TALM and the state of Tool-Use

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Agenda

- 1. Why tool-use
- 2. TALM overview
- 3. Lessons learned
- 4. The future of tool-use

Why tool-use?

Lots of obvious reasons

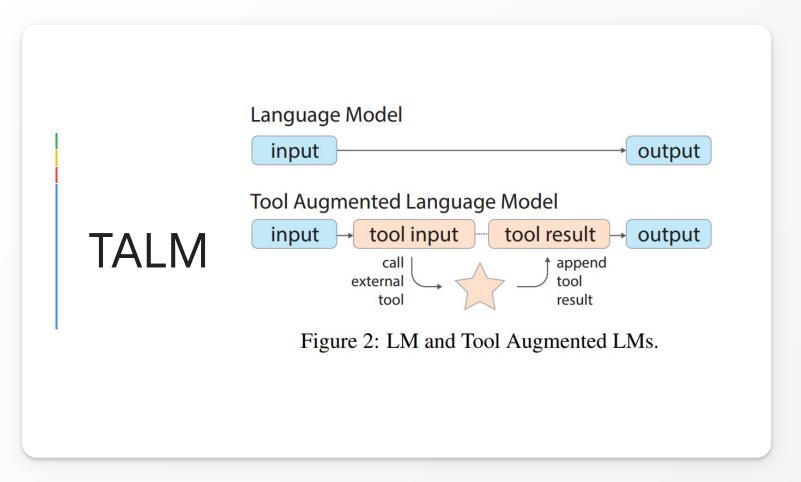
- Modularity
- Offloads computations / functions
- **Parameter efficiency** fewer computations, simpler computations -> fewer parameters needed

Oh yeah and I do suppose

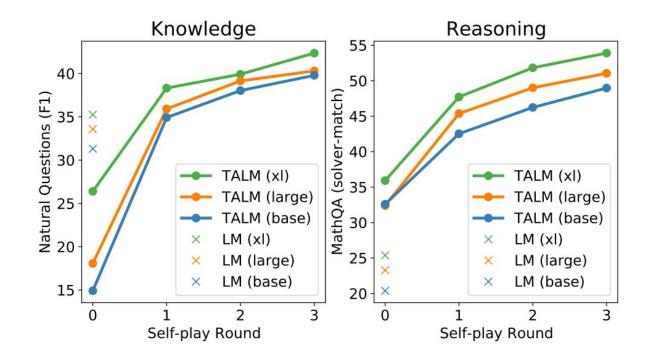
- It's one of the hallmarks of sapient intelligence on Earth
- Tools are essential for addressing the shortcomings of any "thinking system"

The progress of tool-use

- Markov Decision Processes (MDPs) expose
 discrete actions
 - Heirarchical MDPs allow for parametric tool use
- Custom models (fuzzy logic, RL agents, domain specific languages) for parametric tool-use
- Language models expand sequence modelling (MDP representation) capabilities
- TALM goes here
- Few-shot / 0-shot prompting
- Language models begin composing more robust API calls



Results overview



Algorithm Overview

- Expert Iteration
- Obvious Drawbacks: Search space increases exponentially as the induced MDP expands (more tools / steps -> exponentially growing search space)
 - REINFORCE with binary reward signal (good vs bad outcome) is a heavily biased estimator

<i>x</i> : task input, <i>y</i> : task output, <i>t</i> : tool input, <i>r</i> : tool output		
1: T	$= \{x_i, y_i\}_T$	# task set
2: <i>D</i>	$=\{x_j,t_j,r_j,y_j\}_D$	# tool-use set
3: P_{θ}	$\leftarrow pretrained \ LM$	
4: fo	$t \in [0,1,,R]$ do	<pre># self-play rounds</pre>
5:		# finetune LM
6:	$\theta \leftarrow \operatorname*{argmax}_{\theta} \prod_{D} P_{\theta}(y_j x_j, t_j)$	$,r_{j})P_{ heta}(t_{j} x_{j})$
7 : 1	for $x_i, y_i \in T$ do	# iterate task set
8:	for $n \in [0,1,,N]$ do	
9:	$t_n \leftarrow P_\theta(t x_i)$	# sample tool query
10:	$r_n \leftarrow Tool(t_n)$	# call tool API
11:	$y_n \leftarrow P_{\theta}(y x_i, t_n, r_n)$	# get task output
12:	if $ y_n - y_i < th$ then	# filter wrong output
13:	$D \leftarrow D \cup \{x_i, t_n, r_n, y_n\}_1$	
14:		# update tool-use set

Algorithm 1 Iterative Self-Play Algorithm

Lessons Learned

A bitter lesson

- Shortly after publishing TALM, instruct-tuned models really became a thing
- Why go through such an exhaustive search procedure when few-shot/O-shot/prompt tuning methods work?
 - This method only really makes sense for smaller models that don't benefit from prompting methods.
- **Furthermore**, we found that larger language models need significantly fewer finetuning examples to be able to learn tool-use without few-shot examples!

A useful tech demo

- Bootstrapping works!
- **Toolformer** obvious extension to our work
 - Let's augment the loss function with a reward function that tries to signal the causal effects of tool-use at a given timestep
 - This is similar to augmenting the binary self-play reward signal to be less biased towards cases where the model would succeed without tool-use
- Smaller models can **reliably bootstrap their own performance** for simple tasks, dependent almost entirely on the performance of the search procedure

The state, and future of tool-use

Tool-Use and Large Models

- Few-shot/zero-shot/prompt-tuning for large models
 - Open Questions:
 - How do we get LLMs to handle arbitrary, increasingly complex tools?

Tool-Use and Small Models

- Data augmentation via self-play for small models?
 - **Open Questions:**
 - How do we prevent the search space from growing exponentially?
 - More robust data augmentation, representations?
 - Can small models compose like big models?

Conclusion and Q&A

Both large and small models benefit from sampling/training algorithmic improvements! Stay tuned for some exciting advancements from GDM, of course!

[specifically, look forward to a paper addressing the shortcomings of outcome-based (binary reward) RL on implicit MDPs]

[and maybe get my personal contact info too:

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