What we can learn about language from exploring multilingual language models

Isabel Papadimitriou

Stanford NLP

Some context

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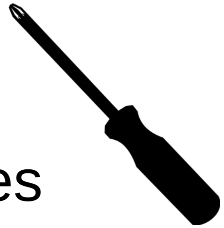

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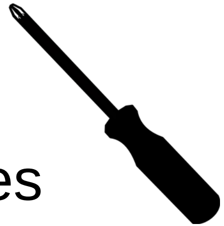

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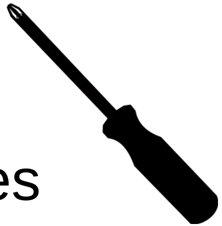

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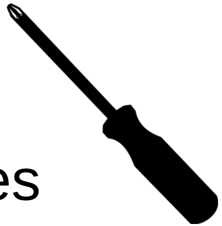

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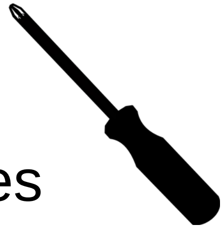

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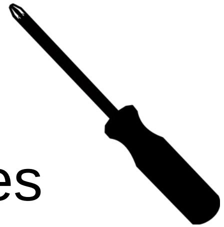

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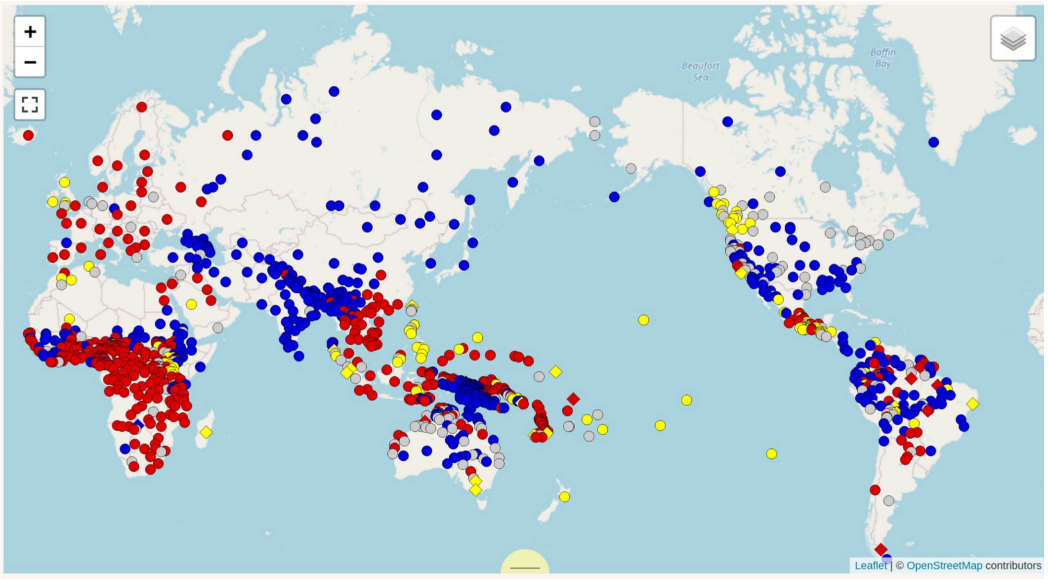
  - We can investigate the **inductive learning biases** that contribute to language learning

This talk:

Using a multilingual lens to approach these questions



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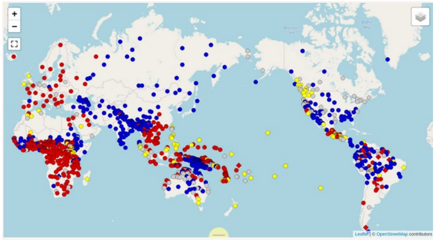

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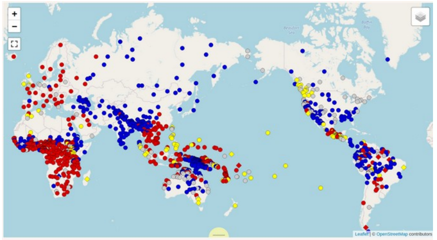

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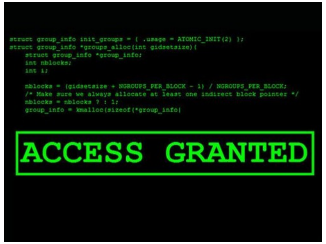

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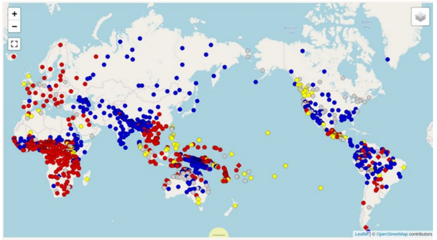

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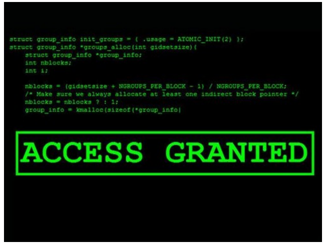

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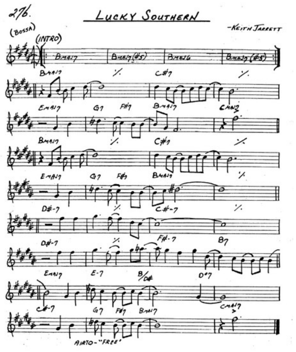
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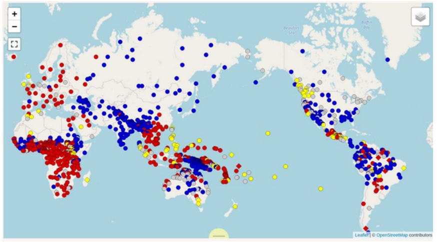

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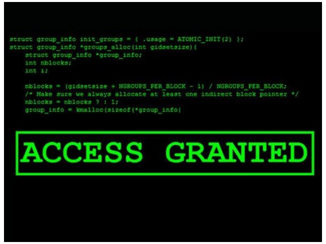

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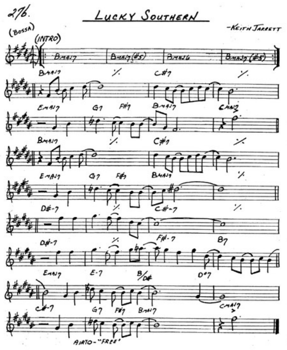
Structural Primitives

{ { } [( )] }

(1 2 3) { 1 2 3 }

Language Variation and Universals

Concrete

Abstract

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- How to understand multifaceted, cross-lingual properties?

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Abstract

- What **inductive learning biases** make good language learners?
- What are the abstractions that underlie language?

Can we really prove anything?

[Baroni 2021, *On the proper role of linguistically-oriented deep net analysis in linguistic theorizing*]

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Representing subjecthood

Transfer learning with syntactic primitives

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- A discrete category, but with subtleties and complexities

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Property: subjecthood

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- Who does what to who, being the subject vs the object

Property: subjecthood

- Who does what to who, being the subject vs the object
- Subjecthood is relevant in basically every utterance, and is handled differently in different languages

Subjecthood is complicated!

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

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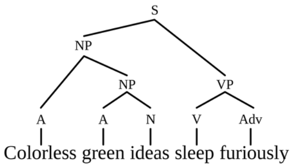
Discrete



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Intransitives

The **glass** broke

Isabel broke the **glass**

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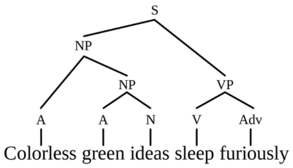

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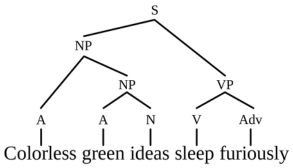

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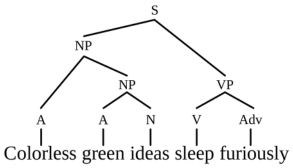

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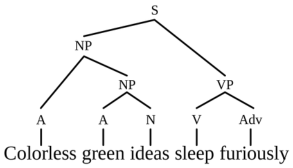

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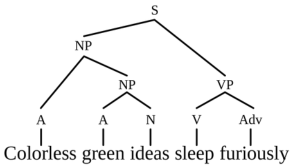

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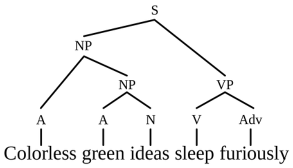

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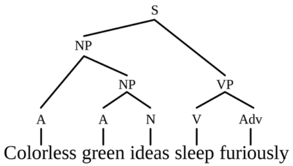

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Multilingual Language Models

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How do they do this for subjecthood?

Subjecthood in Multilingual Language Models

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- Subjecthood is a concrete handle for looking into LM internals

Subjecthood in Multilingual Language Models

- Subjecthood is a concrete handle for looking into LM internals
- LMs give us a concrete view of how multilingual subjecthood ***can*** be represented and influenced

Deep Subjecthood: Higher-Order Grammatical Features in Multilingual BERT

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(EACL 2021)

Three questions:

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- Is subjecthood a universal category?

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The **cat** is chasing the **dog**

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- Zero-shot transfer classifiers from one language to another

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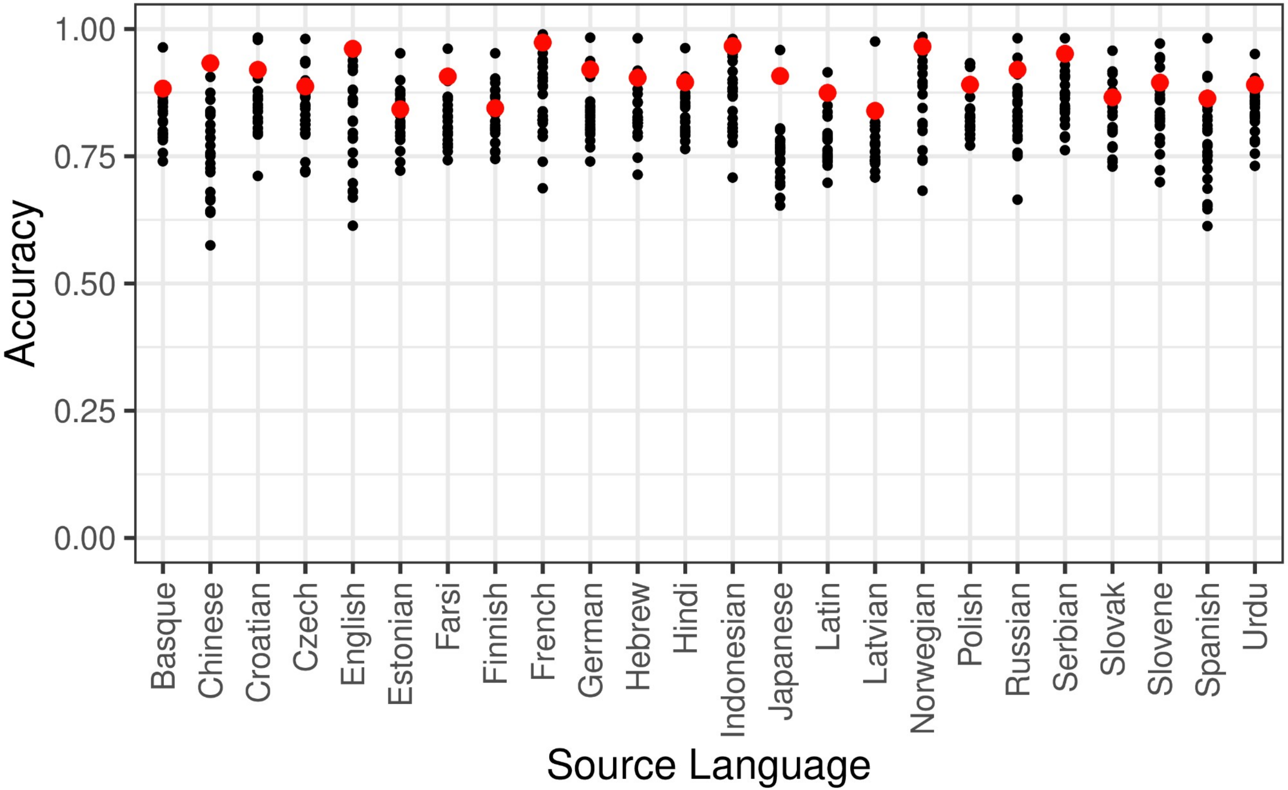
→

?? ??
Τον **σκύλο** τον κυνηγάει η **γάτα**

?? ??
这只**猫**在追那条**狗**

Cross-lingual accuracy is comparable to in-language



Red dots are in-language accuracy, black dots are cross-language

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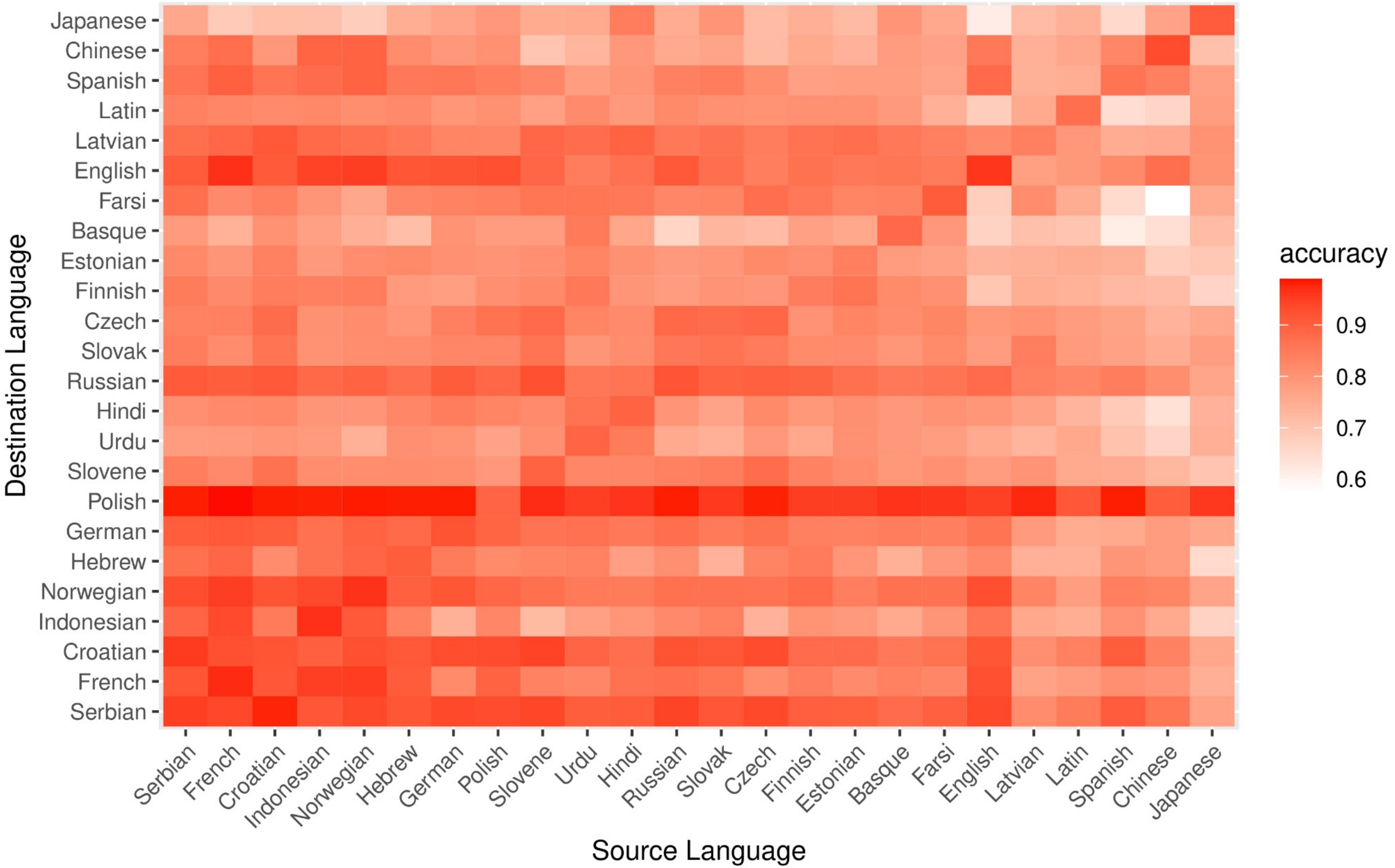

Parallel, Multilingual Subjecthood

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- **Linguistic generalization** in pretrained LMs:
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  - Encode subjecthood separately from language

- Subjecthood is available to a learner as a universal

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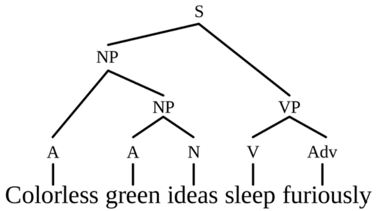
But is subjecthood a simple binary issue?

Discrete



vs.

Prototype

Animacy,
Passive voice,
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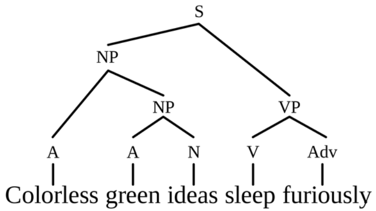

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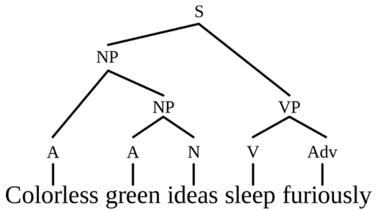

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- Different views on how to think of subjecthood
- Multilingual LMs can help us tease out this conflict

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P(subject) = 0

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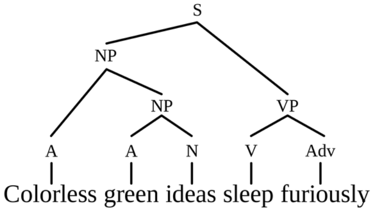

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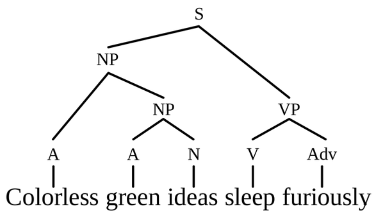

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- Do probe probabilities reflect the effect of other features?

Classifier probabilities show animacy effects

Animacy

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Classifier probabilities show animacy effects

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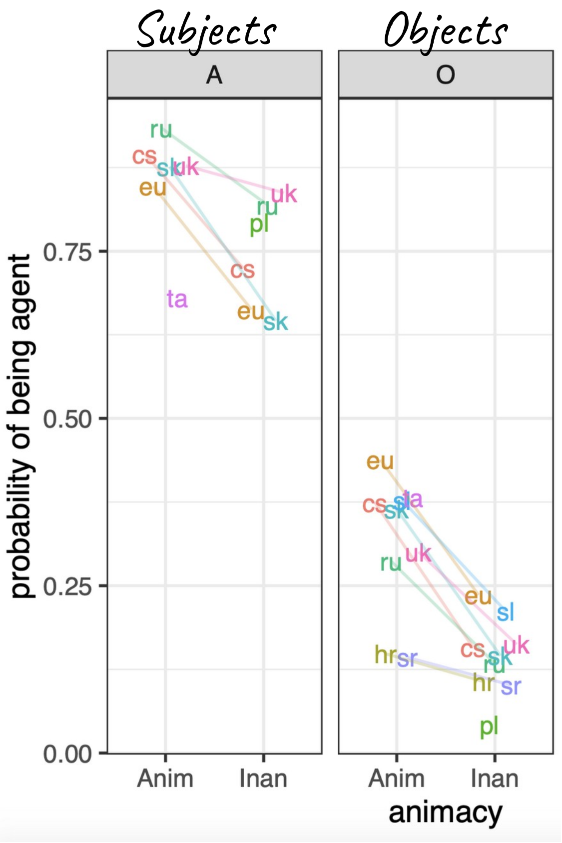

Even when controlling for syntactic role, animacy has an effect

Classifier probabilities show passive voice effects

Passive voice

The **cat** jumped on to the perch

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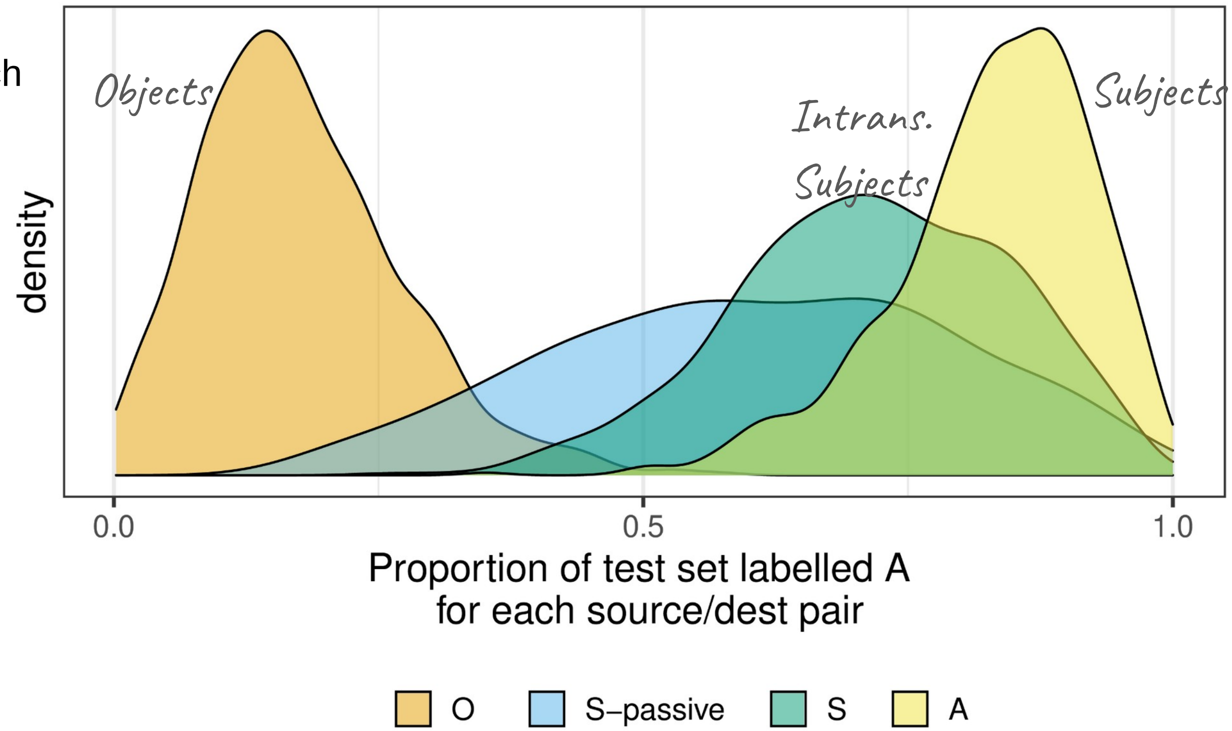

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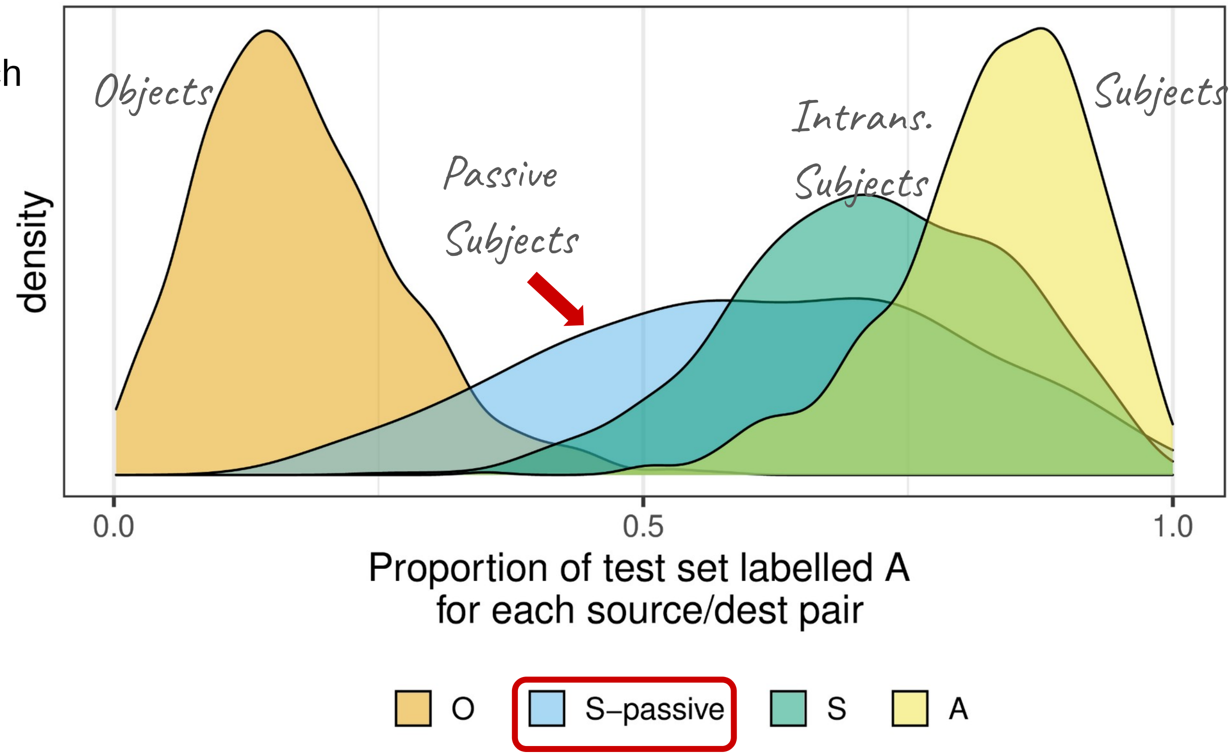


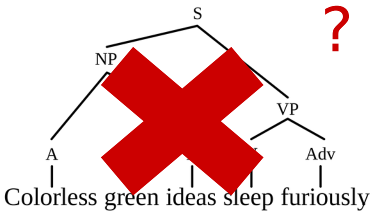
- We see **prototype effects** in mBERT embeddings

- **Many factors** play into making something a subject

Also look at the effect of **case**.
Future work: discourse, information structure (given/new)

But is it all just prototypes?

Discrete



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When classifying grammatical role, BERT doesn't care about word order...except when it matters

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Richard Futrell
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Kyle Mahowald
The University of Texas at Austin
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(ACL 2022)

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

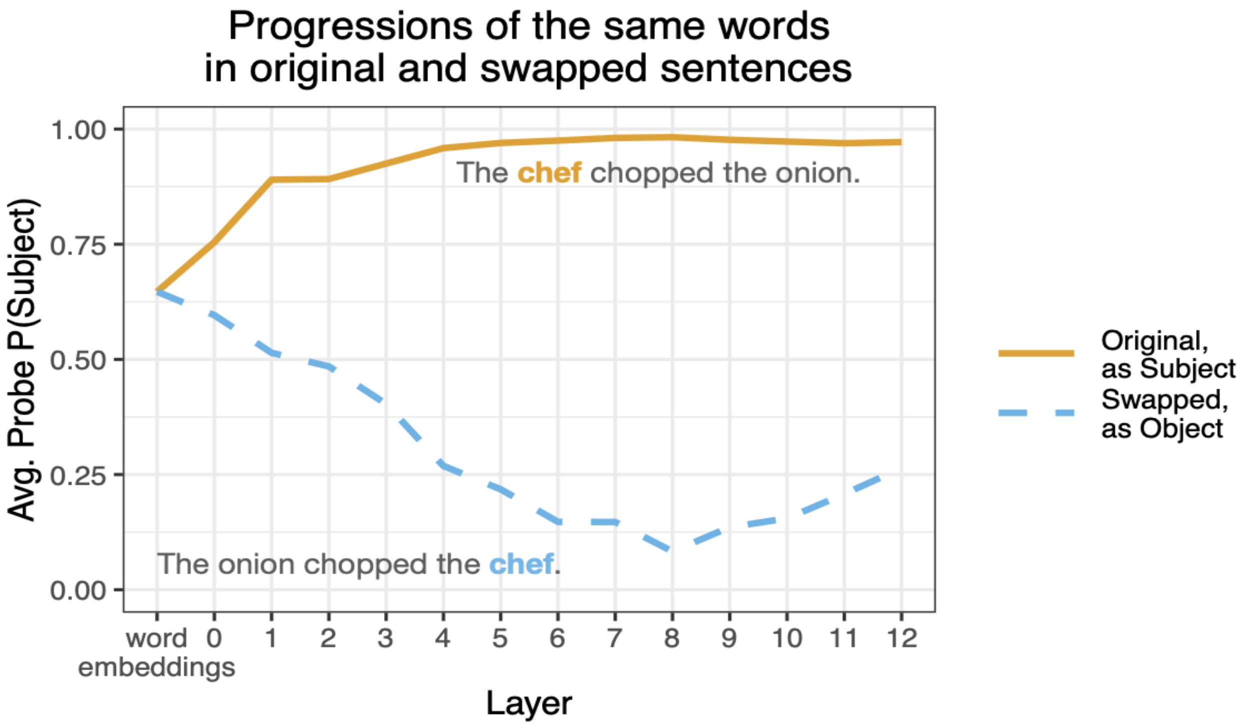
The **chef** chopped the **onion**, The **onion** chopped the **chef**

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

The **chef** chopped the **onion**, The **onion** chopped the **chef**

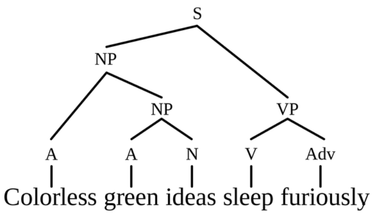
Will the probe tell them apart?

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



Both grammatical subjecthood and prototype effects

Discrete



&

Prototype

Animacy,
Passive voice,
Volitionality,
Agency,
Case,
...

- Future work: *How* can a representation embody both of these types of information?
- LMs as a tool to **better understand this middle ground**

Three questions:

- Is subjecthood a universal category?
- Is subjecthood a discrete category?
- What happens with typological variation?

Typological variation: **Intransitives**

Typological variation: **Intransitives**

- Subjecthood is encoded in parallel between languages

Typological variation: Intransitives

- Subjecthood is encoded in parallel between languages
- But are the **particularities** of each language also encoded?

Typological variation: **Intransitives**

- Subjecthood is encoded in parallel between languages
- But are the **particularities** of each language also encoded?
- **Do we see variation in treatment of intransitives?**

Typological variation: **Intransitives**

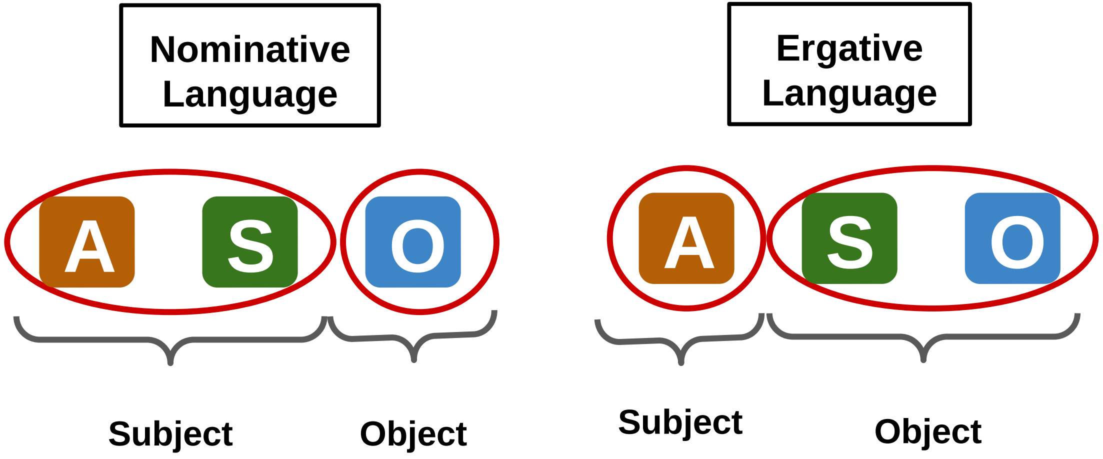
A O

Transitive: The **dog** chased the **cat**

S

Intransitive: The **glass** broke

Ergative languages treat **intransitive subjects** like **objects**



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Typological variation: **Intransitives**

- Subjecthood is encoded in parallel between languages
- But are the **particularities** of each language also encoded?
- **Do we see variation in treatment of intransitives?**
    - Can higher-order information be represented in embedding space?

Hold out intransitives from classifier training

Probabilities: Subjecthood projection space

Transitive object
P(subject) = 0

Transitive subject
P(subject) = 1

Unseen: Intransitives
P(subject) = ??

Hold out intransitives from classifier training

Probabilities: Subjecthood projection space

Transitive object
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Transitive object
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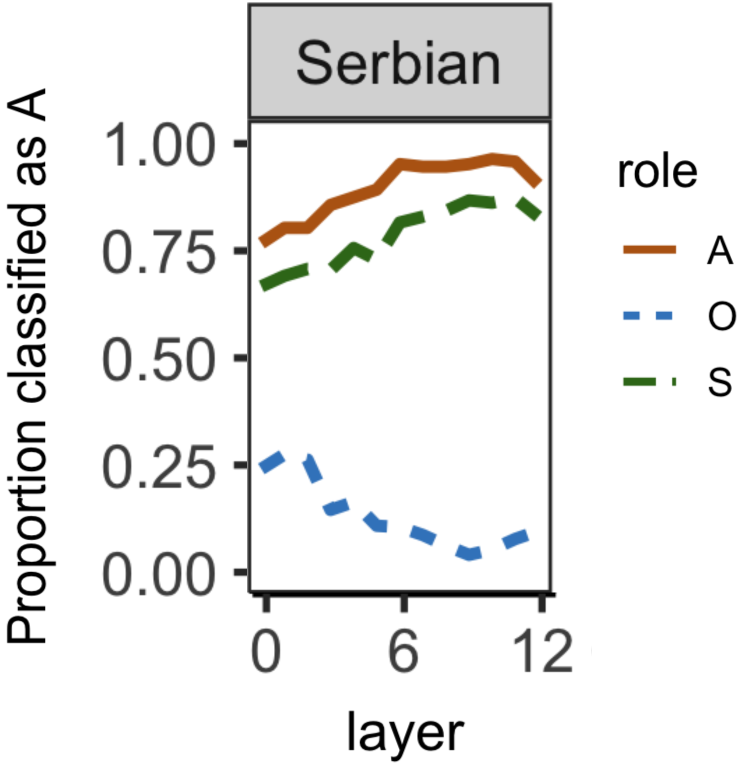
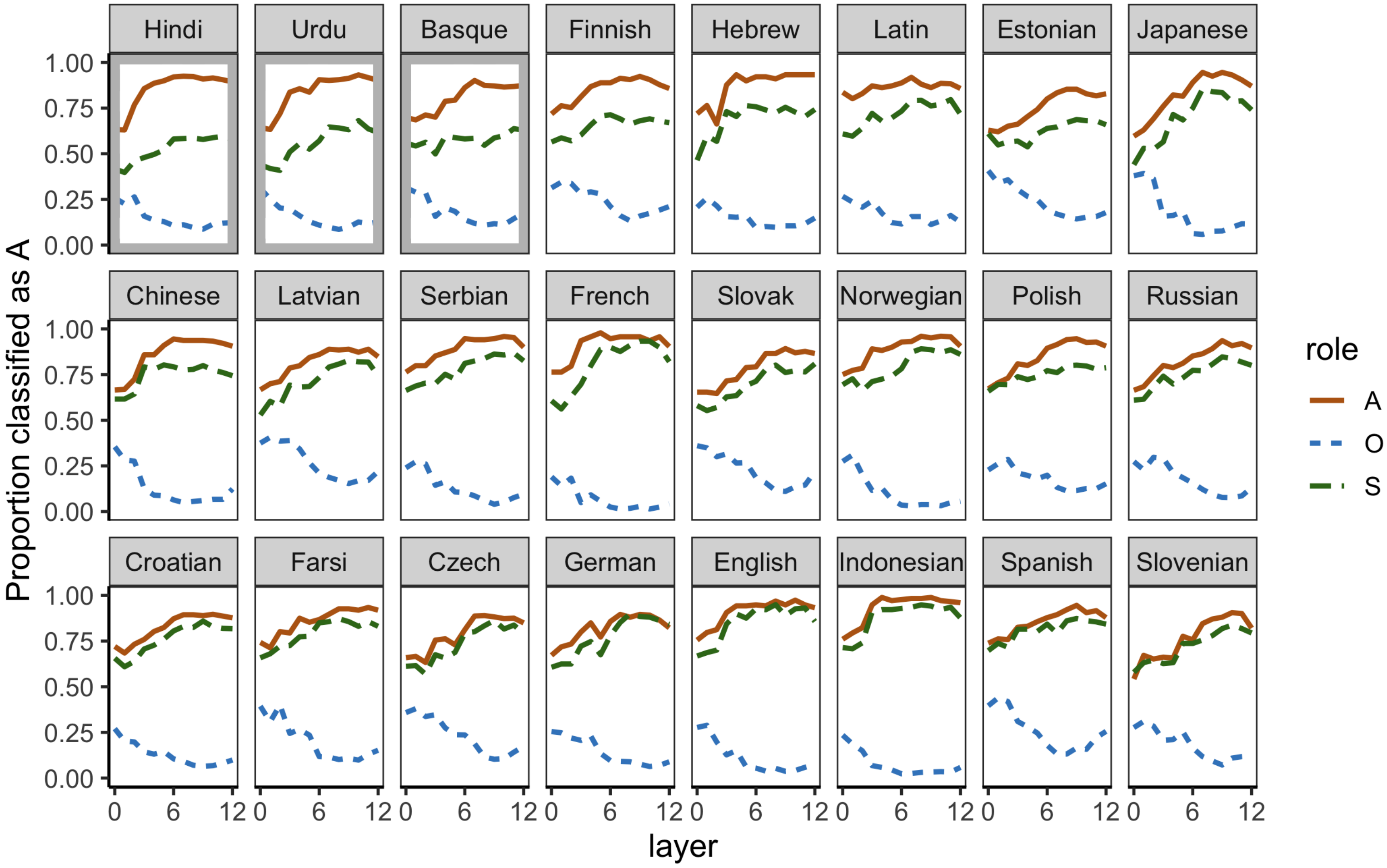
Transitive subject
P(subject) = 1

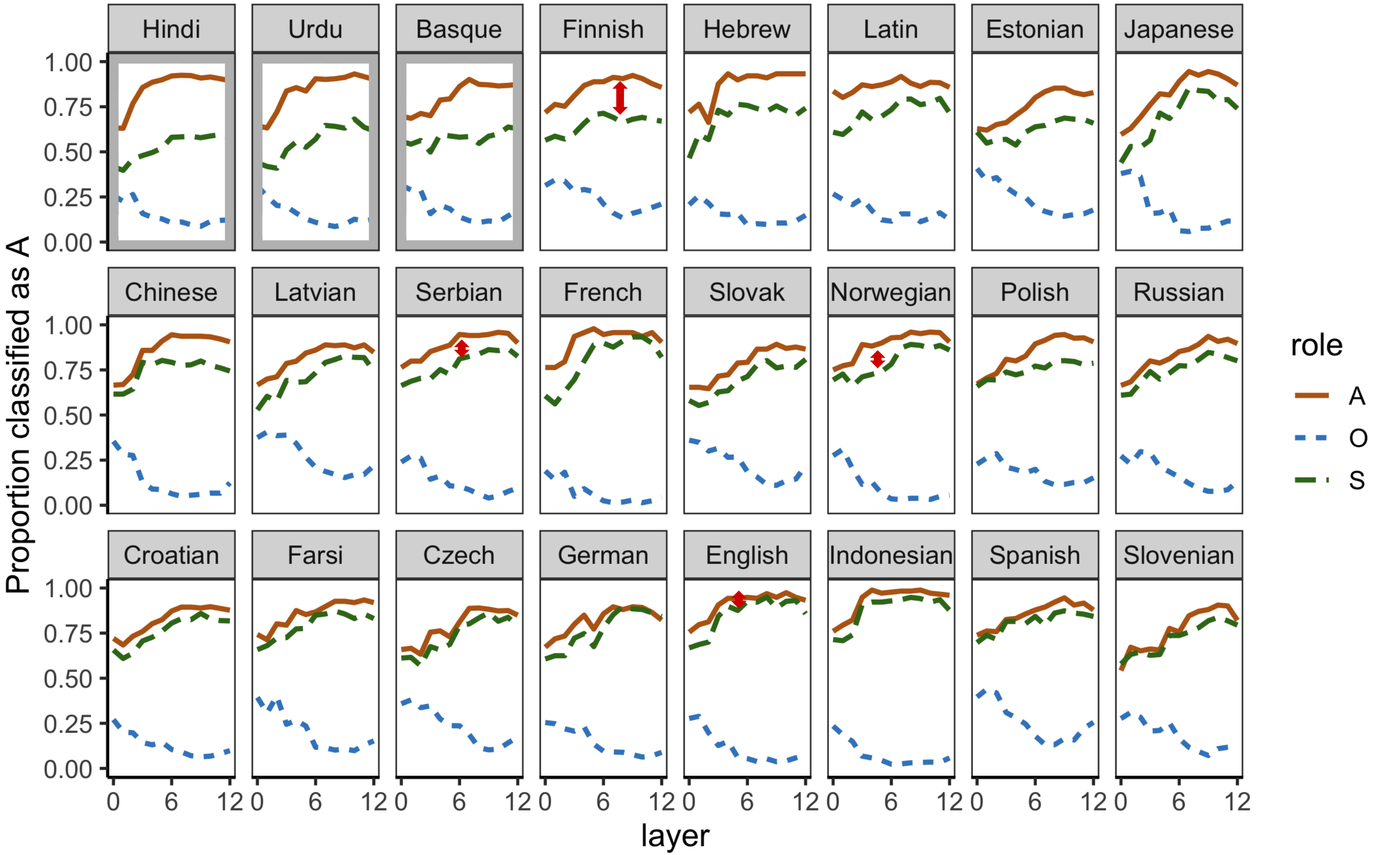
Unseen: Intransitives
P(subject) = ??

- Classifier probabilities show how intransitives align

Transitive Subjects (A) > Intransitive Subjects (S) > Transitive Objects (O)




Hindi
Urdu
Basque
Finnish
Hebrew
Latin
Estonian
Japanese
Chinese
Latvian
Serbian
French
Slovak
Norwegian
Polish
Russian
Croatian
Farsi
Czech
German
English
Indonesian
Spanish
Slovenian
Proportion classified as A
1.00
0.75
0.50
0.25
0.00
0
6
12
layer
role
A
O
S


Hindi
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Norwegian
Polish
Russian
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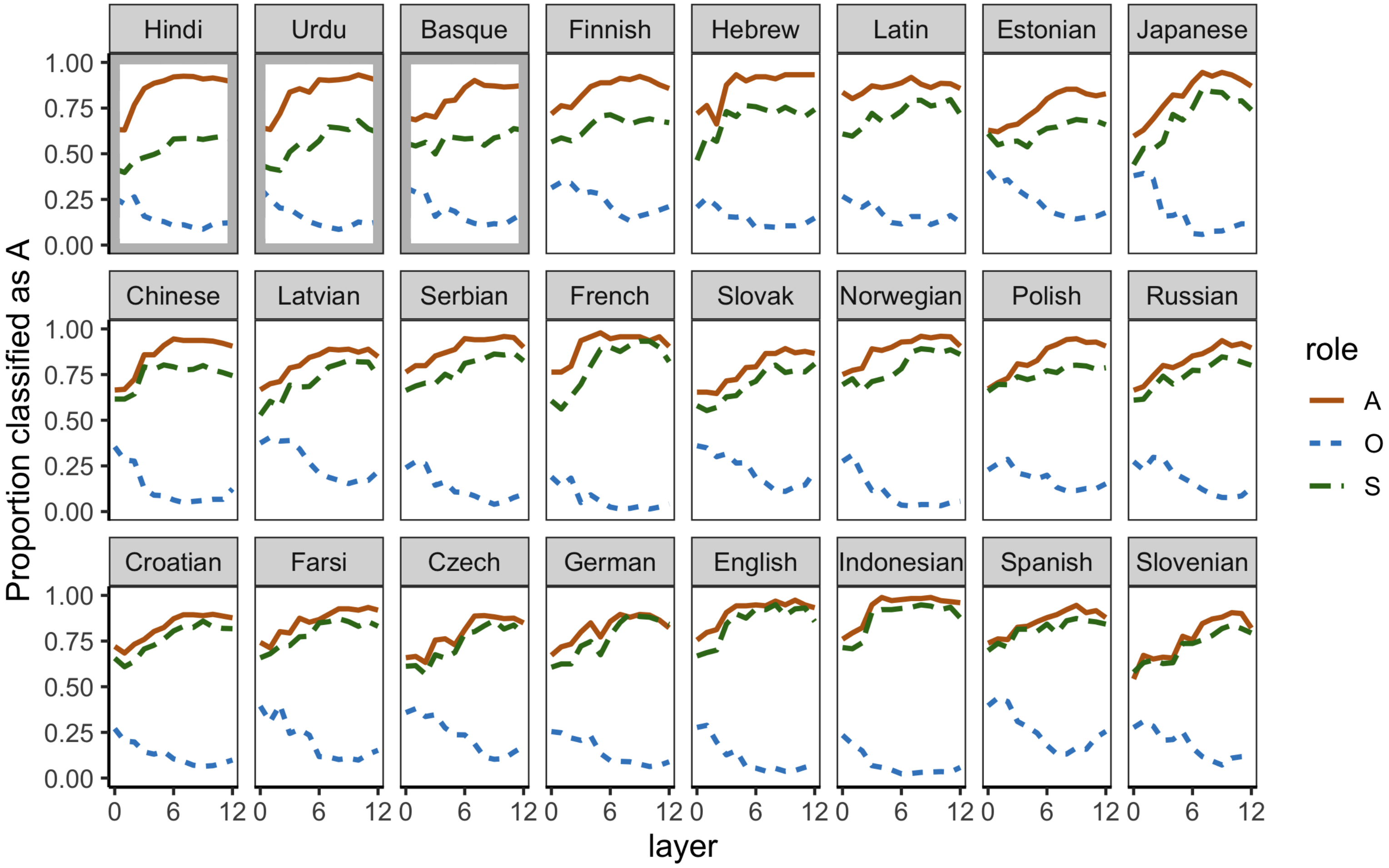

Hindi
Urdu
Basque
Finnish
Hebrew
Latin
Estonian
Japanese
Chinese
Latvian
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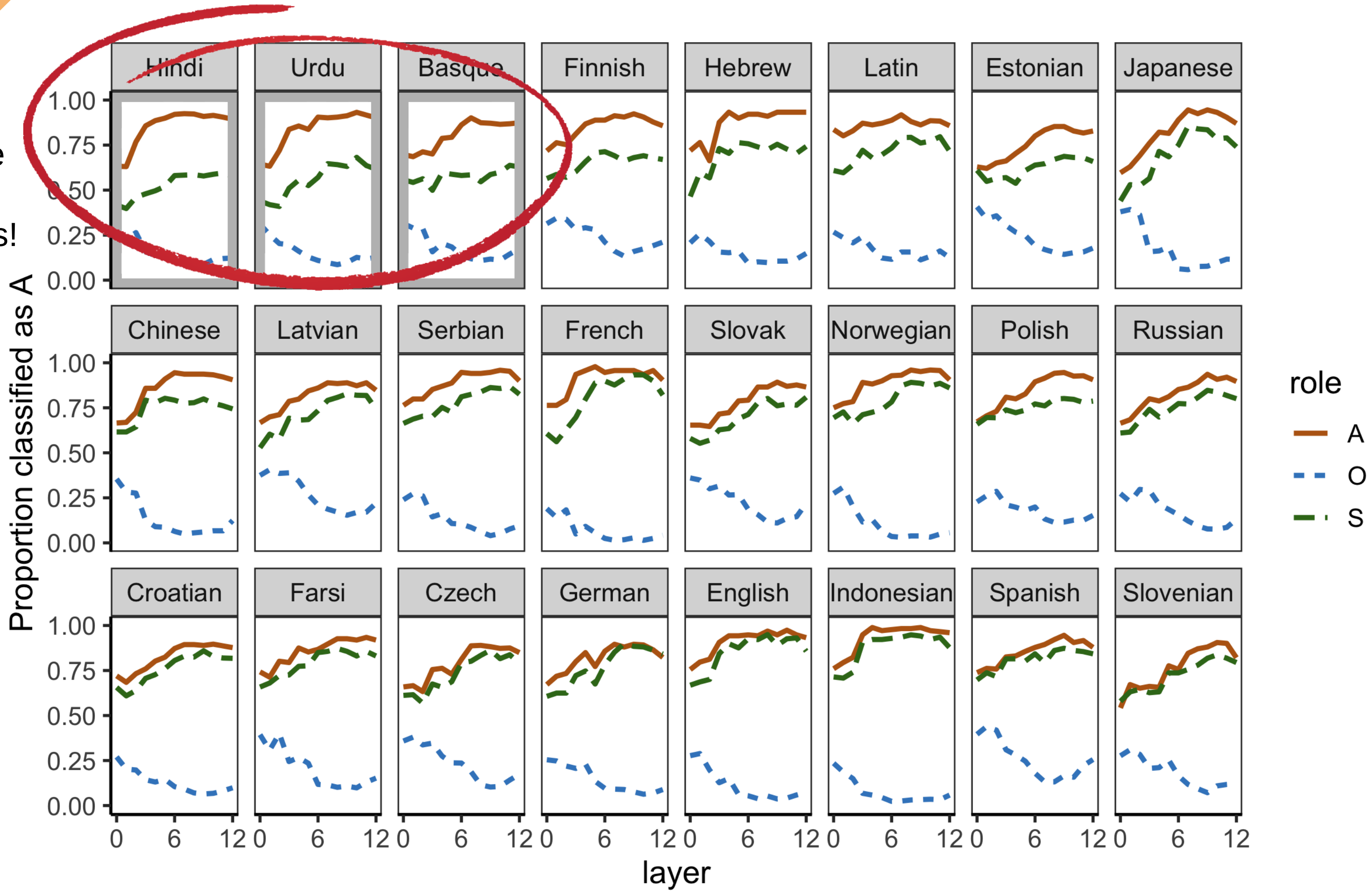
These are ergative languages!



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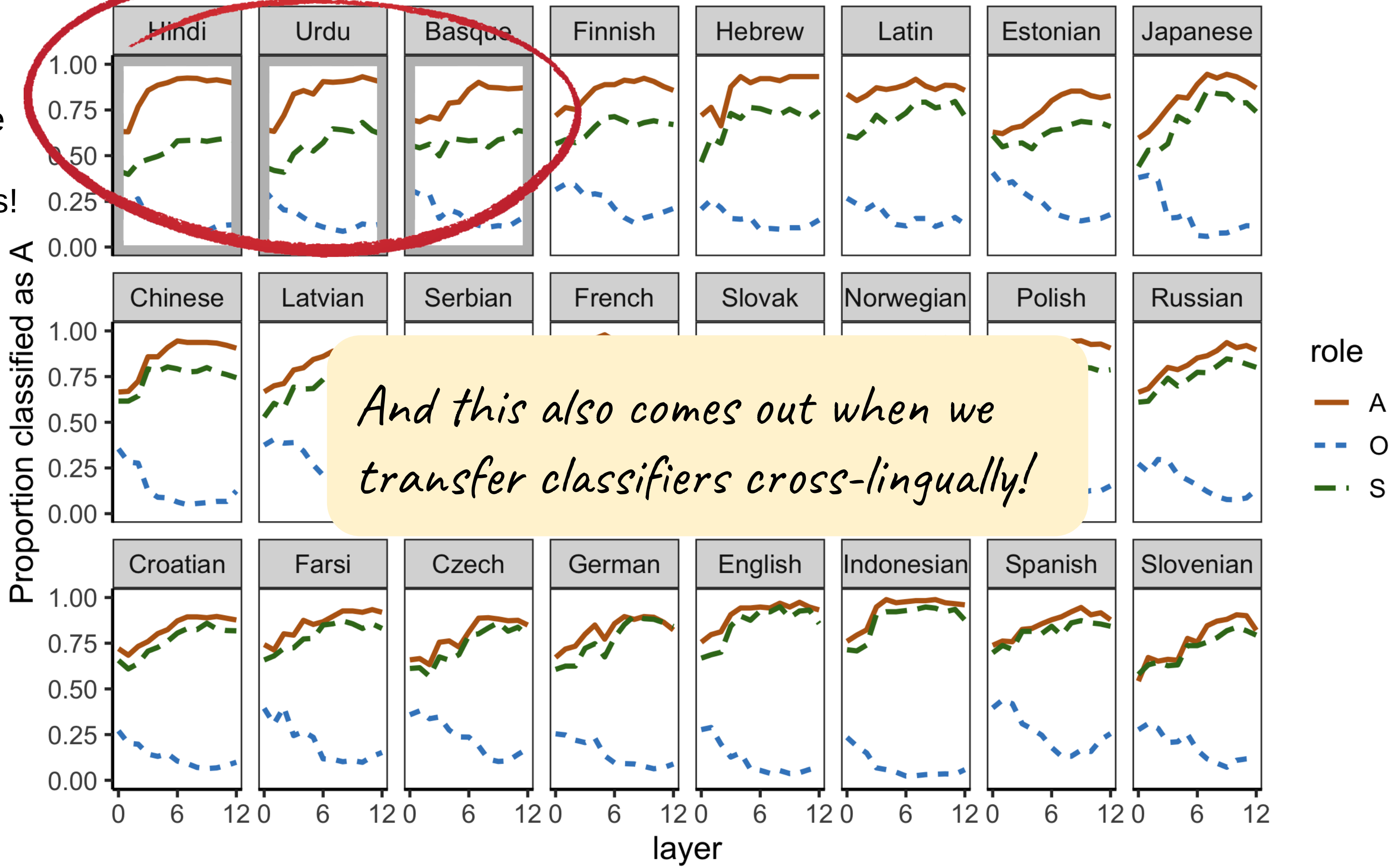

And this also comes out when we transfer classifiers cross-lingually!

Classifiers Reflect Intransitive Alignment

- Alignment of **intransitives** is a feature of a grammar, **not of any one utterance**
- But it is apparent in embedding space, even when they are held out

Subjecthood: what we learned

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Future work: better understanding the geometric expression of these properties

Representing subjecthood

- A discrete category, but with subtleties and complexities
- One coherent continuous space
- How does this work?

Transfer learning with syntactic primitives

- Pretrain on non-linguistic data
- Create learners with known inductive biases
- A window into language learning

Learning Music Helps You Read: Using Transfer to Study Linguistic Structure in Language Models

Isabel Papadimitriou
Stanford University
isabelvp@stanford.edu

Dan Jurafsky
Stanford University
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(EMNLP 2020)

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Main Question:

What structural inductive biases make a good language learner?

We can't really have blank-slate learners that work

[Baroni 2021, *On the proper role of linguistically-oriented deep net analysis in linguistic theorizing*]

We can’t really have blank-slate learners that work

- Small networks can’t model the data well

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We can’t really have blank-slate learners that work

- Small networks can’t model the data well

- Large models come with many inductive biases

This paper:

- But, (if we’re careful about data) pre-training creates a powerful learner with a known inductive learning bias

[Baroni 2021, *On the proper role of linguistically-oriented deep net analysis in linguistic theorizing*]

untrained model, unknown inductive biases

Pretraining,
non-linguistic

Learner whose inductive biases we know

(Because we pretrained them in!)

untrained model, unknown inductive biases

Pretraining,
non-linguistic

Learner whose inductive biases we know

(Because we pretrained them in!)

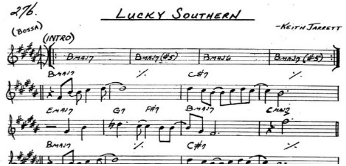
Transfer
learning

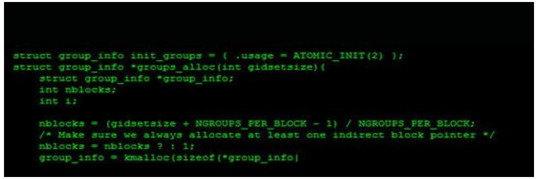
How well can this model
learn from **language** data?

Pretraining data

Pretraining data

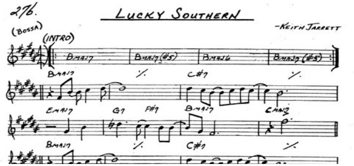
Real Data:

Music

Code



Pretraining data

Real Data:

Music

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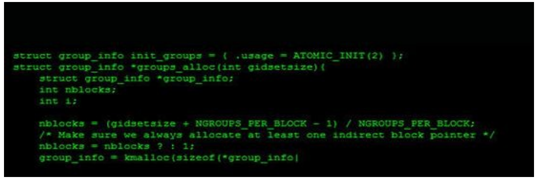
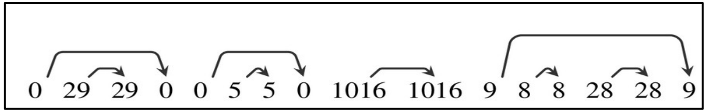
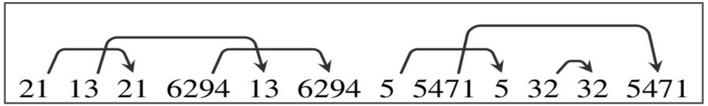


Synthetic Structural Primitives:

Hierarchical



Non-hierarchical



Transfer learning should be *constrained*

- We want to make sure that we're using inductive biases, not re-pretraining

- Two ways of constraining transfer learning:
  - Limit **data**
  - Limit **trainable parameters**

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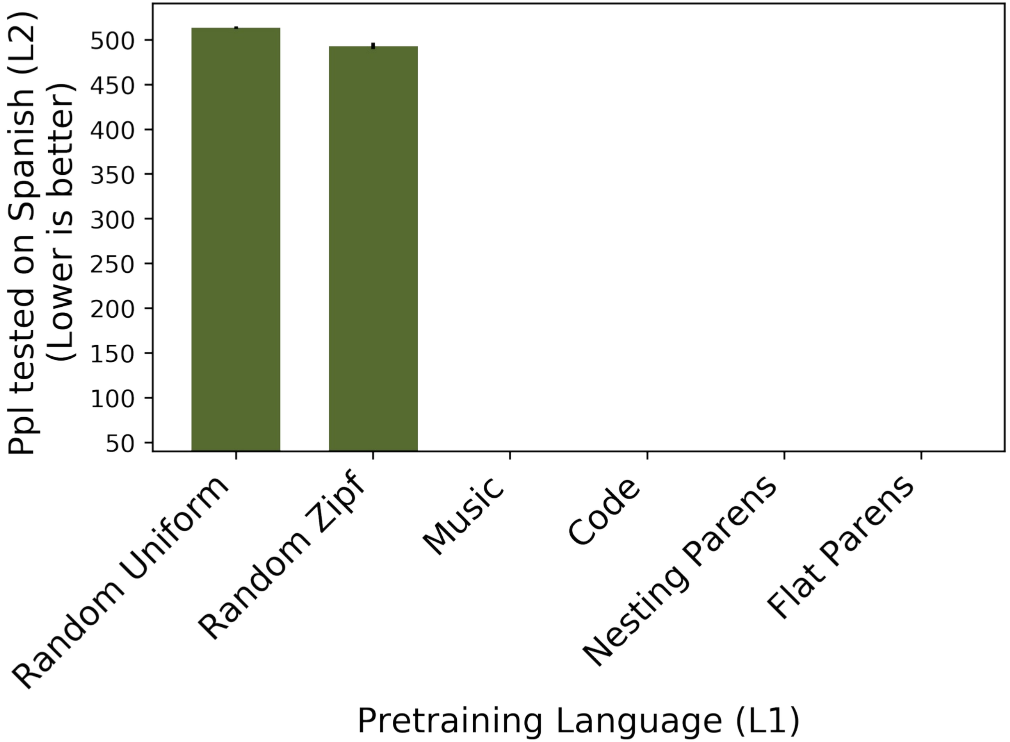
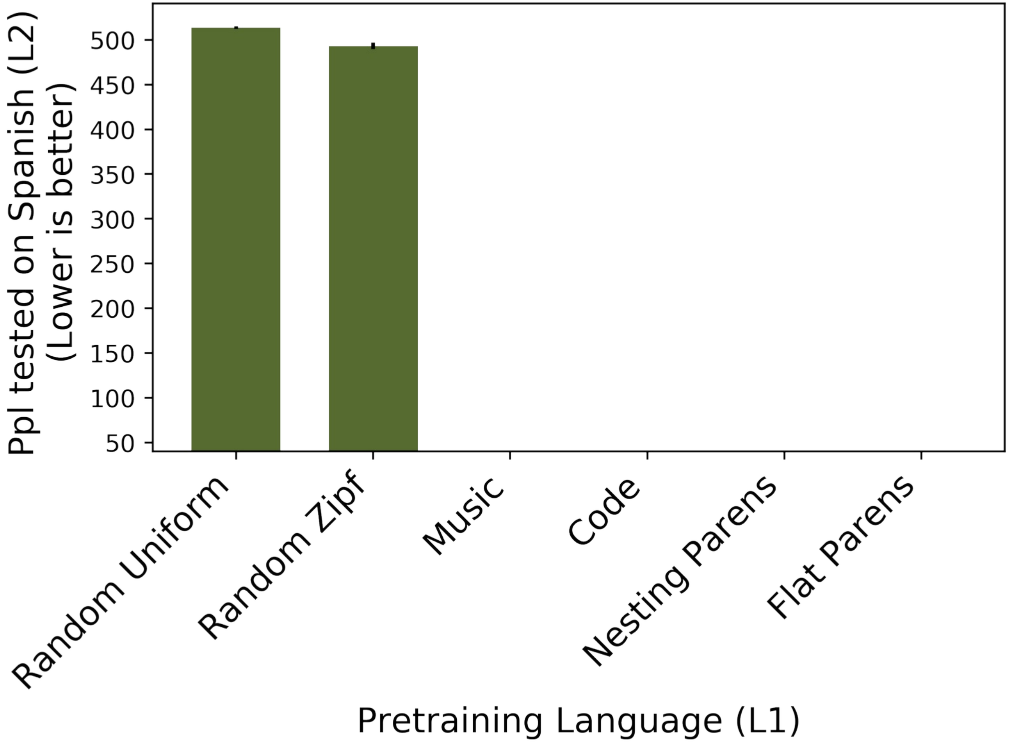
  - Limit **data**
  - Limit **trainable parameters**

Freeze everything except **word embeddings**. Can LM internals be effectively repurposed?

Random Baselines – Randomly sampled tokens



Random Baselines – Randomly sampled tokens



- Control - How far can we get with just word embeddings?

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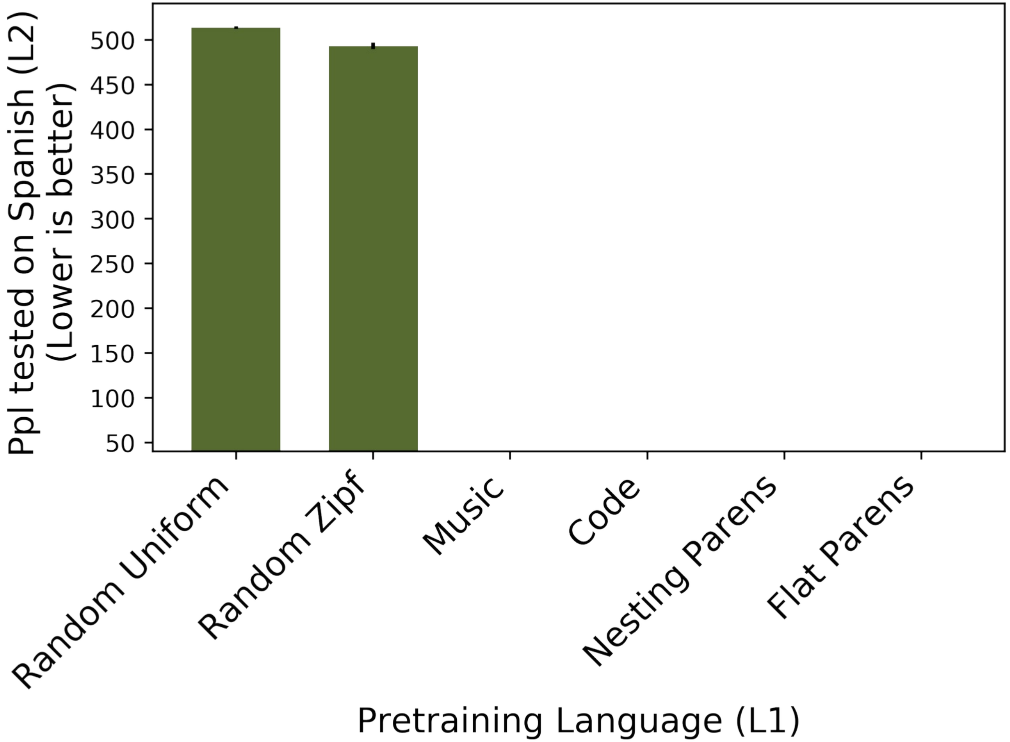

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- Vocabulary distribution has a significant effect

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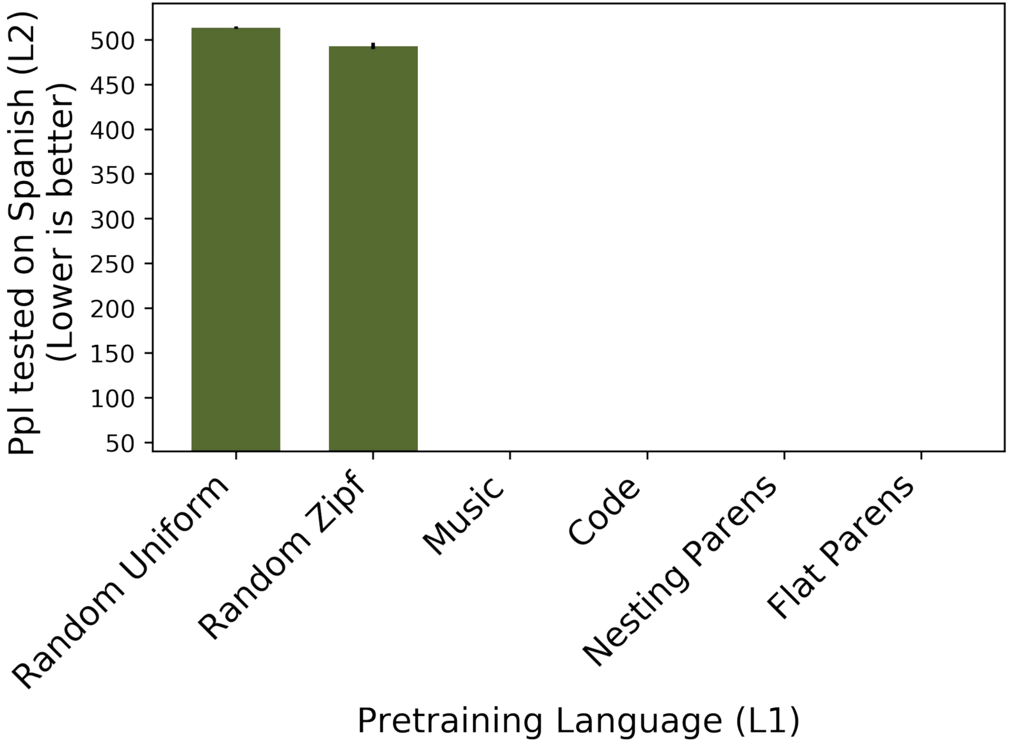

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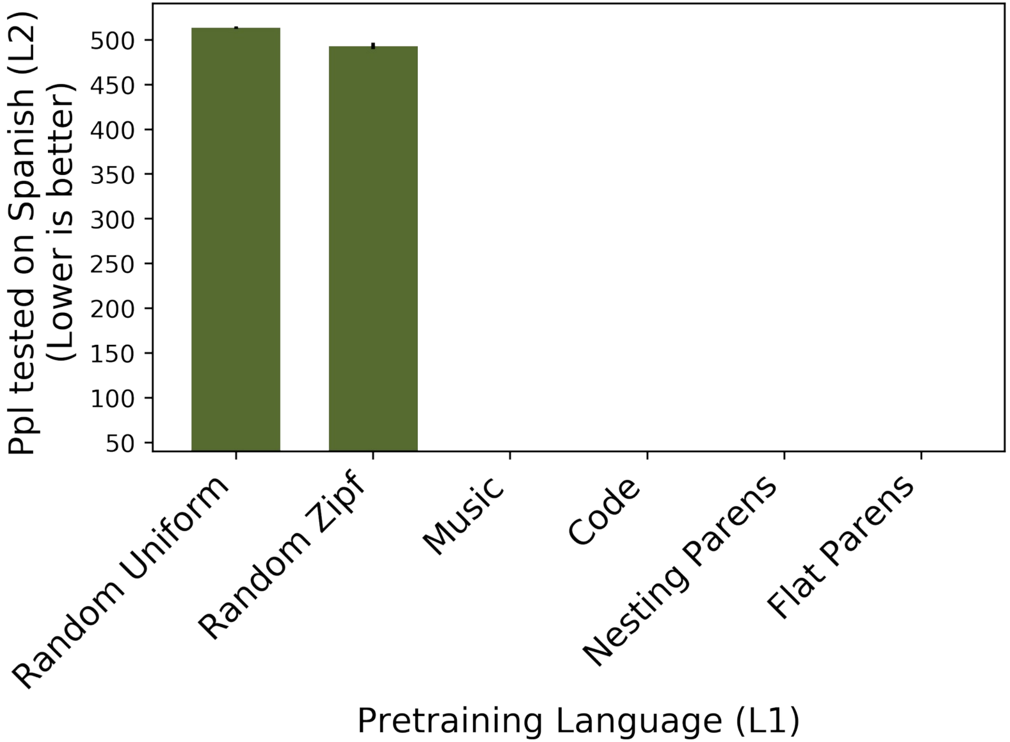

- Control - How far can we get with just word embeddings?
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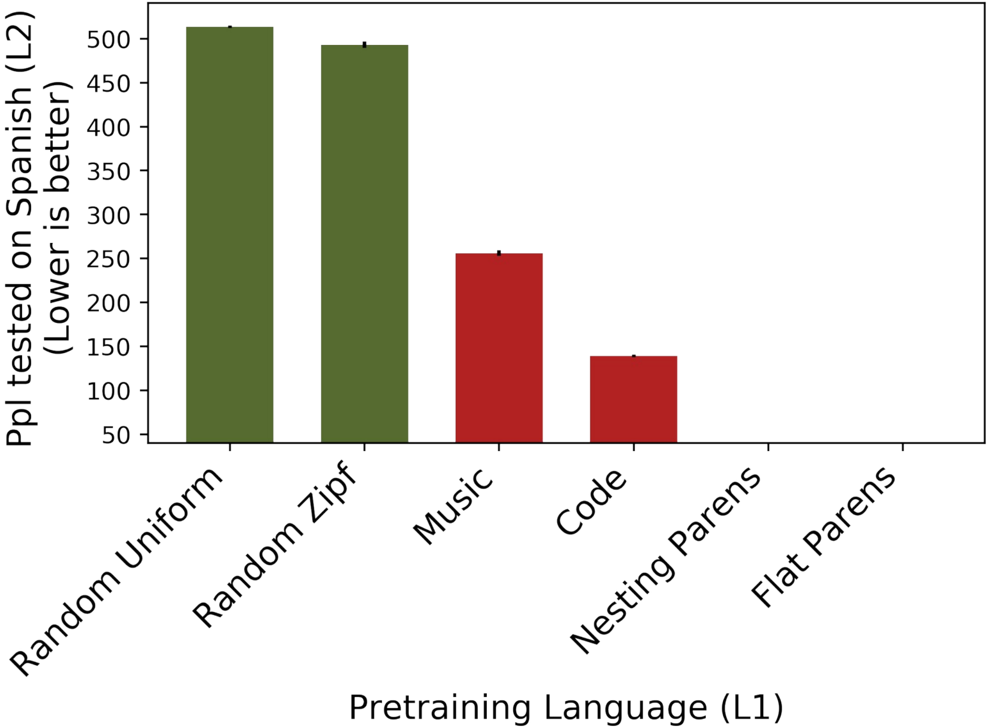
Music and Code

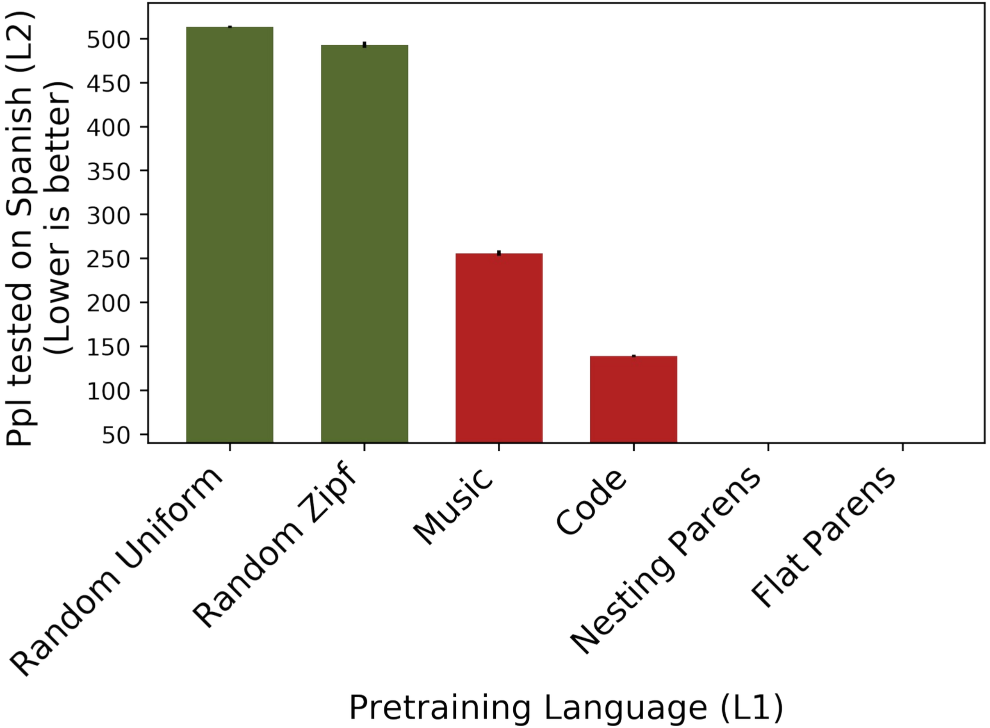
Music: SETVELOCITY_29 NOTEON_47 SHIFTMS_180 SETVELOCITY_57 NOTEON_66...

No comments

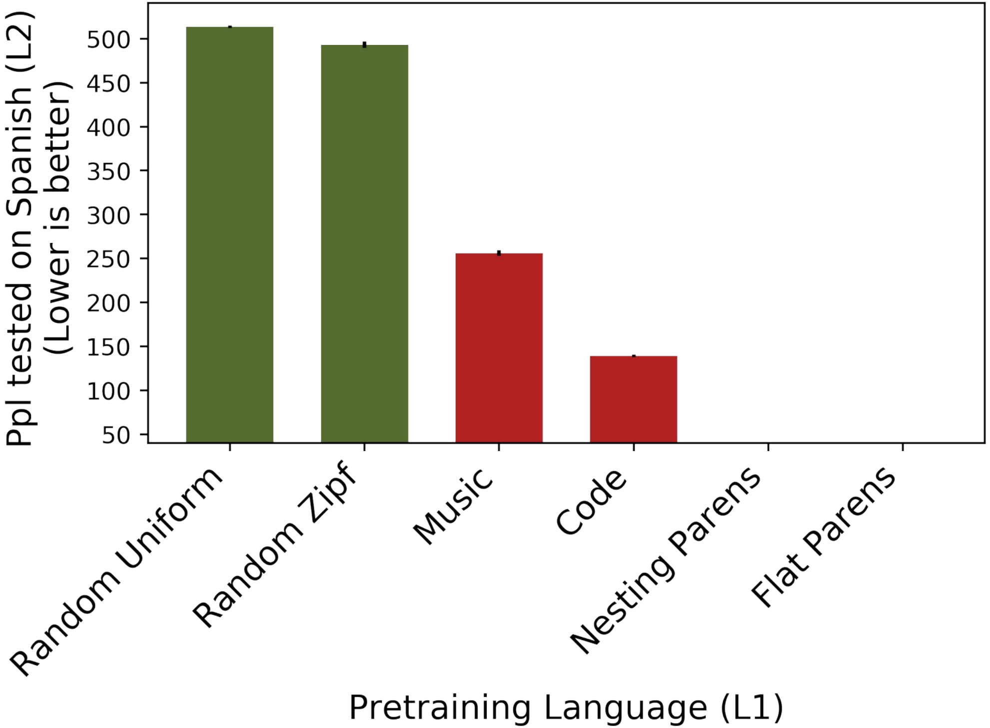
Code: if (coordFactor == 1) { return sum ; } else { result = ...

- Non-linguistic, structured data, with **different surface forms**
- Is this structural bias helpful for language modeling?

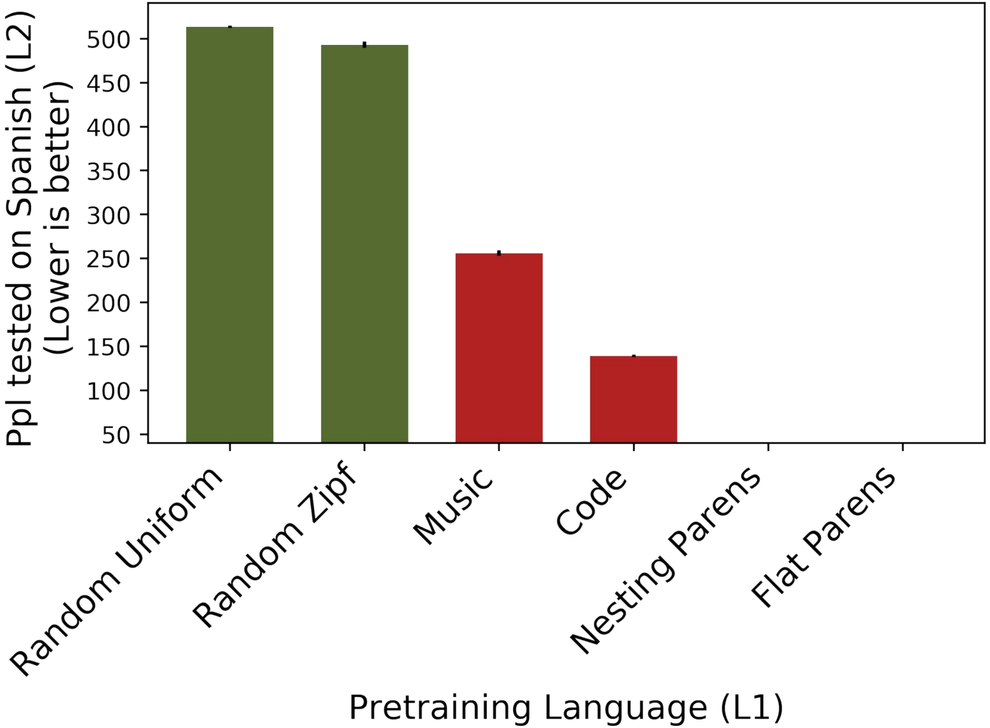

Ppl tested on Spanish (L2)
(Lower is better)
500
450
400
350
300
250
200
150
100
50
Random Uniform
Random Zipf
Music
Code
Nesting Parens
Flat Parens
Pretraining Language (L1)



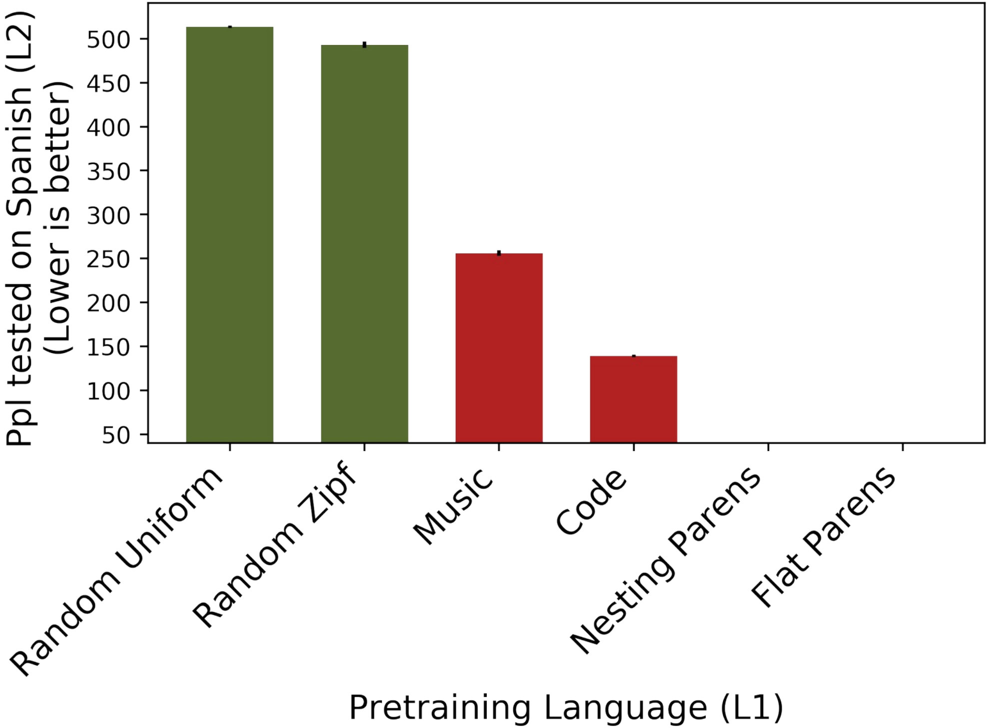
- Impressive improvement in perplexity



- Impressive improvement in perplexity
- MIDI surface form is very different (and vocabulary is just 310 tokens)



- Impressive improvement in perplexity
- MIDI surface form is very different (and vocabulary is just 310 tokens)
- But music and language have structural similarities

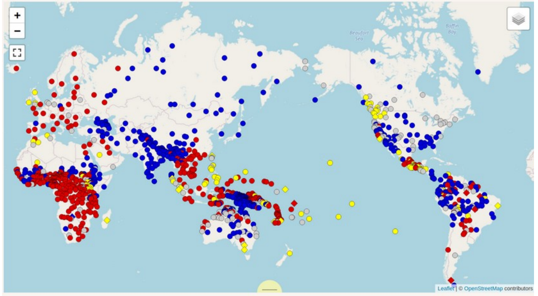


- Impressive improvement in perplexity
- MIDI surface form is very different (and vocabulary is just 310 tokens)
- But music and language have structural similarities

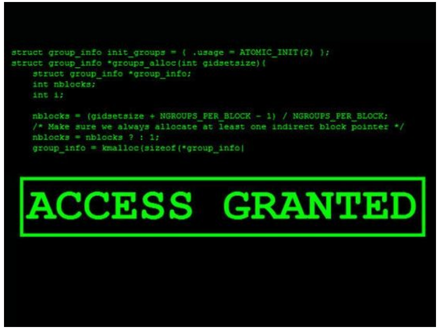
Is this because of hierarchical structures?

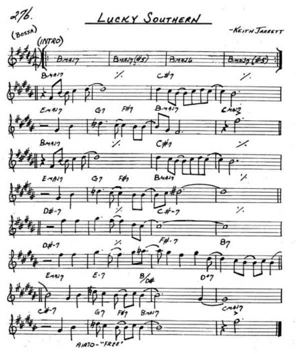
{ { } [( )] }

Human language



Code



Music

This is testable

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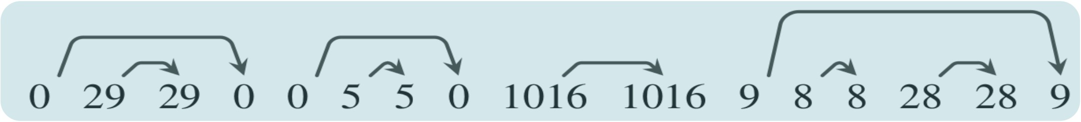
Pretrain on a simple hierarchical structure:

Nesting (Recursive) Parentheses:



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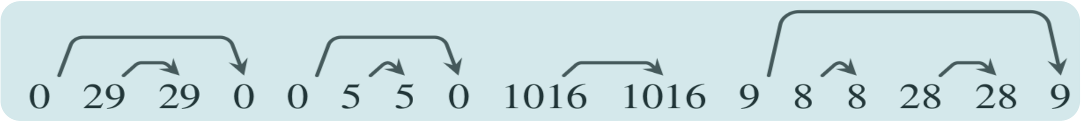
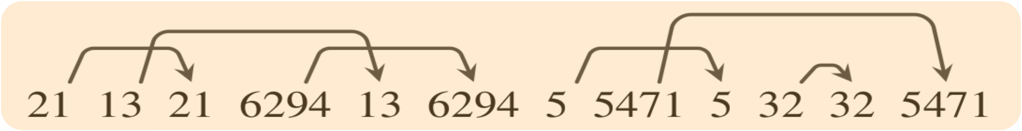
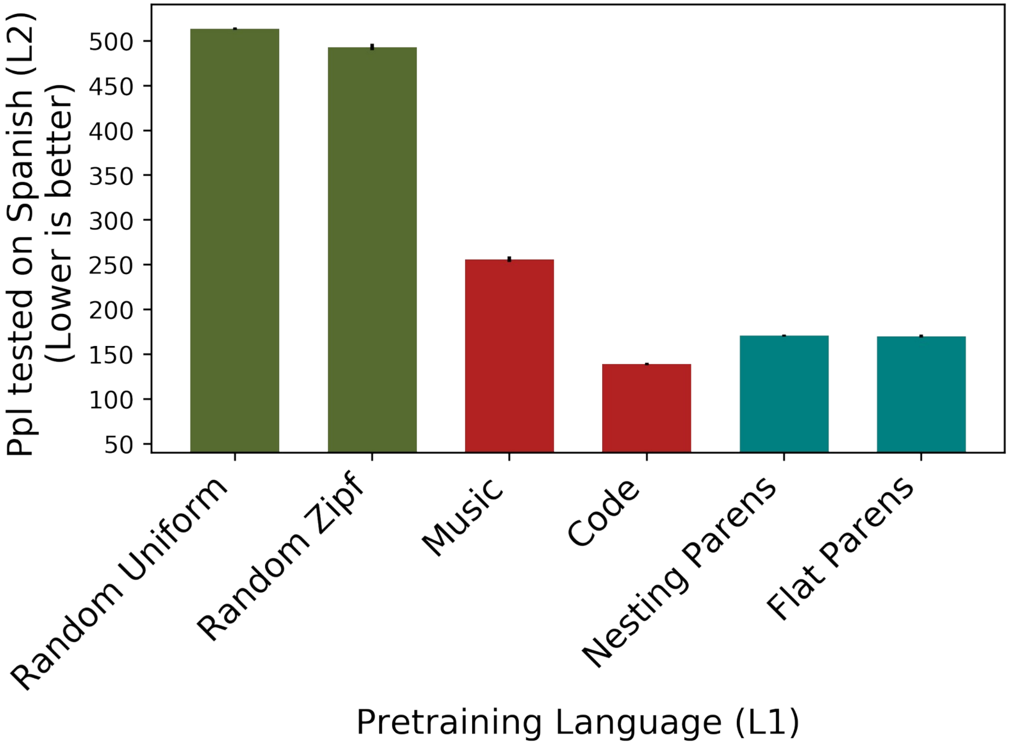


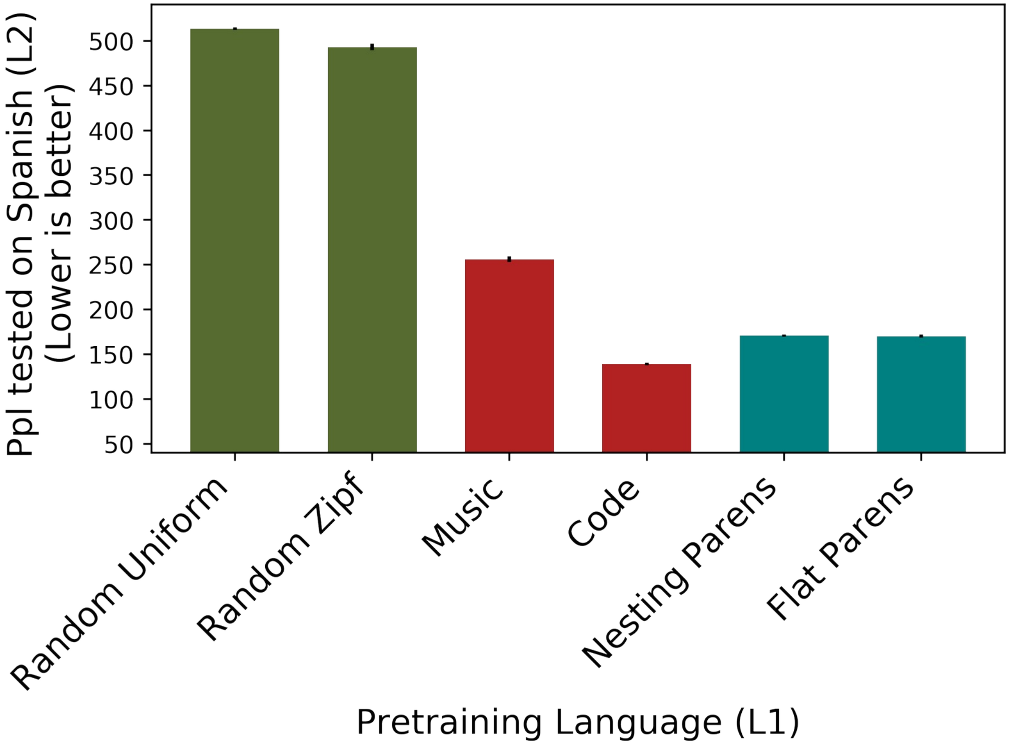
But also have a control:

Flat Parentheses:





- **Simple underlying structure** causes huge increase in performance compared to random

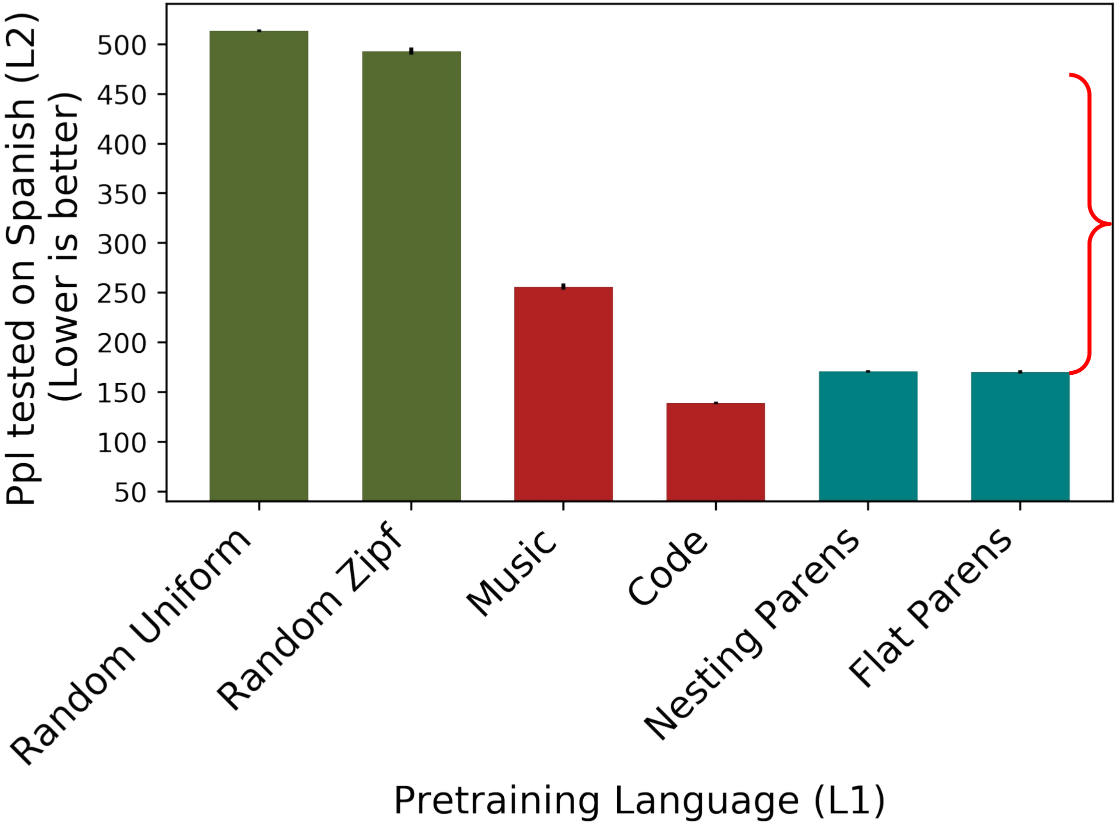


- **Simple underlying structure** causes huge increase in performance compared to random
- Flat parentheses are as good as hierarchical parentheses

Parentheses inductive bias is much better than random

- But the Flat Parentheses corpus is very similar to the Random corpus

Example: 21 13 21 6294 13 6294 5 5471 5 32 32 5471 ...



Difference from placing a random token twice instead of once

What to take away from these experiments?

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- A structural inductive bias **(but not necessarily hierarchical)** helps learn language

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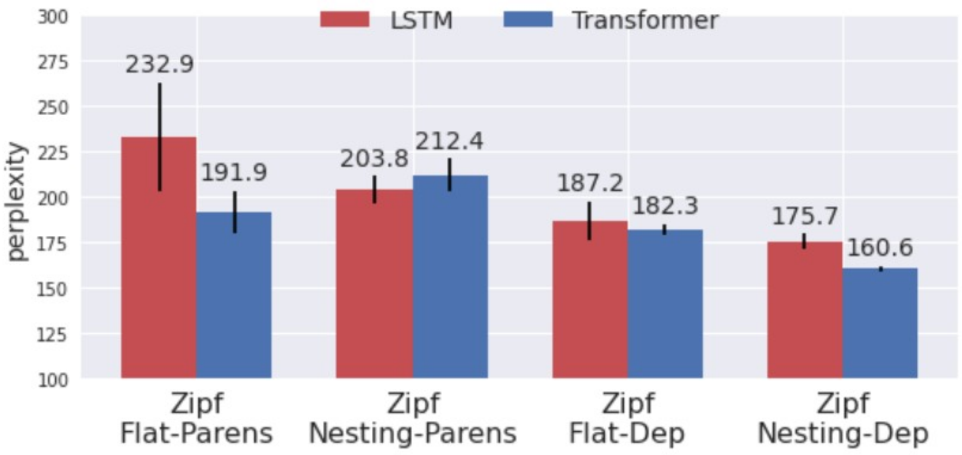
- A structural inductive bias **(but not necessarily hierarchical)** helps learn language
- Flat, head-to-head dependencies are an important learning bias to consider

Results have been reproduced in transformers



(b) Comparison of dependency structures.

[Ri and Tsuruoka, 2022, *Pretraining with Artificial Language:Studying Transferable Knowledge in Language Models*]

[Chiang and Lee, 2021, *On the Transferability of Pre-trained Language Models: A Study from Artificial Datasets*]

Flat parentheses in the wild

Kundan Krishna, Jeffrey Bigham, Zachary C. Lipton (2021) *Does Pretraining for Summarization Require Knowledge Transfer?*

Flat parentheses in the wild

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- Take a nonsense (random) corpus,
- Create “summarization” input-output pairs with **simple summarization-type dependencies**
- Good downstream performance!

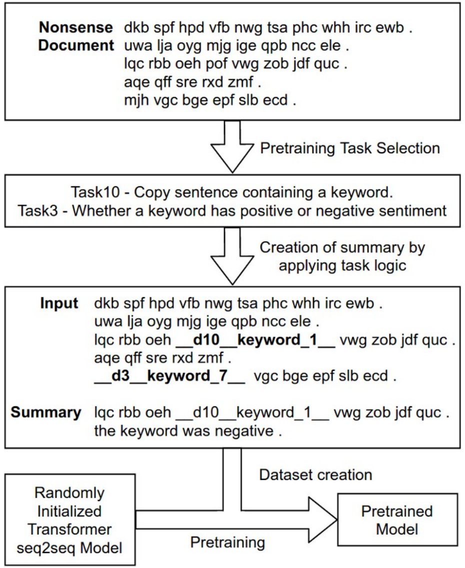

Figure 1: Procedure to create pretraining dataset using the nonsense corpus and our proposed pretraining tasks

How about more **language-like structures**?

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- When we transfer between languages, transfer is correlated with **typological syntactic distance**

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There's a correlation – but can we test causes?

[Wu*, Papadimitriou*, Tamkin*, 2022, *Oolong: Investigating What Makes Crosslingual Transfer Hard with* ***Controlled Studies***]

{ { } [( )] }

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  - We’re in a unique position – we can make **powerful learners** imbued with **known inductive biases**

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- Structural primitives:
  - We're in a unique position – we can make **powerful learners** imbued with **known inductive biases**
  - Flat dependencies are an important and interesting bias

What can we learn from LMs?

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- Exciting moment to be asking cross-lingual questions

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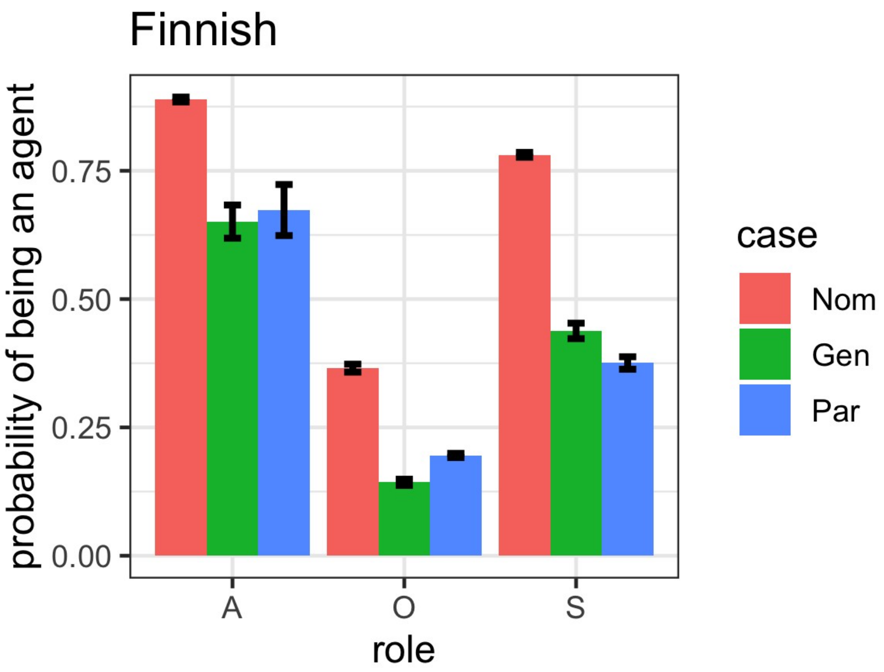
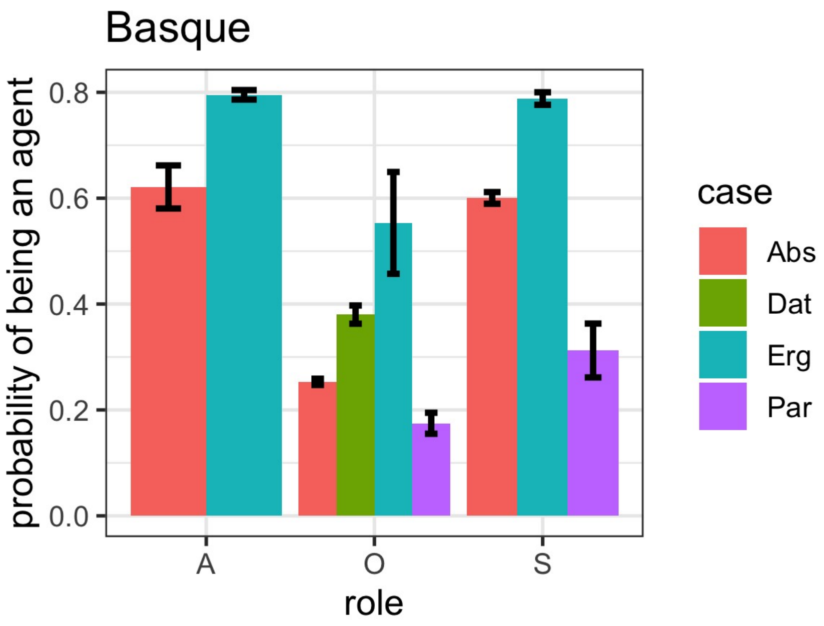
- The embedding space of multilingual LMs suggests how the **complexities and dualities** of universal properties like subjecthood might function

- Pretraining with structural primitives demonstrates what **starting points** make language learning possible
- Exciting moment to be asking cross-lingual questions

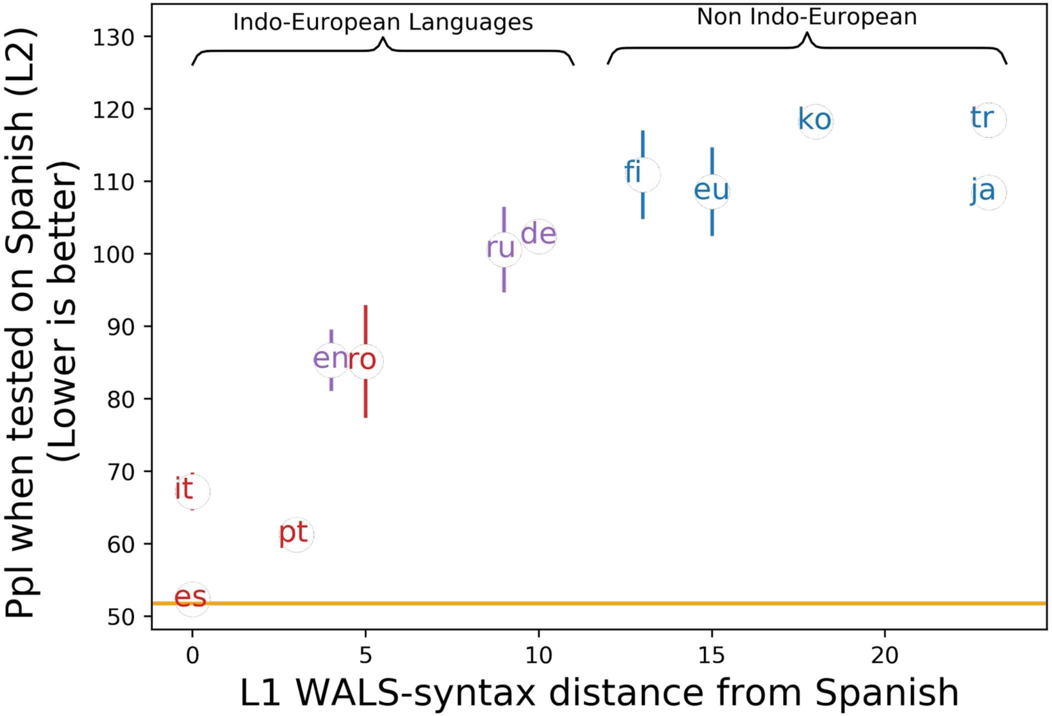
Thanks!

Case

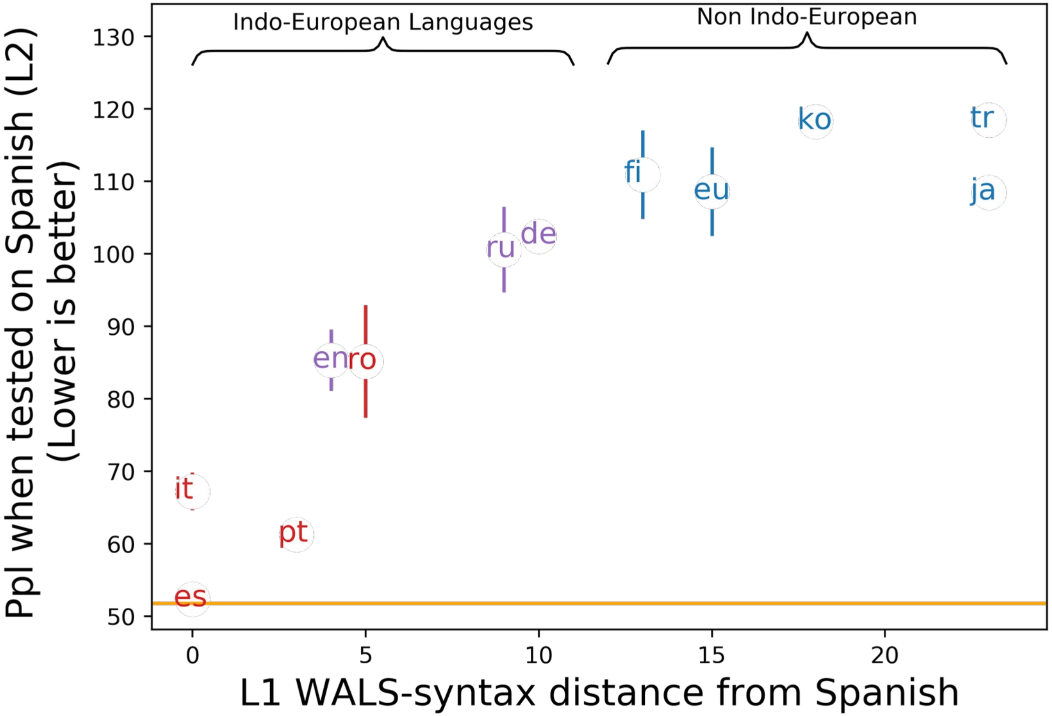

Finnish
probability of being an agent
0.75
0.50
0.25
0.00
A
O
S
role
case
Nom
Gen
Par


Basque
probability of being an agent
0.8
0.6
0.4
0.2
0.0
A
O
S
role
case
Abs
Dat
Erg
Par

Transfer between languages

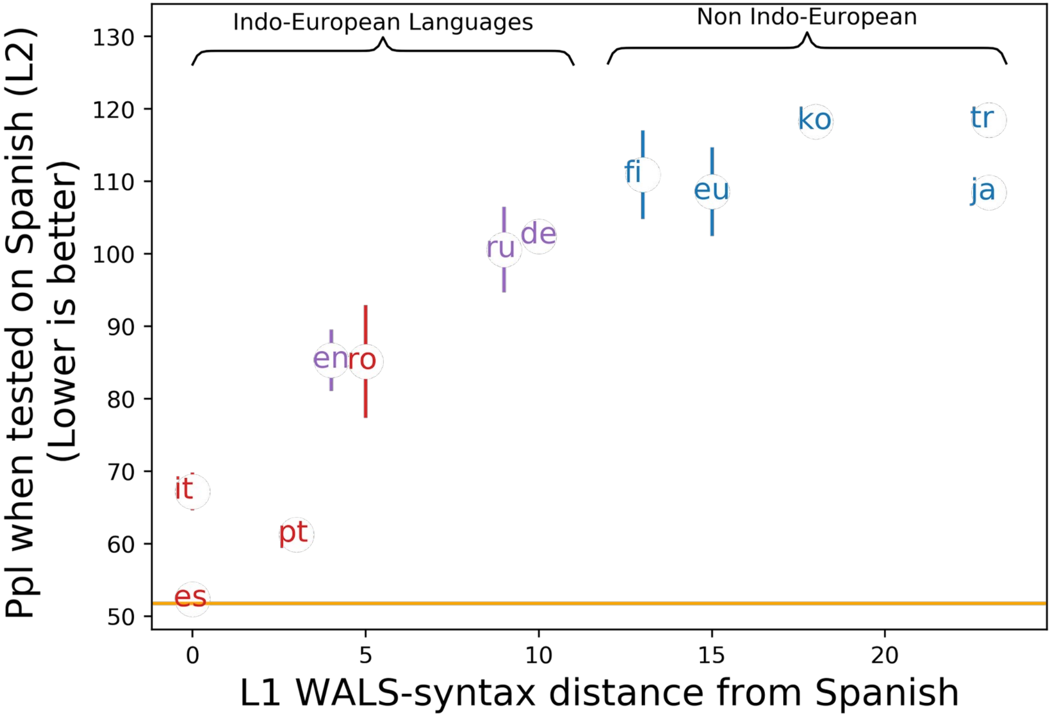


Transfer between languages



- Transfer is correlated with syntactic similarity

Transfer between languages



- Transfer is correlated with syntactic similarity
- Control for vocabulary overlap