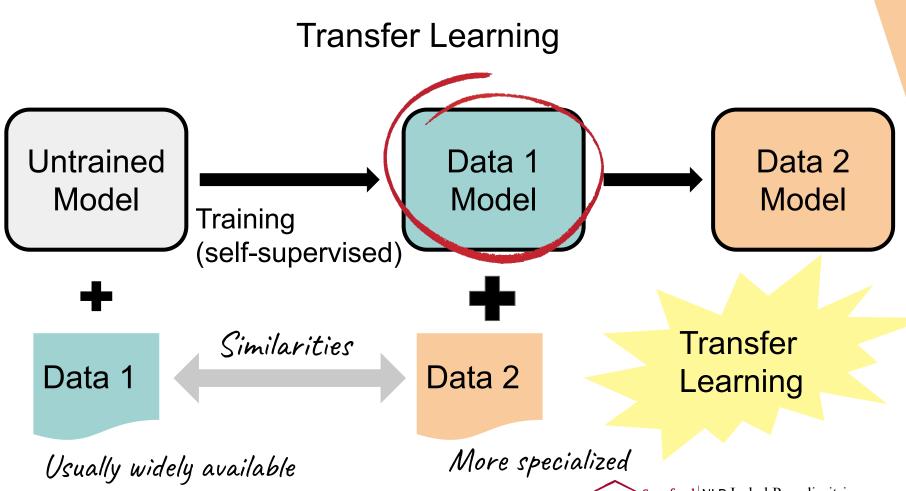
## Structural Transfer Learning: Exploring Neural Models and Language Structure Through Understanding Transfer



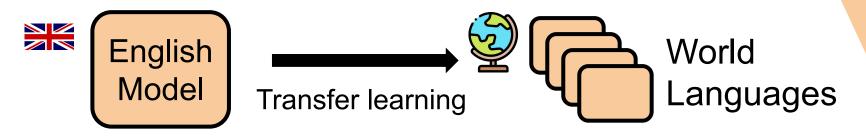
**Isabel Papadimitriou** 





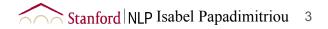
Stanford NLP Isabel Papadimitriou 2

Transfer learning has practical applications

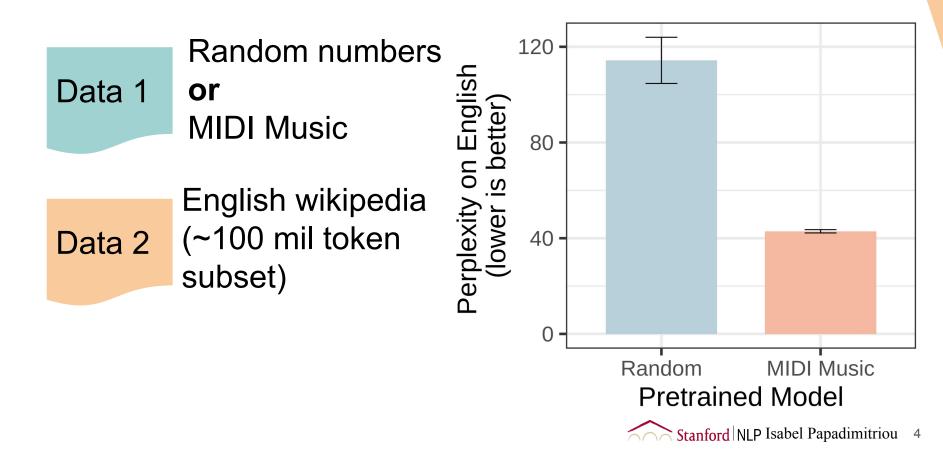


But also an **analysis methodology** for understanding data and learning

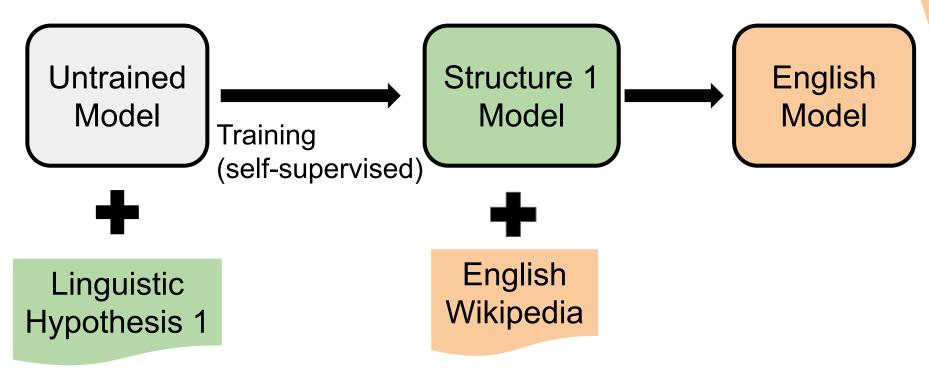
 Power machine learning models let us explore questions about language in new ways

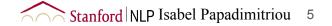


#### Shared structures between modalities

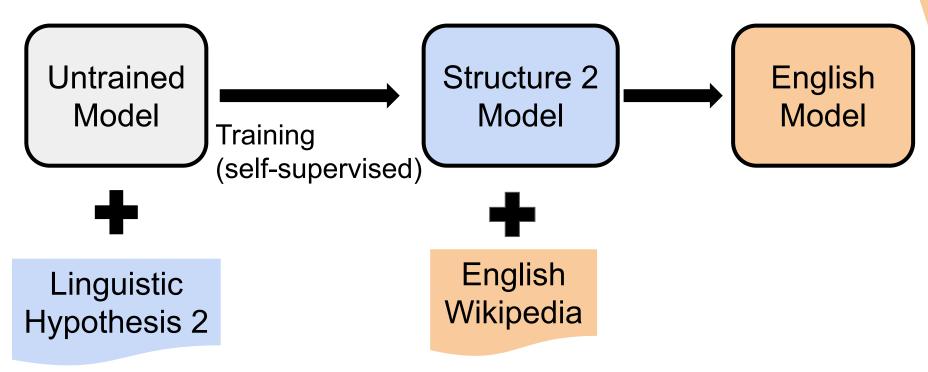


# **Structural Transfer**: a testbed for linguistic structure hypotheses



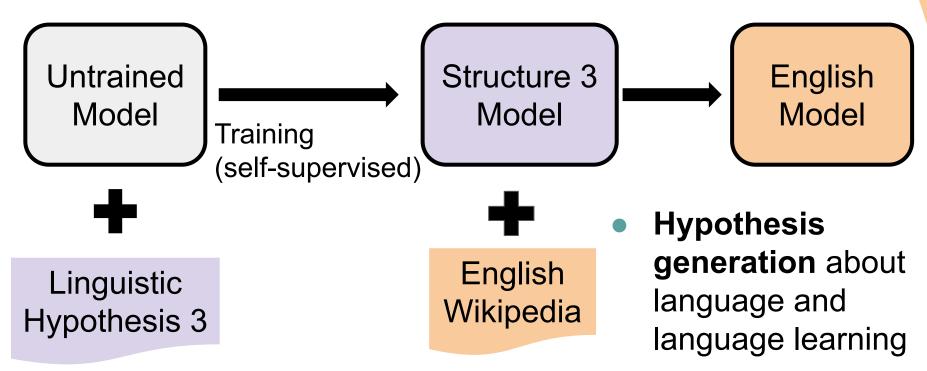


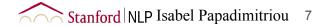
# **Structural Transfer**: a testbed for linguistic structure hypotheses





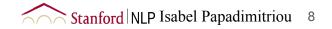
# **Structural Transfer**: a testbed for linguistic structure hypotheses







# Using structural transfer learning to explore the **role of structure** in language and language learning

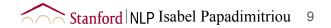


## Transfer learning in NLP

• Recent NLP: pretrain so much, that the task can be described in language. **Prompting** 

#### **Transfer learning now**

- Looking beyond the dominant languages where we can do things like prompting
- And for understanding **structure**



## Structure and language

- Structure is characteristic of human language
- Most obviously in syntax
- But also beyond syntax
  - Meaning, discourse, reference, information structure
- What structural biases are sufficient for language learning?
- (beyond this talk) Role of communication and language use in creating structure

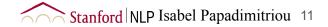
## 1) Recursion

Constituents "Clumping"

The cat sat on the mat

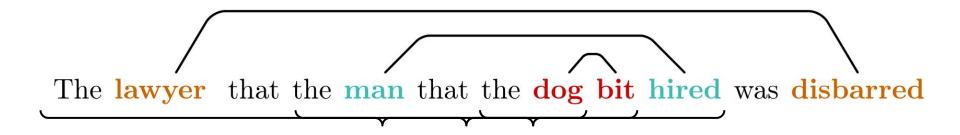
I think that the cat sat on the mat

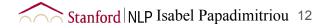
You always accuse me that I think that the cat sat on the mat



#### 1) Recursion

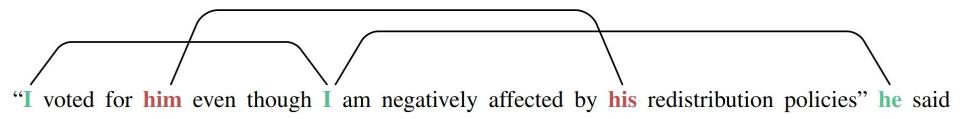
Nesting Context-free

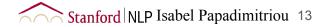




#### 2) Crossing links and dependencies

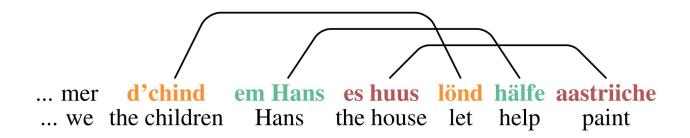
Linking in meaning and reference

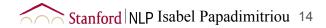




#### 2) Crossing links and dependencies

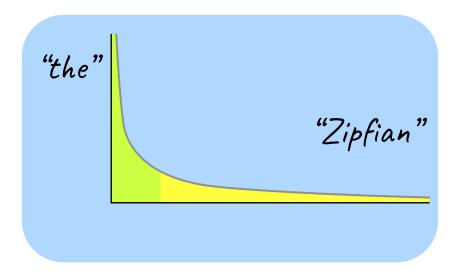
And syntactic structures

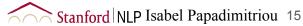




[Schieber 1985]

#### 3) Zipfian vocabulary distribution

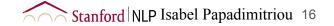




## Outline

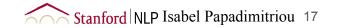
- What structural biases are useful for human language learners?
  - Disentangling the effects of recursive and linking structures

- How does vocabulary distribution transfer as a structural bias?
  - The structural effect of vocabulary



## Outline

- What structural biases are useful for human language learners?
  - Disentangling the effects of recursive and linking structures
- How does vocabulary distribution transfer as a structural bias?
  - The structural effect of vocabulary

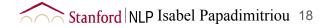


## Exploring inductive bias

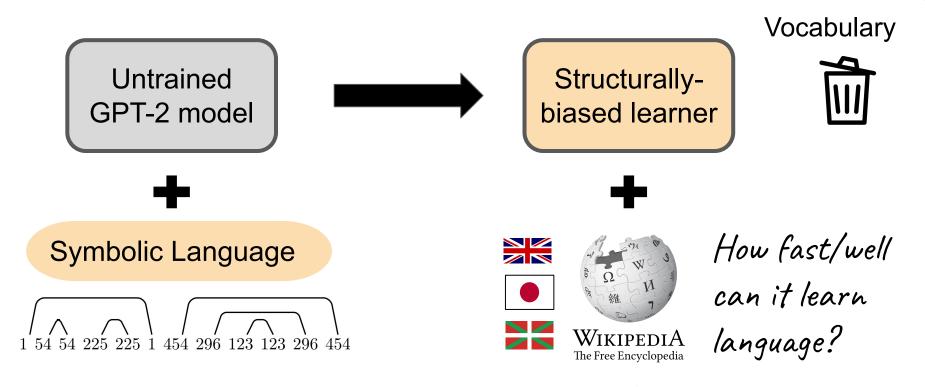


Use transfer learning to test different **structural inductive learning biases** 



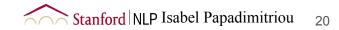


#### Transfer learning methodology

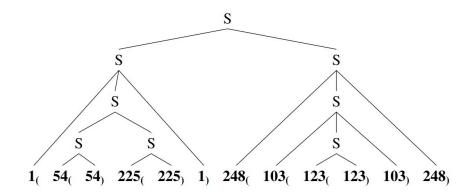


#### Symbolic pretraining languages

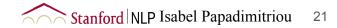
Nesting Parentheses



#### **Nested Parentheses Primitive**

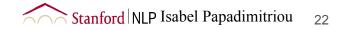


- Well-nested, matching pairs
- Constituents



#### Symbolic pretraining languages

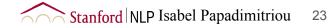
Nesting Parentheses Crossing Dependencies



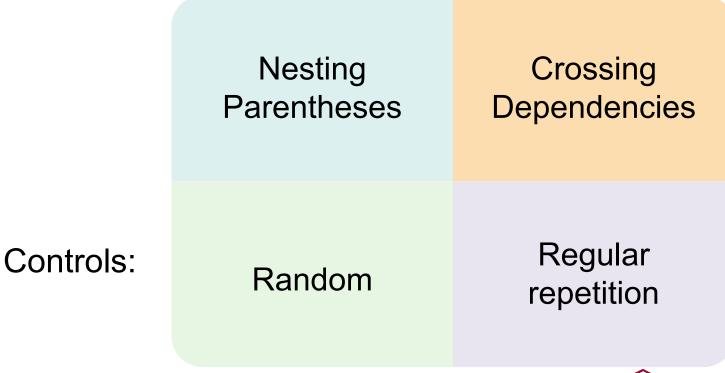
#### **Crossing Dependencies**

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

- Tokens have to match, but not nest
- Where does the structure come from?
  - **Dependency length distribution:** sample from empirical distances of nesting parentheses



#### Symbolic pretraining languages

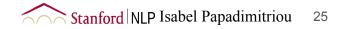


#### Simple Repetition Primitive

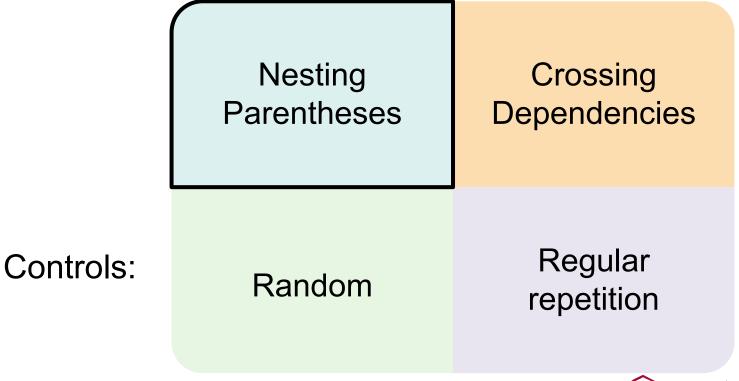
Randomly sample *k* words, then repeat them, then randomly sample *k* words...

#### 499 472 300 345 272 499 472 300 345 272 309 17 15

(Example is for k=5, we do k=10 in experiments)

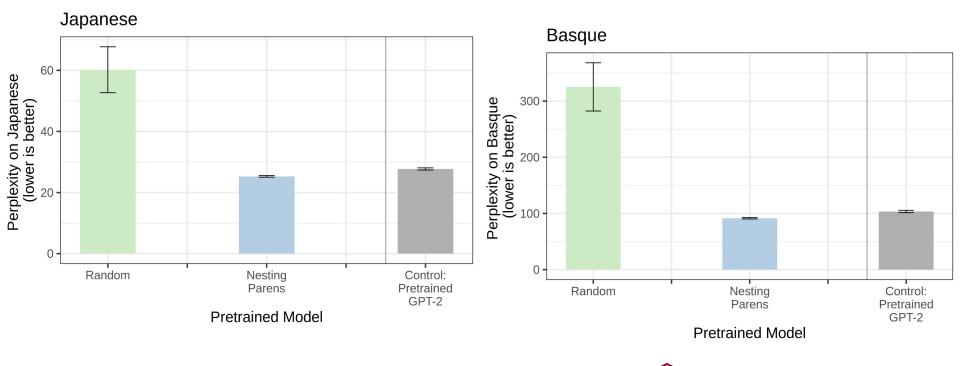


#### Symbolic pretraining languages

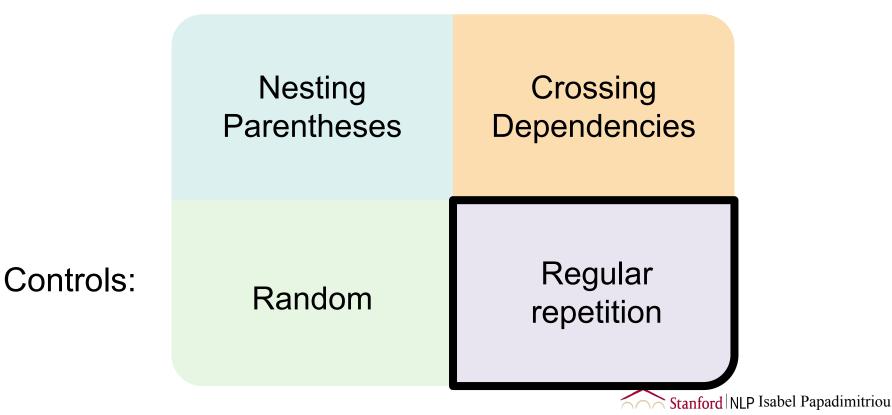


#### Nesting structure helps language learning Baseline – no structure 120 Baseline – English structure Perplexity on English (lower is better) 80 40 Random Nesting Control: Parens Pretrained GPT-2 **Pretrained Model**

#### Multilingual case – Japanese and Basque



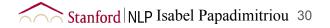
#### Symbolic pretraining languages

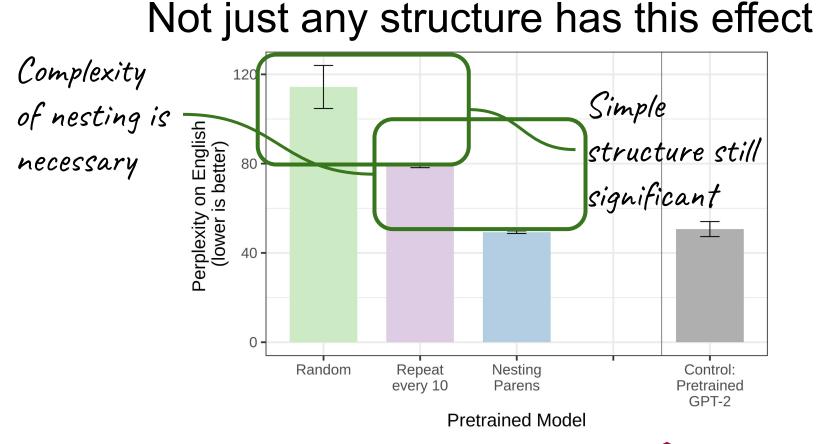




# Question: does **nesting** really help? Or would any structure help?

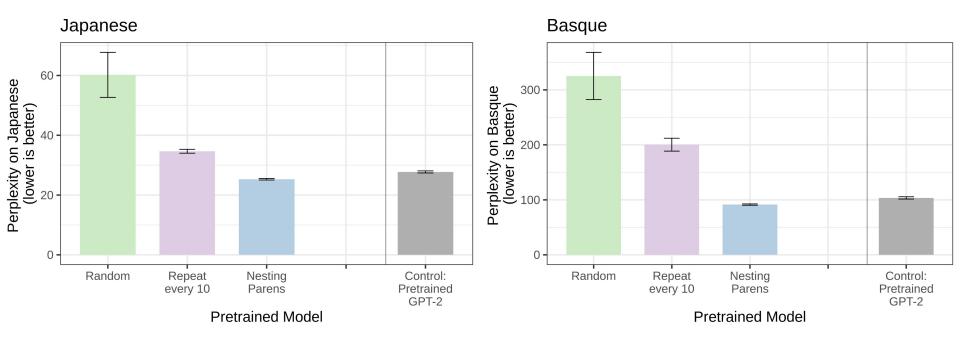
#### 499 472 300 345 272 499 472 300 345 272 309 17 15





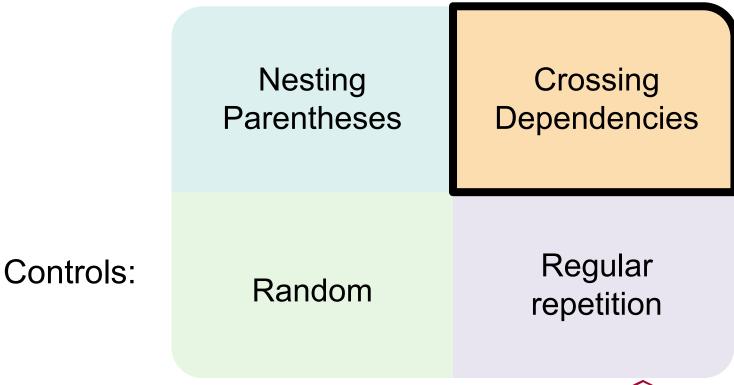


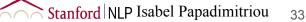
#### Again, a multilingual effect



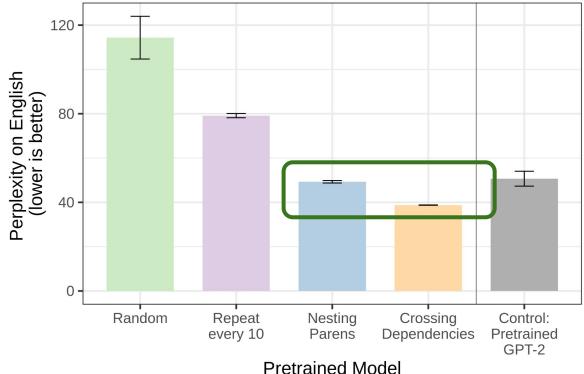


#### Symbolic pretraining languages

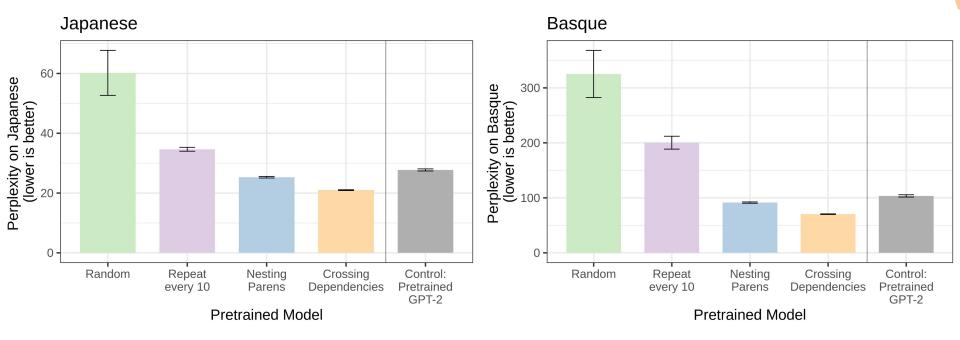


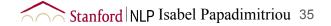


# Crossing links, without nesting, provide a better inductive bias



#### This is also true across languages







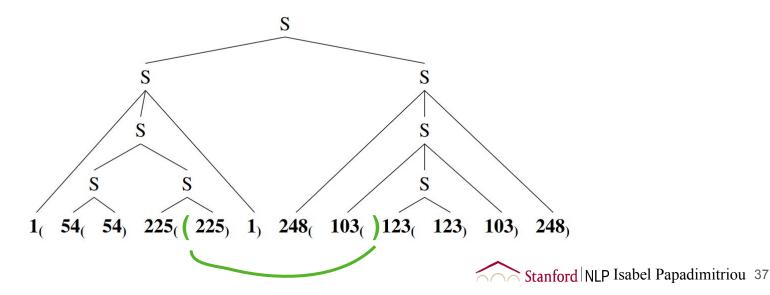
# The kinds of structure that make language are multifaceted

- Structural transfer lets us explore hypotheses about structure in language
- Language as a learnable system, independent of linguistic theory

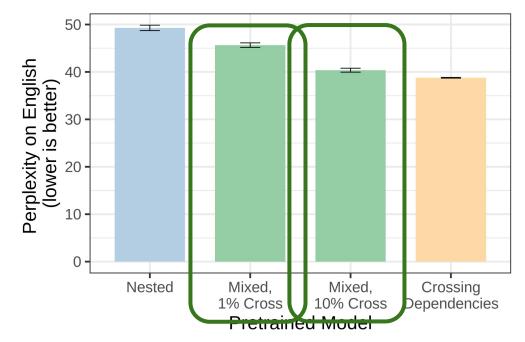


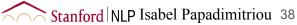
### Mixing nesting and crossing parentheses

A language that is mostly nesting, with 1%, or 10% of parentheses not following the structure

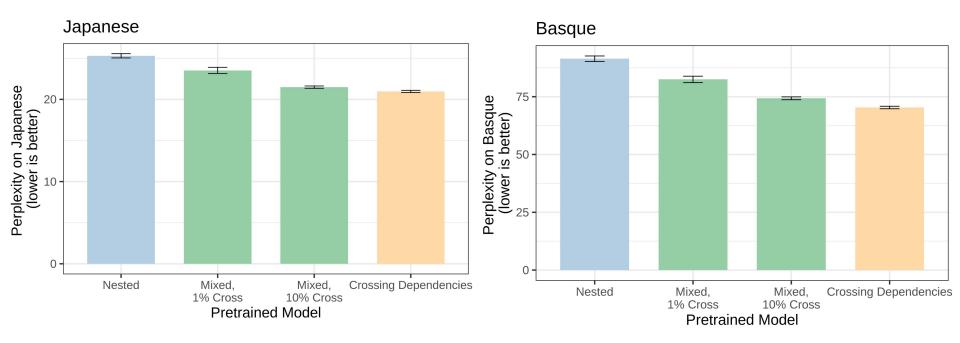


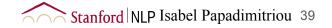
# Slightly breaking constituent structure makes better language learners





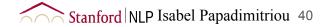
#### Also a multilingual effect





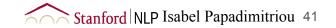
### Structural inductive bias through transfer learning

- Complex structural relationships are important in language
- Multiple crossing dependencies a good starting point for language learning
- Computational models as hypothesis generators: testing linguistic structure in theory-free ways



### Outline

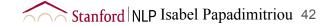
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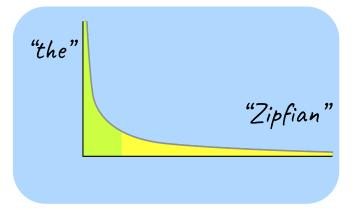
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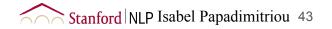
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## The lexicon in linguistics

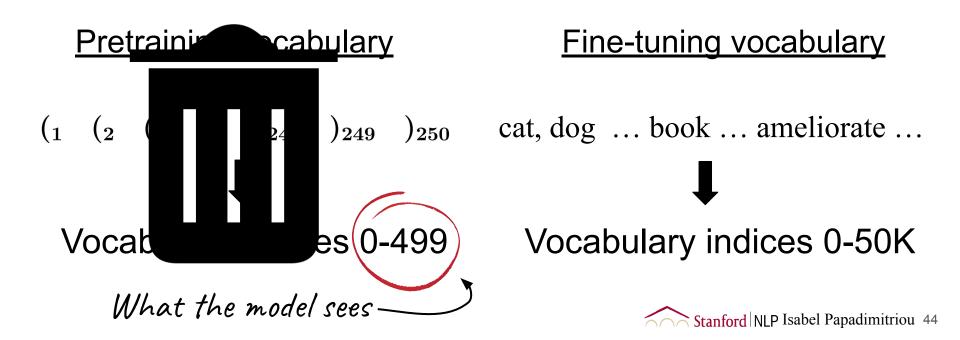
- A good amount of structure is in the vocabulary:
- Vocabulary distribution
- Structure in meaning
- and also in grammar
  - Properties like transitive verb
  - Constructions, like "Let alone"



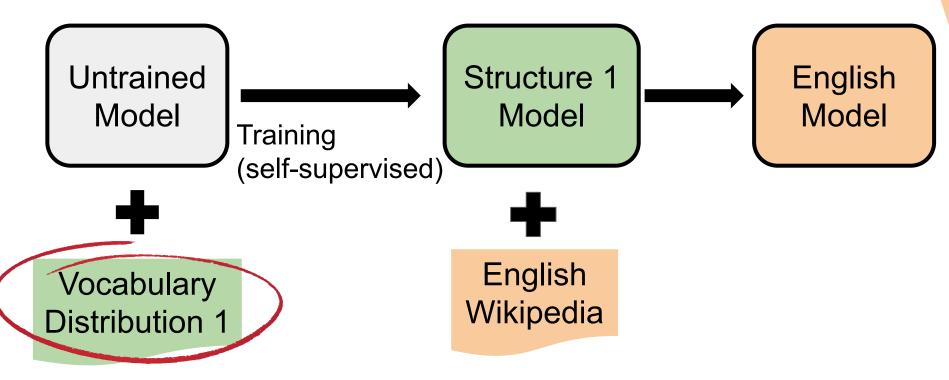


Ο.

## We throw out the vocabulary between pretraining and fine-tuning



# **Structural Transfer**: a testbed for linguistic structure hypotheses

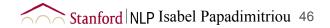




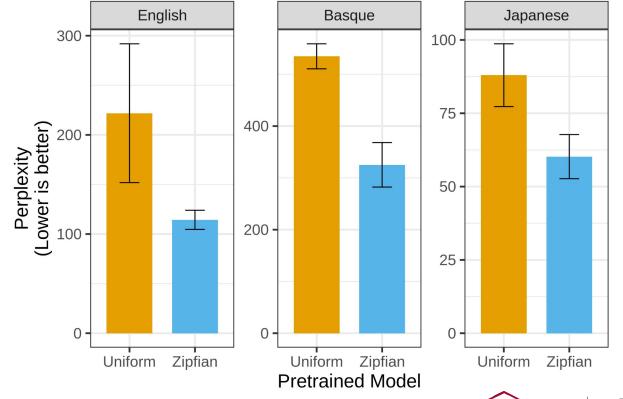


# Does a Zipfian vocabulary distribution in pretraining have a **structural** effect?

Even though we discard vocabulary information



#### Yes, Zipfian information is transferred



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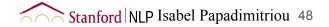
#### ... but does not necessarily combine with structure

Uniform

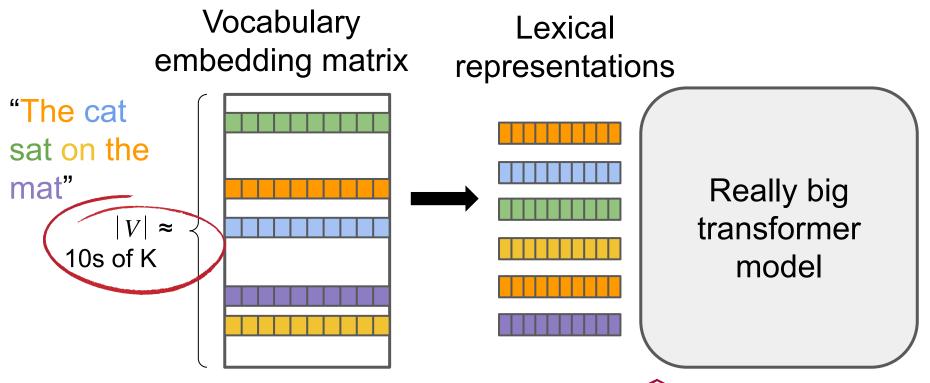
Zipfian

Vocab Distribution

English Basque Japanese 50. Ŧ I 75 -40 20 -Perplexity (Lower is better) 30 50 -20 10 -25 -10 0-0 -0 -Nesting Crossing Nesting Crossing Nesting Crossing Parens Dependencies Parens Dependencies Parens Dependencies Pretrained Model



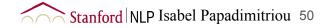
The role of vocabulary in transfer learning is an interesting problem



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# The role of vocabulary in transfer learning is an interesting problem

- A practical problem: without enough data, it's hard to see a word often enough to learn a good vector
- A puzzle: how is structural information separated between vocabulary matrix and model weights?
  - Vocabulary information like distribution can have structural effects



## Transfer learning, language, and structure

- Transfer learning is a test bed for understanding structure in language learning
- Computational models of cognitive processes can't prove anything – but they serve as interesting hypotheses generators
- It's an exciting time: machine learning opens up new avenues for exploring questions in language



