Provable Limitations of Acquiring Meaning from Ungrounded Form: What Will Future Language Models Understand?


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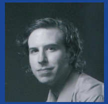
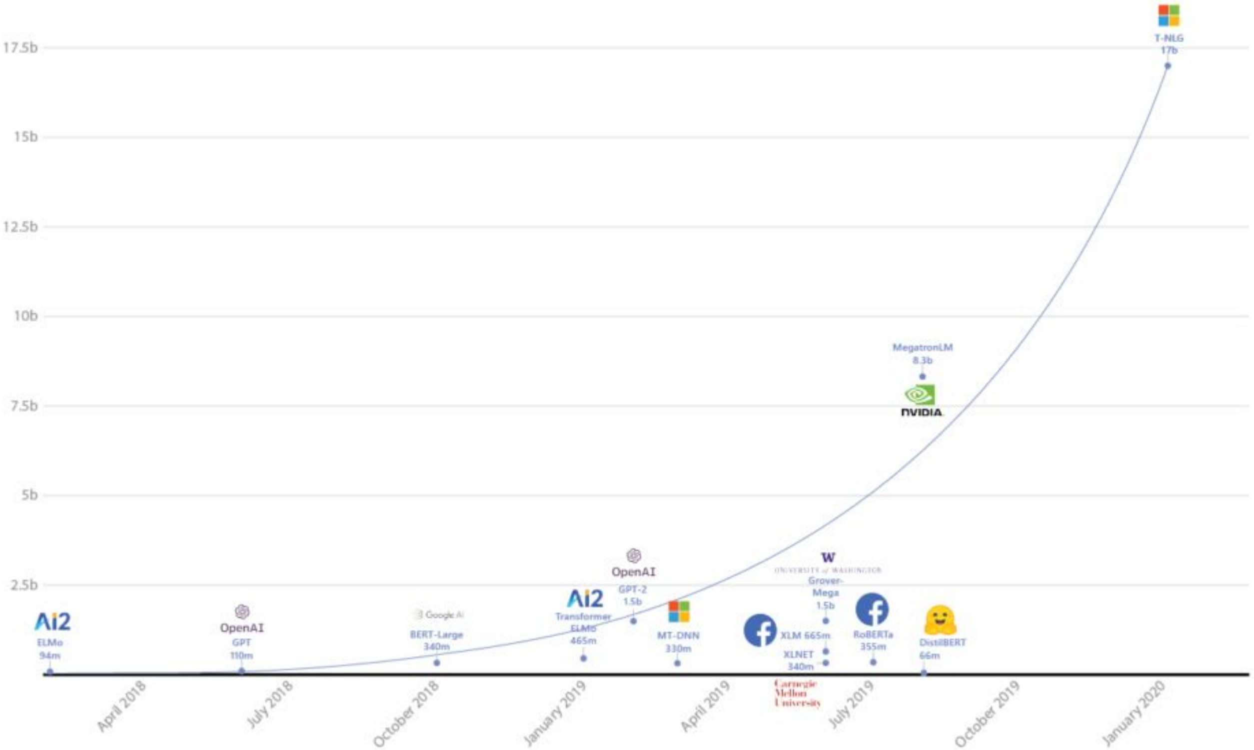

Noah A. Smith

Pretrained LMs are a successful paradigm for NLP



But is pretraining limited?

"A more fundamental limitation of…scaling up any LM-like model, whether autoregressive or bidirectional – is that it may eventually run into (or could already be running into) the limits of the pretraining objective."

Language Models are Few-Shot Learners

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The form/meaning debate

Climbing towards NLU:
On Meaning, Form, and Understanding in the Age of Data

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- Language models are trained on “form”
- But understanding is about “meaning”

Contributions

We formalize and answer a key thought experiment raised by Bender and Koller:

Q: **In principle, can a LM trained on code learn to execute code?**

A: Under some conditions, yes, but in general, no.

Limitations: results depend on our definitions and assumptions

How could language models learn to execute code?

Which is more likely in Python?

```python
assert 1 + 1 == 4
```

```python
assert 2 + 2 == 4
```

Assertion argument (Michael, 2020; Potts, 2020)

1. **Assumption:** programmers intend to write true assertions

2. Therefore, assertions are more likely to appear in training data if they are true

3. ∴ Language model can learn semantic features of expressions (e.g., which = 4)

```
def context():
    x = 2 + 2
    y = 1 + 1
    assert x == 4
```

But are assertions enough to *execute* code?

Our main results:

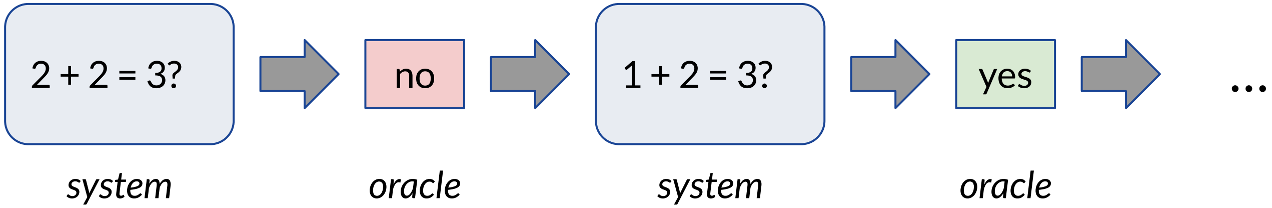
1. Can learn to execute all **transparent languages** using assertions

2. **In general**, cannot learn to execute all languages using assertions

Learning by assertions

Imagine language model learns by *querying* an *assert oracle* function

$$\aleph_L(e, e' \mid \kappa) = \begin{cases} 1 & \text{if } [\![e \mid \kappa]\!]_L = [\![e' \mid \kappa]\!]_L \\ 0 & \text{otherwise.} \end{cases}$$

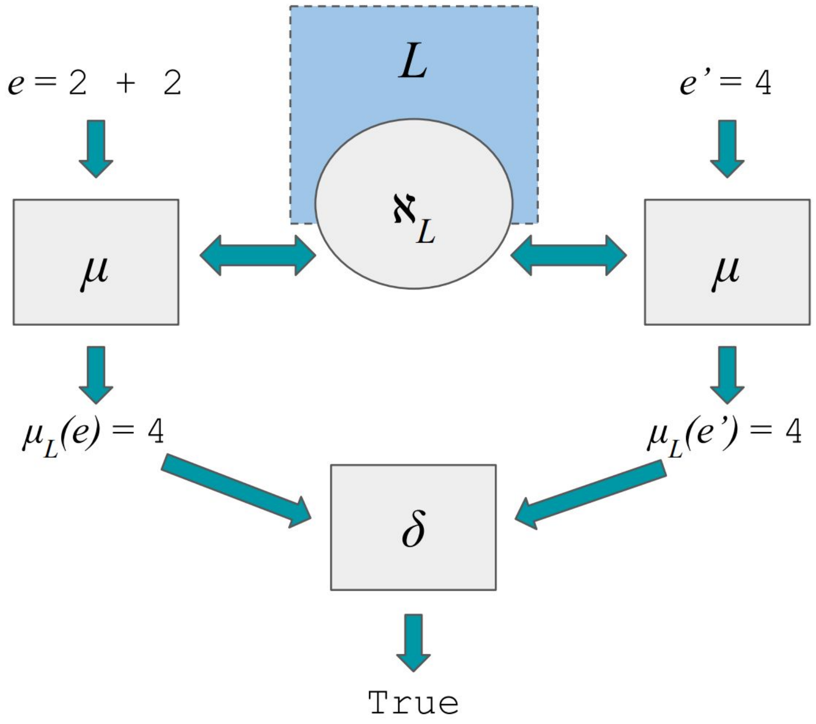


Cf. query learning setup of Angluin (1987)

Defining success: emulation

- A system *emulates* a language if there exists a probe that says whether two expressions are equal given the representations the system produces

- We will analyze what types of languages are *emulatable*



Case 1: transparent languages

A language is transparent if every expression has a canonical semantic value across all contexts

Transparent: $2 + 2$ means 4

Non-transparent: $2 + x$ means ?

#1: transparent languages are emulatable

Theorem 1 (Informal). There exists an algorithm for μ that will emulate any transparent language using assertion queries.

```
from typing import Callable

AssertType = Callable[[str, str, str, str], bool]

def emulate(expr: str, asserteq: AssertType) -> int:
    for idx, cand in enumerate(all_strings()):
        if asserteq(expr, cand, "", ""):
            return idx
```

#2: (some) non-transparent languages are not emulatable

Theorem 2 (Informal). There exists a class of non-transparent languages that no computable function μ can emulate.

Summary of contributions

- First provable “limits of the pretraining objective”
- Formal resolution to the Bender and Koller code thought experiment
    - Transparent yes
    - Non-transparent no

Towards natural language

- Assertion-like contexts exist for natural language also

$$p(\text{New York is urban}) > p(\text{New York is rural})$$

- General takeaway: capabilities of LMs depends on how people create training data (their *intents*, specifically)

(Section 6 of paper: “Towards Natural Language”)

Ongoing research

- Can current LMs learn by assertions?

Zhaofeng Wu, PYI on AllenNLP

- Can an LM trained on natural language implicitly solve NLI?
  - Answer TBD; got some promising theorems
  - Rational Speech Acts theory (Goodman et al., 2016)

Thank you!

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