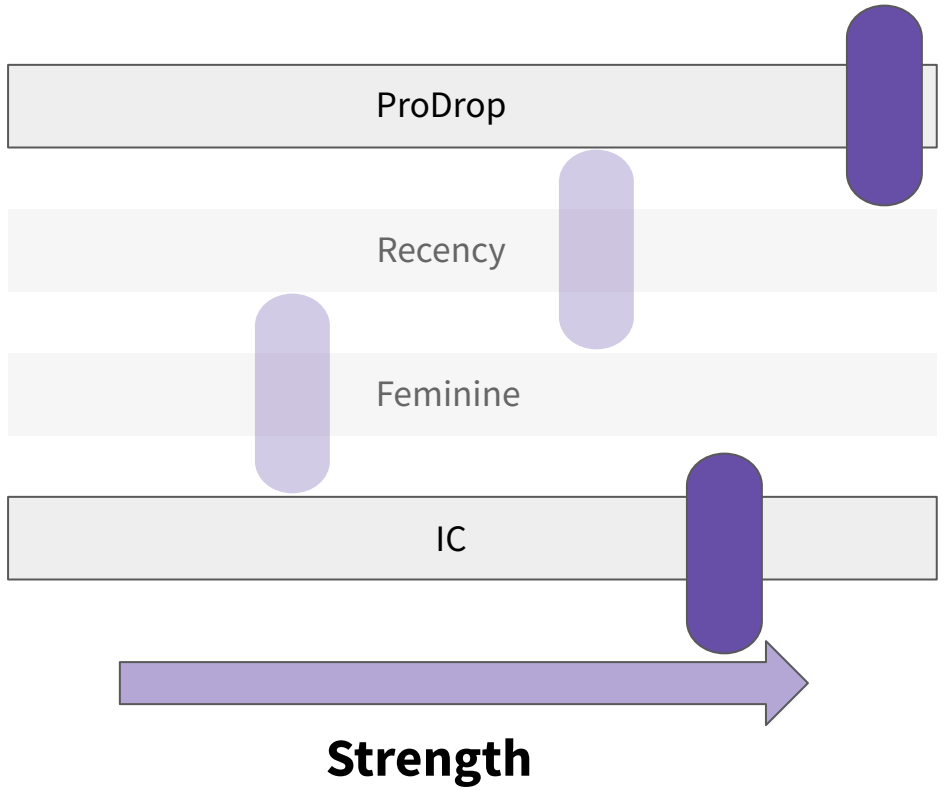
- Implicit Causality is not the only process affecting pronouns
- ProDrop: Overt pronouns in subject position are ungrammatical or dispreferred
  - is happy vs. *he is happy



Processes as Constraints



Processes as Constraints



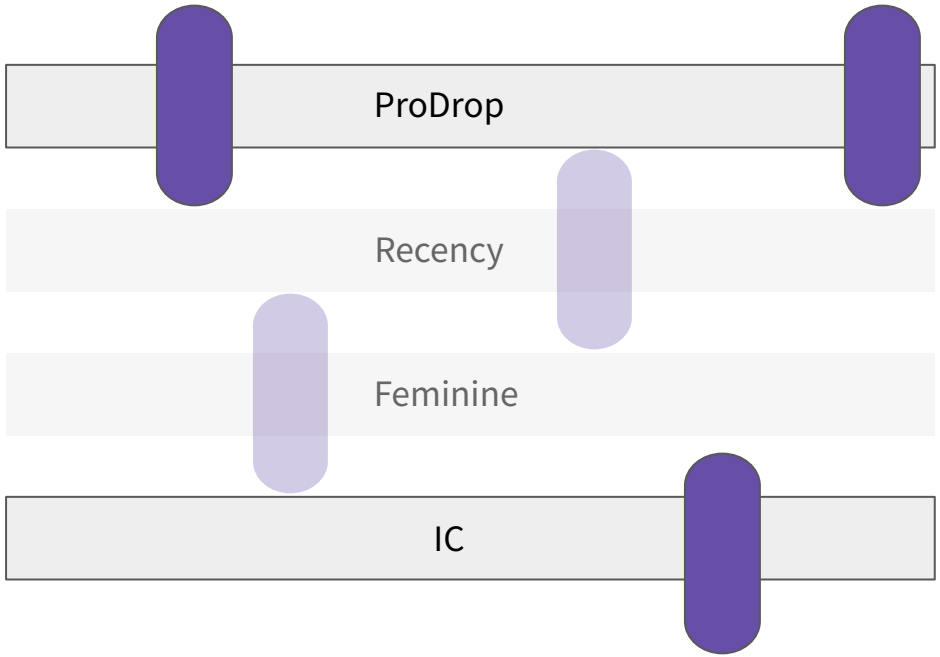
The man admired the woman because __ was there

ProDrop Competes with IC bias

ProDrop outranks IC

Can we promote IC by demoting ProDrop?

Processes as Constraints



The man admired the woman because <u>she</u> was there

Demoting ProDrop with Fine-tuning

Method: Add pronouns to Spanish/Italian ProDrop sentences

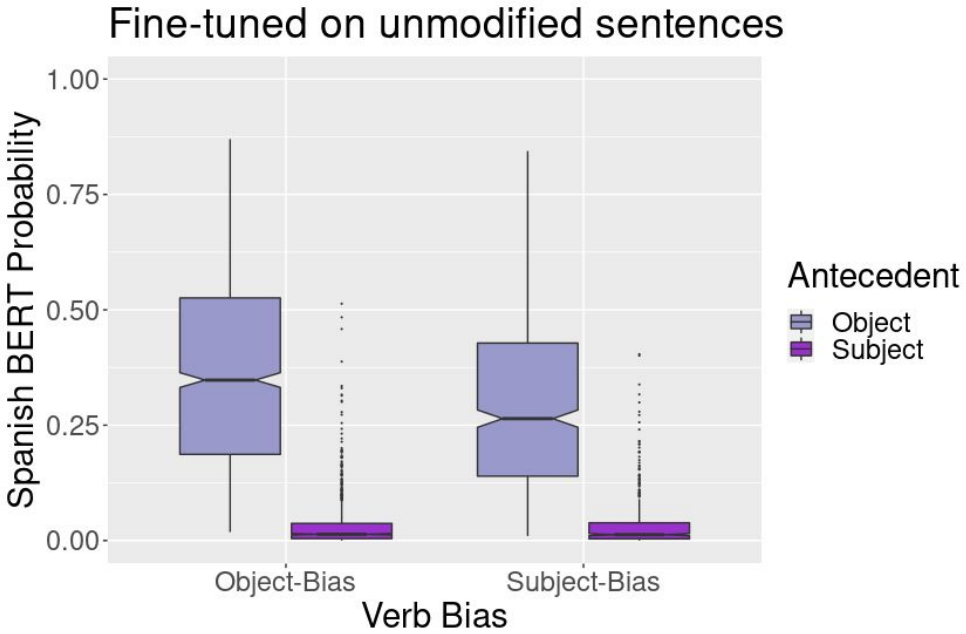
UD datasets (AnCora Spanish, Italian ISDT and VIT)

- Find finite verbs w/o nsubj relation, filtering out test IC verbs
- Added a pronoun matching the verb's person and number
- Resulted in 4000 Spanish sentences (~3500 he/she)
  4600 Italian sentences (~2000 he/she);
  0.005% of original training data

- Fine-tuned Spanish and Italian BERT for 3 epochs (lr=5e-5)

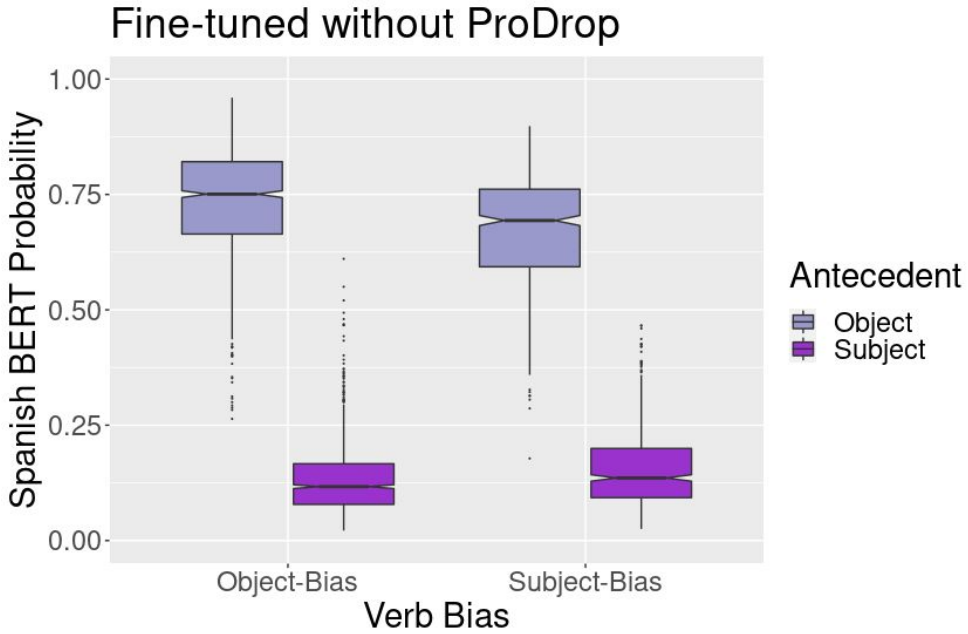
Spanish Baseline

- Unmodified sentences



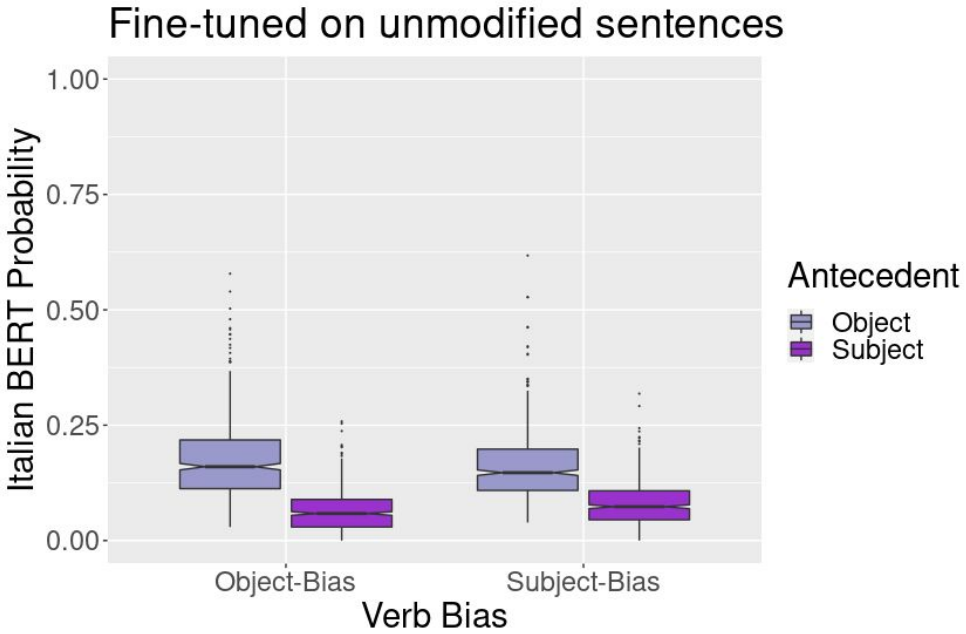
Spanish Fine-tuned

- Sentences without ProDrop



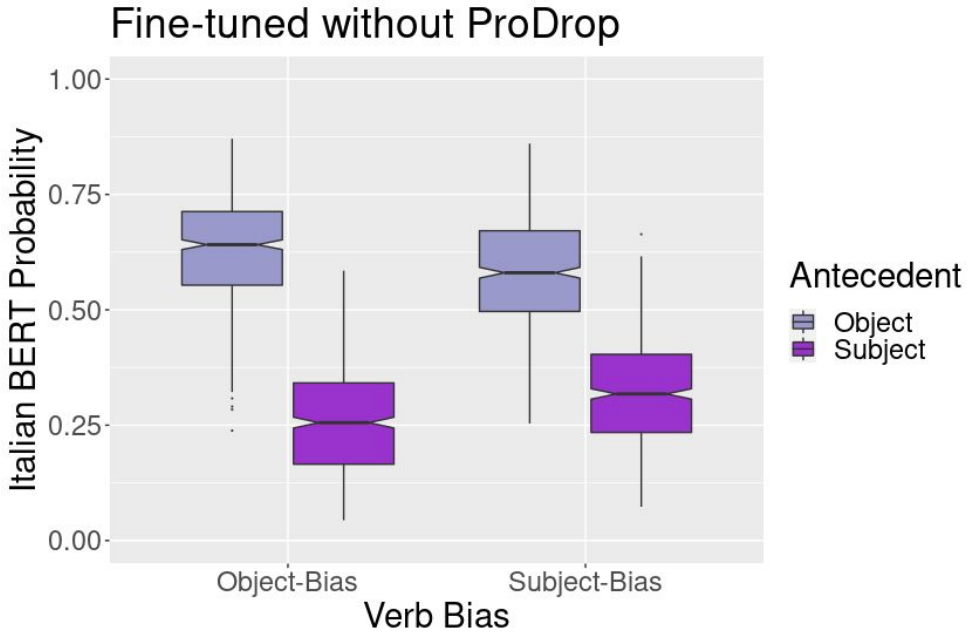
Italian Baseline

- Unmodified sentences



Italian Fine-tuned

- Sentences without ProDrop



Summary

- Standard behavioral probing: IC is only learned by English models
- In fact, Spanish and Italian models also learn IC but it conflicts with ProDrop
- Removing ProDrop via fine-tuning on a small number of ProDrop violations revealed IC knowledge
    - We explicitly train on data for a process we are **not** testing (i.e. we are not training on IC data)

Conclusion

- Adaptation priming is effective for:

- We can probe feature clusters and constraint/feature rankings

- Field too often probes single phenomena (usually in English)
  need to watch for interactions
  (signals compete)

Thanks!

C.Psyd

Cornell NLP