

What can language models teach us about human language?



Isabel Papadimitriou

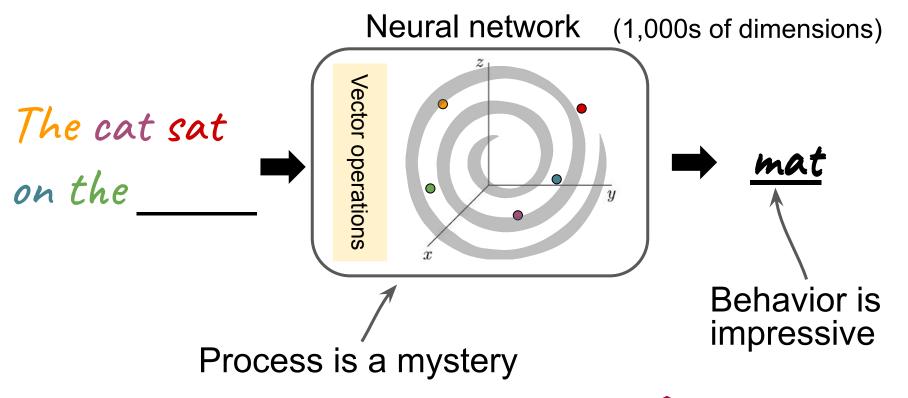
Language Models

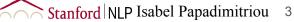
- Artificial models of human language
- eg. ChatGPT

- Recent, huge progress
 - In many cases, a pretty good approximation of novel human language production
- But, we don't know how they do it
- How can we use LMs to learn about language?



What is a language model?





An exciting development for linguistics

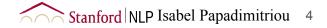
Language models are:

• Very good –

 We have computational models of language that capture a lot of the subtlety of language use

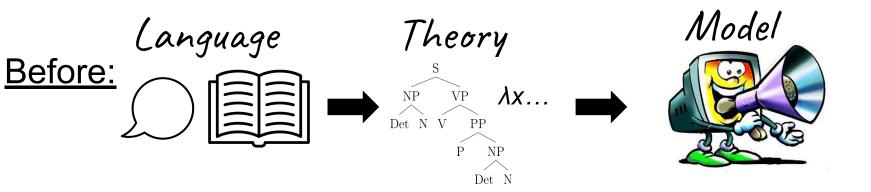
• Very empirically flexible –

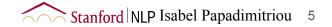
we can control their training and examine their language system



What makes language models so good is precisely *that* we don't understand how they work

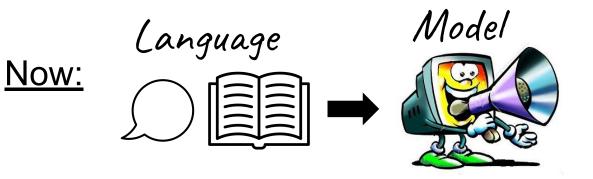
 Language models are not engineering products applying one linguistic theory or analysis





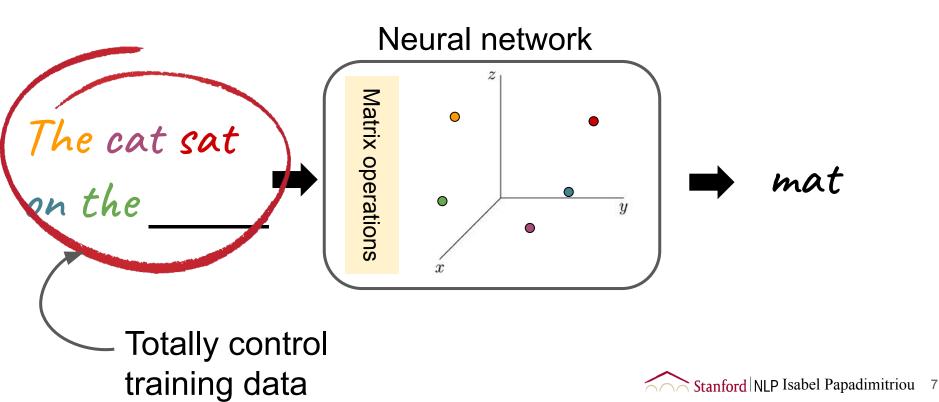
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 Language models are not engineering products applying one linguistic theory or analysis

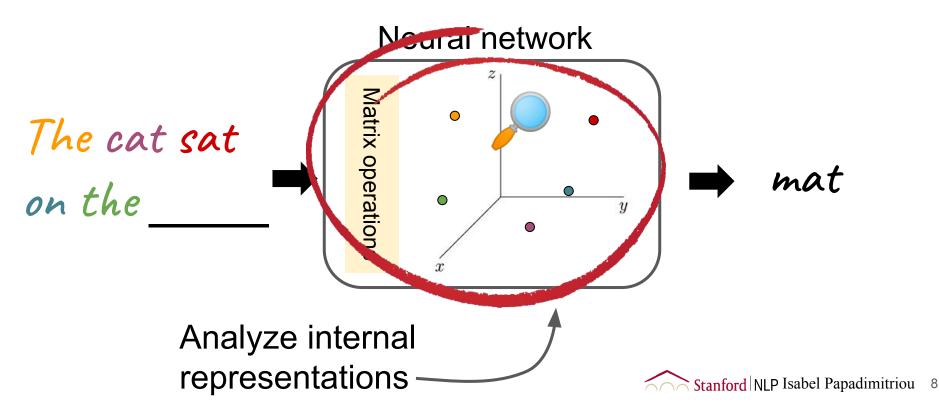


 A functioning theory of possibilities to analyze human language [Baroni 2021]

Empirical flexibility: experiments that are impossible with humans



Empirical flexibility: experiments that are impossible with humans



Language models are:

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Very empirically flexible –

 we can control their training and examine their language system

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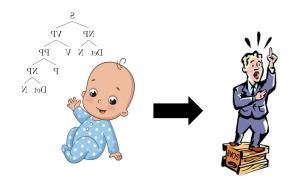
But.. very different from humans –

- Unconstrained language learners
- Continuous high-dimensional space

This talk: methodologies for bridging the gap

Use language models to address two linguistic questions:

What makes language acquisition possible?



[Papadimitriou and Jurafsky 2020, Papadimitriou and Jurafsky 2023]

How do speakers represent syntactic information?

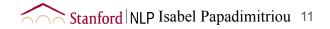


[Papadimitriou et al 2021, Papadimitriou et al 2022]

This talk: methodologies for bridging the gap

- But.. very different from humans
 - Unconstrained language learners
 - Continuous high-dimensional space

1) Bias language models towards theoretically-significant structural constraints

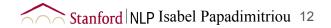


This talk: methodologies for bridging the gap

But.. very different from humans –

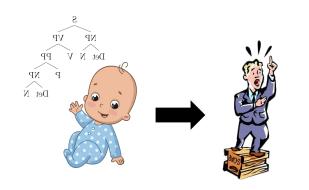
- Unconstrained language learners
- Continuous high-dimensional space

2) Map out the representation of grammatical role in the model's internal space



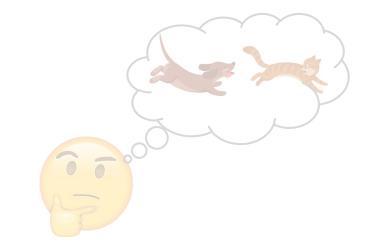
Use language models to address two linguistic questions:

What makes language acquisition possible?



Method: structural injection before LM training

How do speakers represent syntactic information?



Method: subjecthood representation analysis

What does a language learner need to start from?



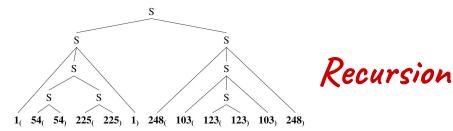
? (no restrictions?)

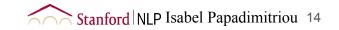
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Language exposure

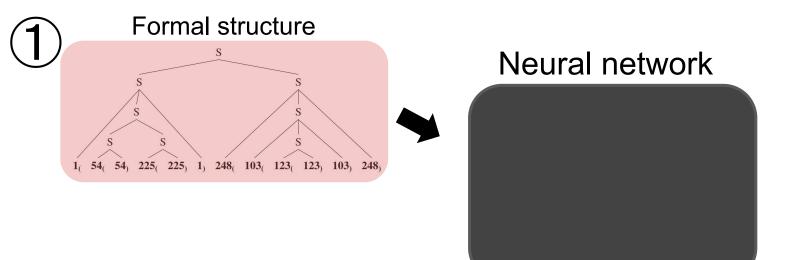
Method: Inject a model with a bias that we choose

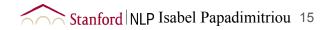
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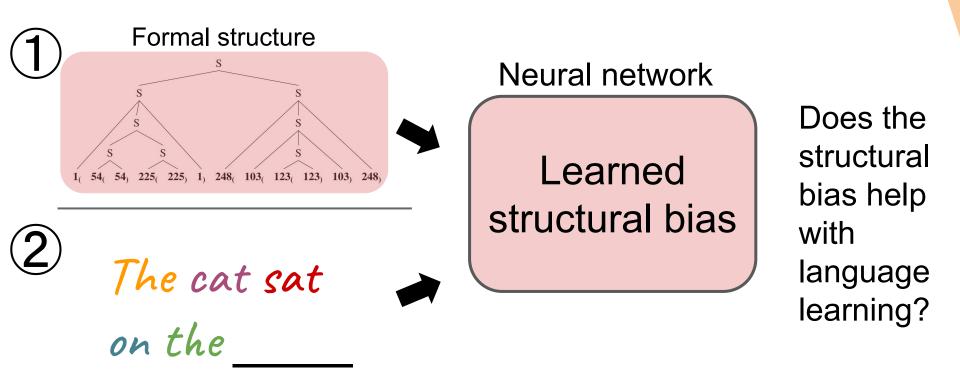


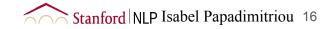
Inject structural language, learn natural language





Inject structural language, learn natural language

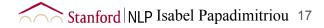




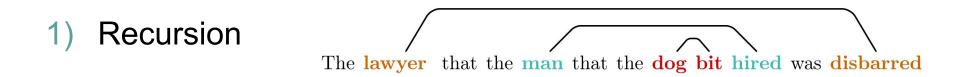
With structural injection, we combine theoretically-significant biases with the power of LMs



LMs let us do hypothesis testing of different biases



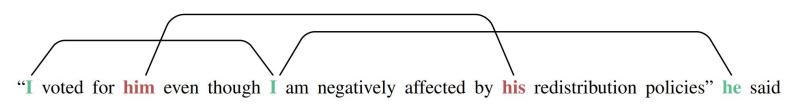
Test three types of structure:



2) Simple regular bias, repetition

And he said this, and he said that

3) Crossing dependencies



Recursion

- Nesting, context-free
- Hypothesis that recursion is what makes language [Hauser Chomsky Fitch 2002]
 The cat sat on the mat

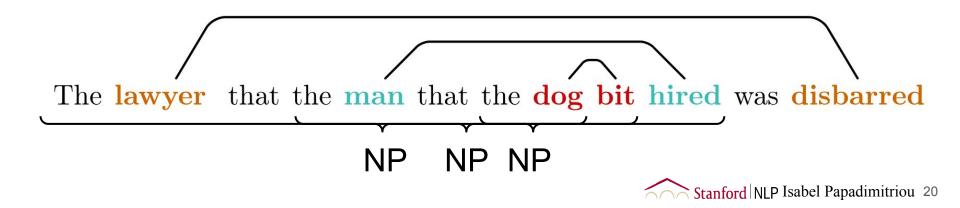
I think that the cat sat on the mat

You always accuse me that I think that the cat sat on the mat

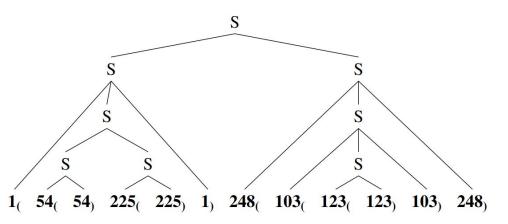


Recursion

- Nesting, context-free
- Hypothesis that recursion is what makes language [Hauser Chomsky Fitch 2002]



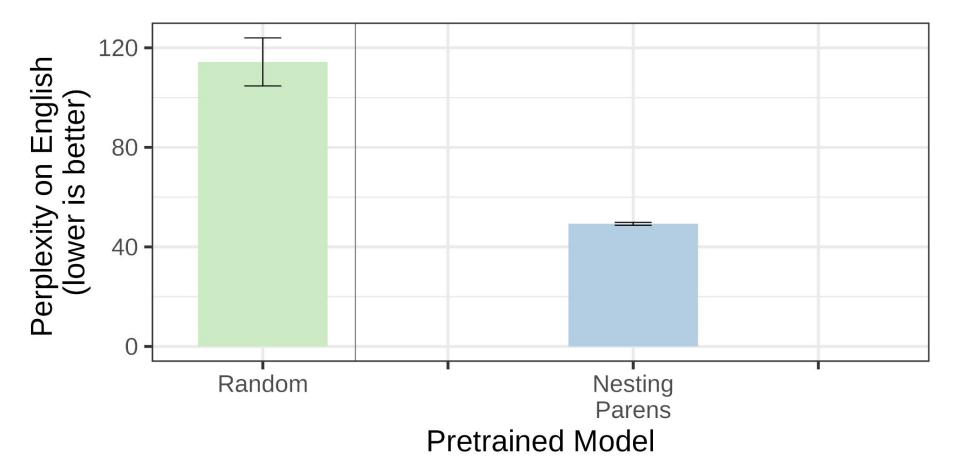
Structural injection formal language: Nesting parentheses



- Well-nested, matching pairs
- Constituents: S strings contain S strings



Recursive bias helps language acquisition

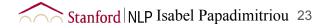


Simple regular bias

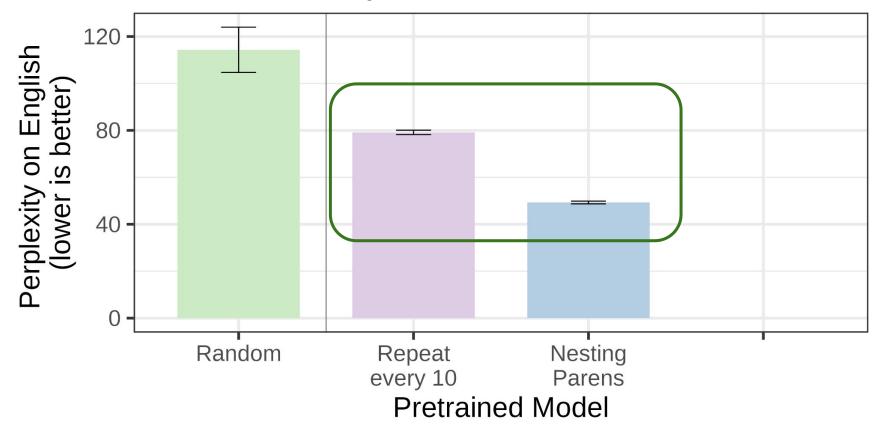
- Is a recursive bias really necessary?
- Test a structural bias that's not very theoretically important in human language

Inject finite repetition language (regular)

$499 \ 472 \ 300 \ 499 \ 472 \ 300 \ 309 \ 18 \ \dots$

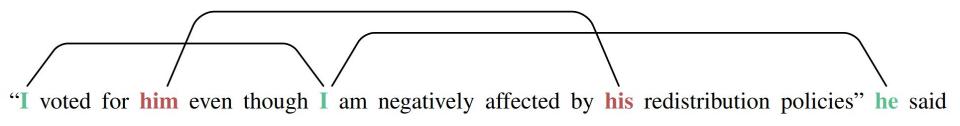


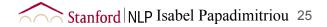
Recursive bias is needed – not just any simple structure



Crossing links and dependencies bias

- Crossing dependencies arise in meaning, reference, discourse, pragmatic relationships
- Example: anaphora

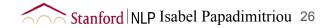




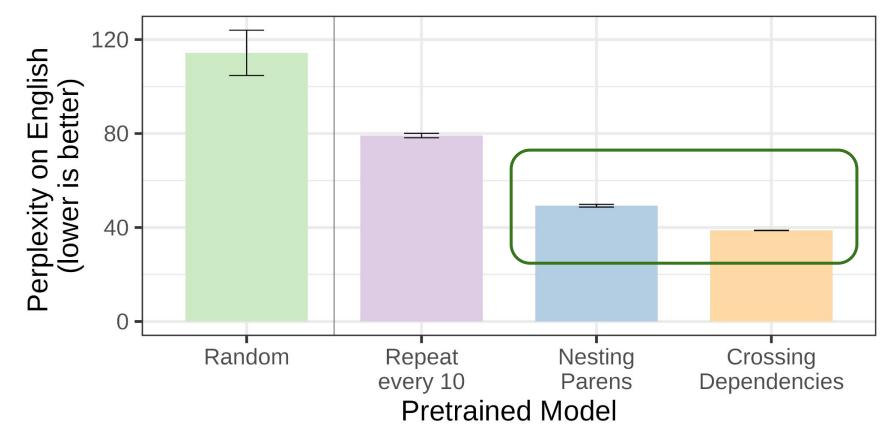
Crossing Dependencies

$$\overbrace{1(54(225(1)54)225)248(248)123(103(123)103)}^{(103)}$$

• Tokens have to **match**, but not **nest**

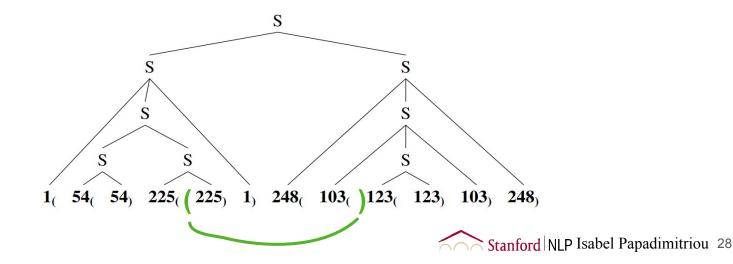


Complex, crossing dependencies provide the best bias – with no recursion

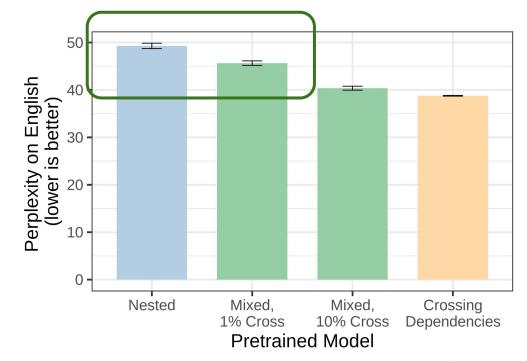


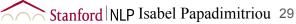
Does crossing-type context sensitive structure always help?

 Mix nesting and cross: mostly nesting, with 1%, or 10% of parentheses not following the structure

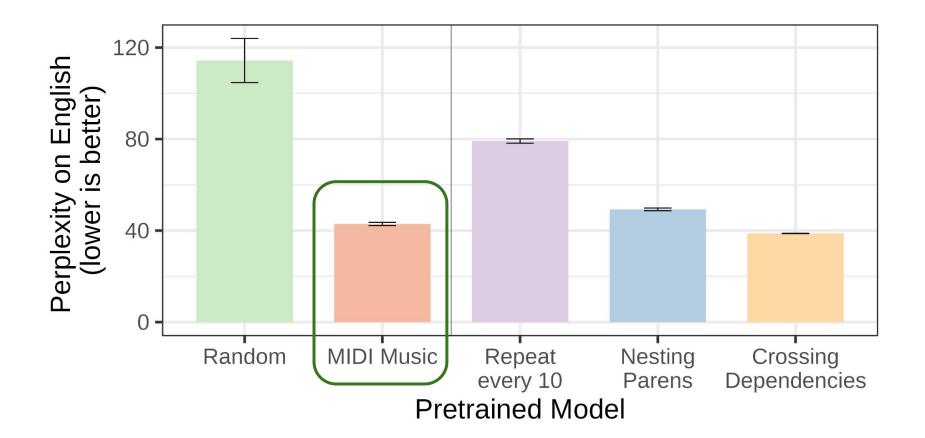


Slightly breaking constituent structure makes better language learners





Are these cognitive biases unique to language?



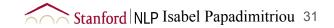
What does a language learner need to start from?



Complex, crossing links 1(54(225(1) 54) 225) 248(248) 123(103(123) 103)

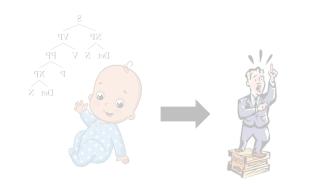
Language exposure

 Importance of bootstrapping meaning, discourse, reference, information structure



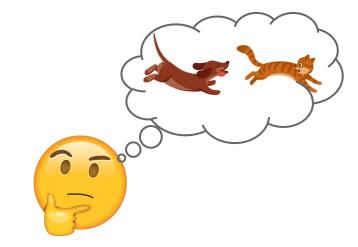
Use language models to address two linguistic questions:

What makes language acquisition possible?



Method: structural injection before LM training

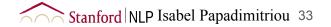
How do speakers represent syntactic information?



Method: subjecthood representation analysis

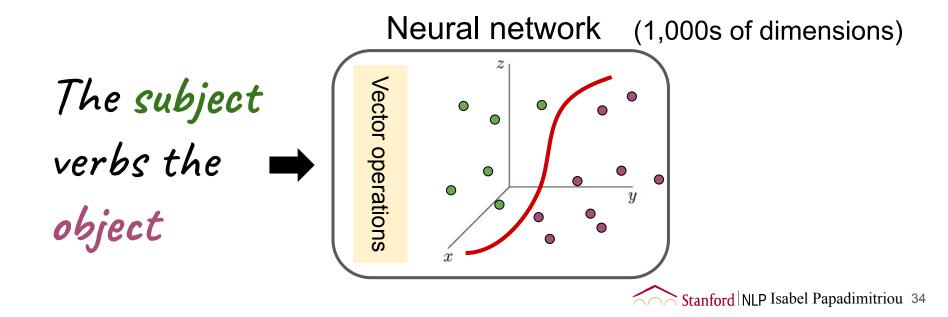


- Who does what to who, being the subject vs the object
- Subjecthood is relevant in basically every utterance, in every language
- How do we represent this relation?



How is subjecthood represented in language models?

Mapping out grammatical role in neural networks

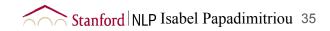




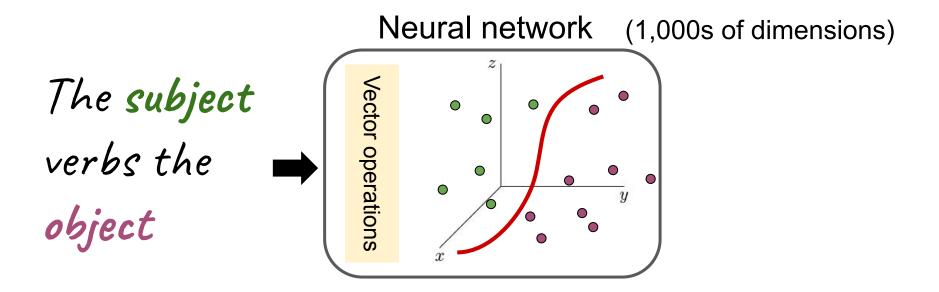
Use LMs to look at subjecthood:

1) Across different languages

2) Interacting with semantics

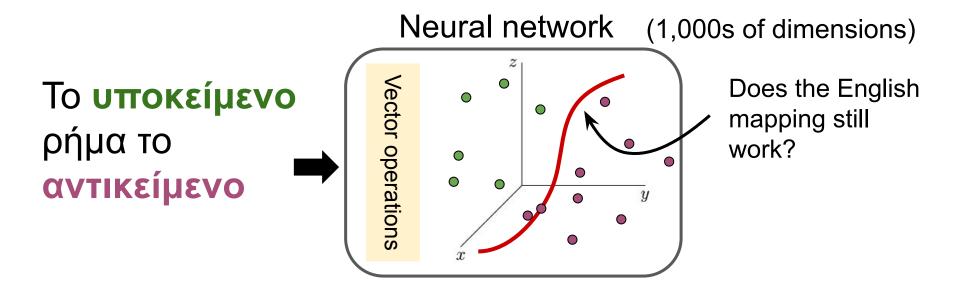


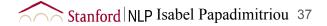
Subjecthood representation in different languages





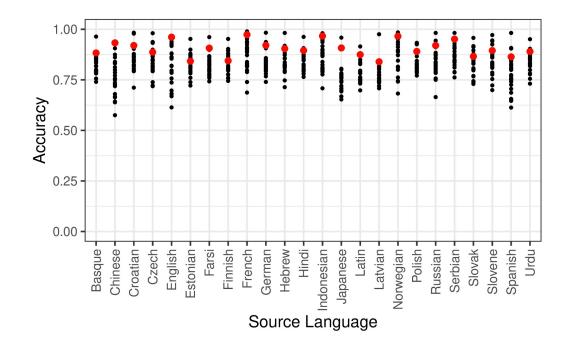
Subjecthood representation in different languages





Subjecthood is cross-lingual

 Subject-object geometry is similar in-language (red) and out-of-language (black)

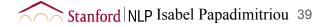


Typology: how languages treat intransitives

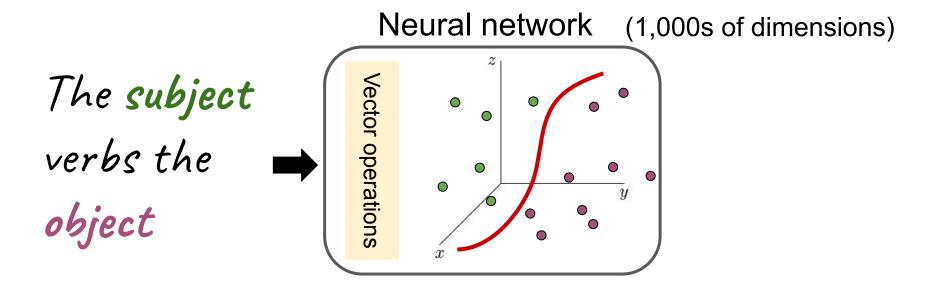
A O Transitive: The dog chased the cat S Intransitive: The glass broke

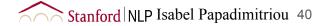




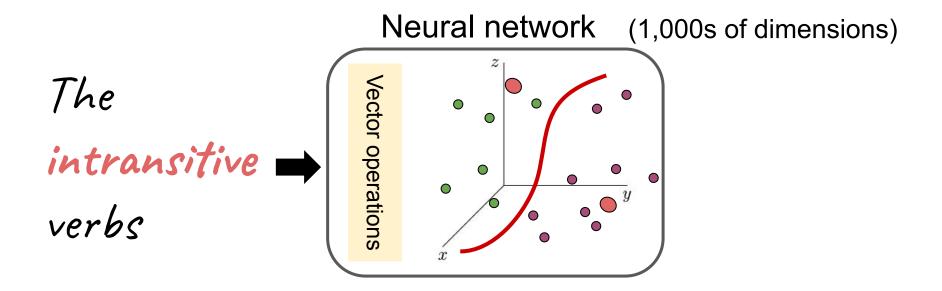


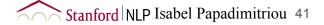
Subjecthood representation of intransitives



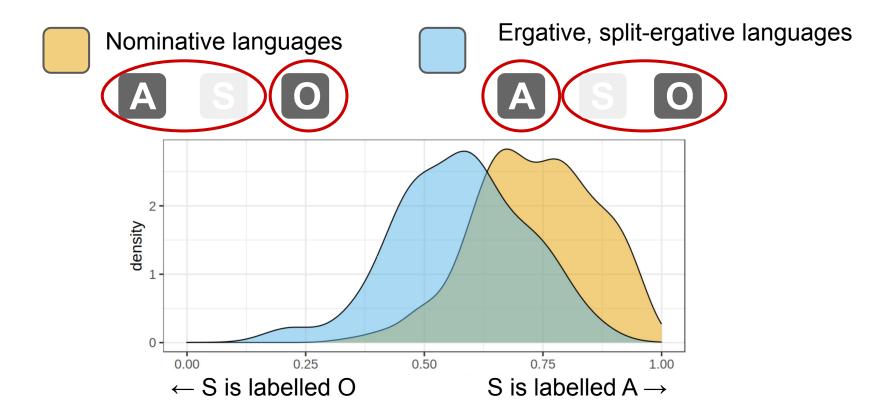


Subjecthood representation of intransitives





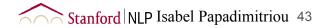
What is the behavior of those universal classifiers on S nouns?





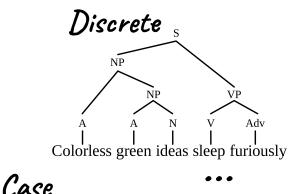
How does this robust cross-lingual representation work?

• **Proposal**: through integrating the grammatical relationship of subjecthood with cross-lingual meaning representation



Subjecthood is complicated, influenced by meaning

Intransitives The **glass** broke **Isabel** broke the **glass**



"There is..."

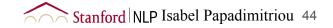
Animacy He ran all day

The fridge ran all day

Passive voice The cat jumped on to the perch The perch was jumped on to by the cat

[Comrie 1989 *Language Universals and Linguistic Typology*] [Hopper and Thompson 1980 *Transitivity in Grammar and Discourse*]

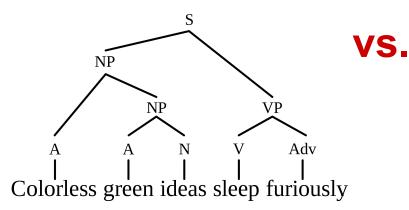
Volitionality Mary punched Sam Mary liked Sam Mary forgot Sam



Is subjecthood a discrete category?



Discrete



Prototype

Animacy,

Passive voice,

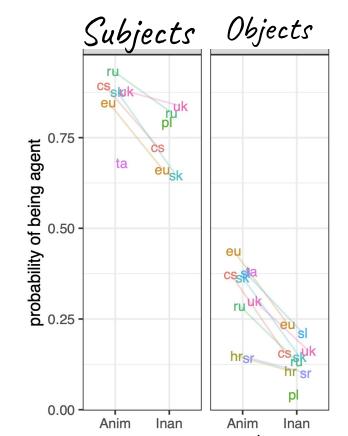
Volitionality,

Agency,

Case,



Classifier probabilities show **animacy** effects, even when controlling for syntactic role



<u>Animacy</u>

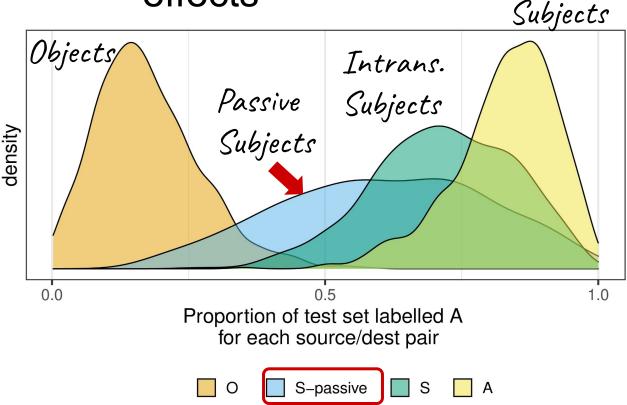
He ran all day

The **fridge** ran all day

Classifier probabilities show passive voice effects

Passive voice The cat jumped on to the perch

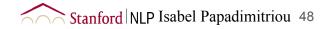
The **perch** was jumped on to by the cat





Prototype effects in LMs: Many factors play into making something a subject

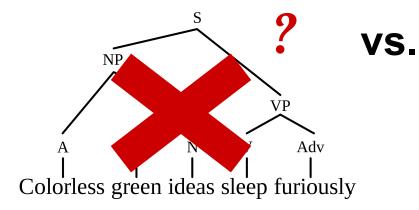
We also look at the effect of **case**. Also working on: discourse, information structure (given/new)



But is it all just prototypes?



Discrete



Prototype

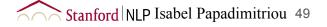
Animacy,

Passive voice,

Volitionality,

Agency,

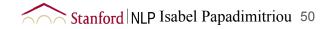
Case,



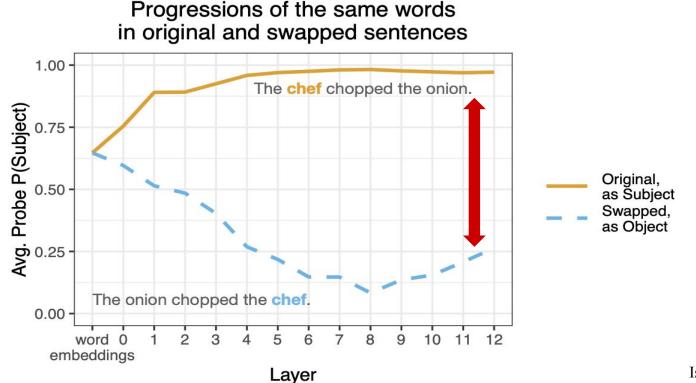
What if we test the same sentences (with the same prototype effects) but we swap the labels?

The chef chopped the onion, The onion chopped the chef Do they have different

classifications?



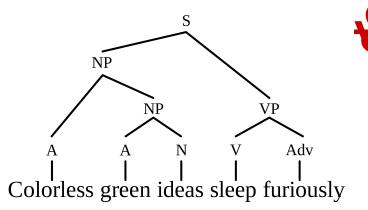
Yes – Representation differences that are caused **only** by syntactic word order



Isabel Papadimitriou 51

Both grammatical subjecthood and prototype effects

Discrete



Prototype

Animacy,

Passive voice,

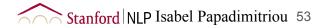
Volitionality,

Agency,

Case,

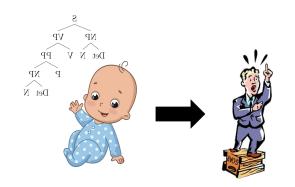
The high-dimensional space of LMs provides a model for a complex notion of subjecthood

 Both grammatical and functional aspects, in one representation model

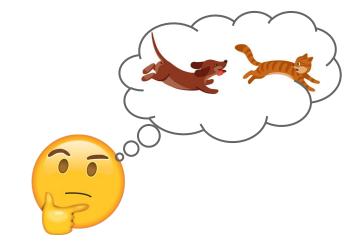


Use language models to address two linguistic questions:

What makes language acquisition possible?



Complex, crossing dependencies bootstrap language learning How do speakers represent syntactic information?



Combine discrete grammatical rules with functional semantics



Language models and language

- Language models are a flexible testbed for thinking about human language
- We can control their training, and inspect their internal representations
- LMs provide tangible models for expanding linguistic theory

Thombs

