Natural Language Processing with Deep Learning

CS224N/Ling284

Shikhar Murty

Lecture 14: Reasoning and Agents

Lecture Plan

Lecture 14: Reasoning and Agents

1. Reasoning in Language Models [35 mins]
2. Mini-break [5 mins]
3. Language Model Agents [40 mins]

- Announcements
  - Project Milestone due on Wed May 22nd at 4:30 pm
  - Your Project Mentors have already reached out to you (If not, let us know via Ed!)
  - Guest lectures on May 21st and May 28th : Students get 0.75% per guest lecture for attending live or writing a reaction paragraph (More details will be on Ed)

Disclaimer: Content for today is an active area of research and still emerging.

Reasoning
(with Large Language Models)

What is Reasoning?

Using ***facts*** and ***logic*** to arrive at an answer

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Deductive Reasoning: Use logic to go from premise to firm conclusion

Premise: All mammals have kidneys
Premise: All whales are mammals
Conclusion: All whales have kidneys

Slide credit: Graham Neubig (11-711 ANLP)

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Observation: When we see a creature with wings, it is usually a bird
Observation: We see a creature with wings.
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Observation: We see a creature with wings.
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Abductive Reasoning: From observation, predict the most likely explanation

Observation: The car cannot start and there is a puddle of liquid under the engine.
Likely Explanation: The car has a leak in the radiator

Slide credit: Graham Neubig (11-711 ANLP)

Reasoning: Formal vs Informal

Formal Reasoning: Follows formal rules of logic along with axiomatic knowledge to derive conclusions.

Informal Reasoning: Uses intuition, experience, common sense to arrive at answers.

For most of this lecture, by “reasoning” we mean informal deductive reasoning, often involving multiple steps

Slide credit: Graham Neubig (11-711 ANLP)

Reasoning in Large Language Models

Large Language models are **REALLY GOOD** at predicting **plausible continuations of text (Lecture-9)**, that respect **constraints in the input (Lecture 10,11)**, and align **well with human preferences (Lecture-10, 11)**.

Question: Can current LLMs reason?

Reasoning in Large Language Models: prompting

Chain-of-thought prompting:

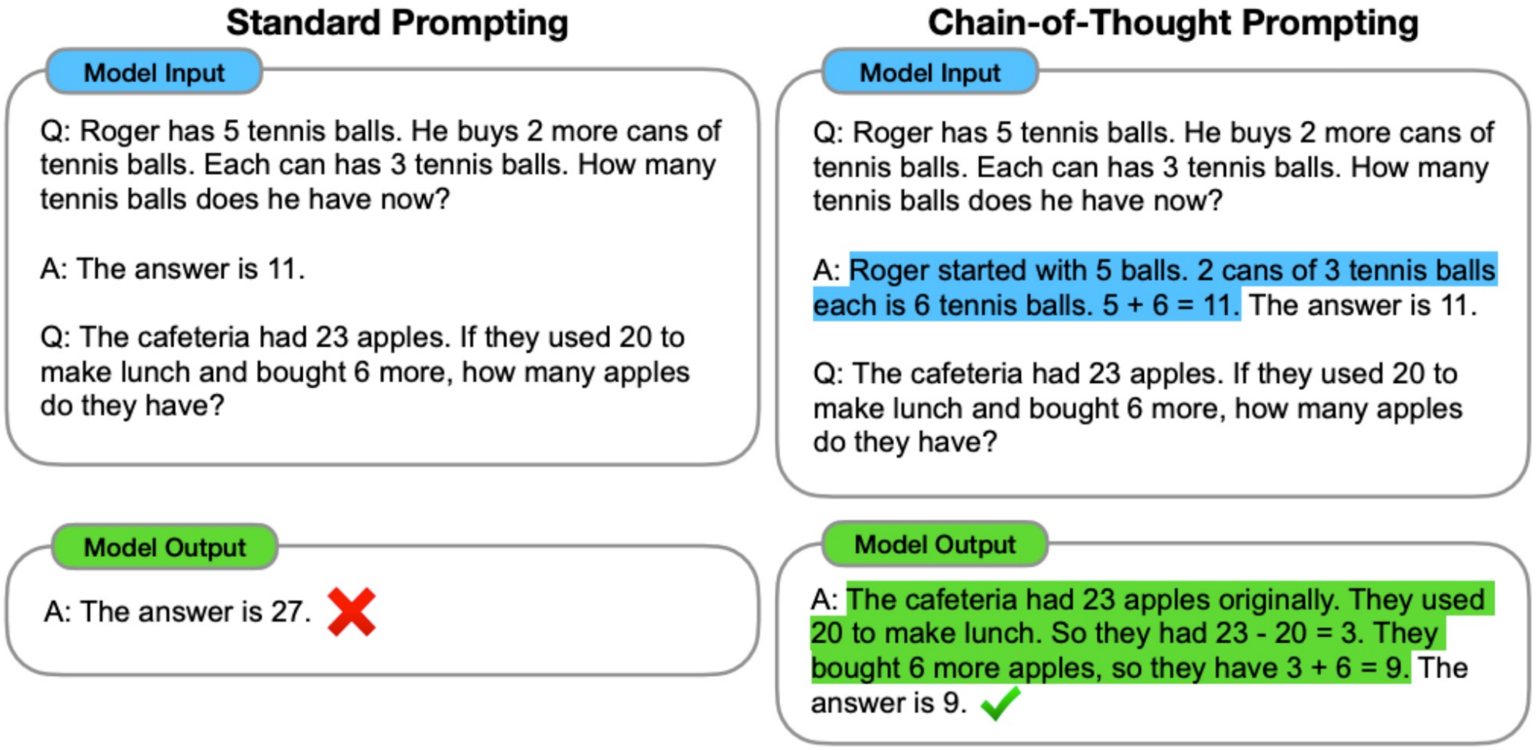
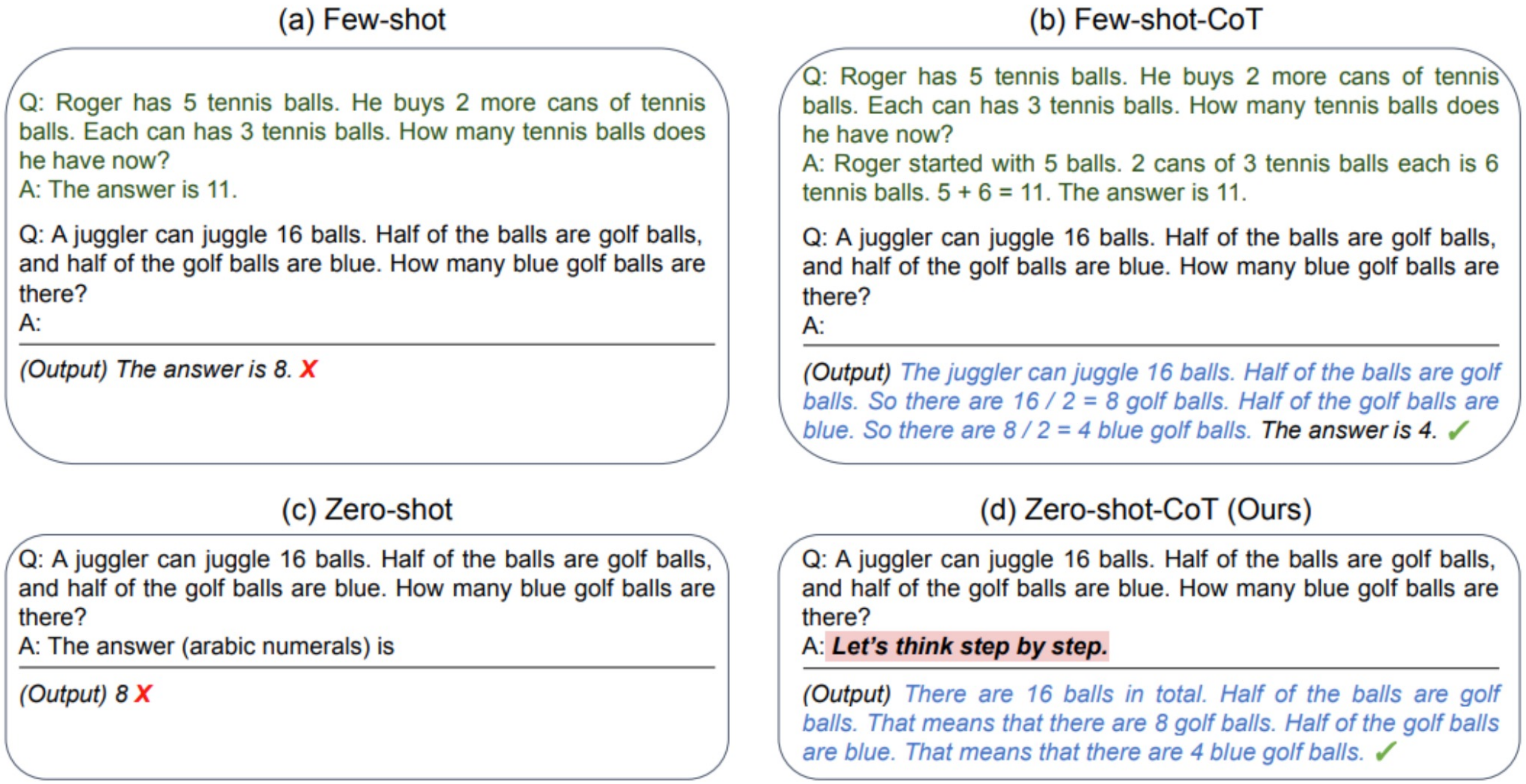


Figure 1: Chain-of-thought prompting enables large language models to tackle complex arithmetic, commonsense, and symbolic reasoning tasks. Chain-of-thought reasoning processes are highlighted.

Source: Wei et al. 2023

Reasoning in Large Language Models: prompting

Zero-shot CoT prompting:

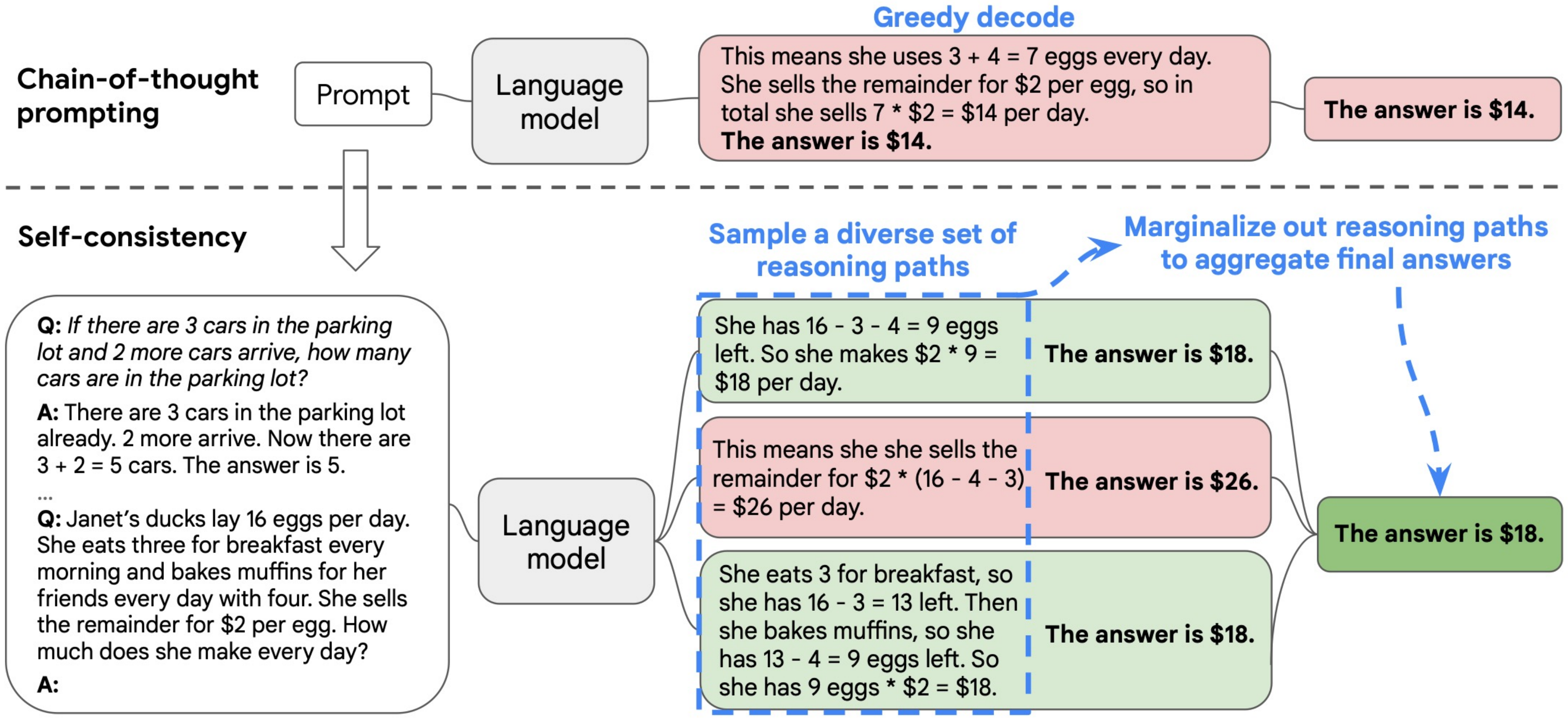


Source: Kojima et al. 2023

Reasoning in Large Language Models: prompting

CoT with "Self-consistency”: Replace greedy decoding with an ensemble of samples…

Main idea: correct reasoning processes have greater agreement than incorrect processes.



Source: Wang et al. 2023

Reasoning in Large Language Models: prompting

	Method	AddSub	MultiArith	ASDiv	AQuA	SVAMP	GSM8K
	Previous SoTA	**94.9**[a]	60.5[a]	75.3[b]	37.9[c]	57.4[d]	35[e] / 55[g]
UL2-20B	CoT-prompting	18.2	10.7	16.9	23.6	12.6	4.1
	Self-consistency	24.8 (+6.6)	15.0 (+4.3)	21.5 (+4.6)	26.9 (+3.3)	19.4 (+6.8)	7.3 (+3.2)
LaMDA-137B	CoT-prompting	52.9	51.8	49.0	17.7	38.9	17.1
	Self-consistency	63.5 (+10.6)	75.7 (+23.9)	58.2 (+9.2)	26.8 (+9.1)	53.3 (+14.4)	27.7 (+10.6)
PaLM-540B	CoT-prompting	91.9	94.7	74.0	35.8	79.0	56.5
	Self-consistency	93.7 (+1.8)	99.3 (+4.6)	81.9 (+7.9)	48.3 (+12.5)	86.6 (+7.6)	74.4 (+17.9)

Out-performs regular CoT on a variety of benchmarks

Source: Wang et al. 2023

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Out-performs regular CoT on a variety of benchmarks

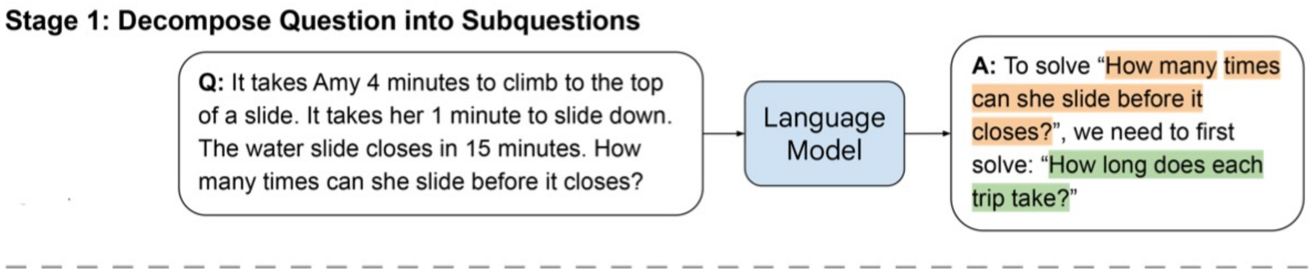
	GSM8K	MultiArith	SVAMP	ARC-e	ARC-c
CoT (Wei et al., 2022)	17.1	51.8	38.9	75.3	55.1
Ensemble (3 sets of prompts)	18.6 $\pm$ 0.5	57.1 $\pm$ 0.7	42.1 $\pm$ 0.6	76.6 $\pm$ 0.1	57.0 $\pm$ 0.2
Ensemble (40 prompt permutations)	19.2 $\pm$ 0.1	60.9 $\pm$ 0.2	42.7 $\pm$ 0.1	76.9 $\pm$ 0.1	57.0 $\pm$ 0.1
Self-Consistency (40 sampled paths)	**27.7** $\pm$ **0.2**	**75.7** $\pm$ **0.3**	**53.3** $\pm$ **0.2**	**79.3** $\pm$ **0.3**	**59.8** $\pm$ **0.2**

Self-consistency is doing more than simple ensembling

Source: Wang et al. 2023

Reasoning in Large Language Models: prompting

Problem decomposition with Least-to-Most prompting



Source: Zhou et al. 2023

Reasoning in Large Language Models: prompting

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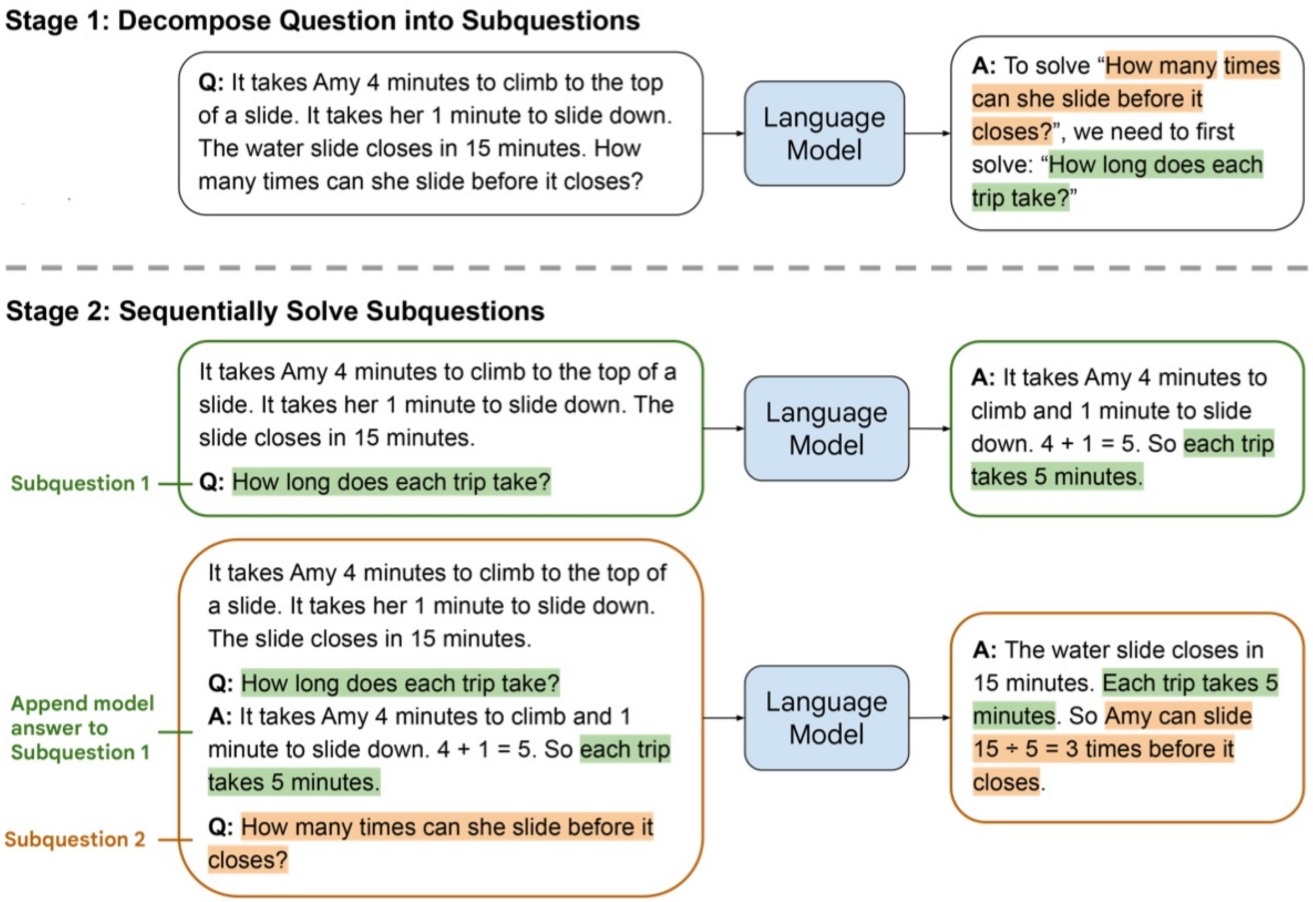

Source: Zhou et al. 2023

Reasoning in Large Language Models: prompting

Least-to-Most prompting for Math reasoning

Standard CoT prompting

Q: Elsa has 5 apples. Anna has 2 more apples than Elsa. How many apples do they have together?
A: Anna has 2 more apples than Elsa, so Anna has 2 + 5 = 7 apples. Elsa and Anna have 5 + 7 = 12 apples together. The answer is 12.

Least-to-most prompting

Q: Elsa has 5 apples. Anna has 2 more apples than Elsa. How many apples do they have together?
A: Let's break down this problem: 1. How many apples does Anna have? 2. How many apples do Elsa and Anna have together?
1. Anna has 2 more apples than Elsa. So Anna has 2 + 5 = 7 apples.
2. Elsa and Anna have 5 + 7 = 12 apples together.

Q: {question}
A: Let's break down this problem:
——
The answer is:

Source: Zhou et al. 2023

Reasoning in Large Language Models: prompting

Least-to-Most prompting for Math reasoning

Accuracy by Steps (GSM8K)	All	2 Steps	3 Steps	4 steps	$\geq$ 5 steps
Least-to-Most	**62.39**	74.53	**68.91**	**59.73**	**45.23**
Chain-of-Thought	60.87	**76.68**	67.29	59.39	39.07

Generalizes to more #steps than in-context example!

Source: Zhou et al. 2023

Reasoning in Large Language Models: prompting

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Generalizes to more #steps than in-context example!

Prompting method	**Accuracy**
Zero-Shot	16.38
Standard prompting	17.06[3]
Chain-of-Thought (original)	61.18
Chain-of-Thought (1-shot)	60.88
Least-to-Most (1-shot)	62.39
Chain-of-Thought (best)	**68.61**[3]
Least-to-Most (best)	68.01

But with enough prompt engineering, CoT $\approx$ Least-to-Most

Source: Zhou et al. 2023

Reasoning in ~~Large~~ Language Models via distillation

So far, we've only looked at prompting >100B parameter models for reasoning

Can we get reasoning-like behavior with smaller LMs by teaching them to imitate larger models?

Orca: Instruction-tuning small LMs with CoT Rationales

1. Collect a wide variety of instructions from the FLAN-v2 collection

Mixture Name	Sampling Algorithm	Original Size	Sampled
CoT	No Sampling	150K	150K
NIV2	Stratified Sampling	5M	440K
FLAN2021	Stratified Sampling	>28.9M	2.5M
T0	Stratified Sampling	85.7M	2M
Dialog	Skipped	22.5M	0

Table 3: Construction of our training data with 5 million samples.

Source: Mukherjee et al. 2023

Orca: Instruction-tuning small LMs with CoT Rationales

1. Collect a wide variety of instructions from the FLAN-v2 collection.
2. Prompt GPT4 or ChatGPT with these instructions along with a system message

System Instruction: You are an AI assistant. User will you give you a task. Your goal is to complete the task as faithfully as you can. While performing the task think step-by-step and justify your steps.

User Instruction: Use the given data to calculate the median.

Input: [7, 3, 8, 2, 10]

Output: To calculate the median, I will follow these steps:
Step 1: Arrange the data in ascending order [2, 3, 7, 8, 10]
Step 2: Determine if the data set has an odd or even number of values
The data set has 5 values, which is an odd number.
Step 3: Find the middle value

Since the data set has an odd number of values, the median is the middle value in the ordered list. The middle value in the list [2, 3, 7, 8, 10] is 7.

Source: Mukherjee et al. 2023

Orca: Instruction-tuning small LMs with CoT Rationales

1. Collect a wide variety of instructions from the FLAN-v2 collection.
2. Prompt GPT4 or ChatGPT with these instructions along with a system message
3. Finetune Llama-13b on outputs generated via ChatGPT + GPT4

Orca: Instruction-tuning small LMs with CoT Rationales

Evaluation: *BigBench-hard*, a collection of 23 Big-Bench tasks with a special focus on multi-step reasoning

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Boolean Expressions

Q: True and False and not True and True is
A: Let's think step by step.
Remember that (i) expressions inside brackets are always evaluated first and that (ii) the order of operations from highest priority to lowest priority is "not", "and", "or", respectively.
We first simplify this expression "Z" as follows: "Z = True and False and not True and True = A and B" where "A = True and False" and "B = not True and True".
Let's evaluate A: A = True and False = False.
Let's evaluate B: B = not True and True = not (True and True) = not (True) = False.
Plugging in A and B, we get: Z = A and B = False and False = False. So the answer is False.

Source: Suzgun et al. 2022

Orca: Instruction-tuning small LMs with CoT Rationales

Evaluation: BigBench-hard, a collection of 23 Big-Bench tasks with a special focus on multi-step reasoning

Data Understanding

Q: Tomorrow is 11/12/2019. What is the date one year ago from today in MM/DD/YYYY?
Options:
(A) 09/04/2018
(B) 11/11/2018
(C) 08/25/2018
(D) 11/02/2018
(E) 11/04/2018
A: Let's think step by step.
If tomorrow is 11/12/2019, then today is 11/11/2019. The date one year ago from today is 11/11/2018. So the answer is **(B).**

Source: Suzgun et al. 2022

Orca: Instruction-tuning small LMs with CoT Rationales

Evaluation: BigBench-hard, a collection of 23 Big-Bench tasks with a special focus on multi-step reasoning

Geometric Shapes

Q: This SVG path element <path d="M 14.19,26.04 L 51.43,39.21 L 58.44,36.69 L 56.63,30.17 L 48.53,26.66 L 14.19,26.04"/> draws a
Options:
(A) circle
(B) heptagon
(C) hexagon
(D) kite
(E) line
(F) octagon
(G) pentagon
(H) rectangle
(I) sector
(J) triangle
A: Let's think step by step.
This SVG path element contains "M" and "L" commands. M takes two parameters (x,y) and moves the current point to the coordinates (x,y). L takes two parameters (x,y) and draws a line from the previous coordinate to the new coordinate (x,y).
This path can be decomposed into 6 separate commands.
(1) M 14.19,26.04: Move the current point to 14.19,26.04.
(2) L 51.43,39.21: Create a line from 14.19,26.04 to 51.43,39.21.
(3) L 58.44,36.69: Create a line from 51.43,39.21 to 58.44,36.69.
(4) L 56.63,30.17: Create a line from 58.44,36.69 to 56.63,30.17.
(5) L 48.53,26.66: Create a line from 56.63,30.17 to 48.53,26.66.
(6) L 14.19,26.04: Create a line from 48.53,26.66 to 14.19,26.04.
This SVG path starts at point 14.19,26.04, creates five consecutive and touching lines, and then returns back its starting point, thereby creating a five-sided shape. It does not have any curves or arches. "pentagon" is the only five-sided polygon on the list.
So the answer is **(G).**

Source: Suzgun et al. 2022

Orca: Instruction-tuning small LMs with CoT Rationales

Task	ChatGPT	GPT-4	Vicuna-13B	Orca-13B
Boolean Expressions	82.8	77.6	40.8	**72.0** (76.5%)
Causal Judgement	57.2	59.9	42.2	**59.9** (41.8%)
Date Understanding	42.8	74.8	10.0	**50.0** (400.0%)
Disambiguation QA	57.2	69.2	18.4	**63.6** (245.7%)
Formal Fallacies	53.6	64.4	47.2	**56.0** (18.6%)
Geometric Shapes	25.6	40.8	3.6	**20.8** (477.8%)
Hyperbaton	69.2	62.8	44.0	**64.0** (45.5%)
Logical Deduction (5 objects)	38.8	66.8	4.8	**39.6** (725.0%)
Logical Deduction (7 objects)	39.6	66.0	1.2	**36.0** (2900.0%)
Logical Deduction (3 objects)	60.4	94.0	16.8	**57.6** (242.9%)
Movie Recommendation	55.4	79.5	43.4	**78.3** (80.6%)
Navigate	55.6	68.8	46.4	**57.6** (24.1%)
Penguins in a Table	45.9	76.7	15.1	**42.5** (181.8%)
Reasoning about Colored Objects	47.6	84.8	12.0	**48.4** (303.3%)
Ruin Names	56.0	89.1	15.7	**39.5** (151.2%)
Salient Translation Error Detection	40.8	62.4	2.0	**40.8** (1940.0%)
Snarks	59.0	87.6	28.1	**62.4** (122.0%)
Sports Understanding	79.6	84.4	48.4	**67.2** (38.8%)
Temporal Sequences	35.6	98.0	16.0	**72.0** (350.0%)
Tracking Shuffled Objects (5 objects)	18.4	25.2	9.2	**15.6** (69.6%)
Tracking Shuffled Objects (7 objects)	15.2	25.2	5.6	**14.0** (150.0%)
Tracking Shuffled Objects (3 objects)	31.6	42.4	23.2	**34.8** (50.0%)
Web of Lies	56.0	49.6	41.2	**51.2** (24.3%)
Average	48.9	67.4	23.3	**49.7** (113.7%)

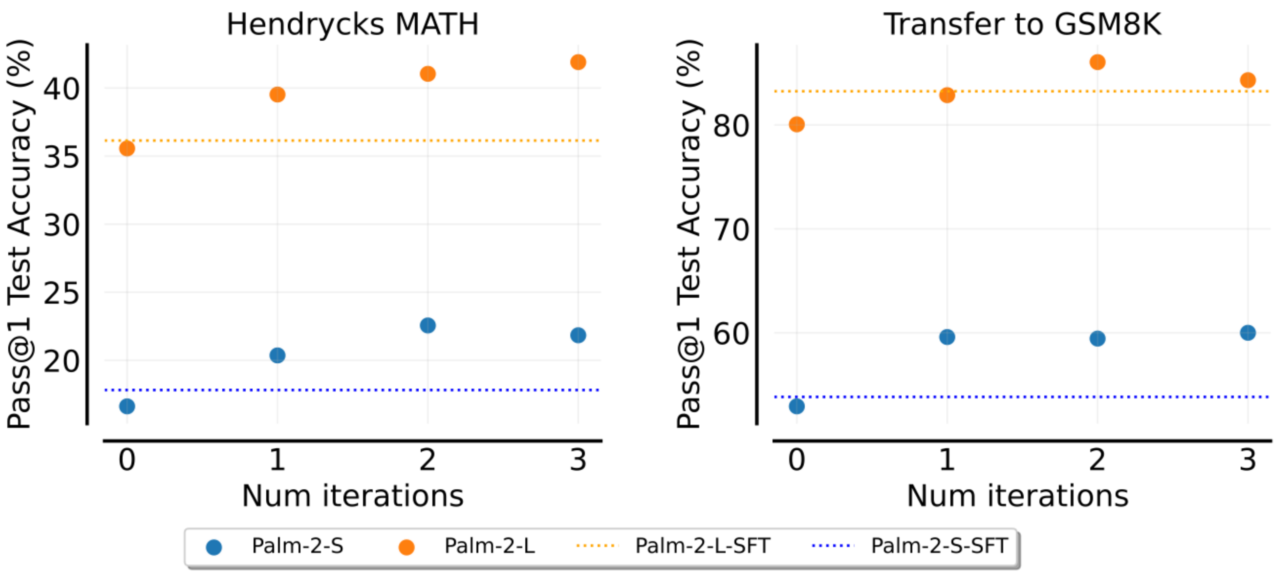
- Outperforms Vicuna-13B
- Outperforms ChatGPT!
- GPT-4 has potential data contamination issues with Bigbench-hard

Source: Mukherjee et al. 2023

Reasoning by Finetuning LMs on their own outputs?

ReST^{EM} alternates between the following two steps:

1. `Generate (E-Step):` Given reasoning problem, sample multiple solutions from language model. Filter based on some (problem specific) function [answer correctness for math problems]
2. `Improve (M-Step):` Update the language model to maximize probability of filtered solutions, using supervised finetuning



Source: Singh et al. 2024

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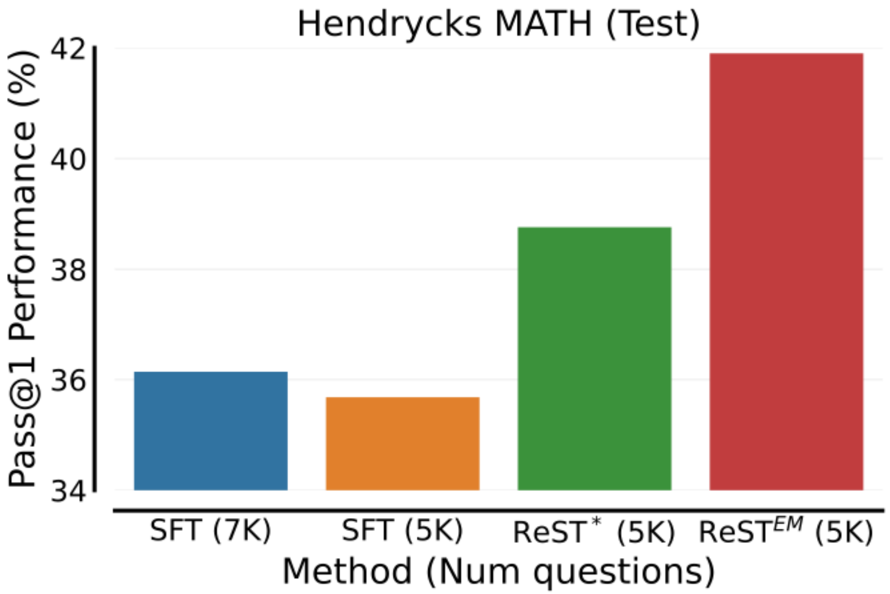


Source: Singh et al. 2024

Can Language Models Reason?

The Economist

Science and technology | Generative AI

Large language models' ability to generate text also lets them plan and reason

TechTalks

Large language models have a reasoning problem

The New York Times

Microsoft Says New A.I. Shows Signs of Human Reasoning

WIRED

Some Glimpse AGI in ChatGPT. Others Call It a Mirage

?

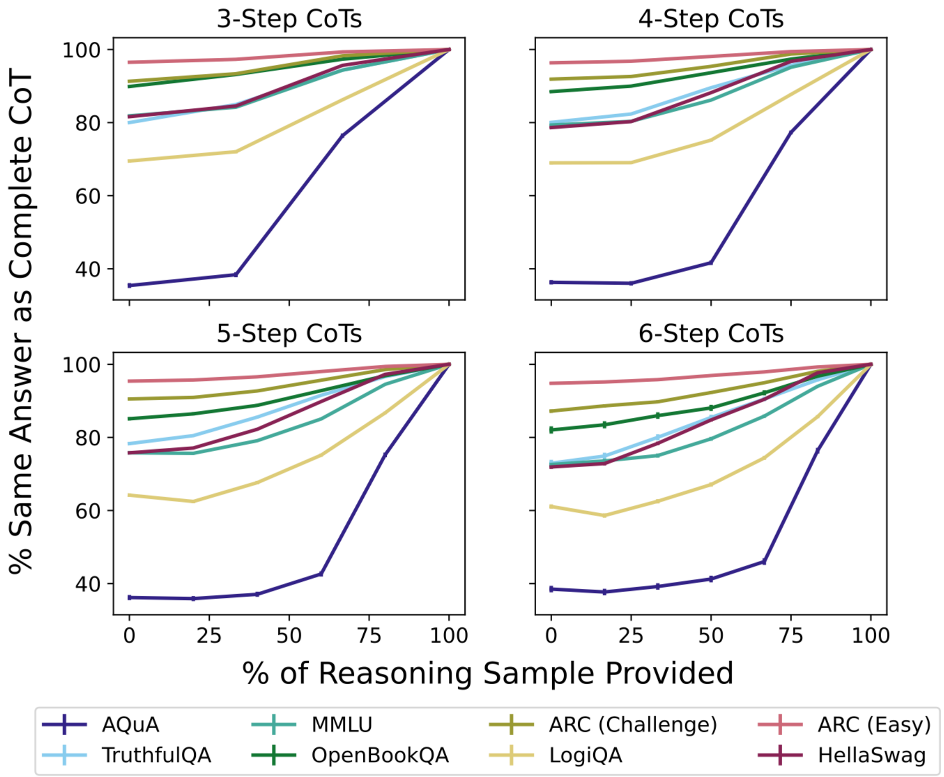
?

Let's look at some more careful evaluation to see if reasoning in LMs is systematic

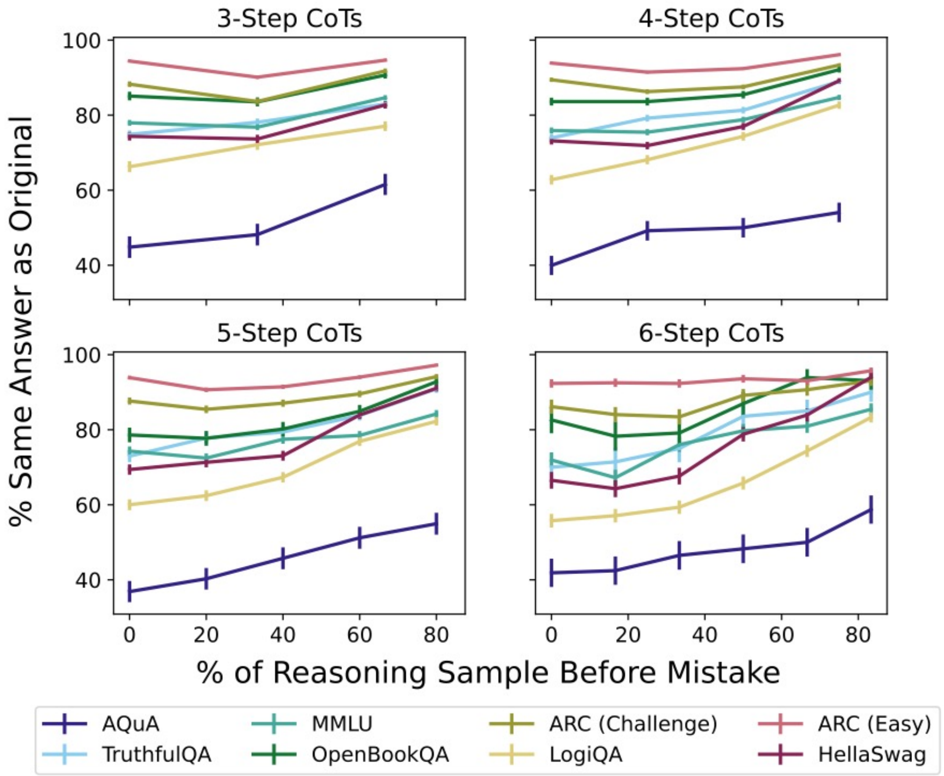
Source: https://aiguide.substack.com/p/can-large-language-models-reason

Can Language Models Reason?

CoT Rationales are often not faithful



Models do not always need the full rationale to answer correctly → rationale may be post-hoc?

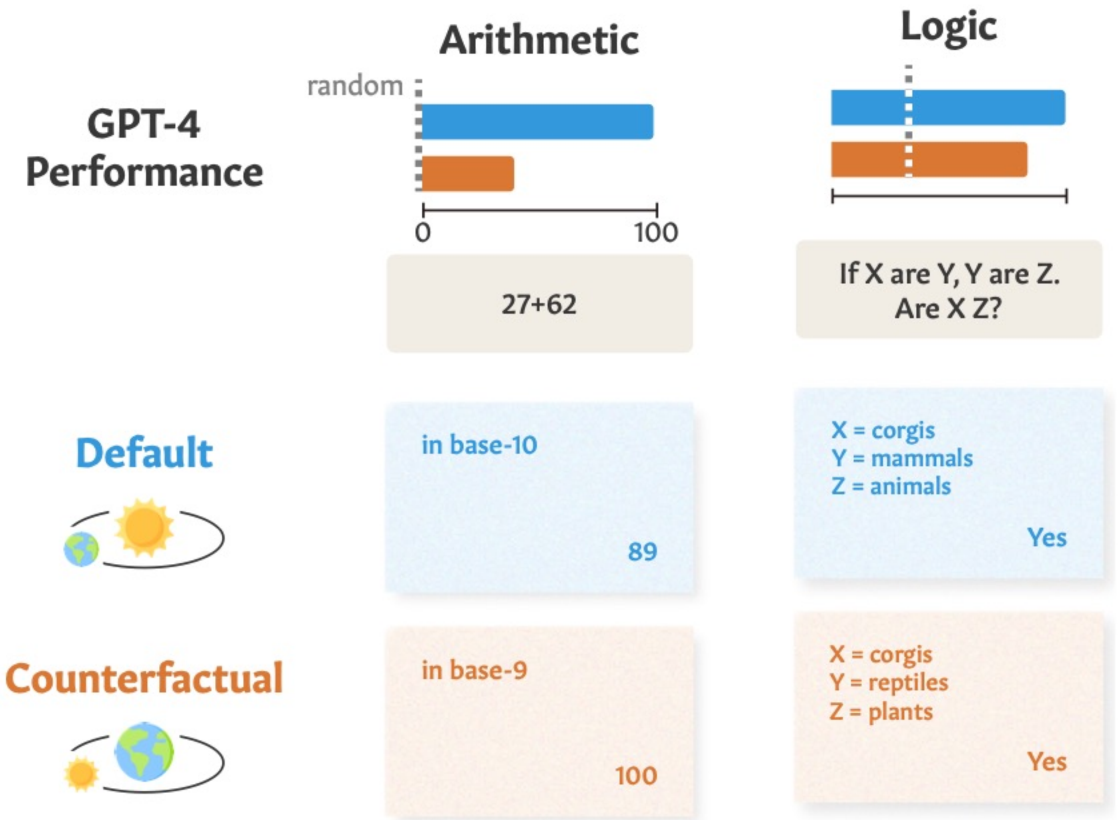


Sometimes, models answer correctly even with an incorrect rationale..

Source: Lanham et al. 2023

Can Language Models Reason?

Reasoning vs Memorization: Using Counterfactuals



Source: Wu et al., 2024

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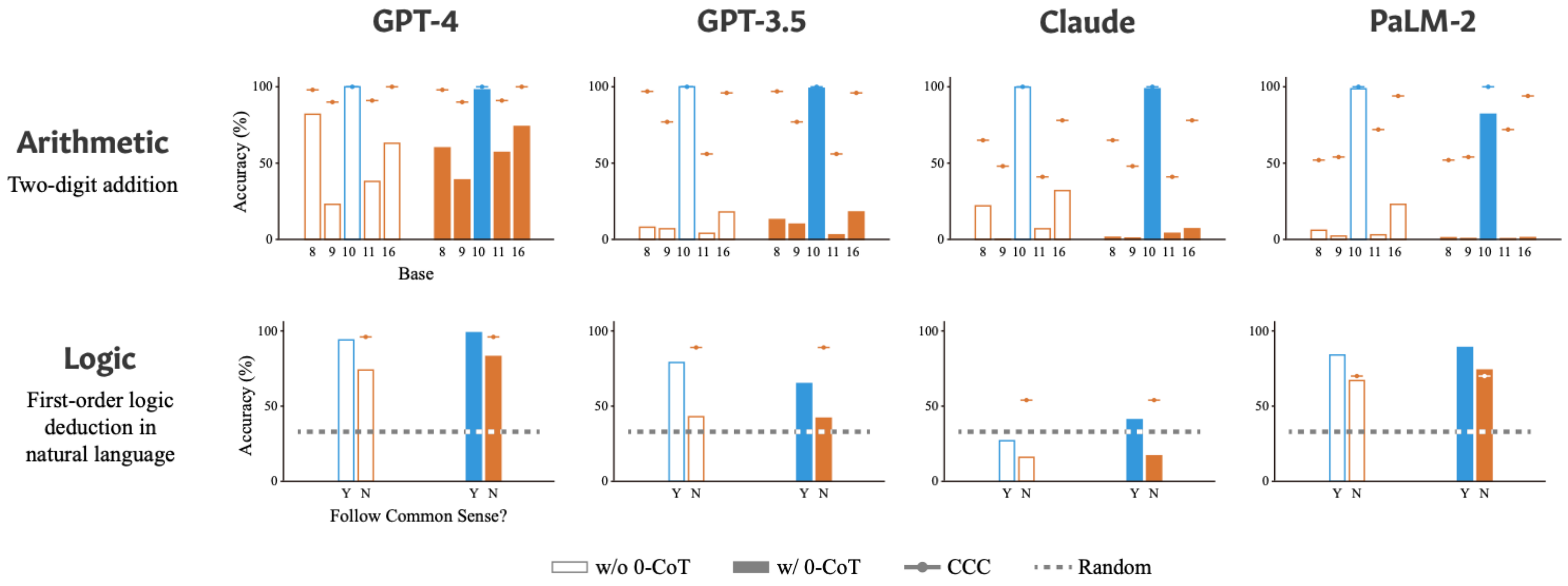
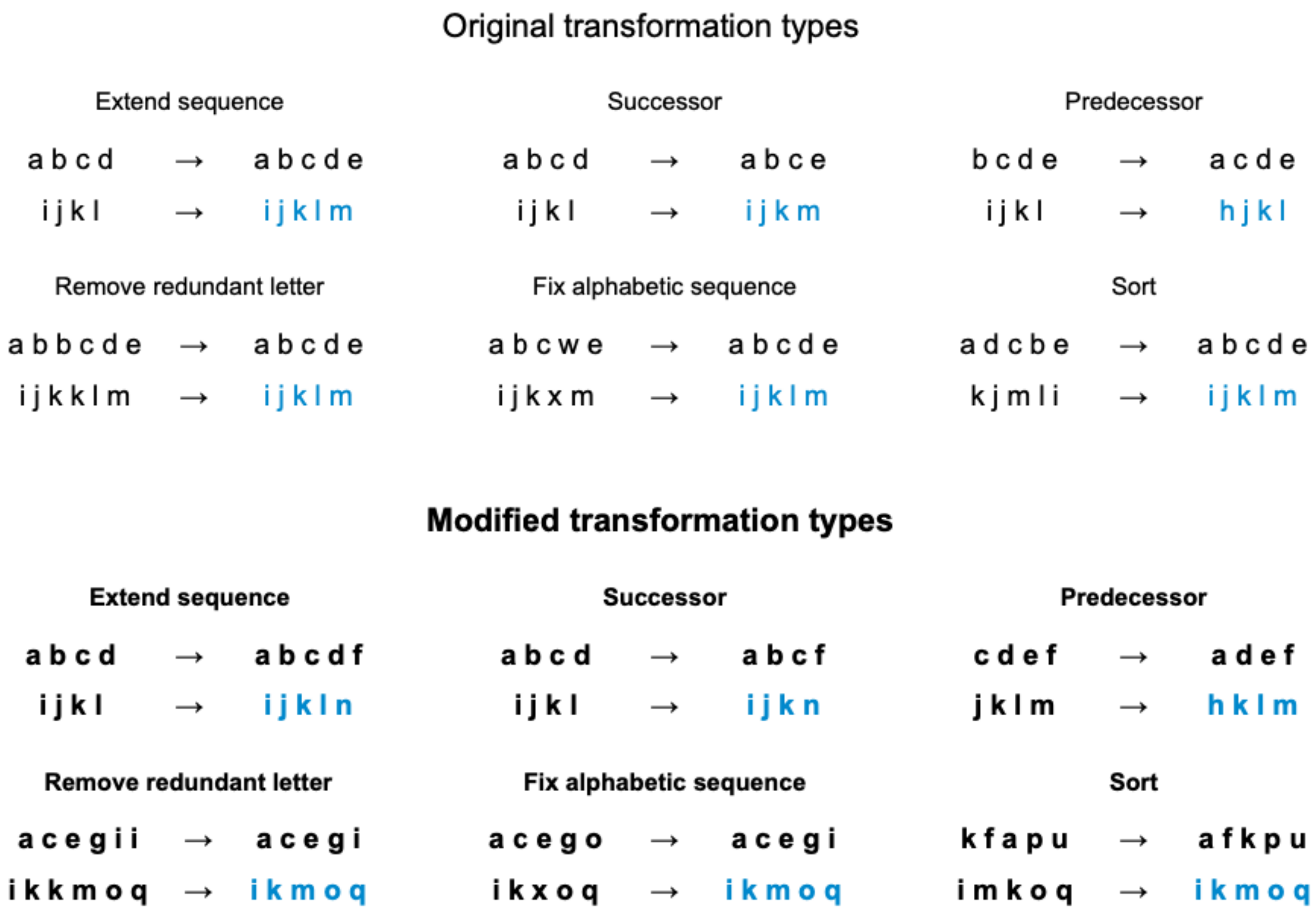


Source: Wu et al., 2024

Can Language Models Reason?

Reasoning vs Memorization: Counterfactuals for Analogical Reasoning



Source: Hodel et al. 2024

Can Language Models Reason?

Reasoning vs Memorization: Counterfactuals for Analogical Reasoning

Original transformation types

Extend sequence

a b c d → a b c d e
i j k l → i j k l m

Successor

a b c d → a b c e
i j k l → i j k m

Predecessor

b c d e → a c d e
i j k l → h j k l

Remove redundant letter

a b b c d e → a b c d e
i j k k l m → i j k l m

Fix alphabetic sequence

a b c w e → a b c d e
i j k x m → i j k l m

Sort

a d c b e → a b c d e
k j m l i → i j k l m

Modified transformation types with synthetic alphabet

Synthetic alphabet

x y l k w b f z t n j r q a h v g m u o p d i c s e

Extend sequence

x y l k → x y l k b
t n j r → t n j r a

Successor

x y l k → x y l b
t n j r → t n j a

Predecessor

l k w b → x k w b
n j r q → z j r q

Remove redundant letter

x l w w f t → x l w f t
t t j q h g → t j q h g

Fix alphabetic sequence

x l w r t → x l w f t
t j p h g → t j q h g

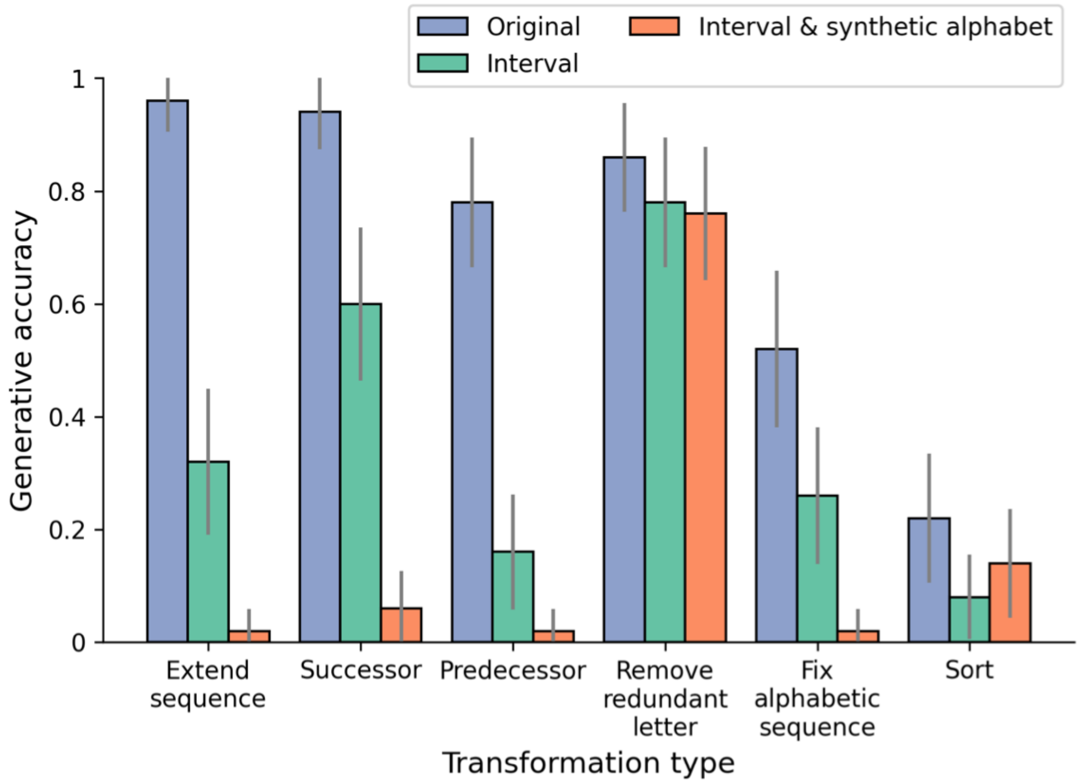
Sort

x l f w t → x l w f t
j t q h g → t j q h g

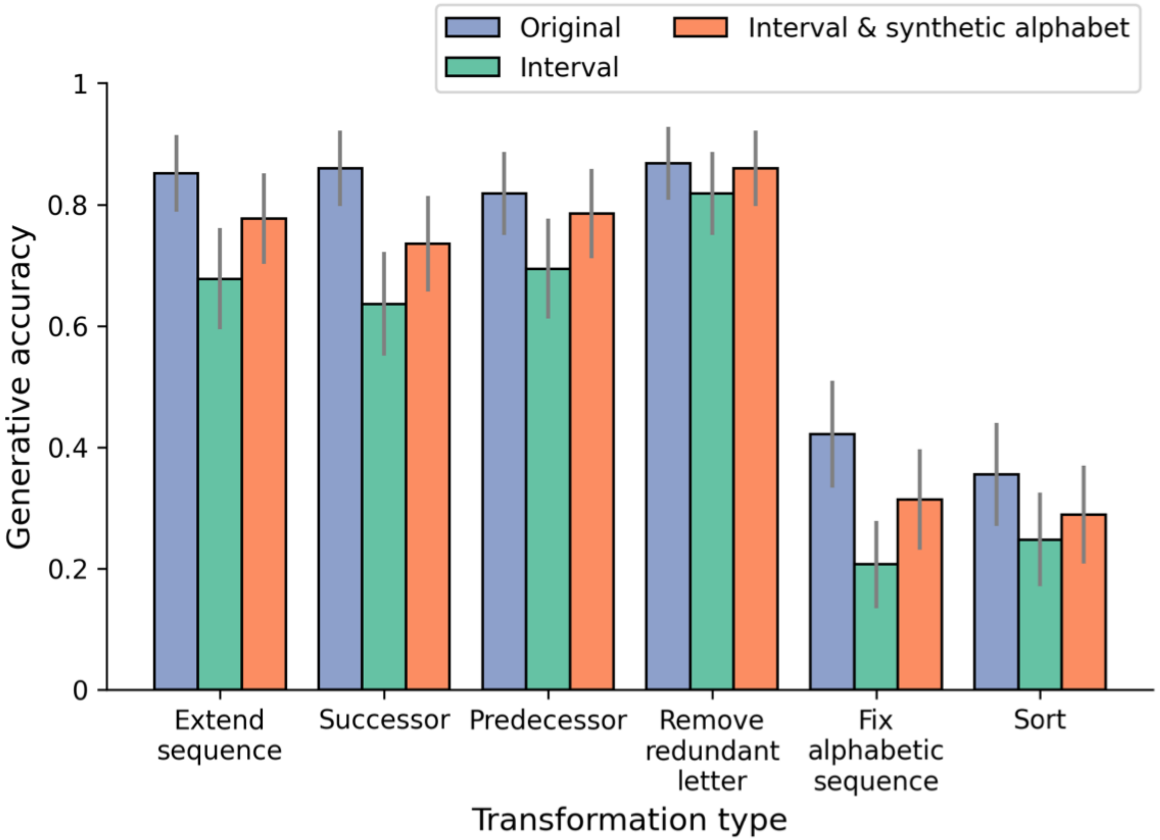
Source: Hodel et al. 2024

Can Language Models Reason?

Reasoning vs Memorization: Counterfactuals for Analogical Reasoning



Significant drop in performance for GPT-4 → evidence of spurious reasoning?



No drop in performance for humans

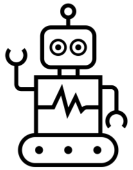
Source: Hodel et al. 2024

Language Model Agents

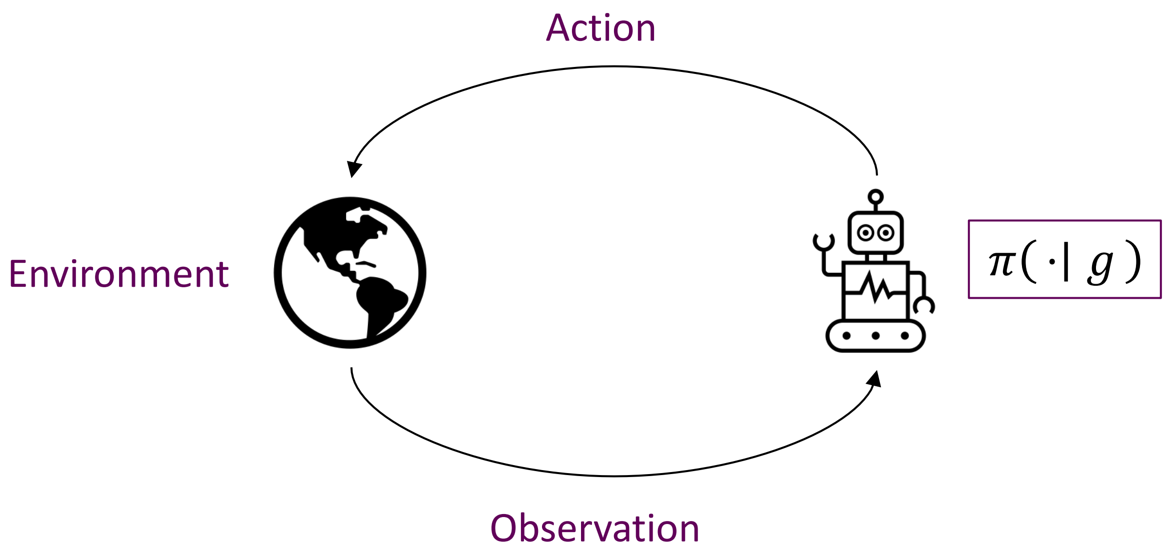
with some slides borrowed from Frank Xu (CMU)

Some Terminology

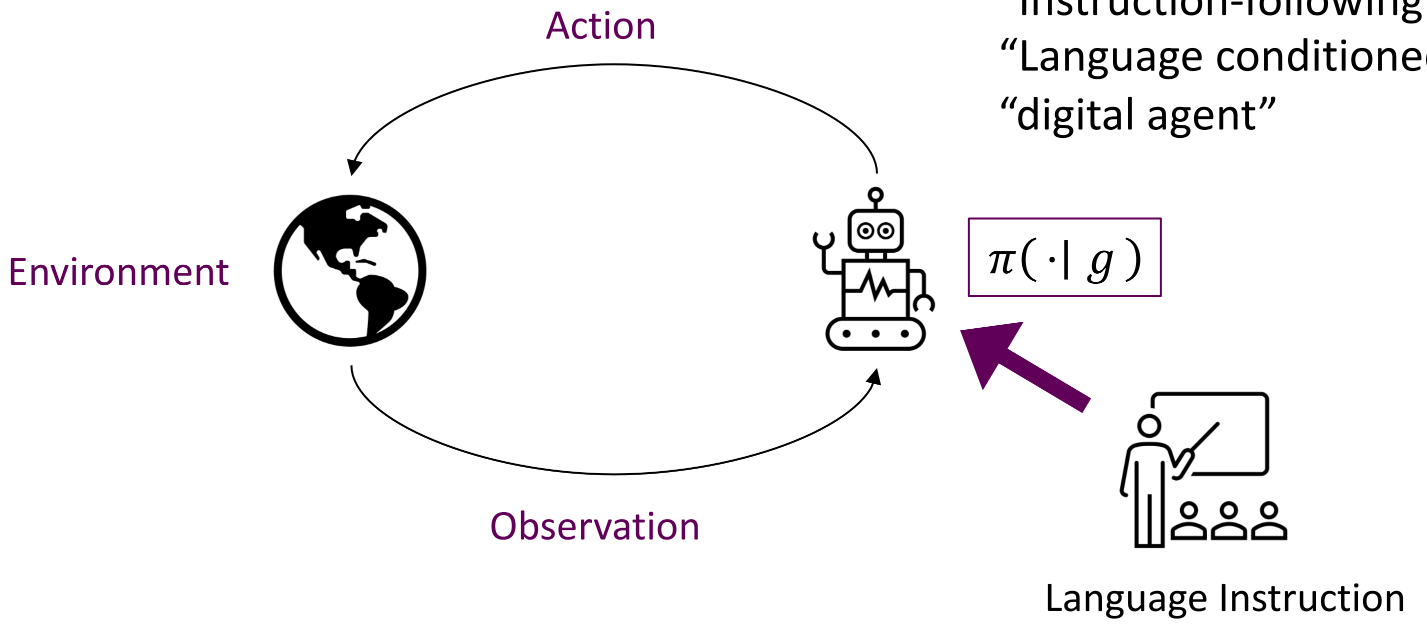
Environment 

 $\boxed{\pi(\cdot|\, g\,)}$

Some Terminology



Some Terminology

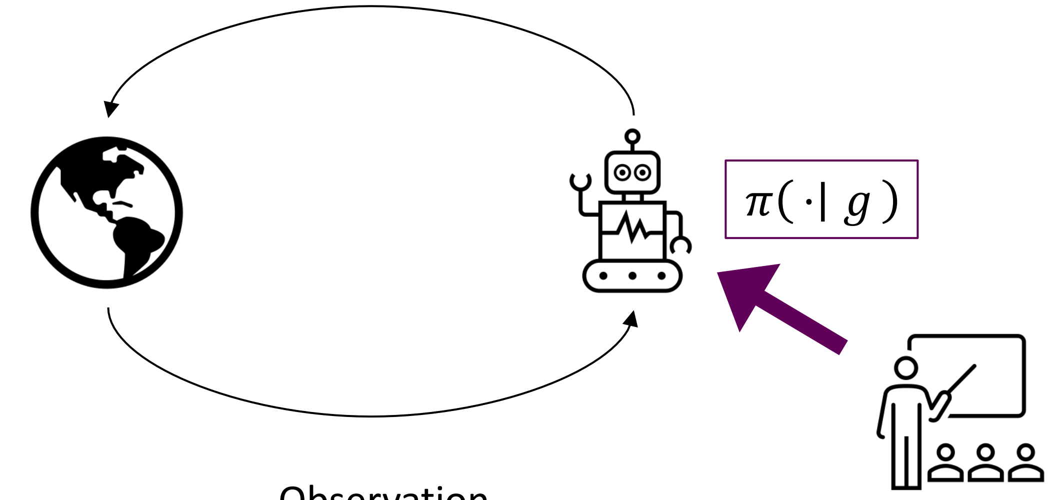


"Instruction-following agent"
"Language conditioned policy"
"digital agent"

Some Terminology

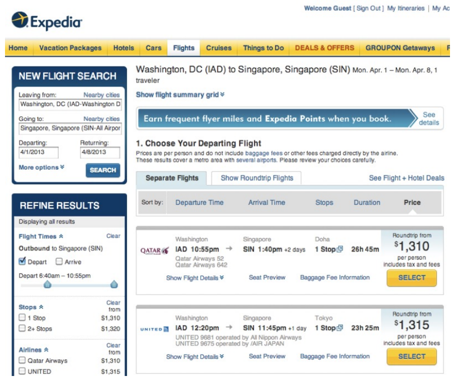
Type … on …, Click on …, Choose … from dropdown, …

Environment



Observation

“Book a flight from San Francisco to New York”

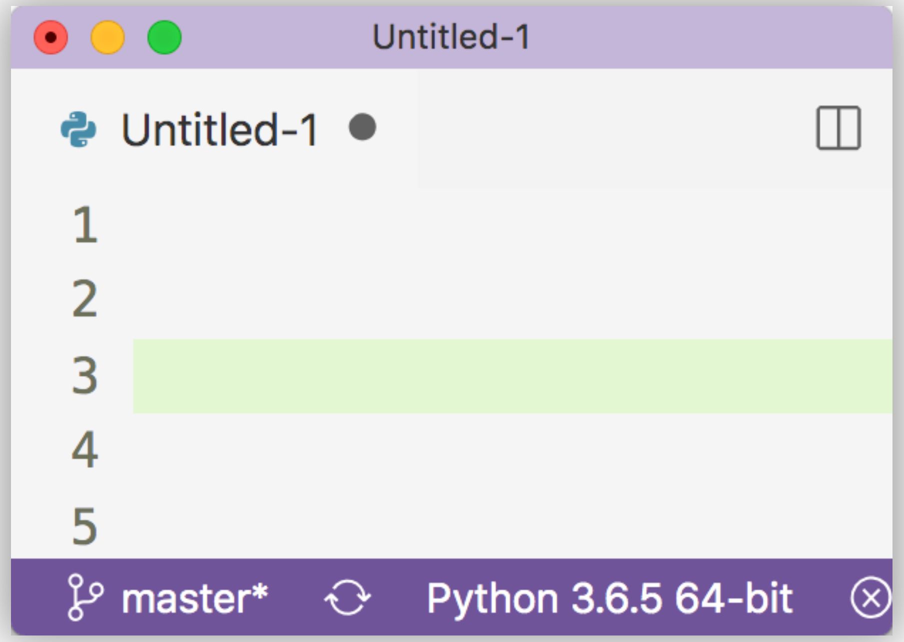


webarena.onestopshop.com

```
<li>
 <div>
   <a href="..."><img src="..."></a>
   <div class>
     <a href="...">Outdoor Patio …
</a>
     <div>
         <span>Rating:</span>
         <div>
           <span>82%</span>
         </div>
         <a href="…#reviews">12
<span>Reviews</span></a>
```

Raw pixels as observation? **HTML DOM as observation?**

Applications: Natural Language Interfaces



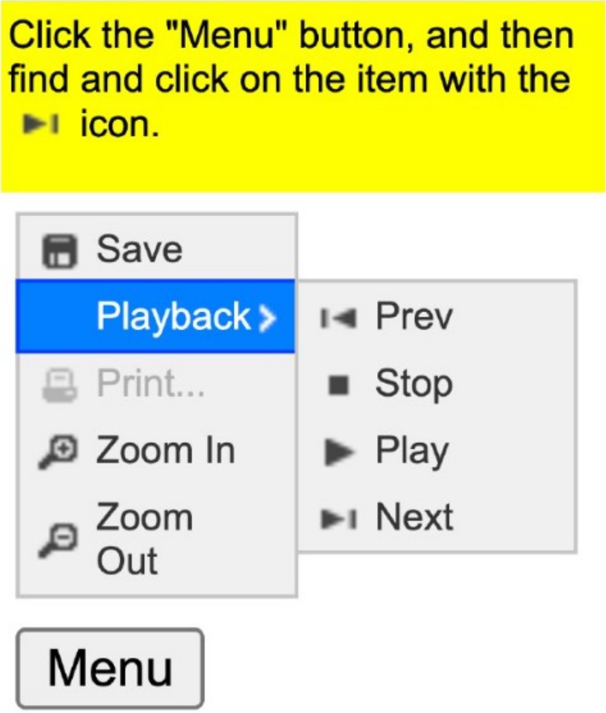
Virtual Assistants

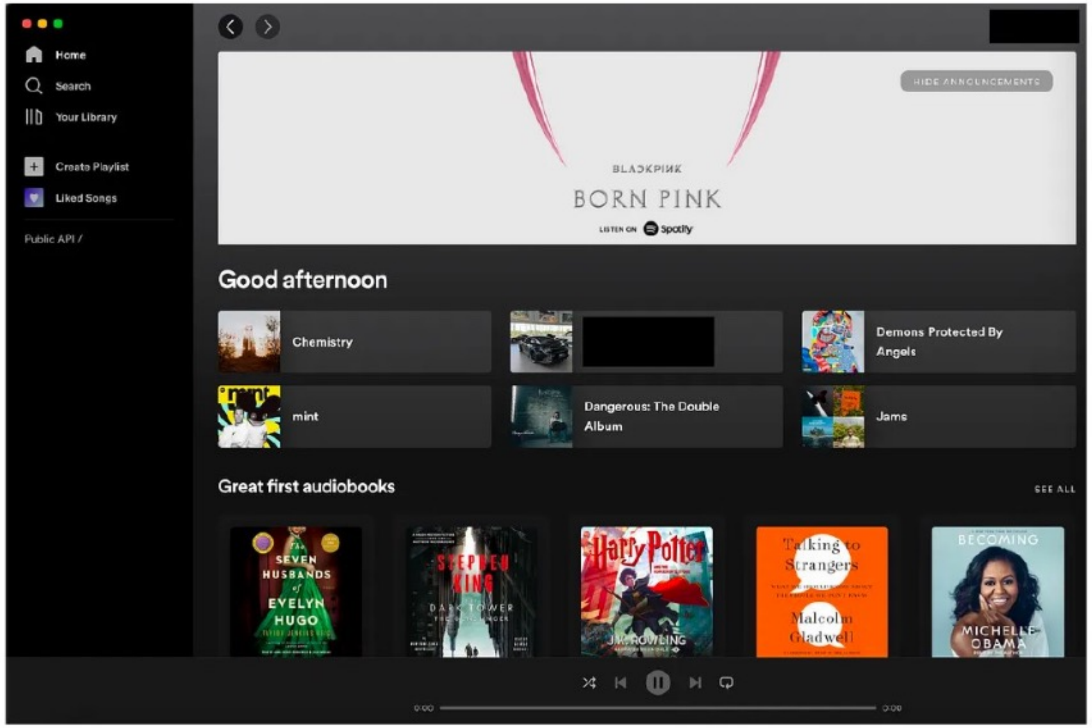
- *Set an alarm at 7 AM*
- *Remind me for the meeting at 5pm*
- *Play Jay Chou's latest album*

Natural Language Programming

- *Sort my_list in descending order*
- *Copy my_file to home folder*
- *Dump my_dict as a csv file output.csv*

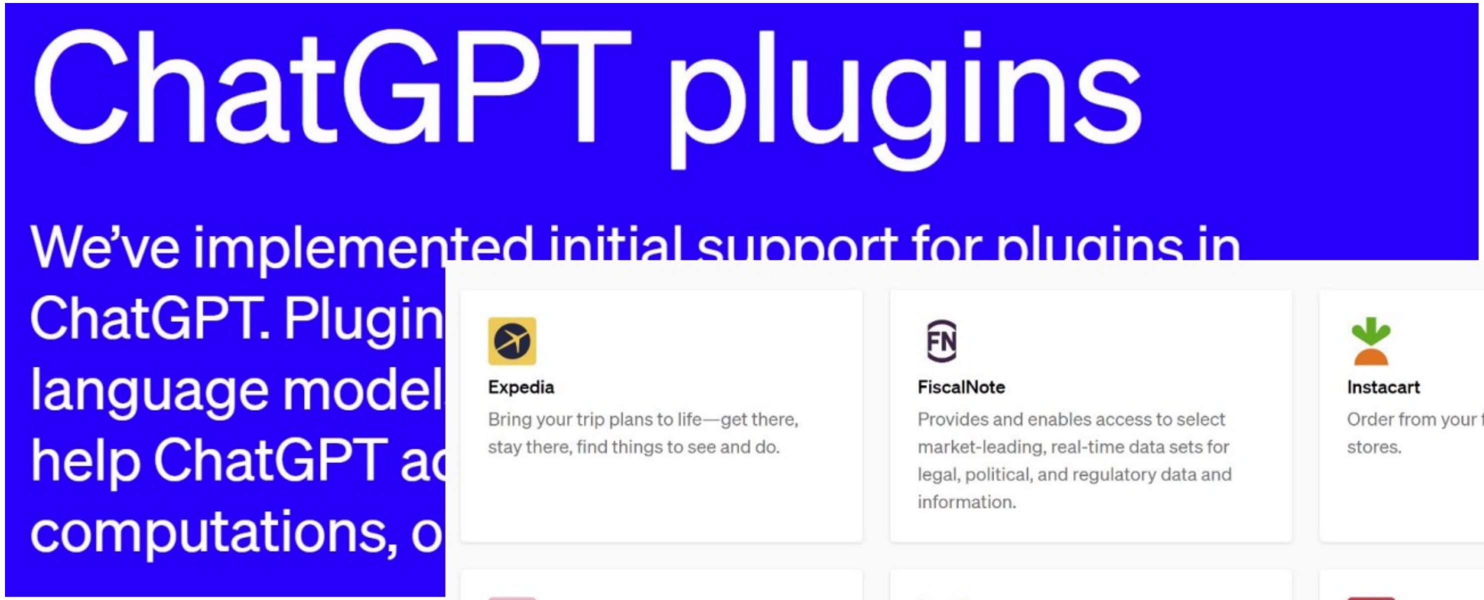
Applications: UI automation

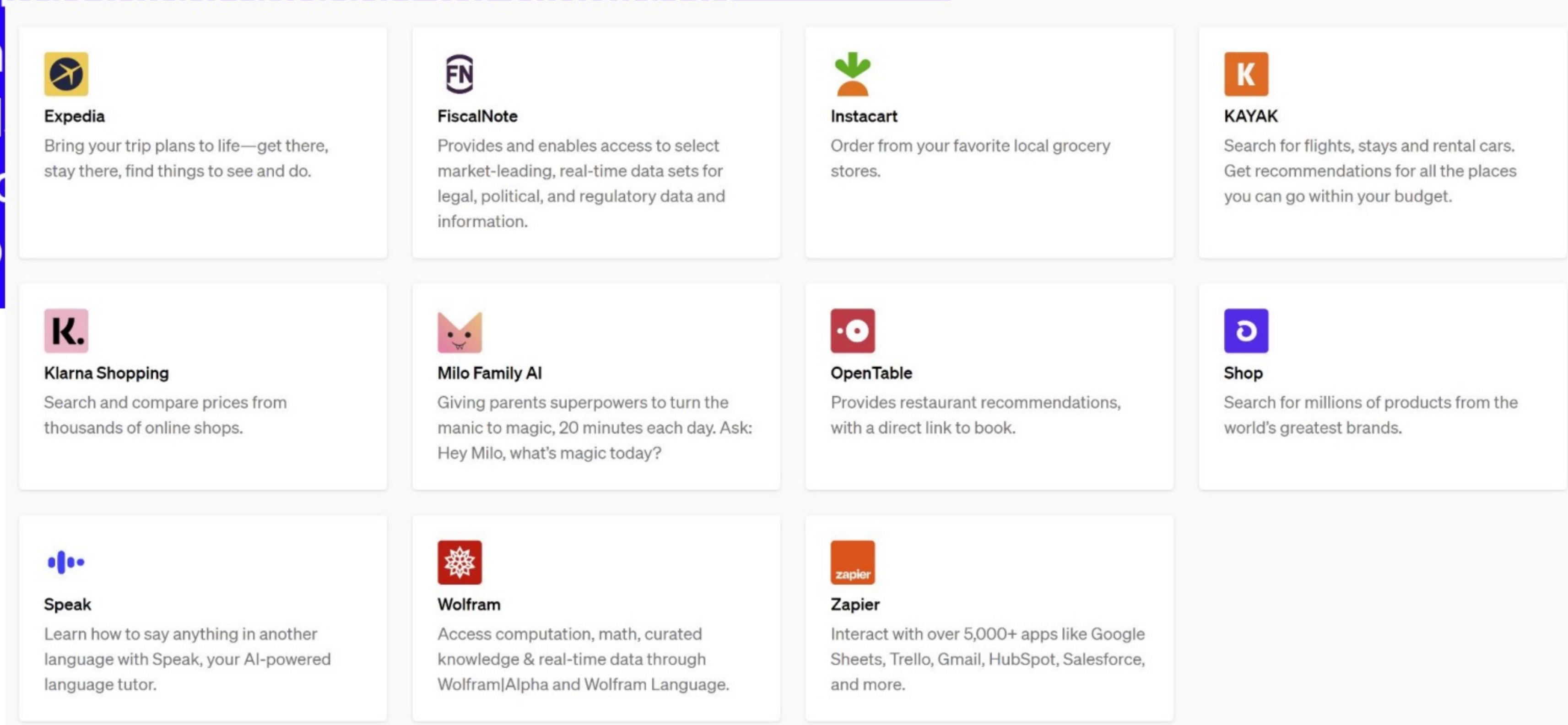




“Play some synthwave songs”

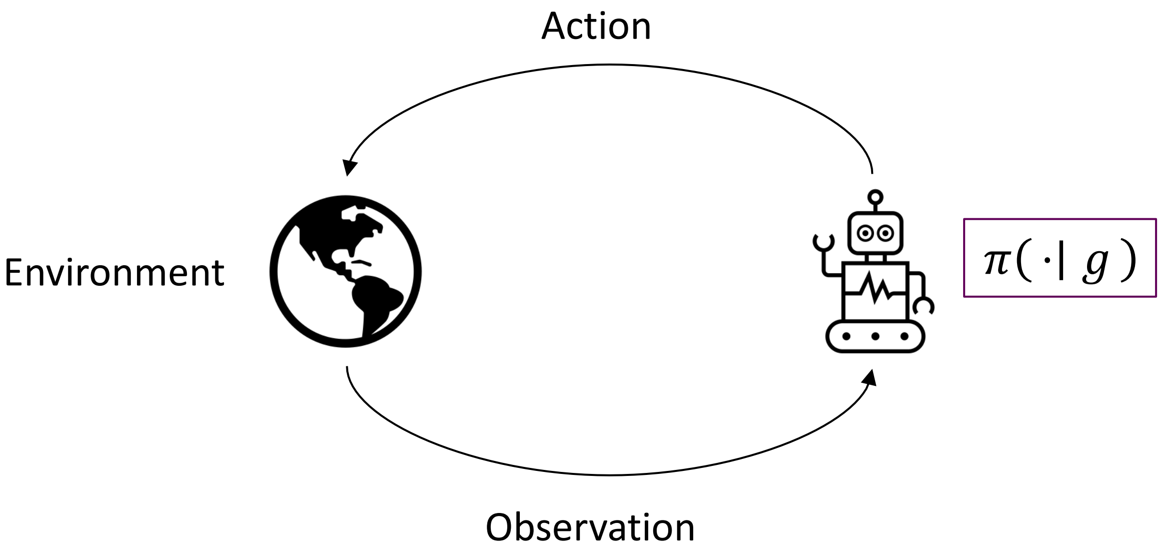
Applications: Multi-step "Tool use"





[ChatGPT plugins]

Instruction following agents [Pre LLMs]



a) What states border Texas
$\lambda x.state(x) \wedge borders(x, texas)$

b) What is the largest state
$\arg\max(\lambda x.state(x), \lambda x.size(x))$

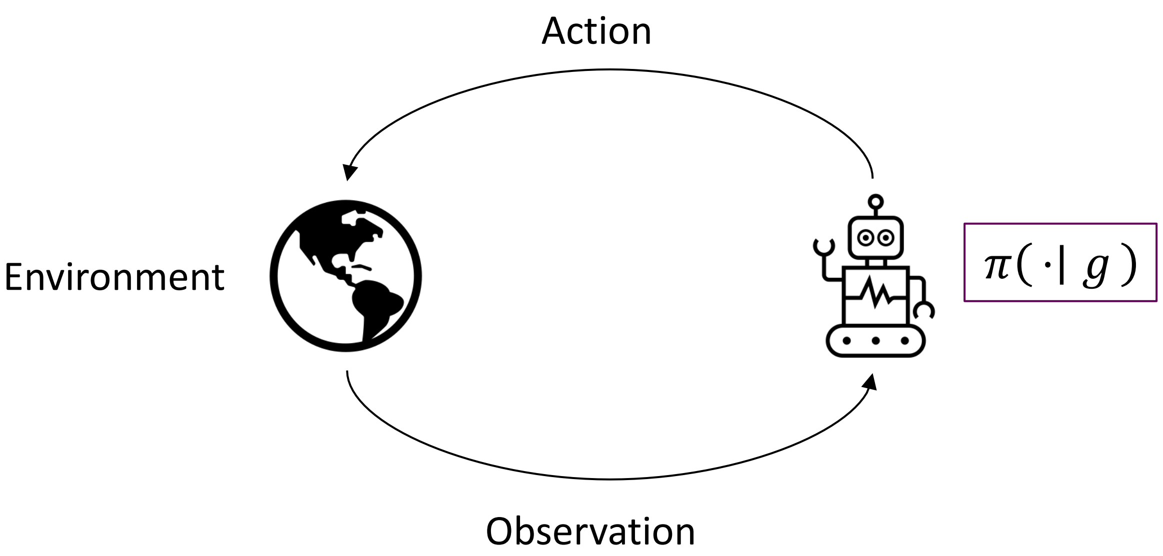
c) What states border the state that borders the most states
$\lambda x.state(x) \wedge borders(x, \arg\max(\lambda y.state(y),$
$\lambda y.count(\lambda z.state(z) \wedge borders(y, z))))$

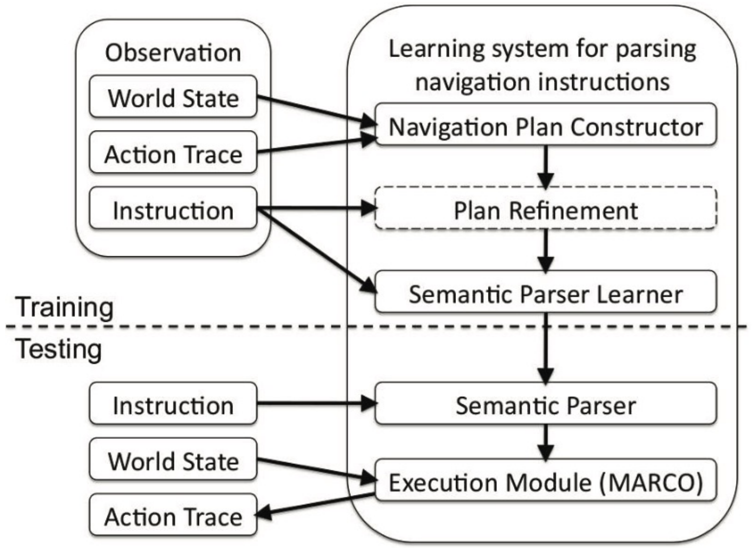
Idea #1: Directly map from instructions to action sequences like Machine Translation
[works well for simple grounded environments like text2sql, knowledge graph querying]

$$\max_{\theta} p_\theta(\{a_1, a_2, \ldots\} \mid g)$$

Source: Zettlemoyer et al. 2012

Instruction following agents [Pre LLMs]





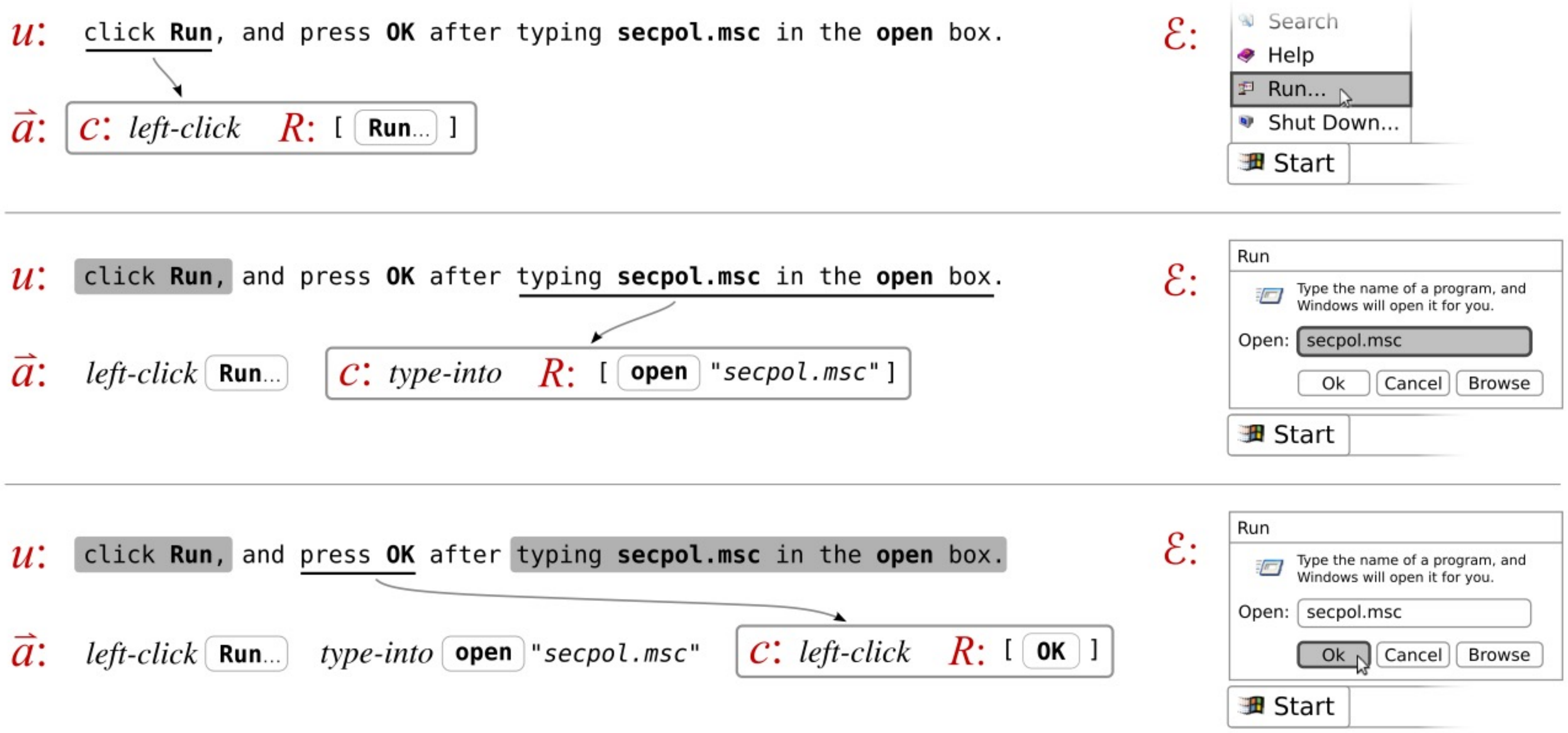
Instruction: "Place your back against the wall of the 'T' intersection. Turn left. Go forward along the pink-flowered carpet hall two segments to the intersection with the brick hall. This intersection contains a hatrack. Turn left. Go forward three segments to an intersection with a bare concrete hall, passing a lamp. This is Position 5."

Parse: Turn ( ),
Verify (back: WALL),
Turn (LEFT),
Travel ( ),
Verify (side: BRICK HALLWAY),
Turn (LEFT),
Travel (steps: 3),
Verify (side: CONCRETE HALLWAY)

Idea #2: Infer executable, structured plans from (instruction, trajectory) pairs and train a model to go from instructions to plans

Source: Chen and Mooney 2011

Instruction following agents [Pre LLMs]

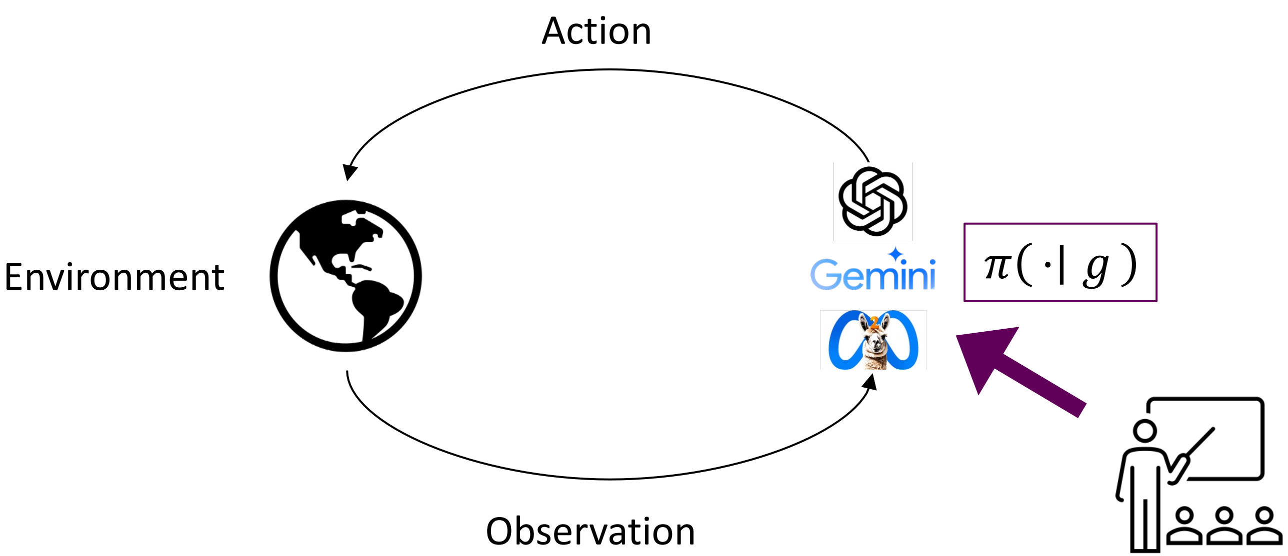


Idea #3: Use RL to directly map instructions to actions

$$\max_{\theta} \mathbb{E}_{a \sim \pi_\theta} R(a; \text{instruction}, \text{ observation})$$

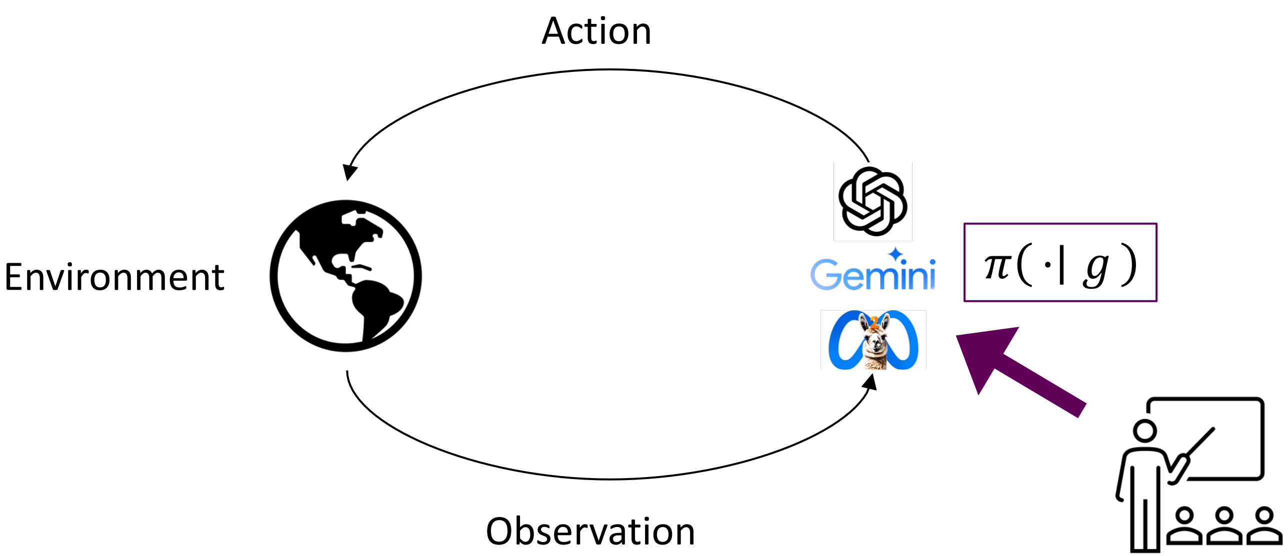
Source: Branavan et al. 2009

Instruction following agents [in 2024]



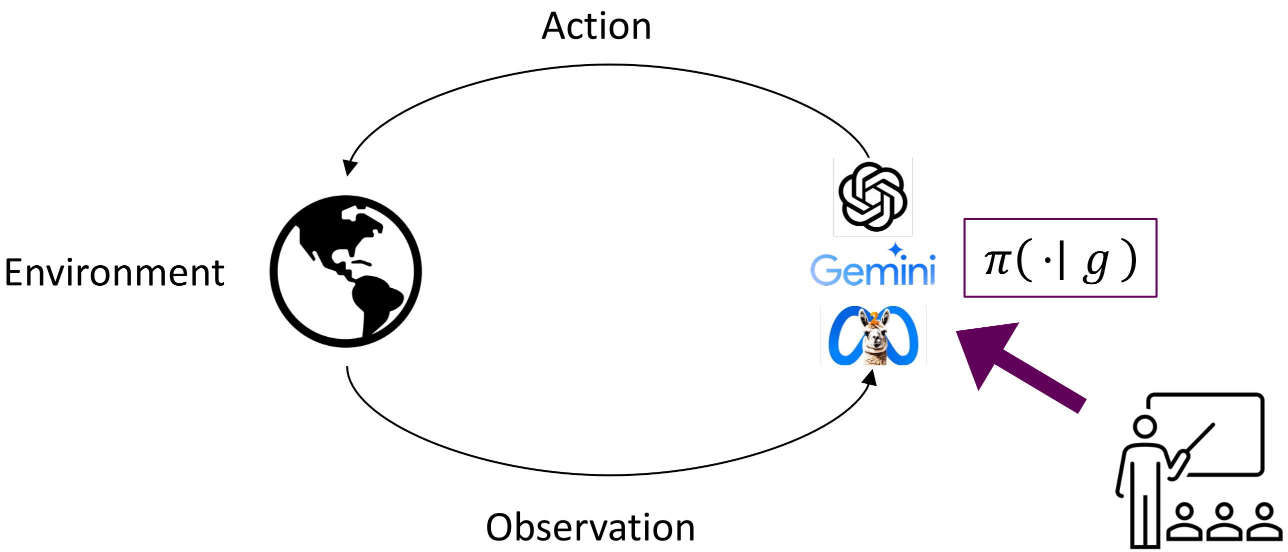
$$p(\tau \mid g) = p(s_1, a_1, s_2, a_2, \ldots \mid g) = \prod_t p(s_t \mid s_{t-1}, a_t) \times \pi(a_t \mid \tau_{\leq t}, g)$$

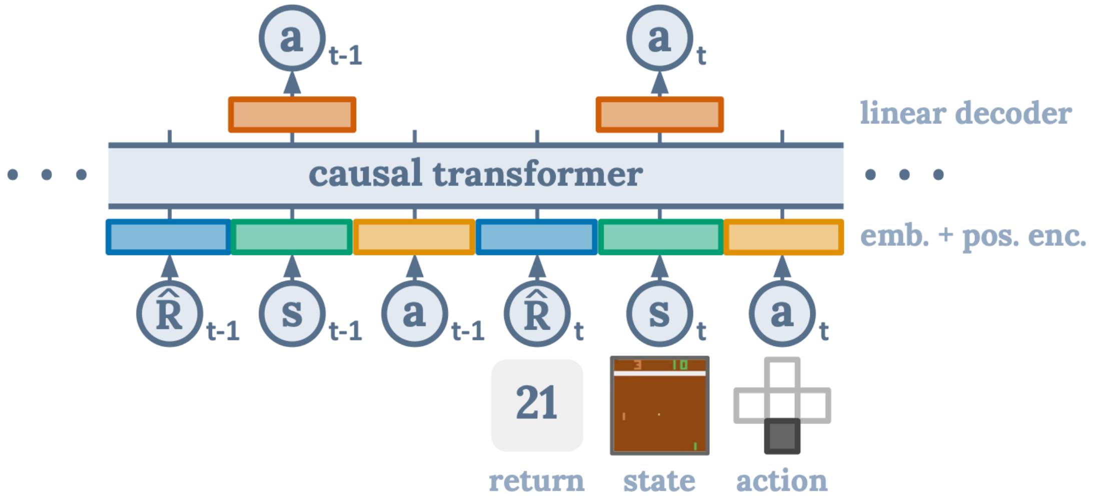
Instruction following agents [in 2024]



$$p(\tau \mid g) = p(s_1, a_1, s_2, a_2, \ldots \mid g) = \prod_t \underbrace{p(s_t \mid s_{t-1}, a_t)}_{\text{Transition dynamics}} \times \underbrace{\pi(a_t \mid \tau_{\leq t}, g)}_{\text{Agent policy}}$$

Instruction following agents [in 2024]





Source: Chen et al. 2021

Main Idea: **Generative trajectory modeling** with causal transformers!

$$p(\tau \mid g) = p(s_1, a_1, s_2, a_2, \ldots \mid g) = \prod_t p(s_t \mid s_{t-1}, a_t) \times \pi(a_t \mid \tau_{\leq t}, g)$$

Transition dynamics

Agent policy
(with a transformer!)

A Simple Language Model Agent with ReACT

```
You are an agent capable of the following actions:
1. Type X on Y
2. Move mouse to
3. Click on X
4. Type Char x on Y

Your objective is to follow user instructions, by mapping them into a sequence of
actions.
Instruction: {g}

So far, you have taken the following actions and observed the following
environment states:

Previous Actions and Observations:
o1:
a1:

o2:
a2:
…

After executing these actions, you observe the following HTML state: <HTML state>

Now, think about your next action:
Thought: [model-pred]

Now, take an action:
Action: [model-pred]
```

$$\pi_{\mathrm{LM}}(\cdot \mid \tau_{\leq t}, g)$$

1. Action space in text
2. Instruction in text
3. Previous observations and actions
4. Provide current observation [as text]

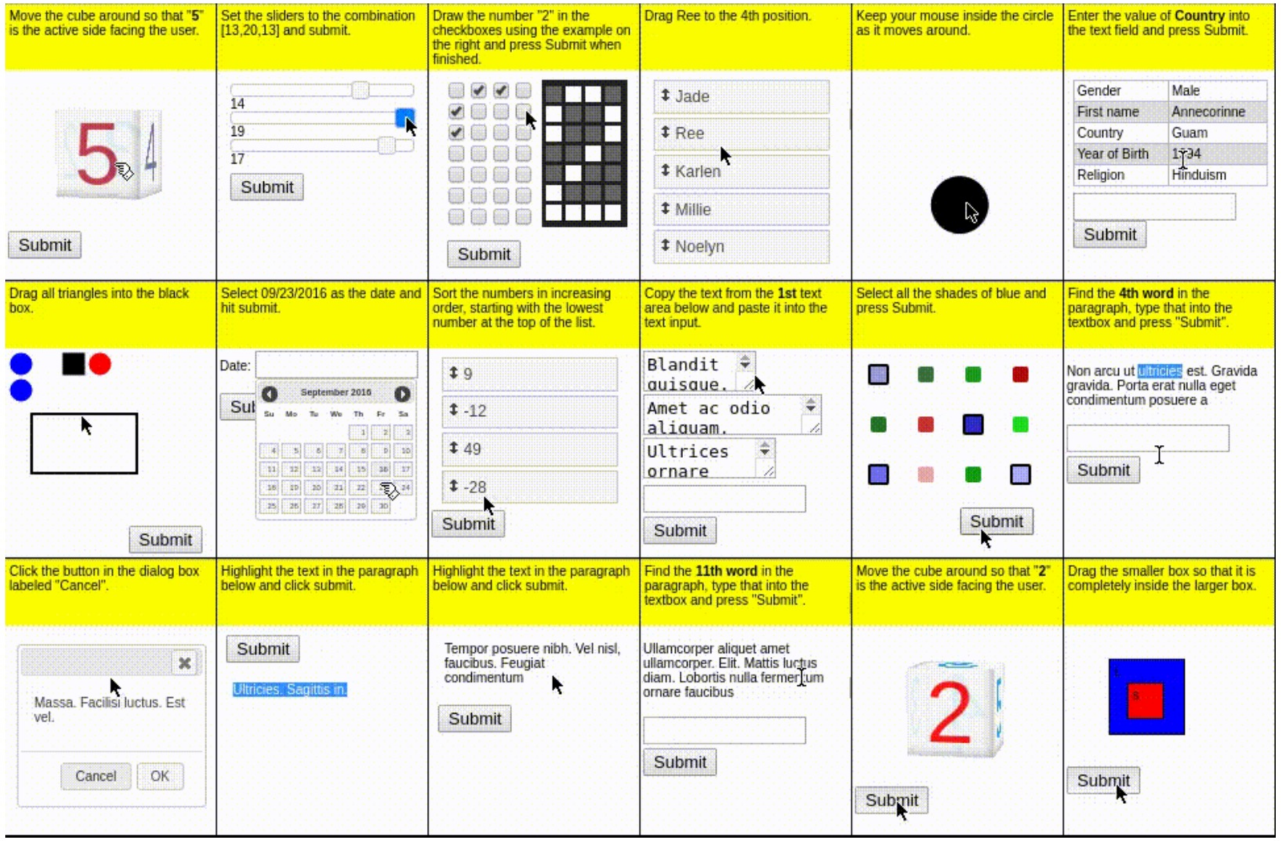
Model generates next action (sequence prediction task), use that action to update environment and repeat!

Mostly, just CoT prompting in a loop

Source: Yao et al. 2023

Some popular benchmarks for LM agents:

MiniWoB++



Sandboxed environment evaluating basic browser interactions across a range of applications from social media to email clients

Evaluates functional correctness

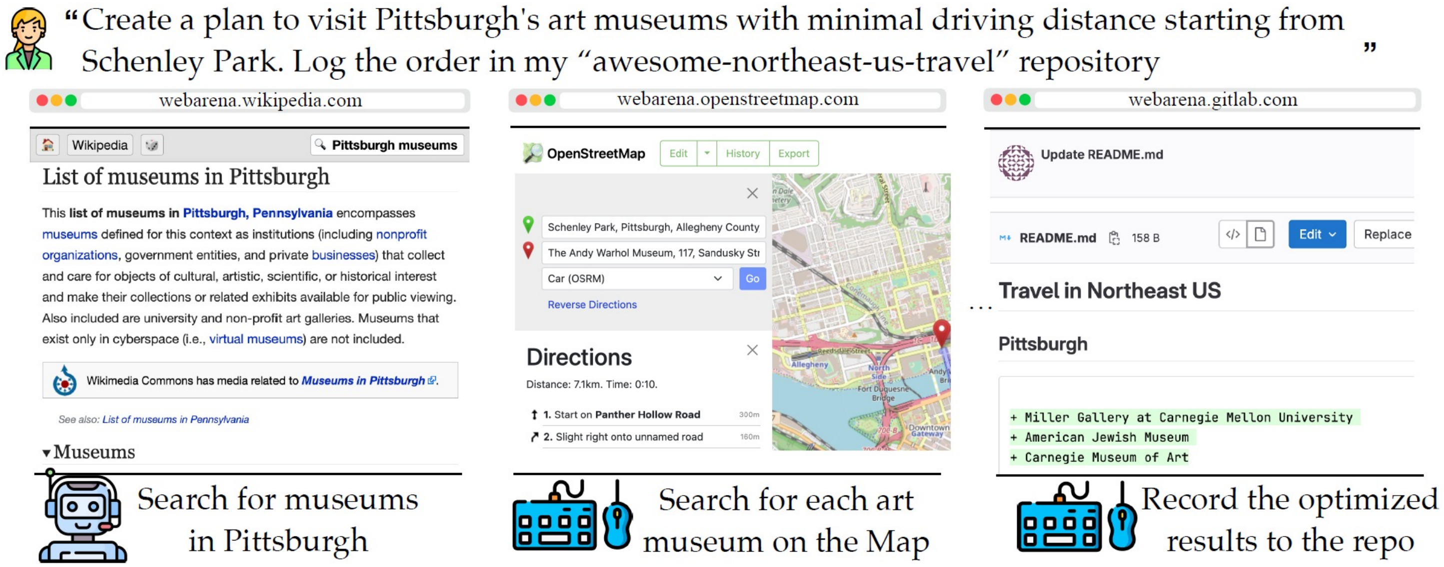
Not real world (limited functionality)

Relatively short-horizon

Zero-shot performance far from perfect!

Source: Shi et al. 2017

Some popular benchmarks for LM agents:
WebArena



Environment with sandboxed approximations of real websites spanning e-commerce, social media!

Additional utility tools: Maps, calculators, scratchpads, Wikipedia…

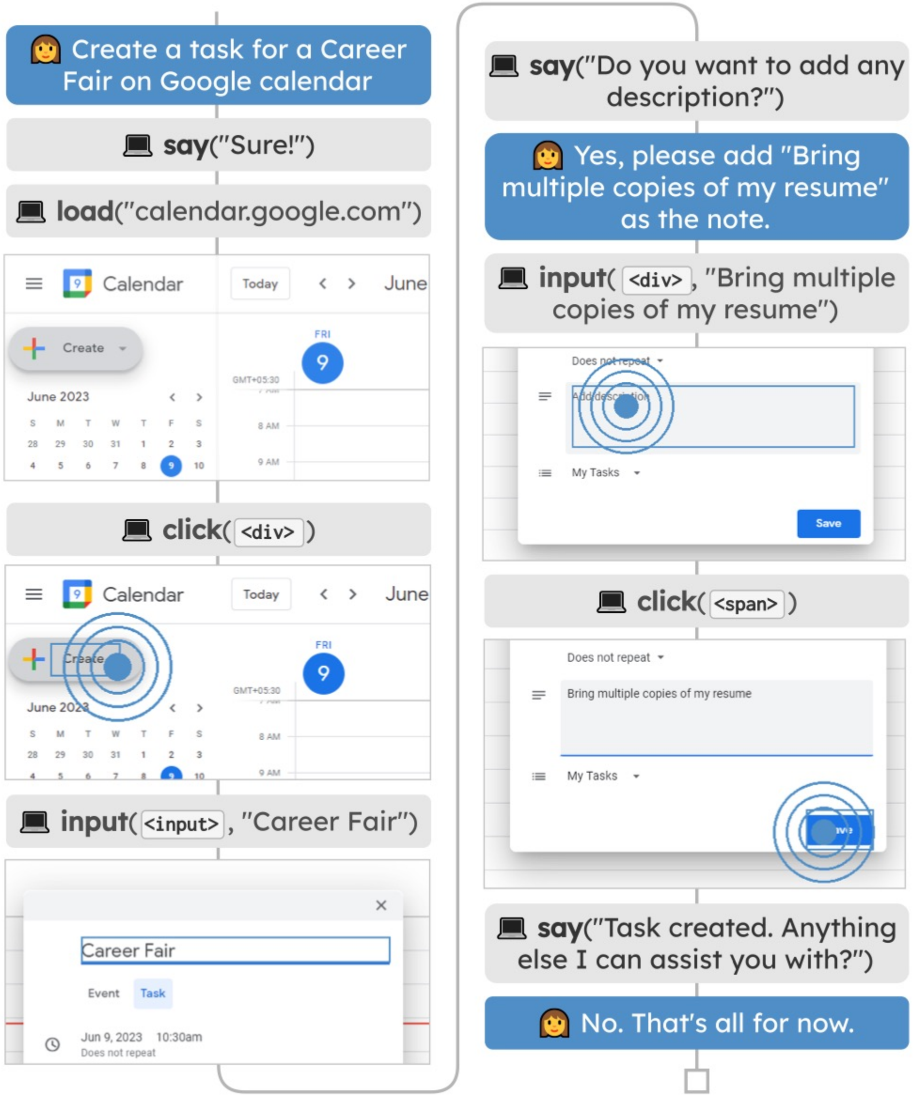
Multi-tab browsing

Long-horizon tasks

Evaluates functional correctness

Source: Zhou et al. 2024

Some popular benchmarks for LM agents:
WebLINX



Web-interactions on real websites

Conversational: includes a new "say" action to communicate with human to gather information

Multi-tab browsing

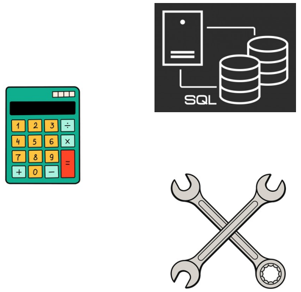
Turn-level metrics for evaluation

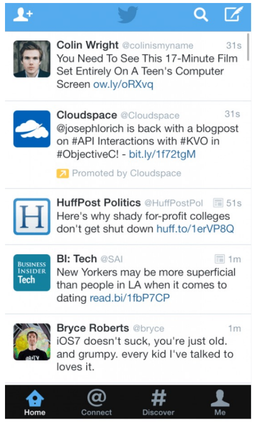
Not an environment, but a collection of interactions

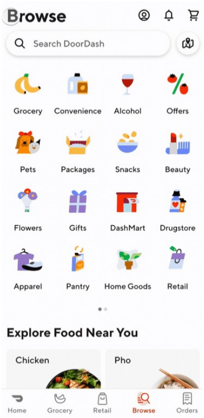
Source: Lù et al. 2024

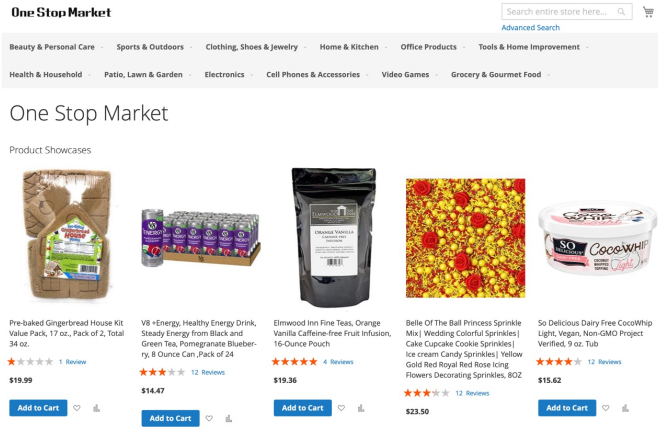
Training data for Language Model Agents

- Standard practice: In-context learning with few-shot demonstrations of humans performing following similar instructions.
- This is still not scalable / reliable









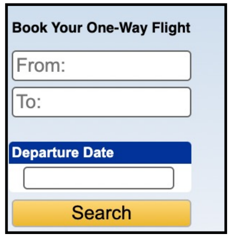
1000s of environments, many kinds of interactions possible…

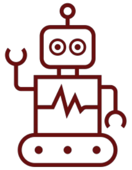
Can agents autonomously explore their environments
to construct high quality synthetic demonstrations?

Use Exploration + Model Generated Data!

Prompt: Given a website, take actions of the following format to explore….

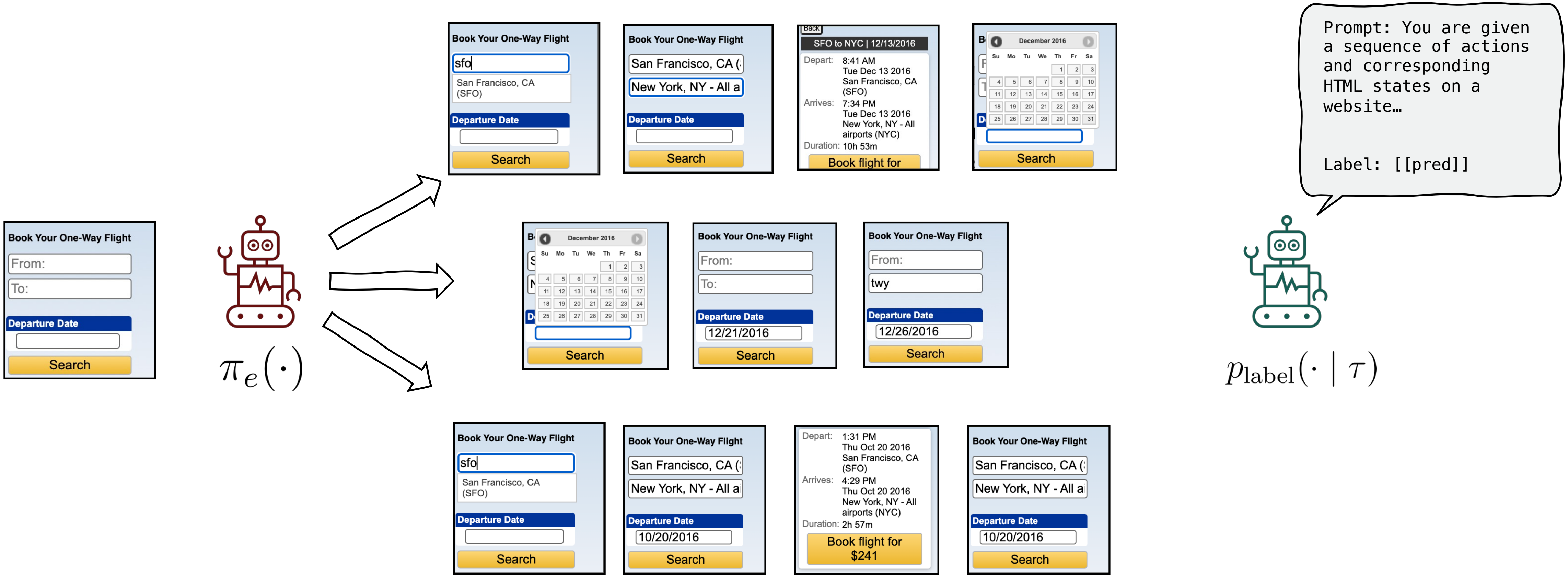
Action: [[pred]]





$\pi_e(\cdot)$

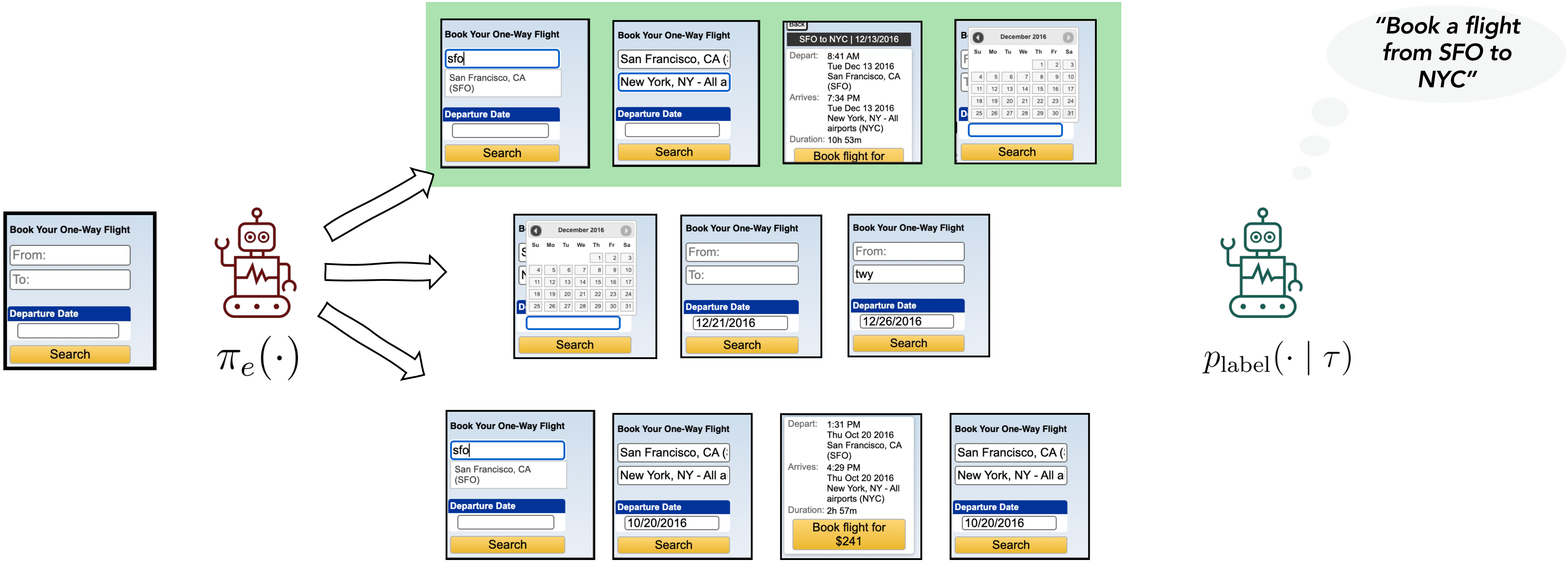
Use Exploration + Model Generated Data!



How can we decide if a sequence of interactions is meaningful?

Use Natural Language!

Use Exploration + Model Generated Data!



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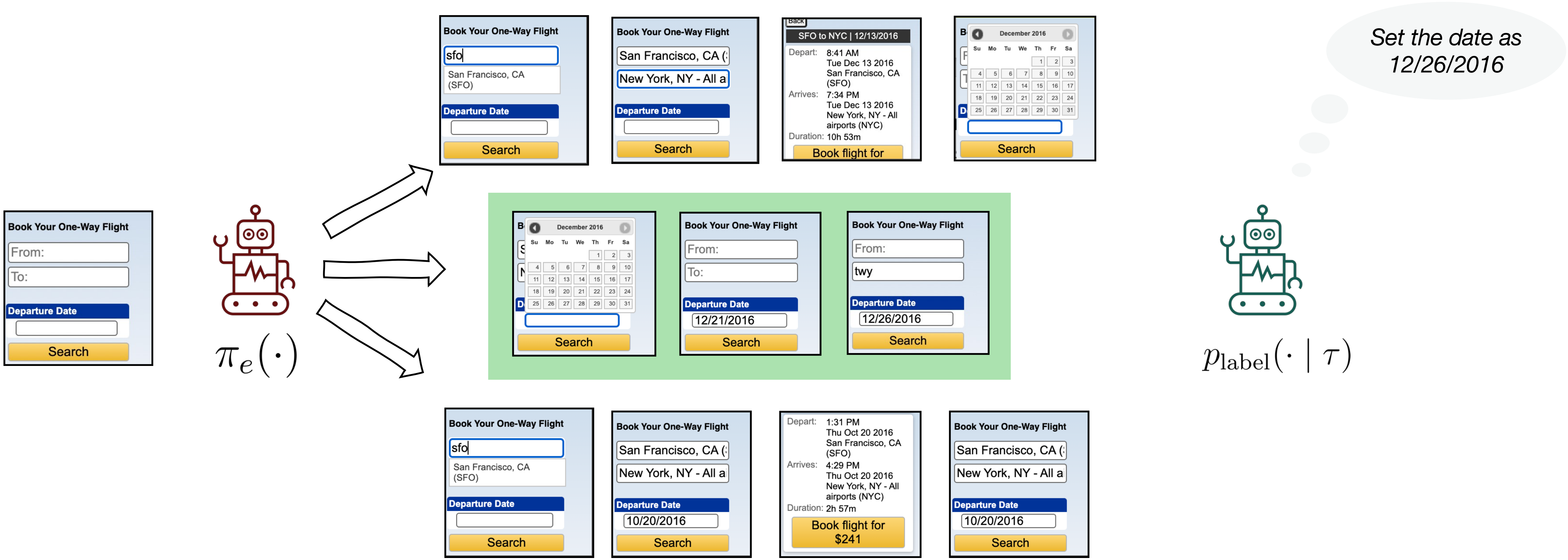

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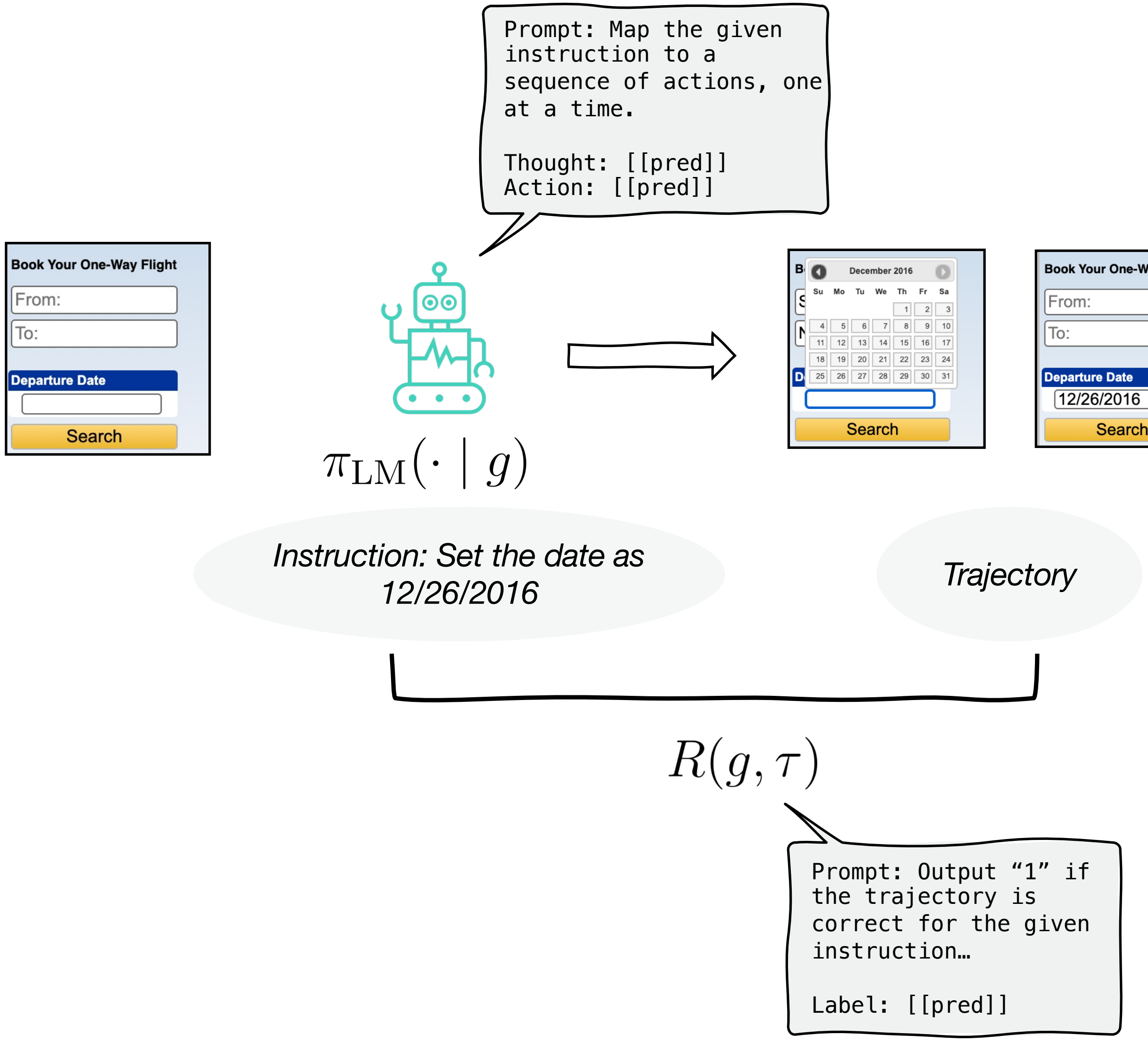
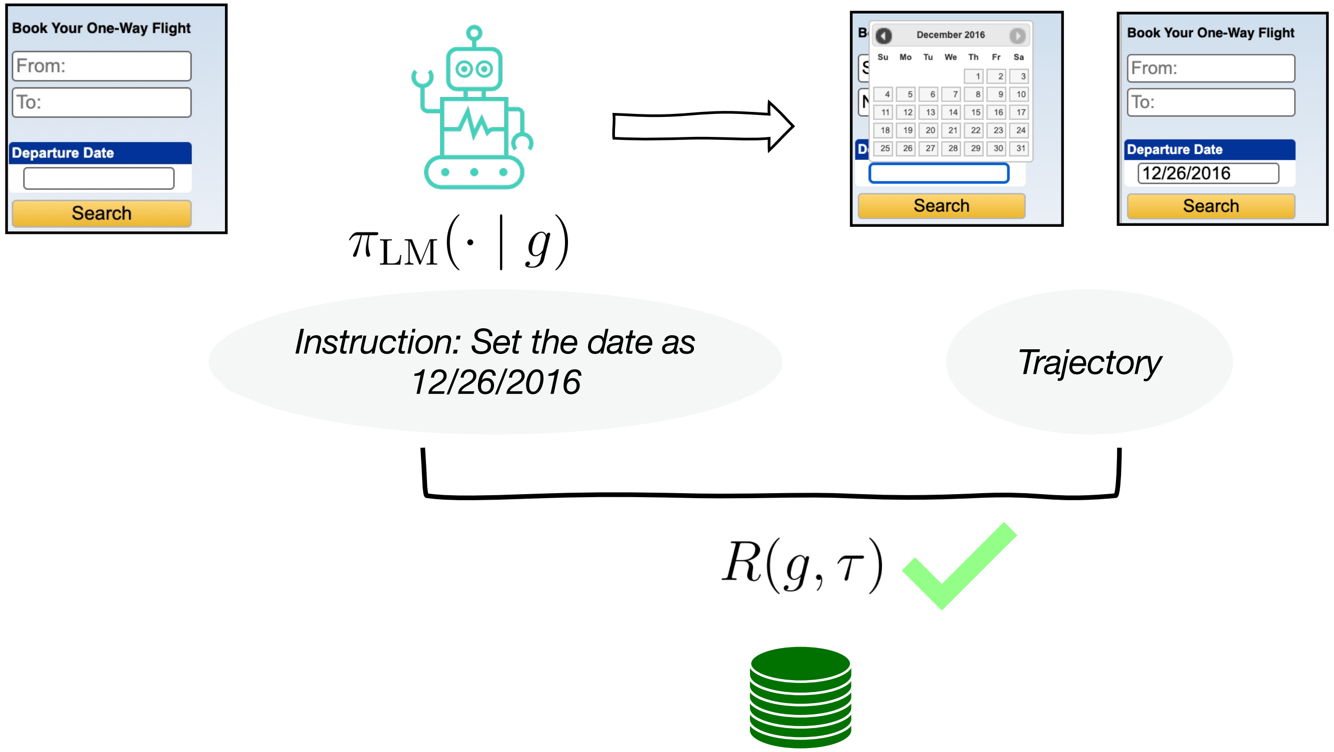
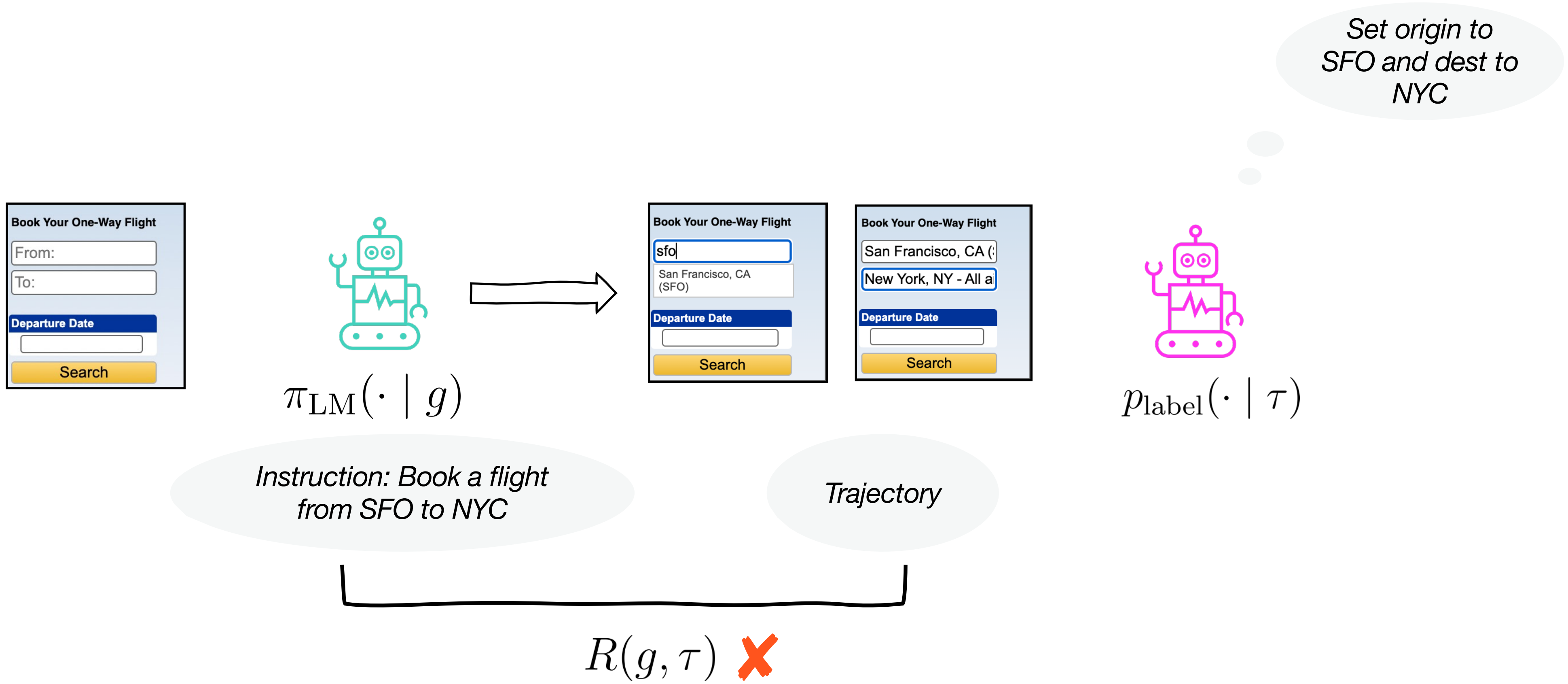


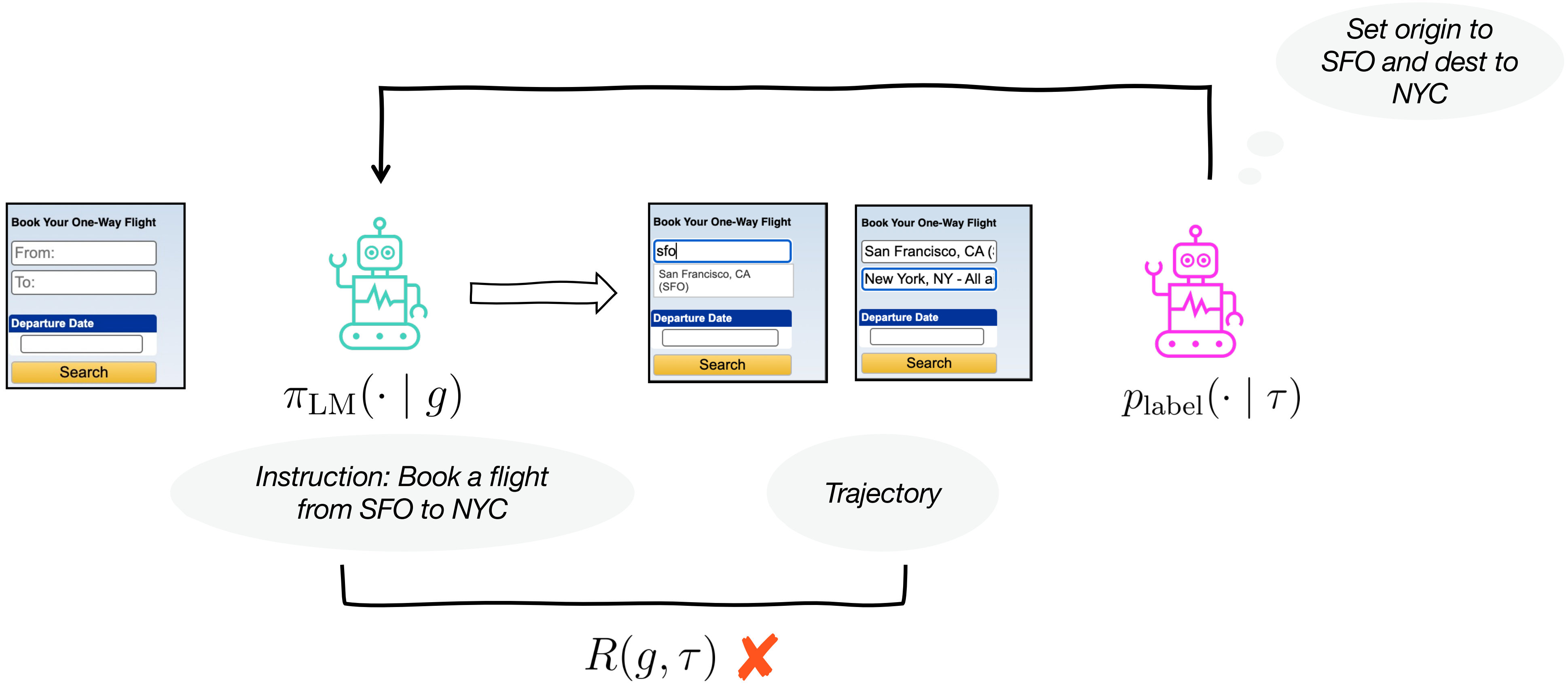
Use Exploration + Model Generated Data!



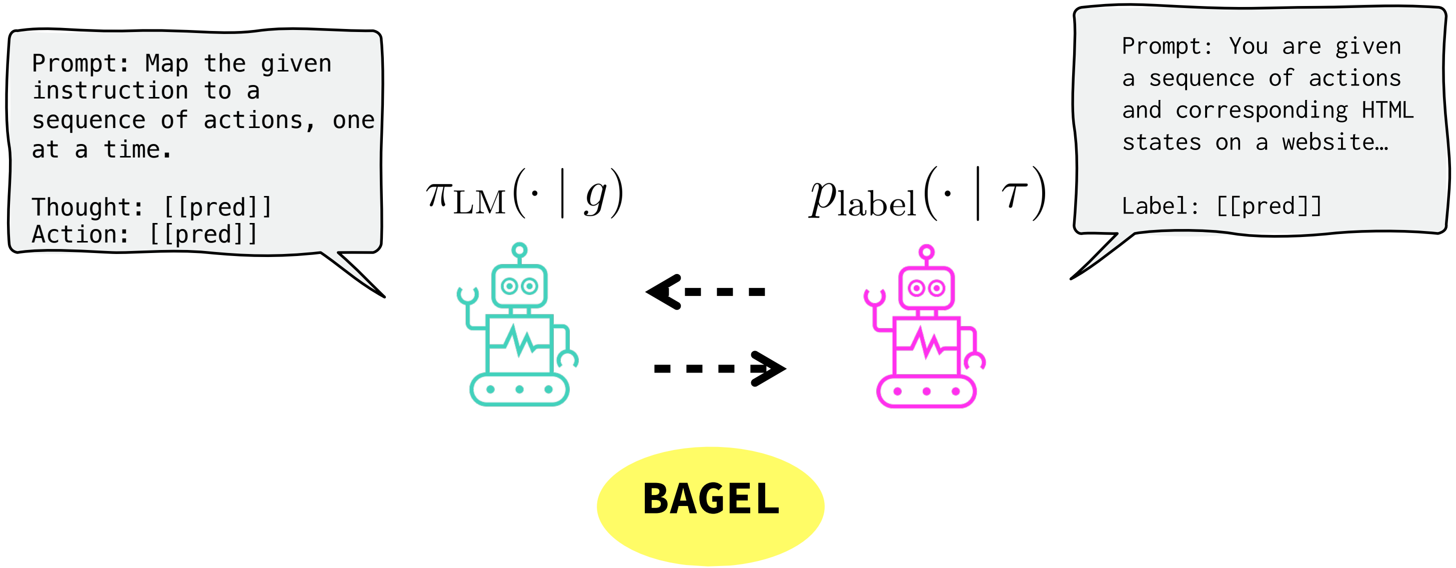
Use Exploration + Model Generated Data!



Use Exploration + Model Generated Data!

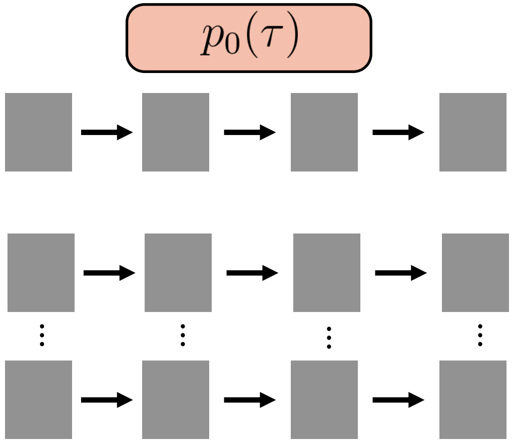


BAGEL: Use Exploration + Model Generated Data!

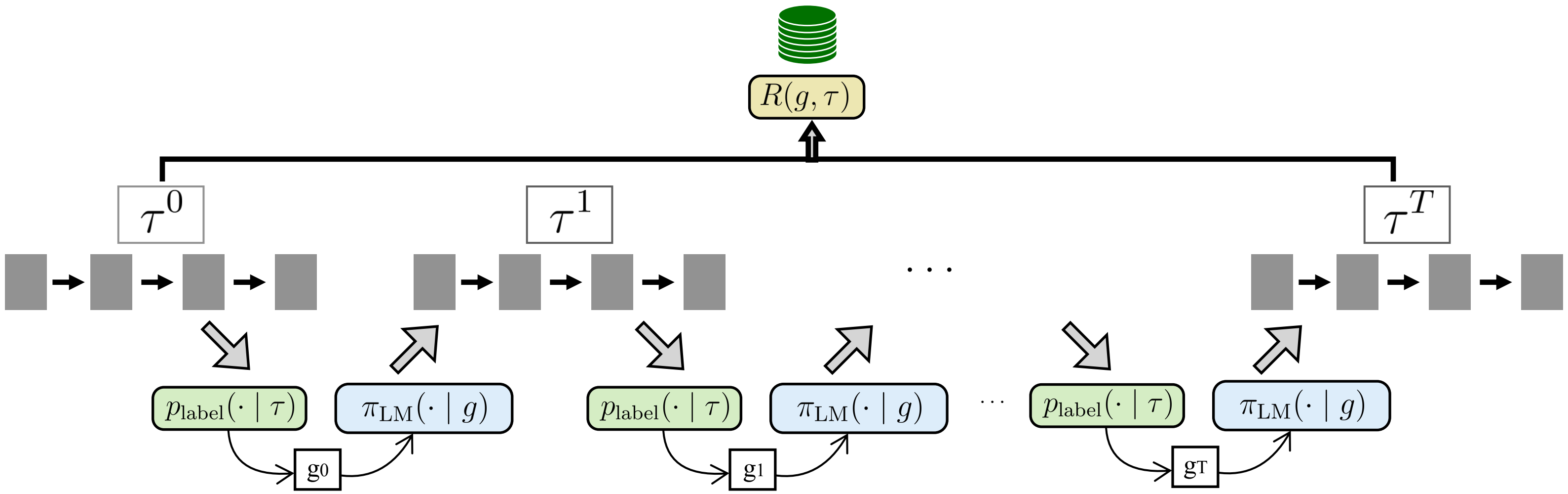


(Bootstrapping Agents by Guiding Exploration with Language)

BAGEL: Use Exploration + Model Generated Data!



1. Explore Environment to collect trajectories



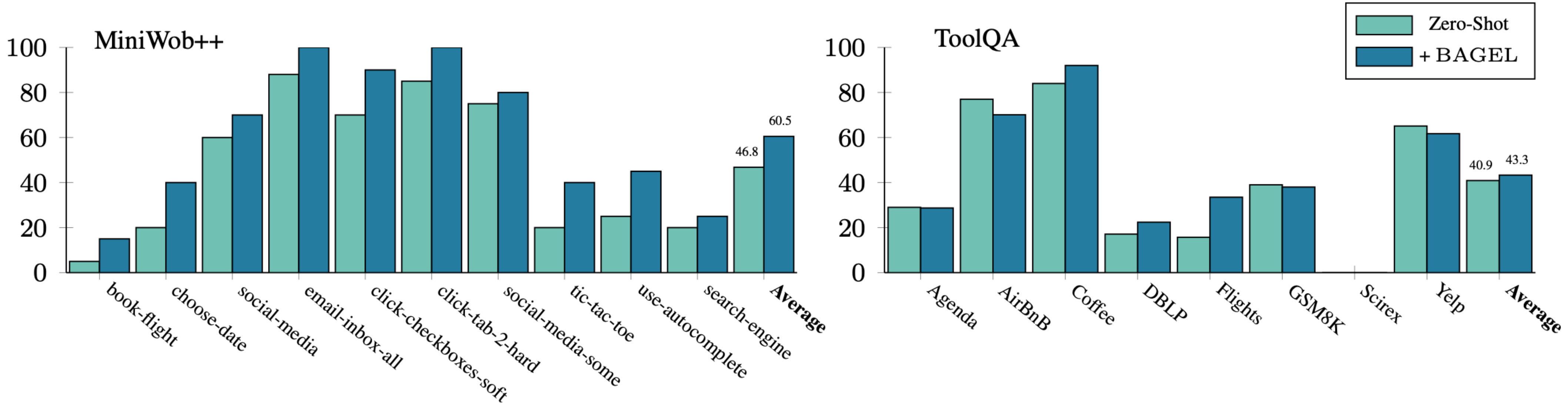
2. Create Synthetic demonstrations via iterative re-labeling

"Book the cheapest flight from Denver to LA"

3. Instruction-Following (Inference Time): Retrieve Relevant Demonstration via retrieval to use as in-context exemplars

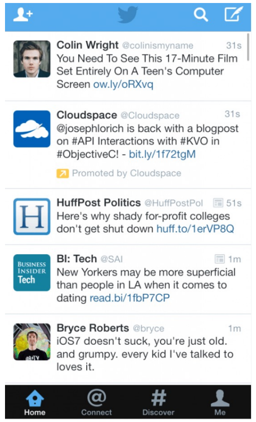
Finetuning possible too!

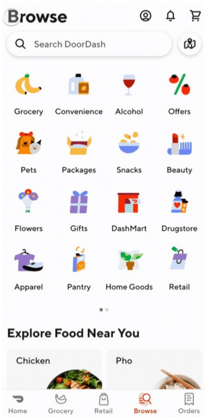
BAGEL: Use Exploration + Model Generated Data!

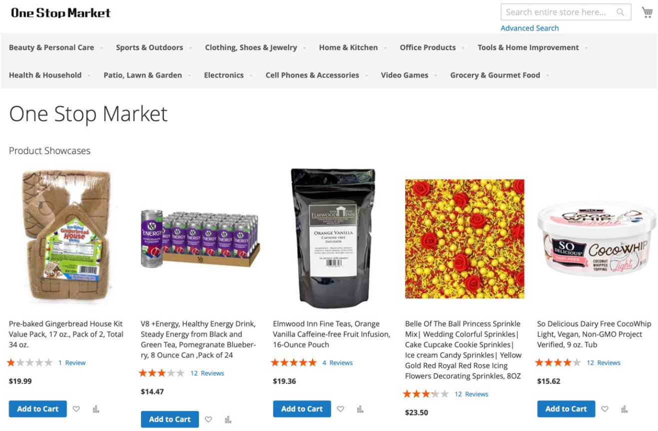


13% point improvement on MiniWoB++ and 2.5% improvement on multi-step tool use, using PALM-2 as the base language model, with no human supervision

Multimodality?



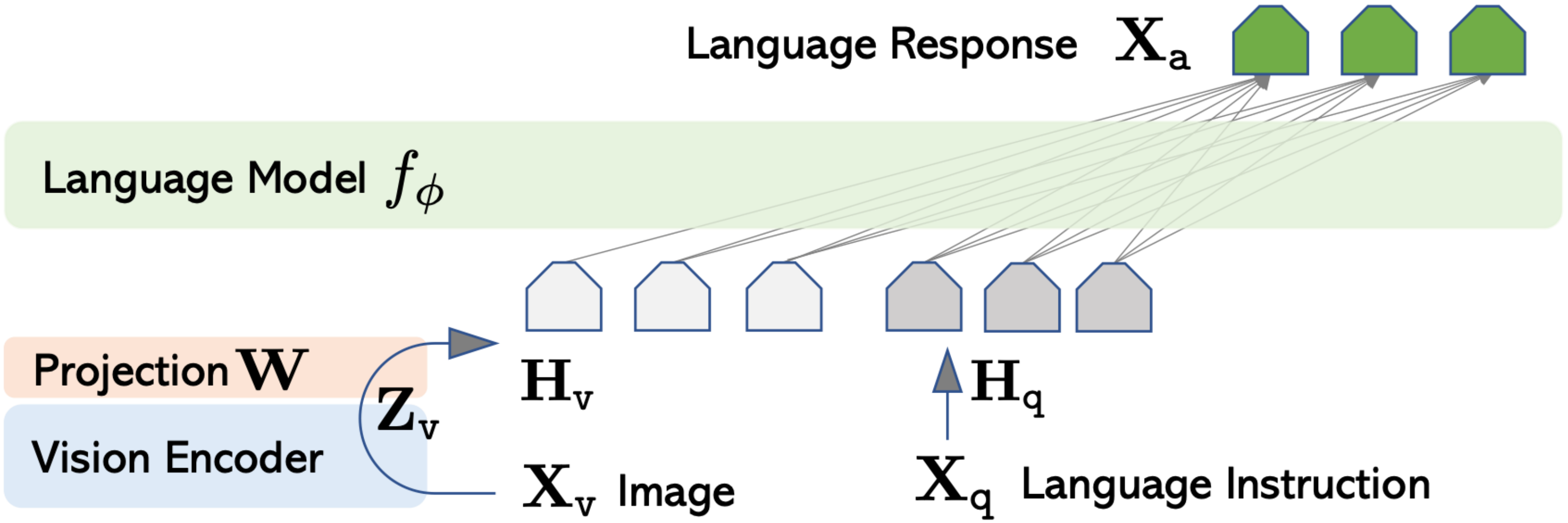




- So far, we've looked at using text-only language models for agents
- This is intractable for real-world UIs with very long HTML
- Can we instead operate directly over pixel space?

Multimodality

LLaVA



Prompt GPT-4 to generate instructions and responses given textual descriptions of images

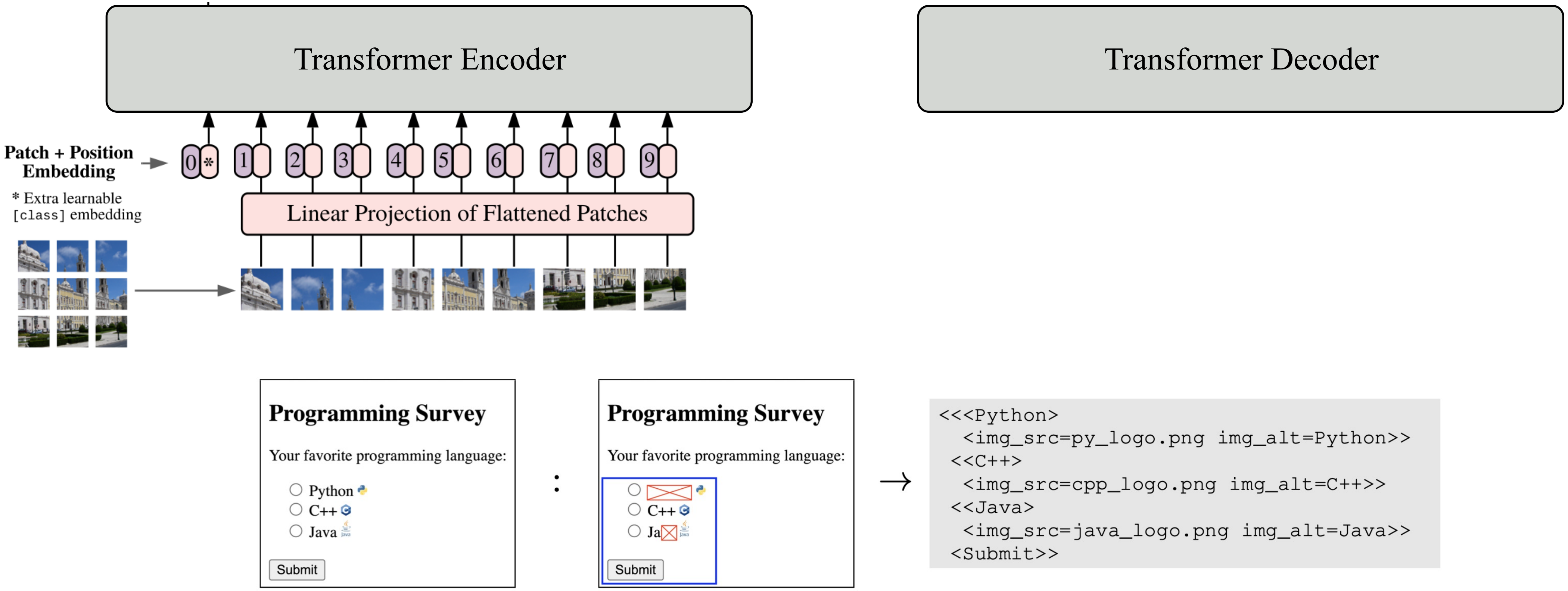
Finetune a CLIP encoder jointly with a Vicuna-13B decoder on this data

Source: Liu et al. 2023

Multimodality

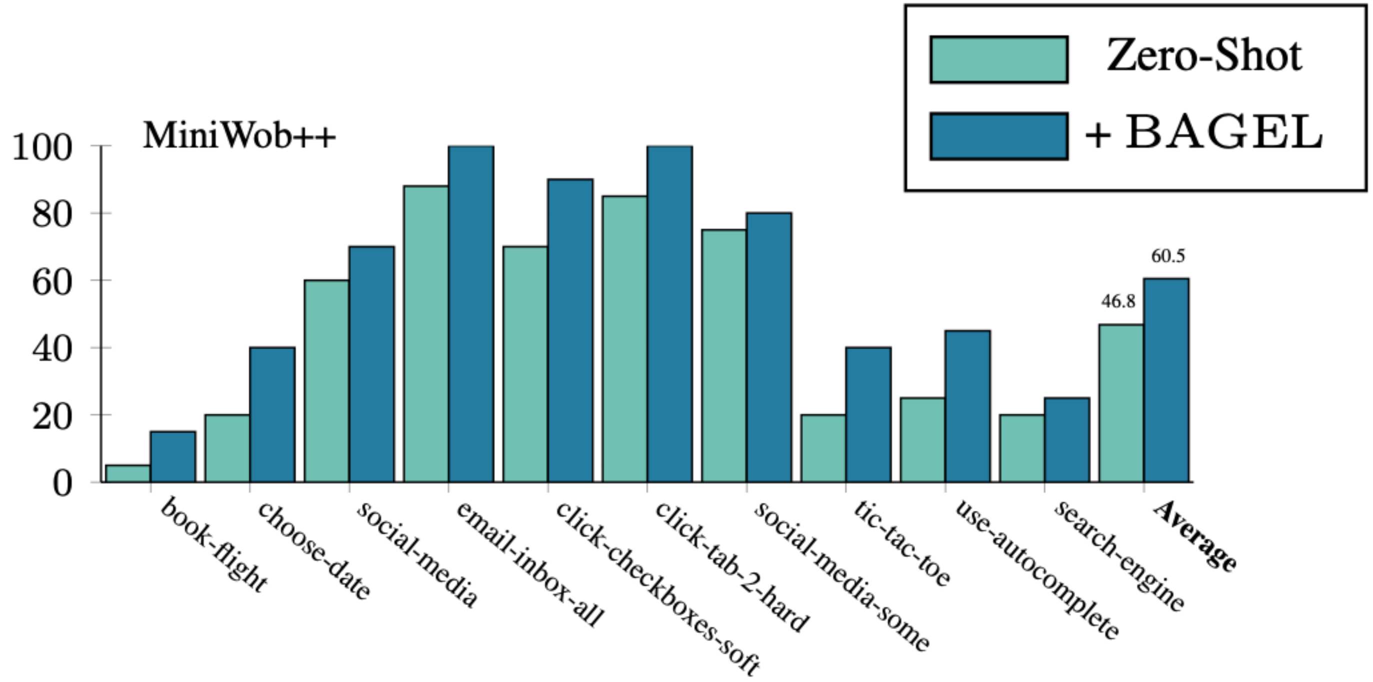
Pix2Struct

Finetune a ViT encoder and a transformer decoder on a new HTML screenshot parsing task



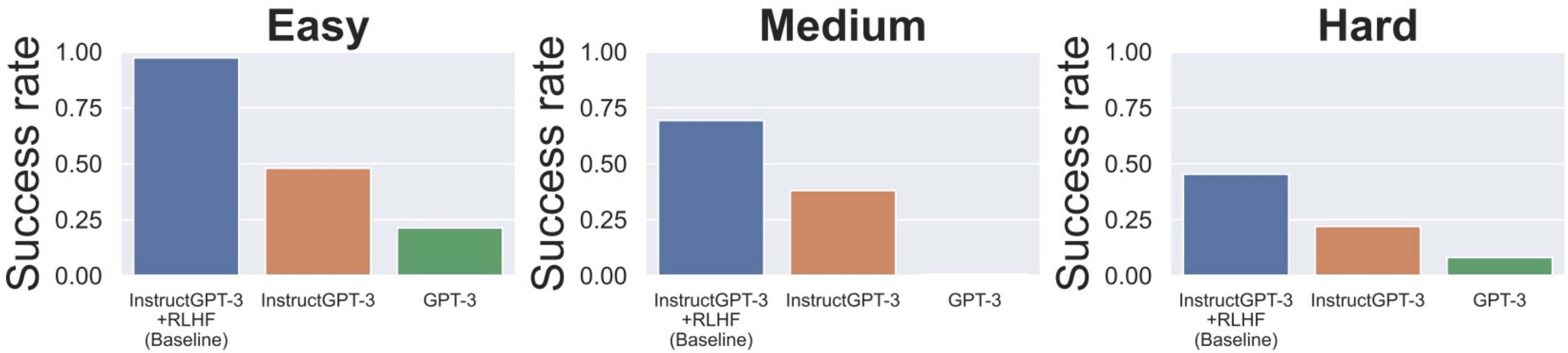
Source: Lee et al. 2023

LM Agents is an emerging application!



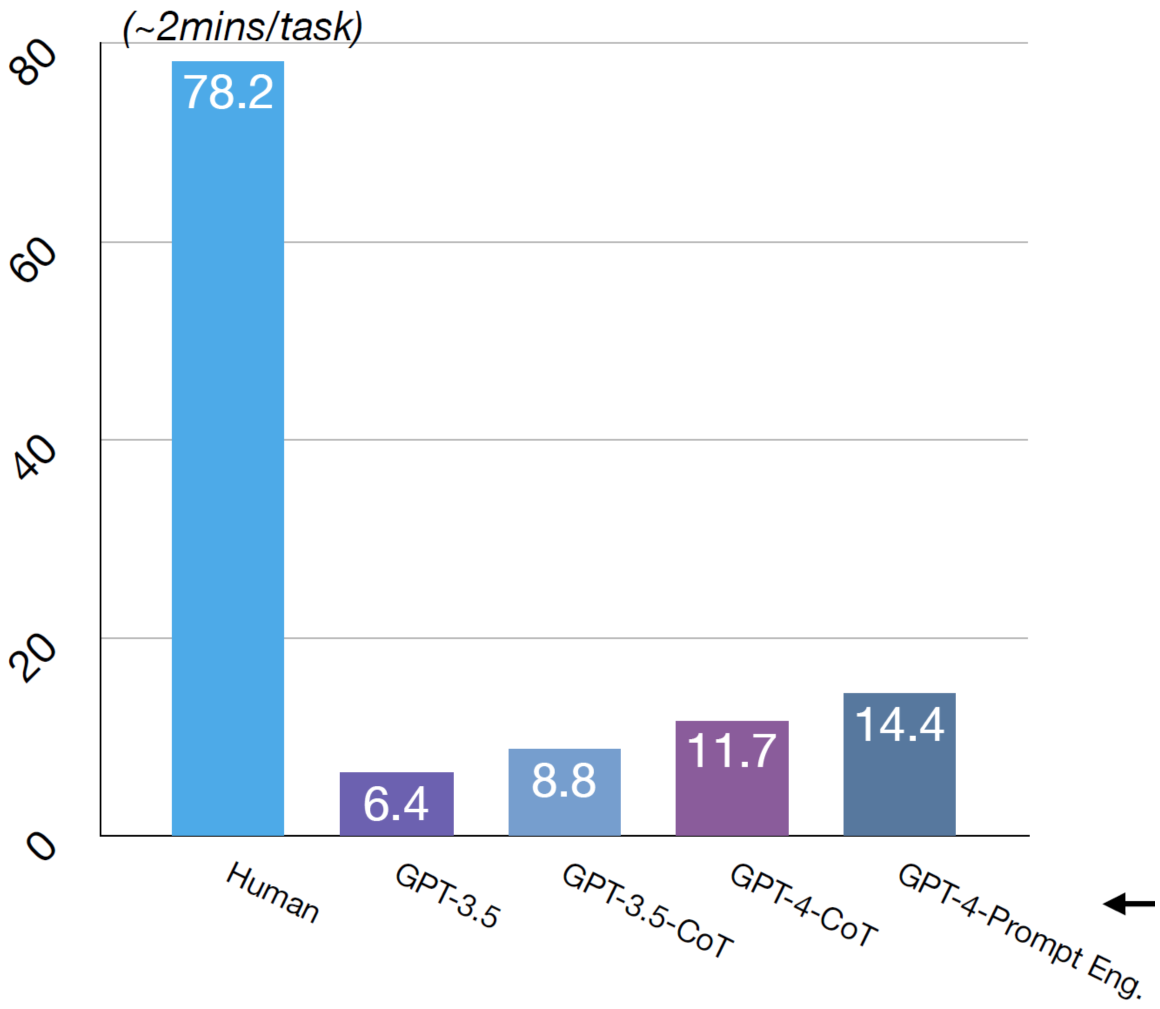
The "prompting gap": without extensive prompting / bespoke few-shot examples, competitive LMs are far from perfect on even the simplest environments

LM Agents is an emerging application!



Long-horizon planning is hard: Even on simple benchmarks, performance drops drastically on tasks that require longer horizon planning.

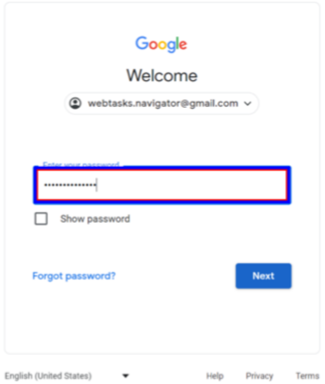
LM Agents is an emerging application!



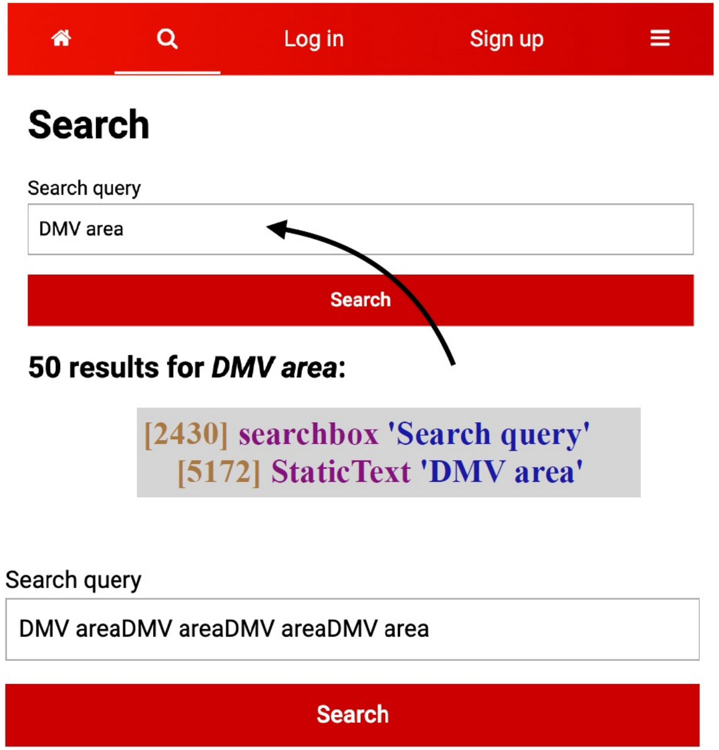
Latest Work: BrowserGym 25%
More prompt engineering
More observation/action interface engineering

LM Agents is an emerging application!

S2: Open Google translate and sign in using the following credentials: [email] [password]



Reference (B): [password]
GPT-4V (R): [email]
LLaMA (B): [password]



Lecture-14 Recap

- Reasoning in Language Models:
  - Via prompting
  - By distilling rationales from big LMs into small LMs
  - By finetuning LMs on their own rationales, iteratively
  - Counterfactual evaluation reveals reasoning may not be systematic

- Language Model Agents:
  - Prompting and in-context learning
  - BAGEL for synthetic demonstrations: exploration and iterative relabeling
  - Multimodality
  - Benchmarks still challenging

💡 Lots to be done to drive further improvements!