## Could a purely self-supervised Foundation Model achieve grounded language understanding?



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Santa Fe Institute, April 2022

### Could a Machine Think?

Classical AI is unlikely to yield conscious machines; systems that mimic the brain might

by Paul M. Churchland and Patricia Smith Churchland

SCIENTIFIC AMERICAN January 1990

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## Could a purely self-supervised Foundation Model achieve grounded language understanding?



#### Yes (I don't see why not)

Christopher Potts, Thomas Icard, Eva Portelance, Dallas Card, Kaitlyn Zhou, John Etchemendy. 2021. <u>Philosophy of understanding</u>. In *On the opportunities and risks of Foundation Models*.

#### A quick summary of "Could a machine think?"

#### THE CHINESE ROOM

Axiom 1. Computer programs are formal (syntactic).

Axiom 2. Human minds have mental contents (semantics).

Axiom 3. Syntax by itself is neither constitutive of nor sufficient for semantics.

Conclusion 1. Programs are neither constitutive of nor sufficient for minds.

Searle is aware of [neural networks] but thinks they too will be devoid of real semantic content. To illustrate their inevitable failure, he outlines a second thought experiment, the Chinese gym, which has a gymnasium full of people organized into a parallel network. From there his argument proceeds as in the Chinese Room.

We find this second story far less responsive or compelling than his first. [...] If such a system were assembled on a suitably cosmic scale, with all its pathways faithfully modeled on the human case, we might then have a large, slow, oddly made but still functional brain on our hands.

We should not assume that scale (and perhaps speed) are irrelevant.

y-axis no longer remotely to scale! we are ≈5,000 slide heights above the original graph PaLM (Google; 540B)
Megatron-Turing NLG (MS; NVIDIA; 530B)

**GPT-3 (OpenAI; 175B)** 

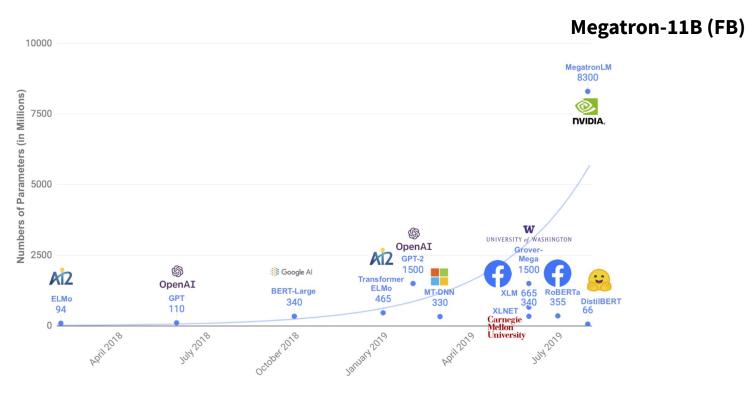


Figure 1: Parameter counts of several recently released pretrained language models.

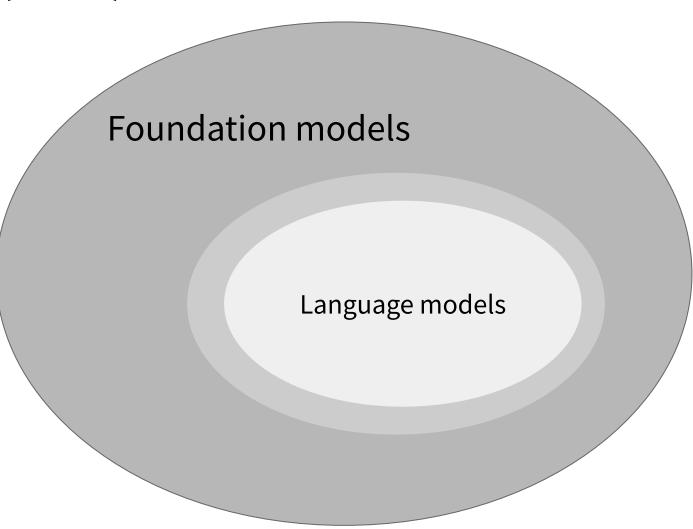
From Sanh et al. 2019

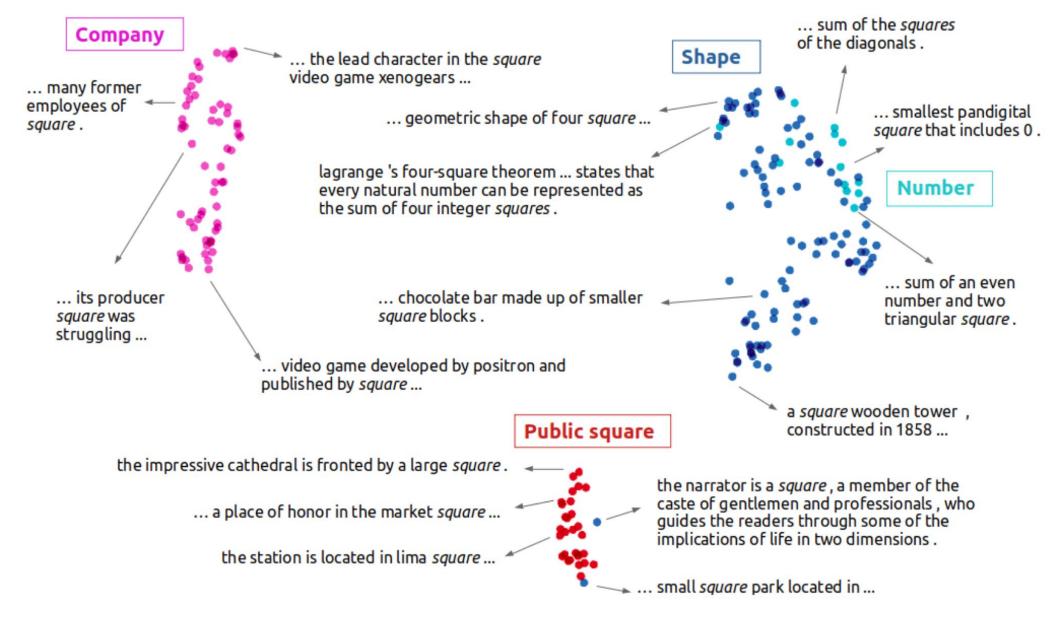
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#### Foundation Models (FMs)

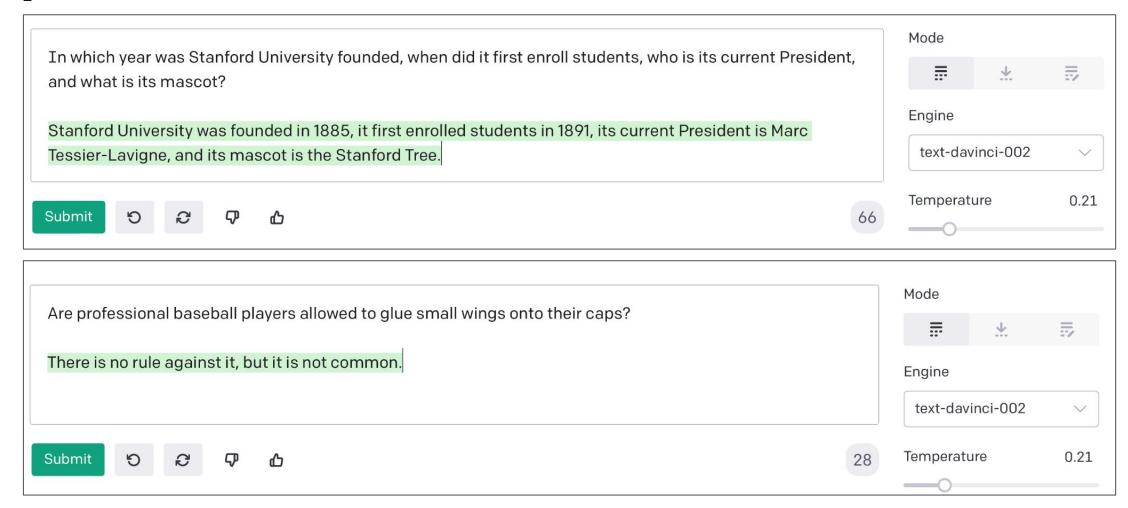
- Pretrained
- Multi-purpose
- Adaptable
- (Large)
- (Self-supervised)

foundation reflects the functional goal

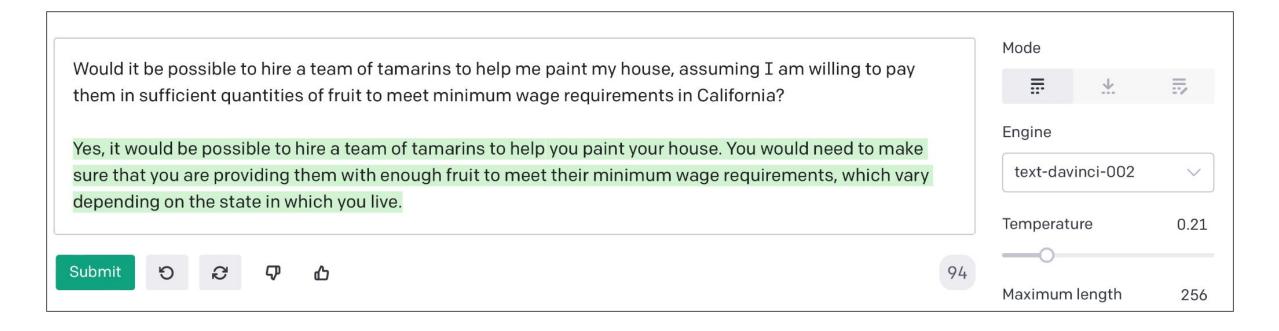




#### **OpenAl GPT-3**



#### **OpenAl GPT-3**



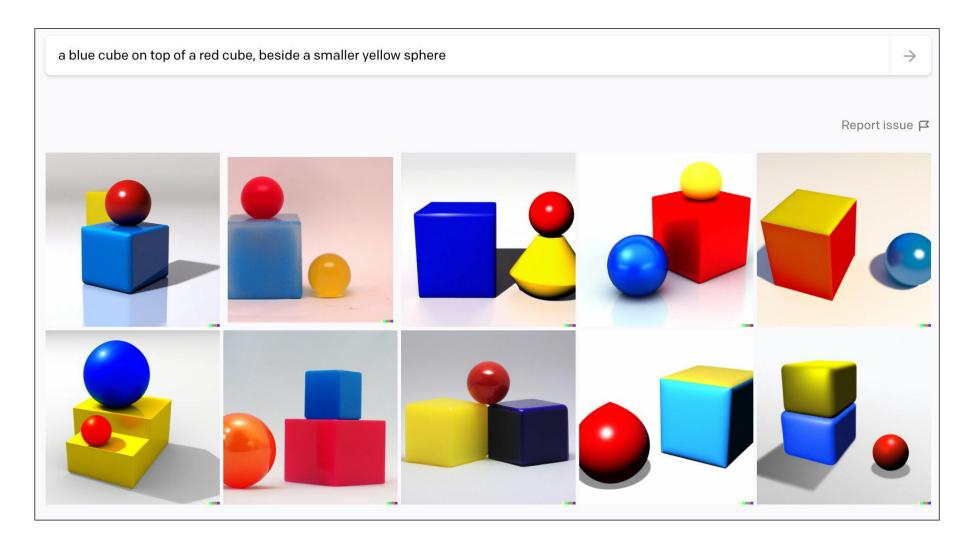
### **OpenAl DALL-E 2**





@ dschnurr

### **OpenAl DALL-E 2**



Imagine A Game With Infinite Adventures, As Unique As Your Own Life...

### AI DUNGEON 2

Create your own world







Unlike virtually every other game in existence, you are not limited by the imagination of the developer in what you can do. Any thing you can express in language can be your action and the AI dungeon master will decide how the world responds to your actions.

# Could a purely self-supervised Foundation Model achieve grounded language understanding?

#### **Self-supervision**

- 1. The model's *only* objective is to learn co-occurrence patterns in the sequences it is trained on.
- 2. Alternatively: to assign high probability to attested sequences.
- 3. Generation then involves sampling from the model.
- 4. The sequences can contain anything.
- 5. The objective can't mention specific symbols or relations between symbols (no standard supervision).

#### Two paths to world-class AI chess?

#### **Deeper Blue of the Future**

- 1. Structured space of actions
- 2. Hard-coded rewards
- 3. Millions of games played

#### **GPT-1000**

1. Trained on billions of sequences of chess notation using only self-supervision:

```
You: Black [SEP] f4 d5 ... Qc7 [SEP] White wins. [SEP]
You: Black [SEP] e4 e5 ... Qh3 [SEP] Black wins. [SEP]
```

- 2. Bias in the training data for wins.
- 3. No separate notion of legal move, reward, etc.
- 4. When playing, simply generates new moves.

## Could a purely self-supervised Foundation Model achieve grounded language understanding?

#### **Conceptions of semantics**

David Lewis: "Semantics with no treatment of truth conditions is not semantics."

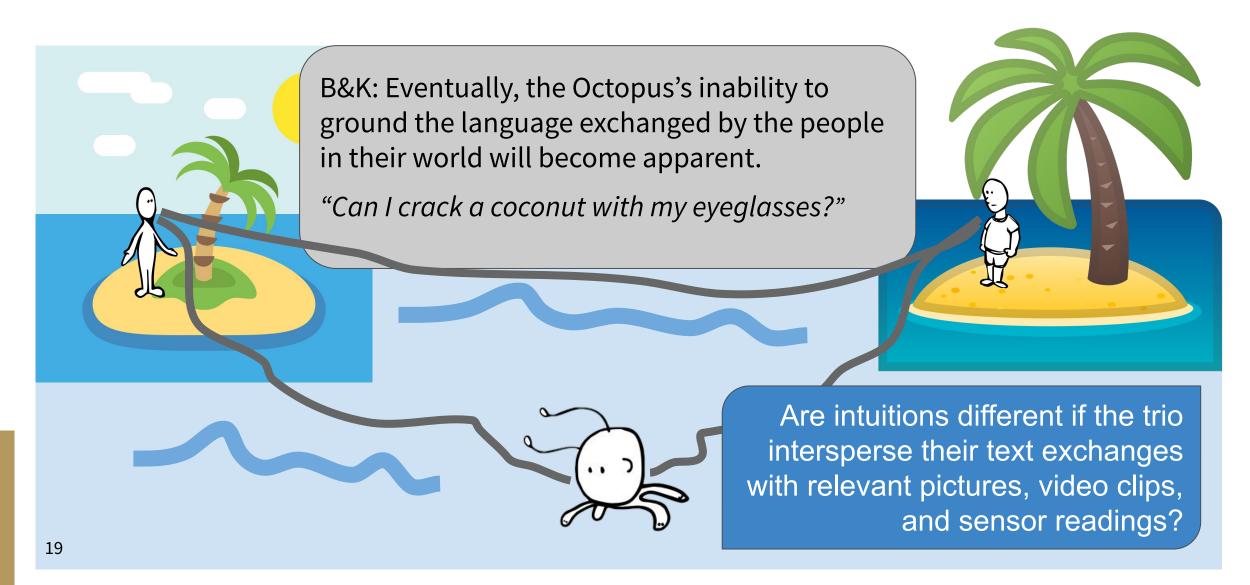
Jackendoff: Semantics as subjective, internalist judgment.

Jerrold Katz: "The arbitrariness of the distinction between form and matter reveals itself"

Natural logic: Language as proof system; model theory optional.

Will Merrill: Rich truth-conditional semantics can be induced from distributional data with certain biases towards discourse consistency.

#### **Bender & Koller 2020:** Symbol streams lack crucial information



#### **Multi-modal streams**

Here's how you make a peanut / butter and jelly sandwich : //



### Metaphysics and epistemology of understanding

Behavioral: understanding is purely dispositional and behavioral.

Internalism: understanding is achieving the right links between language and internal representations.

Referentialism: understanding is achieving the right links between language and the world.

Behavioral tests, once passed by Als, are usually dismissed.

We need methods for *structural* analysis and assessment of models.

#### Behavioral testing: Tricky with Foundation Models

What is pragmatics?

What is semantics?

What do these fields have in common?

[Questions about linguistics?]

Q: What is pragmatics?

A: The study of language use

Q: What is phonology?

A: the study of systems of

sounds in language

Q: What is semantics?

A:

#### Behavioral testing: Tricky with Foundation Models

Premise: every reptile danced

Hypothesis: every turtle moved

Label: entailment

Premise: no turtle ran

Hypothesis: a turtle moved

Label: [babbling]

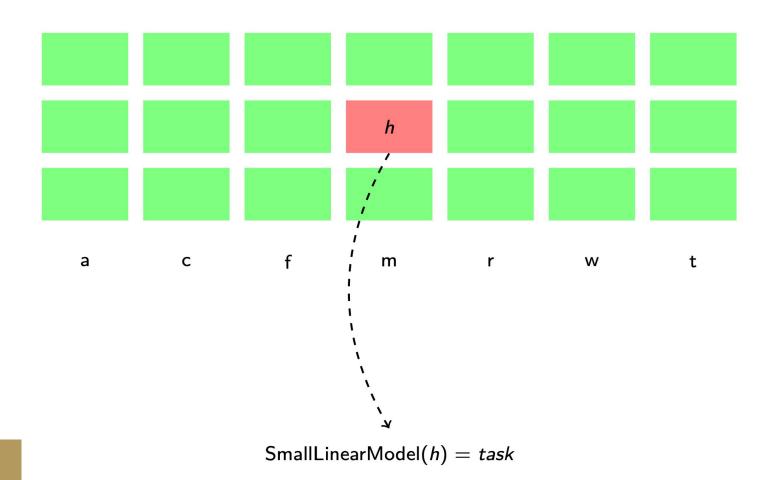
Q: If every reptile danced, did every turtle move?

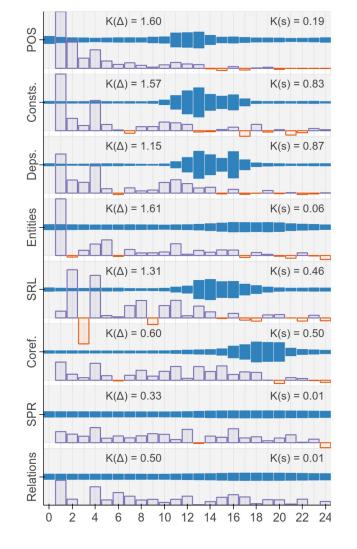
A: Yes.

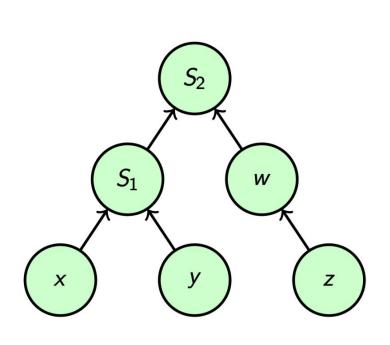
Q: If no turtle ran, did a turtle move?

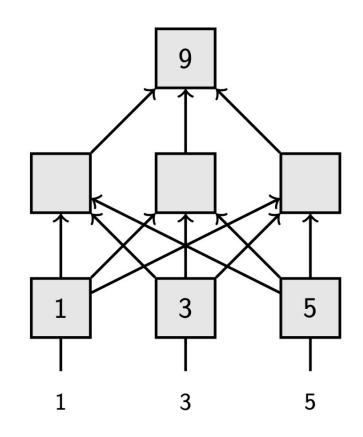
A: Maybe.

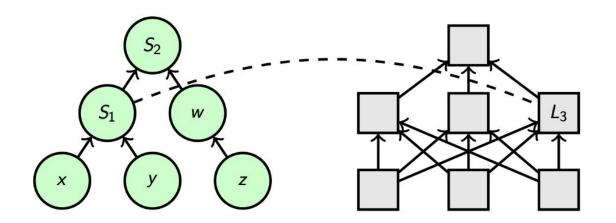
#### Internalism at work: Probing internal representations

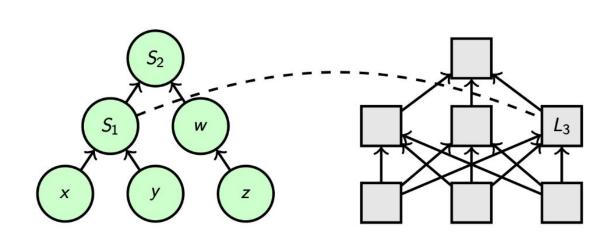


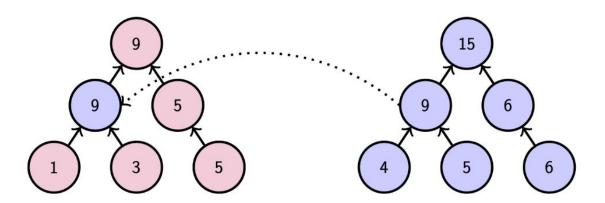


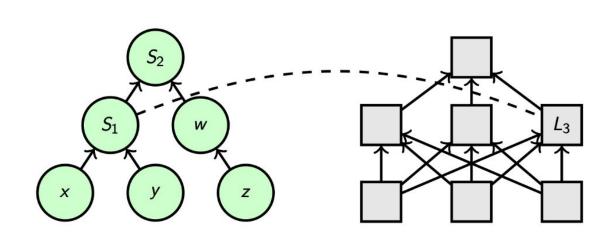


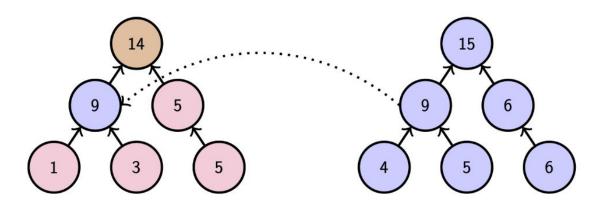


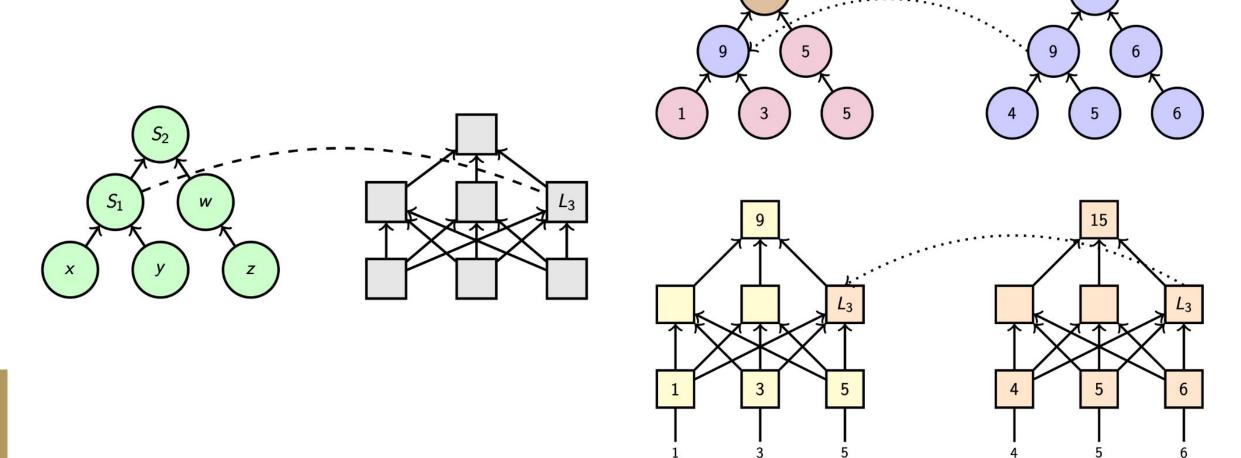


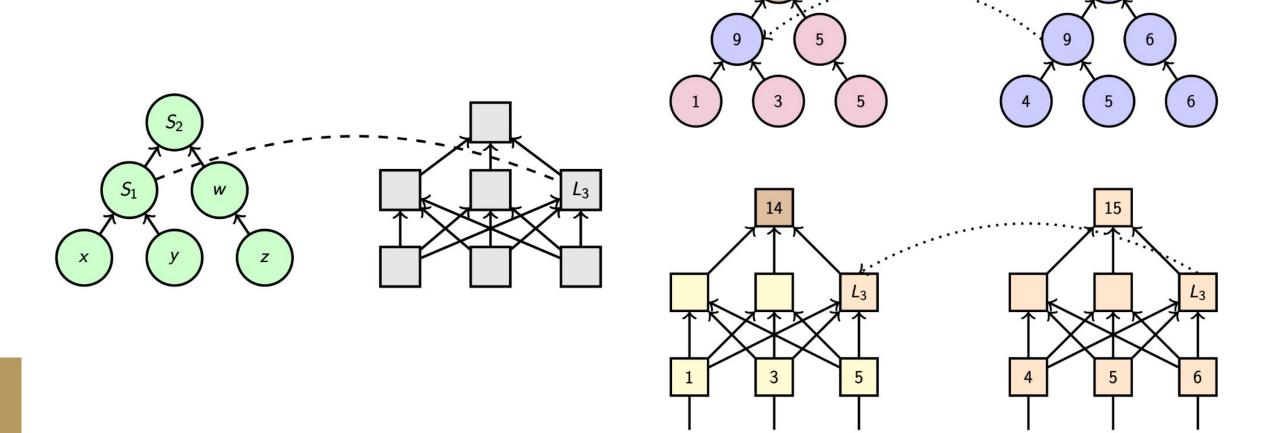


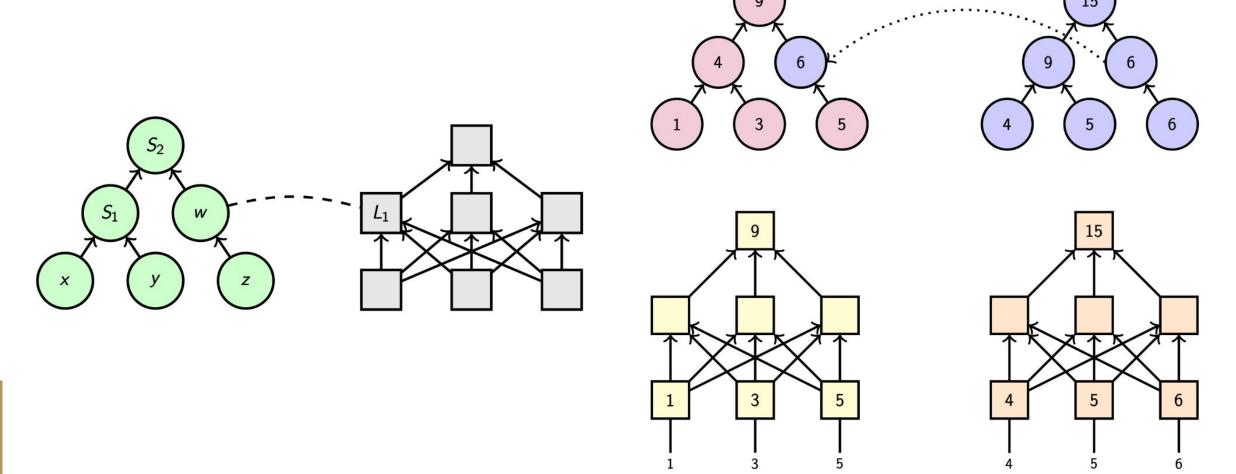


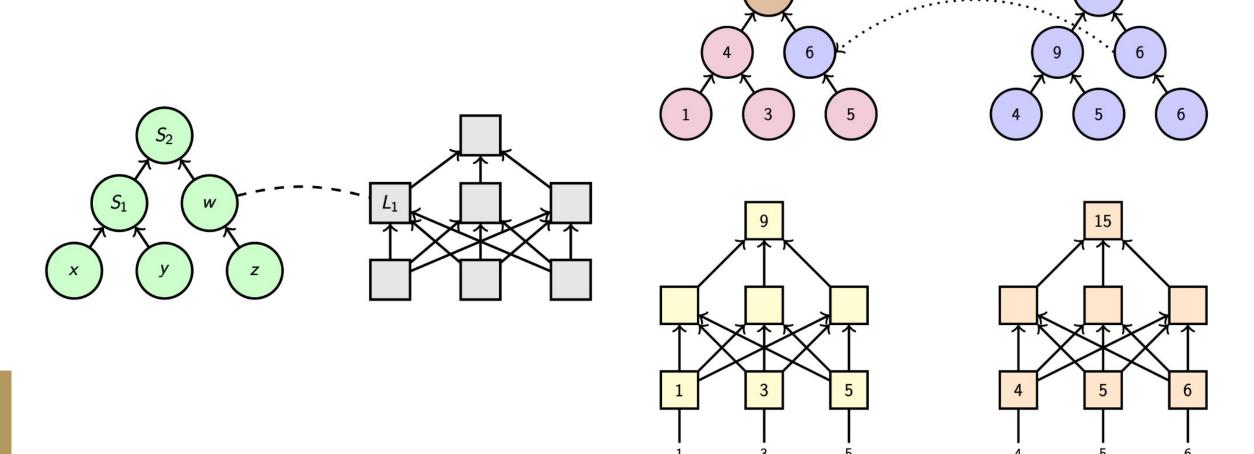


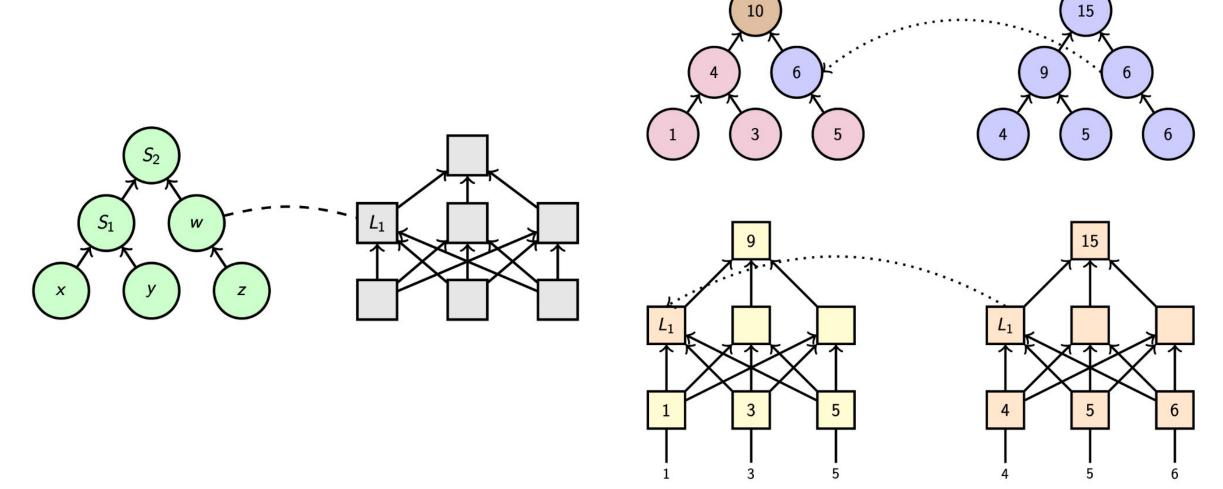


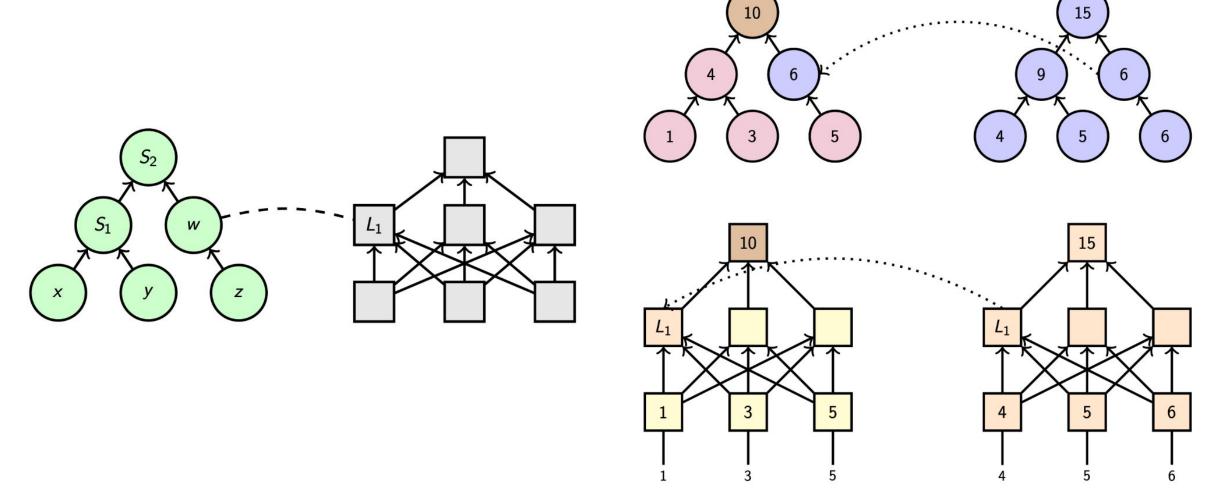


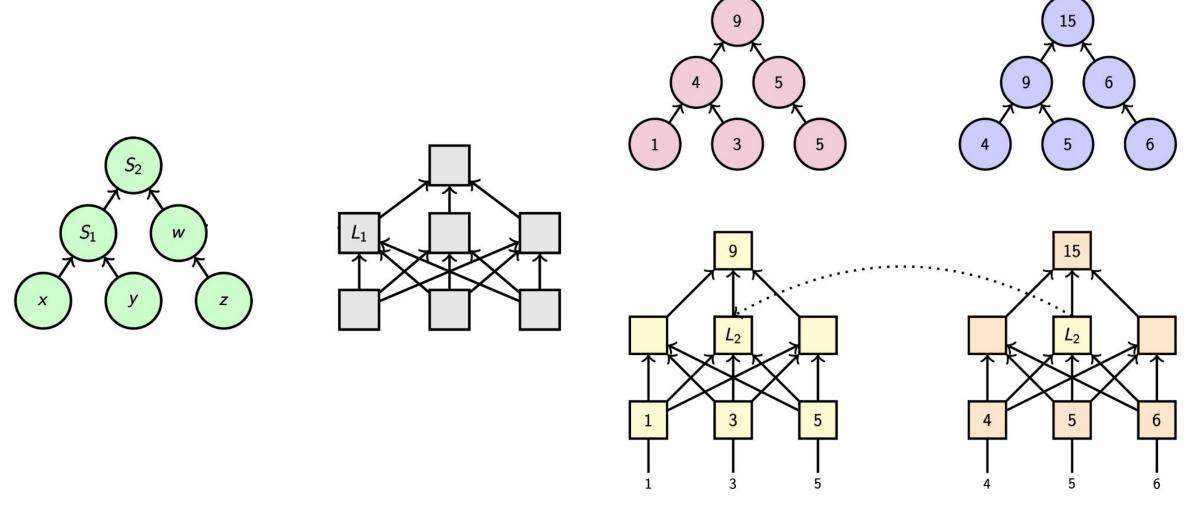












### Findings of causal abstraction in large networks

- Fine-tuned BERT models succeed at hard, out-of-domain examples involving lexical entailment and negation because they are abstracted by simple monotonicity programs.
- Models succeed at the MNIST Pointer Value computer vision task because they are abstracted by simple programs like "if the digit is 6, then the label is in the lower left".
- Models can be trained through interchange intervention training to better conform to high-level causal models/programs.

#### If a Foundation Model

- succeeds at hard language generalization tasks in a domain; and
- simulates a high-level causal model of that domain and the language used to describe it

then surely it has achieved grounded language understanding in that domain.

## Could a purely self-supervised Foundation Model achieve grounded language understanding?

Yes (I don't see why not)

Thank you!

### **Appendix**

### **Github Copilot (OpenAI Codex)**

```
send_tweet.py
```

#### Github Copilot (OpenAI Codex)



#### Pure self-supervision vs. regular supervision

#### Standard supervision for nervous anticipation

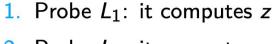
My palms started to sweat as the lotto numbers were read off.	nervous anticipation = 1
I took a deep breath as the curtain started to rise on my debut night.	nervous anticipation = 1
I couldn't shake a deep feeling of unease about the whole affair.	nervous anticipation = 0

Foundation Model "Few-shot in-context learning"

Hey model, here is an example of nervous anticipation: "My palms started to sweat as the lotto numbers were read off."

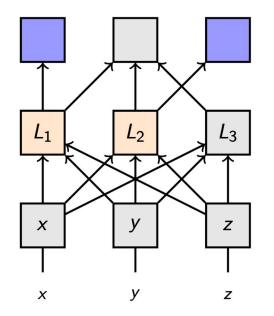
Hey model, here's an example without nervous anticipation: "..."

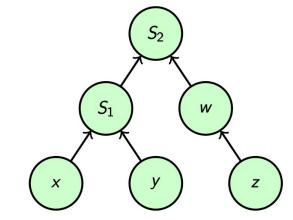
#### Probing does not support causal inferences



2. Probe  $L_2$ : it computes x + y

3. Aha!





4. But  $L_2$  has no impact on the output!

$$W_1=\left(egin{array}{c} 0 \ 0 \ 1 \end{array}
ight) \quad W_2=\left(egin{array}{c} 1 \ 1 \ 0 \end{array}
ight) \quad W_3=\left(egin{array}{c} 1 \ 1 \ 0 \end{array}
ight)$$

$$\mathbf{w} = \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} \quad (\mathbf{x}W_1; \mathbf{x}W_2; \mathbf{x}W_3) \mathbf{w}$$