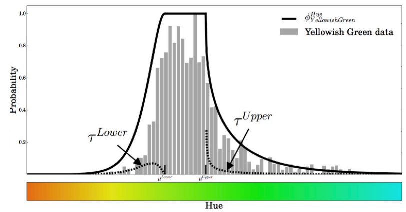
CS388: Natural Language Processing

Lecture 22: Multimodality, Language Grounding

Greg Durrett

TEXAS
The University of Texas at Austin



McMahan and Stone (2015)

Announcements

- FP due April 28
- Presentations on last two class days

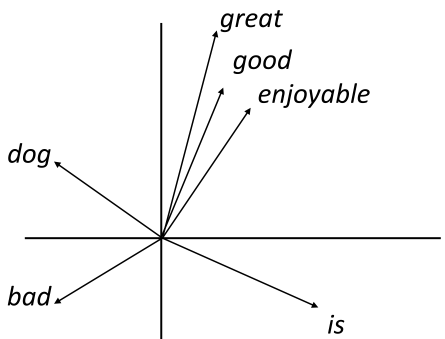
Today's Lecture

- Classic grounding
- Multimodality
- Language and vision models
- Language and manipulation

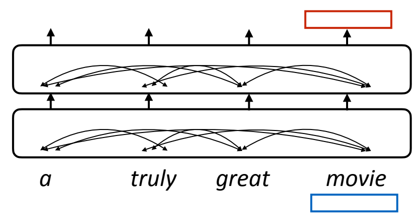
Classic Grounding

Language Grounding

- How do we represent language in our models?
- How did we learn these representations? What do the vectors "mean"?



non-contextualized



contextualized

Language Grounding

- Harnad defines a "symbol system": we have symbols (e.g., strings) manipulated on the basis of rules, and these symbols ultimately have "semantic interpretation"
  - "Fodor (1980) and Pylyshyn (1980, 1984)…emphasize that the symbolic level (for them, the mental level) is a natural functional level of its own, with ruleful regularities that are independent of their specific physical realizations"
- Harnad challenges the idea that fully symbolic approaches can work well.
- Argues that "horse" is something that should be understood bottom-up through grounding. "Zebra" = "horse" + "stripes" could emerge this way, but he claims it cannot through a top-down symbolic system
- What does it mean to "understand" the symbols that get manipulated?

Harnad (1990) *The Symbol Grounding Problem*

Searle's Chinese Room

- Suppose we have someone in a room with a long list of rules, dictionaries, etc. for how to translate Chinese into English. A Chinese string is passed into the room and an English string comes out. The person is not a speaker of Chinese, but merely follows the rules and looks things up in the dictionaries to produce the translation.
- Does the person understand Chinese? Does the room? (the "system"?)
- Searle argues that (a) the room is like an AI system producing Chinese translations; (b) the operator in the room (the AI) does not "understand" Chinese. Harnad summarizes :

The interpretation will not be intrinsic to the symbol system itself: It will be parasitic on the fact that the symbols have meaning for us, in exactly the same way that the meanings of the symbols in a book are not intrinsic, but derive from the meanings in our heads.

Searle (1980)

Language Grounding

- Bender and Koller separate form and meaning. Meaning = communicative intent. The role of the speaker/listener are crucial in language, LMs lack the underlying intent
- They propose the "octopus" experiment to show how form alone can fail.
  An octopus is eavesdropping on a conversation between A and B (using deep-sea communication cables). Suddenly, the octopus decides to cut the cable and impersonate B.
- A has an emergency and asks how to construct something with sticks to fend off a bear. The octopus can't help because it can't simulate this novel situation.

Bender and Koller (2020) *Climbing towards NLU*

Counterarguments

- We can't necessarily learn semantics from predicting next characters alone without execution. Consider training on:

```
x = 2
y = x + 2
print(y)
```

- **However**, assertion statements are sufficient to teach us some semantics! (but this can still break down)

```
x = 2
y = x + 2
assert(y == 4)
```

- For language: similar argument. Assume people say true things. Consider saying a pair of sentences x_1, x_2; given enough examples, the fact that x_2 should not be contradicted by x_1 tells us something

Merrill et al. (2021) *Provable Limitations of Acquiring Meaning from Ungrounded Form*

Merrill et al. (2022) *Entailment Semantics can be Extracted from an Ideal Language Model*

Where are we?

- Lots of philosophy about these models!
- Nevertheless, it seems there's a hierarchy in terms of their understanding:

pure LM < LM fine-tuned on supervised data

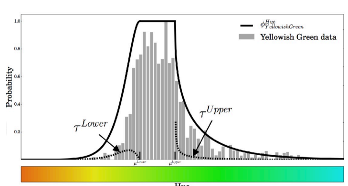
pure LM < vision+language LM < vision+language+manipulation LM < ...

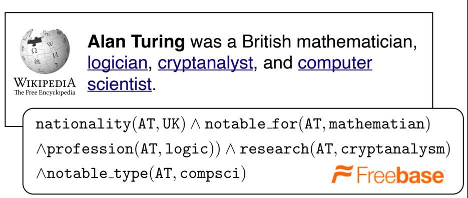
GPT-4 is here! (↑ vision+language LM)

PaLM-E (later) (↑ vision+language+manipulation LM)

Language Grounding

- There are many things that we can ground language in! Focus on vision today.
- How to associate words with sensory-motor experiences
- How to associate words with meaning representation



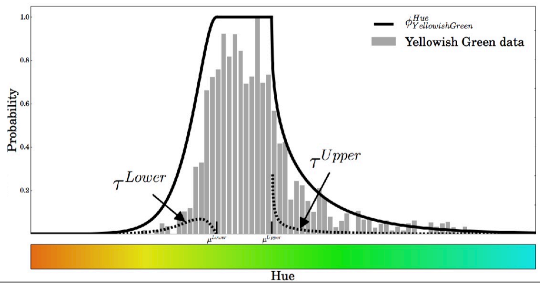


Multimodality, Language Grounding

some slides from Eunsol Choi

Language Grounding

- What does "yellowish green" mean?
- Formal semantics: yellowish green is a predicate. Things are either yellowish green or not. No connection to real color
- Grounding in perceptual space:

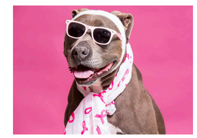


McMahan and Stone (2015)

Perception

- Visual: *green* = [0,1,0] in RGB
- Auditory: *loud* = >120 dB
- Taste: sweet = >some threshold level of sensation on taste buds
- High-level concepts:


cat


dog


running


eating

Learning from Interaction

1. Use feedback from control application to understand language

Walk across the bridge

Reward +1

Alleviate dependence on large scale annotation

2. Use language to improve performance in control applications


Score: 7


+

1. **Ghosts** chase and try to kill you
2. Collect all the **pellets**
3. …

Score: 107

Other Grounding

- **Temporal concepts**
  - *late evening* = after 6pm. Ground in a time interval
  - *fast, slow* = describing rates of change
- **Spatial Relations**
  - *left, on top of, in front of*: how should we ground these?
- **Functional:**
  - *Jacket:* keeps people warm
  - *Mug*: holds water
- **Size:**
  - Whales are *larger* than lions
- **Focus today: grounding in images**

Language and Vision Models

Grounding in Images

- How would you describe this image?

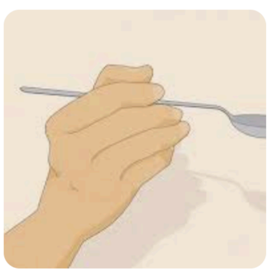
- What does the word "*spoon*" evoke?

the girl is licking the spoon of batter

Grounding Spoon

Winco 0005-03 7 3/8" Dinner Spoon...

$7.16



wikiHow

How to Hold a Spoon: 13 Steps (...

GO Indiegogo

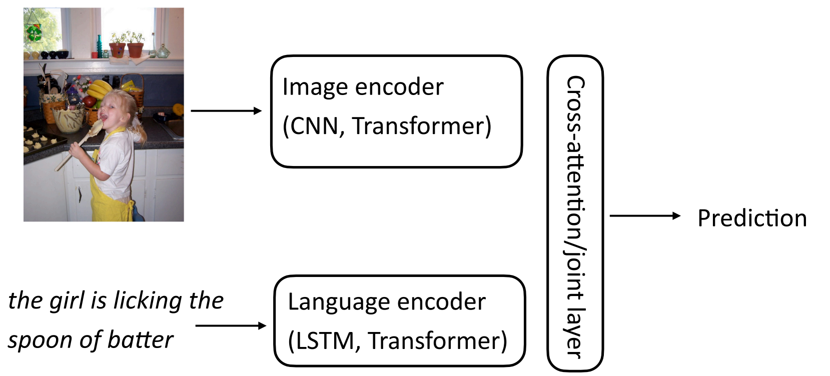
Spoon that Elevates Taste ...

Grounding Language in Images

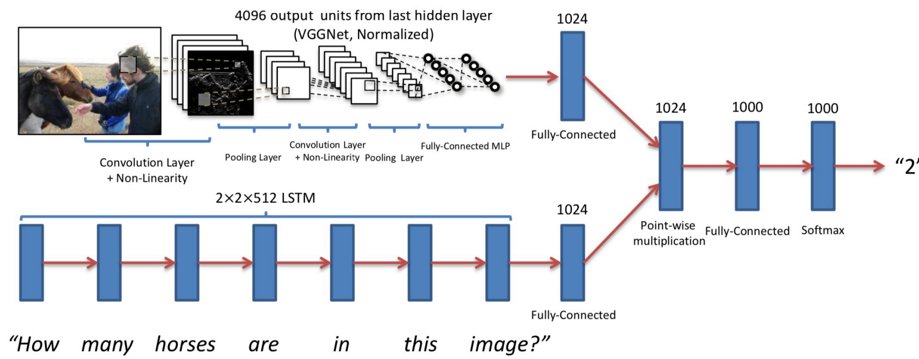
- Syntactic categories have some regular correspondences to the world:
  - Nouns: objects
  - Verbs: actions
  - Sentences: whole scenes or things happening

- Tasks:
  - Object recognition (pick out one most salient object or detect all of them)
  - Image captioning: produce a whole sentence for an image

Language-vision Models



Visual Question Answering



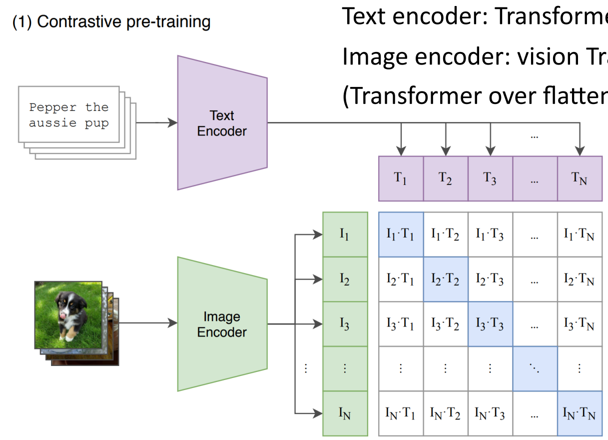
Agrawal et al., 2015

Language-vision Pre-training

Text encoder: Transformer

Image encoder: vision Transformer

(Transformer over flattened patches)



Radford et al., 2021

Language-vision Pre-training

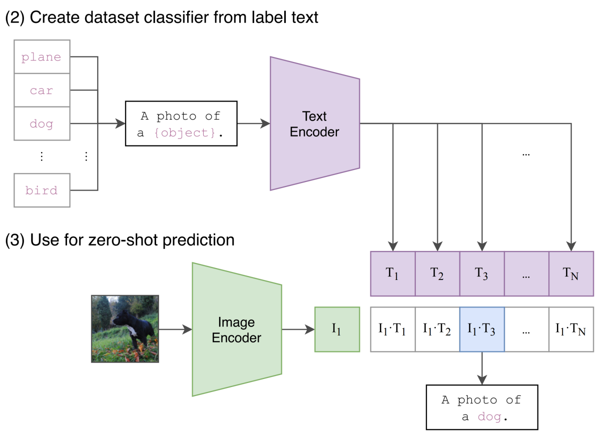
	T_1	T_2	T_3	...	T_N
I_1	$I_1 \cdot T_1$	$I_1 \cdot T_2$	$I_1 \cdot T_3$	...	$I_1 \cdot T_N$
I_2	$I_2 \cdot T_1$	$I_2 \cdot T_2$	$I_2 \cdot T_3$	...	$I_2 \cdot T_N$
I_3	$I_3 \cdot T_1$	$I_3 \cdot T_2$	$I_3 \cdot T_3$	...	$I_3 \cdot T_N$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
I_N	$I_N \cdot T_1$	$I_N \cdot T_2$	$I_N \cdot T_3$	...	$I_N \cdot T_N$

- Contrastive objective: each image should be more similar to its correspond caption than to other captions

$$\text{maximize } \mathrm{softmax}(I_1^T T_i)[1] + \mathrm{softmax}(I_2^T T_i)[2] + \ldots$$

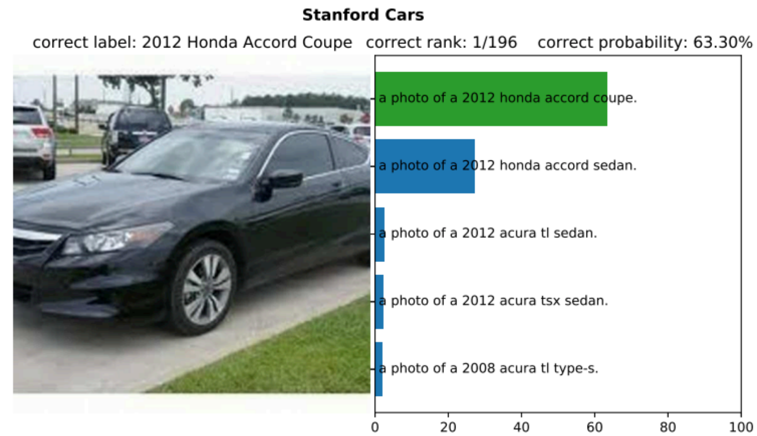
Radford et al., 2021

Language-vision Pre-training

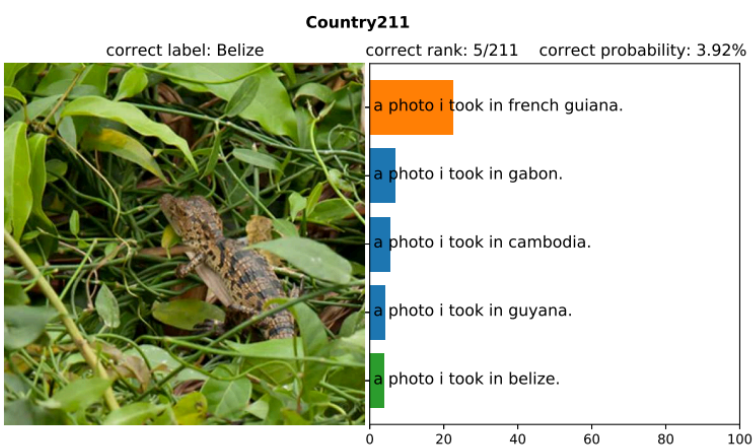


Radford et al., 2021

CLIP: Zero-shot Results



CLIP: Zero-shot Results



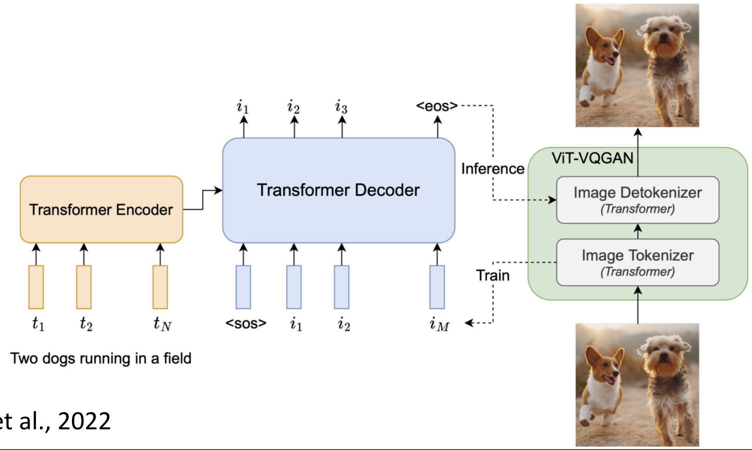
Parti

- Autoregressive text-to-image model (differs from the diffusion models you may have seen, like Stable Diffusion or DALL-E)

A. *A photo of a frog reading the newspaper named "Toaday" written on it. There is a frog printed on the newspaper too.*

Yu et al., 2022

Parti



Yu et al., 2022

Manipulation: SayCan, PaLM-E

SayCan

- Most models like CLIP are just vision+language. What about interaction with the world?

SayCan

- Probability of taking an action decomposes as follows:

$$p(c_i|i, s, \ell_\pi) \propto p(c_\pi|s, \ell_\pi)p(\ell_\pi|i)$$

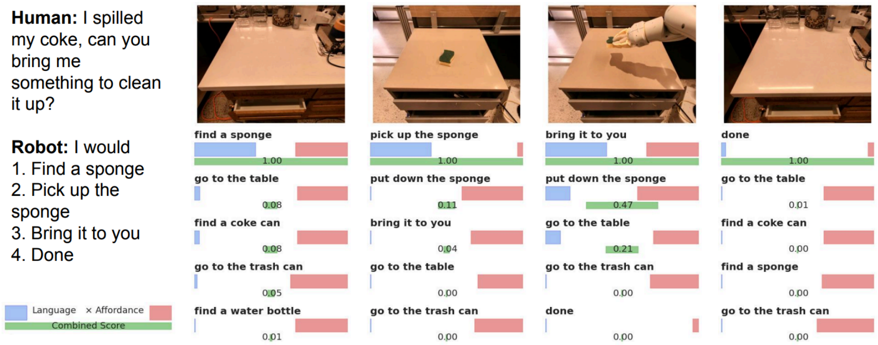
p(skill possible given world state) p(language description of skill | instruction)

- Individual skills are learned in advance, form affordance models for that skill
- Train a single multi-task policy that conditions on the lang description
- Do you think this is a grounded language model?

SayCan

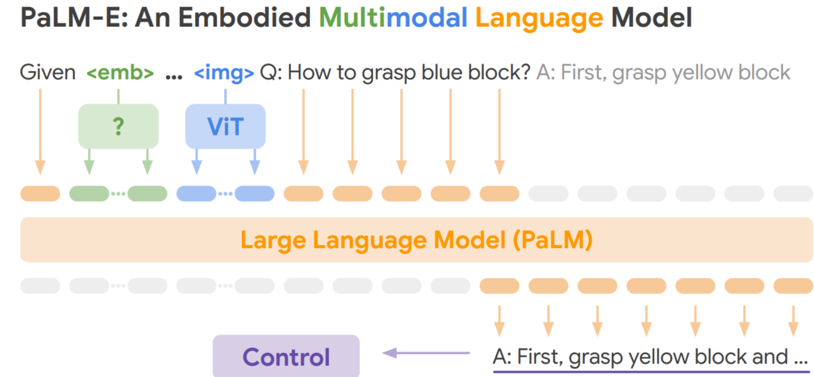
Human: I spilled my coke, can you bring me something to clean it up?

Robot: I would
1. Find a sponge
2. Pick up the sponge
3. Bring it to you
4. Done

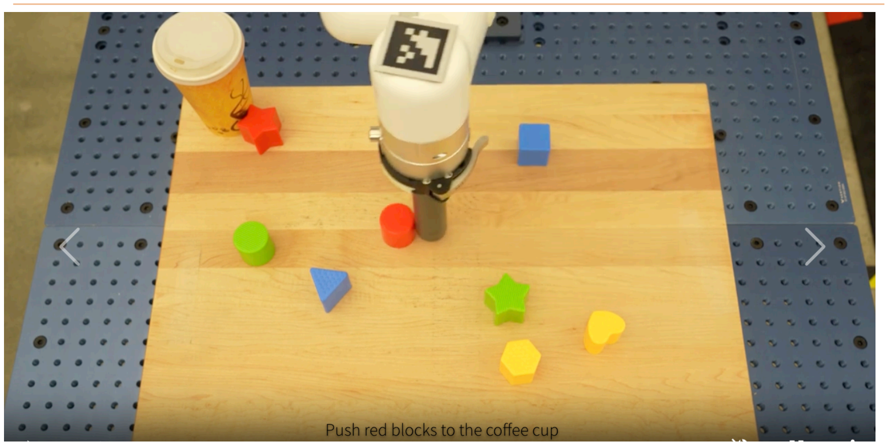


PaLM-E

- Most models like CLIP are just vision+language



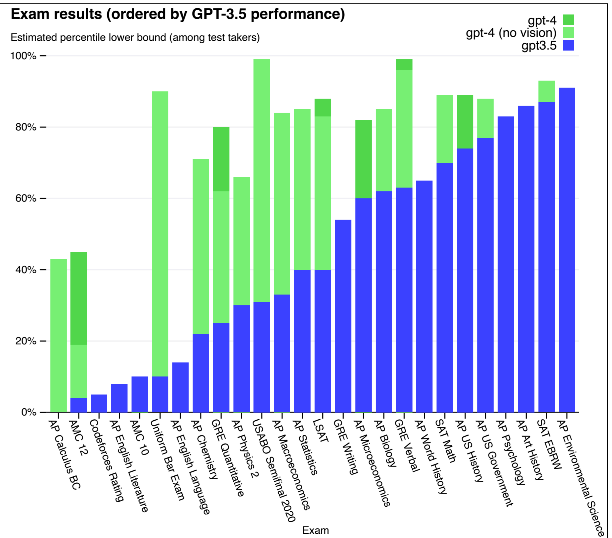
PaLM-E



Where are we today

- Explosion of multimodal pre-training for {video, audio, images, interaction} x text
- Many of these methods are Transformer-based
- Still haven't seen large-scale multimodal pre-training of this form advance text-only tasks, but there's potential!
- Impact of images on GPT-4 is unclear

GPT-4



- Dark green: additional performance from vision pre-training
- This graph is hard to read and doesn't make sense…

Takeaways

- Is the lack of grounding in text-only pre-trained models a problem?
- Multimodal methods can allow us to learn representations for images as well as text and provide a path towards language grounding
- Pre-training on text and other modalities is more and more common and unlocking new capabilities for models