What we can learn about language from exploring multilingual language models

Isabel Papadimitriou
Some context

At last, we have language models that model language (pretty well!)

This gives us two things: a mystery, and a scientific tool
How are language models a tool?

● We have language learners that learn in front of our eyes
● We can investigate this in ways we never could before
● By looking into their representations…
  ○ We can relate complex linguistic properties
● By observing learning under controlled conditions…
  ○ 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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Using a multilingual lens to approach these questions
Language Variation and Universals

Concrete

● How to understand multifaceted, cross-lingual properties?
● **LM Embedding spaces** provide a plausible testing ground.

Abstract

● What **inductive learning biases** make good language learners?
● What are the abstractions that underlie language?
Can we really prove anything?

No

- But an LM is a **concrete theory** for how to model a language
- We can investigate it, and it’s outside the box
- Computational models provide **possibilities**, and **interesting cases** we’d not considered

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

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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!

**Intransitives**

The **glass** broke

**Isabel** broke the **glass**

**Passive voice**

The **cat** jumped on to the perch

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

**Discrete**

```
  S
 / \ 
NP VP
  / |  
/  |  
A   Y   Adv
```

Colorless green ideas sleep furiously

**Animacy**

**He** ran all day

The **fridge** ran all day

**Case**

**Volitionality**

**Mary** punched **Sam**

**Mary** liked **Sam**

**Mary** forgot **Sam**

[Comrie 1989 *Language Universals and Linguistic Typology*

[Hopper and Thompson 1980 *Transitivity in Grammar and Discourse*]
Multilingual Language Models

- They represent different **words**, in different **contexts**, in different **languages**
- All in one high-dimensional space

How do they do this for subjecthood?
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:

- Is subjecthood a universal category?
- Is subjecthood a discrete category?
- What happens with typological variation?
Main experimental tool:

- Train a **binary classifier** on mBERT embeddings to distinguish **subjects** from **objects** in one language.
- Zero-shot transfer classifiers from one language to another.

Subject  Object
The **cat** is chasing the **dog**

Τον σκύλο τον κυνηγάει η γάτα
?? ??

这只**猫**在追那条**狗**
Cross-lingual accuracy is comparable to in-language accuracy.

Red dots are in-language accuracy, black dots are cross-language accuracy.
Cross-lingual accuracy is comparable to in-language
Parallel, Multilingual Subjecthood

- **Linguistic generalization** in pretrained LMs:
  - Encode subjecthood separately from language
- Subjecthood is available to a learner as a universal
Three questions:

- Is subjecthood a universal category?
- Is subjecthood a discrete category?
- What happens with typological variation?
But is subjecthood a simple binary issue?

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

- Train a **binary classifier** on mBERT embeddings to separate **subjects** from **objects** in one language

**Probabilities:** Subjecthood projection space

- **Object**
  - $P(\text{subject}) = 0$

- **Subject**
  - $P(\text{subject}) = 1$

- *How*, not *if*, the classifier encodes subjecthood
Main experimental tool:

- Train a **binary classifier** on mBERT embeddings to separate **subjects** from **objects** in one language

**Probabilities**: Subjecthood projection space

- **Object**
  - $P(subject) = 0$
- **Subject**
  - $P(subject) = 1$

**How**, not **if**, the classifier encodes subjecthood
Do probe probabilities reflect the effect of other features?
Classifier probabilities show animacy effects

Animacy

He ran all day

The fridge ran all day

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
The perch was jumped on to by the cat
● 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

Prototype

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

Colorless green ideas sleep furiously
When classifying grammatical role, BERT doesn’t care about word order...except when it matters

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(ACL 2022)
What if we test the probe on the same sentences \textit{(with the same prototype effects)} but we swap the labels?

The \textbf{chef} chopped the \textbf{onion}, \quad \textbf{The onion} chopped the \textbf{chef}

\textit{Will the probe tell them apart?}
Yes – Representation differences that are caused **only** by syntactic word order
Both grammatical subjecthood and prototype effects

- 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

- 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**

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

Intransitive: The **glass** broke
Ergative languages treat **intransitive subjects** like **objects**.
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

- Classifier probabilities show how intransitives align

Probabilities: Subjecthood projection space

- Transitive object
  \( P(\text{subject}) = 0 \)

- Transitive subject
  \( P(\text{subject}) = 1 \)

- Unseen: Intransitives
  \( P(\text{subject}) = \text{??} \)
Transitive Subjects (A) > Intransitive Subjects (S) > Transitive Objects (O)
These are ergative languages!

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

- Subjecthood representation can be, and is, **multilingual**
- Prototype effects **co-exist** with discrete grammatical classes
- **Higher-order information** (like what to do with intransitives) is represented in the same space as meaning

Future work: better understanding the geometric expression of these properties
Representing subjecthood

- A discrete category, but with subtleties and complexities
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- 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
Main Question:
What structural inductive biases make a good language learner?
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!)

Transfer learning

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

Real Data:

Music

Code

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**
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*

    Freeze everything except *word embeddings*. Can LM internals be effectively repurposed?
Random Baselines – Randomly sampled tokens

- Control - How far can we get with just word embeddings?
- Vocabulary distribution has a significant effect
Music and Code

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

**Music:**

MIDI

```
SETVELOCITY_29 NOTEON_47 SHIFTMS_180 SETVELOCITY_57 NOTEON_66...
```

**Code:**

Java

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

No comments
- 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

Pretrain on a simple hierarchical structure:

Nesting (Recursive) Parentheses:

But also have a control:

Flat Parentheses:
• **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
Difference from placing a random token twice instead of once
What to take away from these experiments?

- A structural inductive bias \textbf{(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]
Isabel Papadimitriou

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

- 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?

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

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

● **Subjecthood:** One embedding space can encode
  ○ A property *generalized* across languages
  ○ A discrete property also influenced by *prototype* effects
  ○ **Higher order features** of the language

```
{
}[
()]
```

● **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?

- 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.

**Thanks!**