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

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Outline

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- What is Meaning ?
- The Octopus Test
- On Climbing the Right Hills
- Conclusion

Introduction

Introduction

Recently we have a huge number of papers about language models like BERT or GPT-2 that claim that their model can “understand” natural language or captures “meaning”

Examples:

- In order to train a model that **understands** sentence relationships, we pre-train for a binarized next sentence prediction task. (Devlin et al., 2019)
- Using BERT, a pretraining language model, has been successful for single-turn machine **comprehension** . . . (Ohsugi et al., 2019)
- The surprisingly strong ability of these models to **recall factual knowledge** without any fine-tuning demonstrates their potential as unsupervised open-domain QA systems. (Petroni et al., 2019)

Aim

Human-analogous natural language understanding is a grand challenge and a language model cannot learn "meaning" when it is trained only on form.

What is Meaning ?

What is Meaning ?

Form:

- It is any observable realization of language: marks on a page, pixels, or byte in a digital representation of text, or movements of the articulators

Meaning:

- It is the relation between the form and something external to language

What is Meaning ?

Communicative intent:

- It is something outside of a languages
- They are many types:
  - To convey some information to the other person
  - To ask a person to to do something
  - To socialize

Meaning:

- is the relation $M \subseteq E \times I$
- Which contains pairs *(e, i)* of natural language expressions *e* and the communicative intents *i*
- “Understand” refers to the process of retrieving *i* given *e*

What is Meaning ?

Conventional meaning:

- It is an abstract object that represents the communicative potential of a form

Linguistic system provides a relation:

- $C \subseteq E \times S$
- Which contains pairs *(e, s)* of expressions *e* and their conventional meanings *s*

Like the meaning relation *M, C* connects language to objects outside of the language

What is Meaning ?

Example:

- The photographer asked: “Please, can you do a Napoleon for the camera ?”

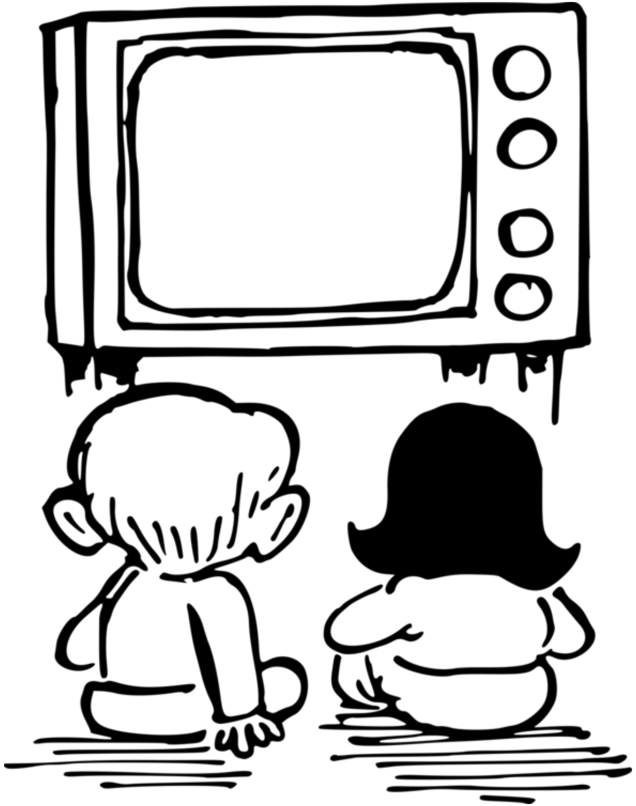
A natural language model that is trained purely on form will not learn meaning.

- There is not sufficient signal to learn:
  - The relation *M* between a form and the non-linguistic intent of human language users
  - The relation *C* between a form and the standing meaning the linguistic systems assigns to each form

To provide some signals to the model :

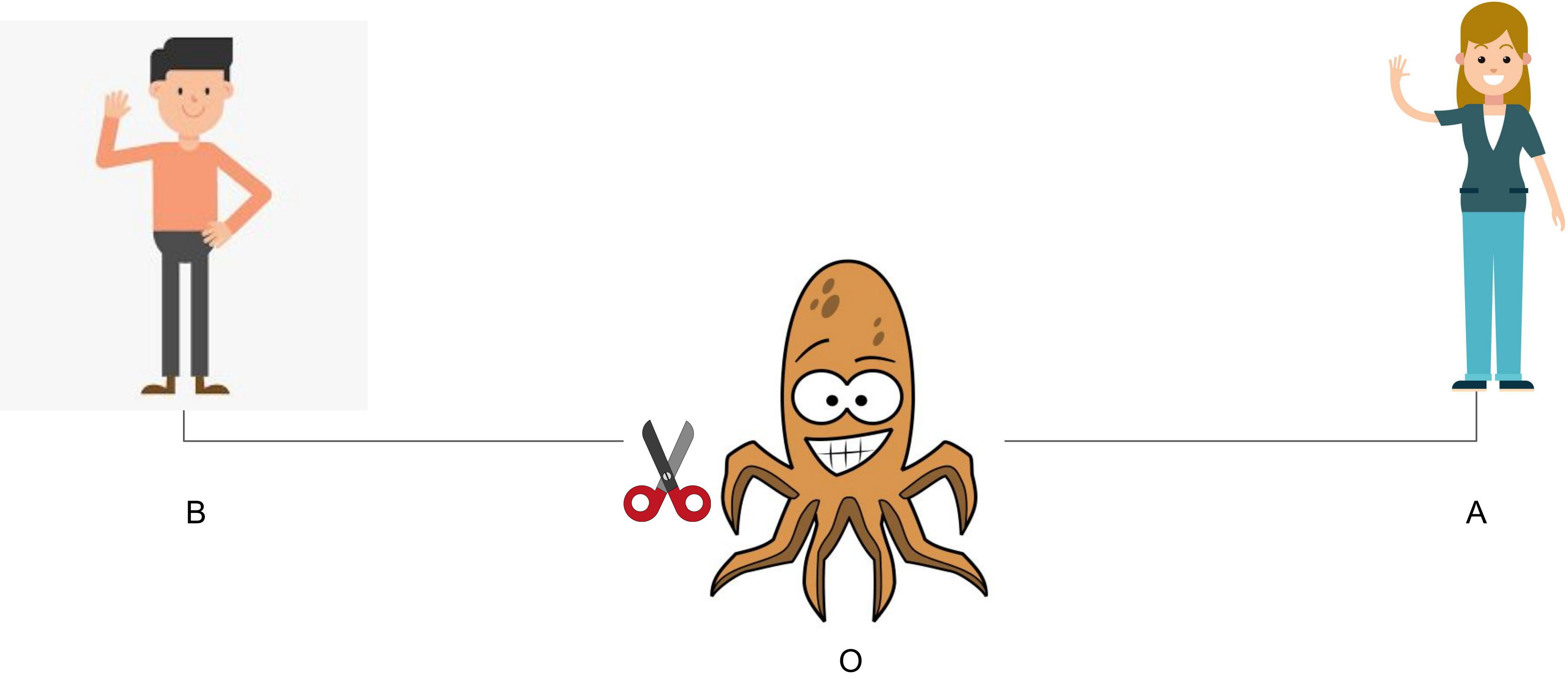
- We have to augment the data with perceptual data such as photos or other modalities
- Interaction data such as dialogue corpus

Human Language Acquisition



The Octopus Test

The Octopus Test



Experiments

Java Program:

- Imagine we trained a language model on all the well-formed Java code published on Github
- Input is only the code
- It is not paired with bytecode, nor a compiler, nor sample inputs and outputs for any specific program

We then ask the model to execute a sample program ???

We expect a correct program output

Right?

Wrong !!!

Experiments

GPT-2 on fighting a bear with sticks:

- **Robinson cried out, “Help! I’m being chased by a bear! All I have is these sticks. What should I do?” The survivalist said, “Here’s what you can do.** Go back to civilization. Take your gun...
- **Robinson cried out, “Help! I’m being chased by a bear! All I have is these sticks. What should I do?” The survivalist said, “Here’s what you can do.** #YouCanDoIt.” Police officers were quick to respond, finding a 3-foot female grizzly bear wandering off a dirt road near the shoreline...
- **Robinson cried out, “Help! I’m being chased by a bear! All I have is these sticks. What should I do?” The survivalist said, “Here’s what you can do.** Place these sticks over your head. Your heart will stop and you will not feel fear...

Experiments

GPT-2 on Arithmetic Operation:

- **Three plus five equals** seven," he replied. "Right, but I think that there should be more points added when our first family get in a power game, and even more when I start speaking like her mother!"...
- **Three plus five equals** ten" Bosh In this case, the conditions only need to be satisfied once, instead of...
- **Three plus five equals** five, right? Right? In the Catholic Church they say they don't look at church history, and no, I'm not going to say that I'm infallible either...

On Climbing the Right Hill

On Climbing the Right Hills

Bottom-up Perspective:

- A scientific results counts as a success if it solves a specific challenge

Top-down Perspective:

- The focus on the remote end goal of offering a complete, unified theory for the entire field

On Climbing the Right Hills

Hillclimbing Diagnostics:

- Ask top-down questions
- Be aware of the limitations of tasks
- Value and support the work of carefully creating new tasks
- Evaluate models of meaning across tasks
- Perform through analysis of both errors and successes

Conclusion

Conclusion

In this paper:

- Argued that model cannot learn the meaning from form alone
- It is call to use the proper language when talking about the success of language models
- Encouraged researchers to have a top-down perspective on NLP

Thank you !!!

Additional Slides

Some Possible Counterarguments

Counterarguments:

- “But” ‘meaning ‘ doesn’t mean what you say it means”
- “But meaning could be learned from …”
- “But there is so much form out there -- surely that is enough”
- “But aren’t neural representations meaning too?”
- “But BERT improves performance on meaning-related tasks, so it must have learned something about meaning”

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