Agent Frameworks

CS6960 MultiModal LLM Agents

Kenneth Marino

Slide credits: Yoav Artzi, Shuyan Zhou, Xinyun Chen, others

Announcements

- HW1 due in two weeks
  - See Syeda's note in announcements / read the new instructions
  - Basically just asking you to read the intro unit to the HF Agents tutorial and write some boilerplate code
- HW0
  - Hopefully you're done
  - Can give an extension if you recently joined the course
- Paper Presentations starting today
- Projects
  - Start thinking of ideas
  - We're working on a list of "starter ideas"
  - Read through papers in area you're interested in

Recommended Readings

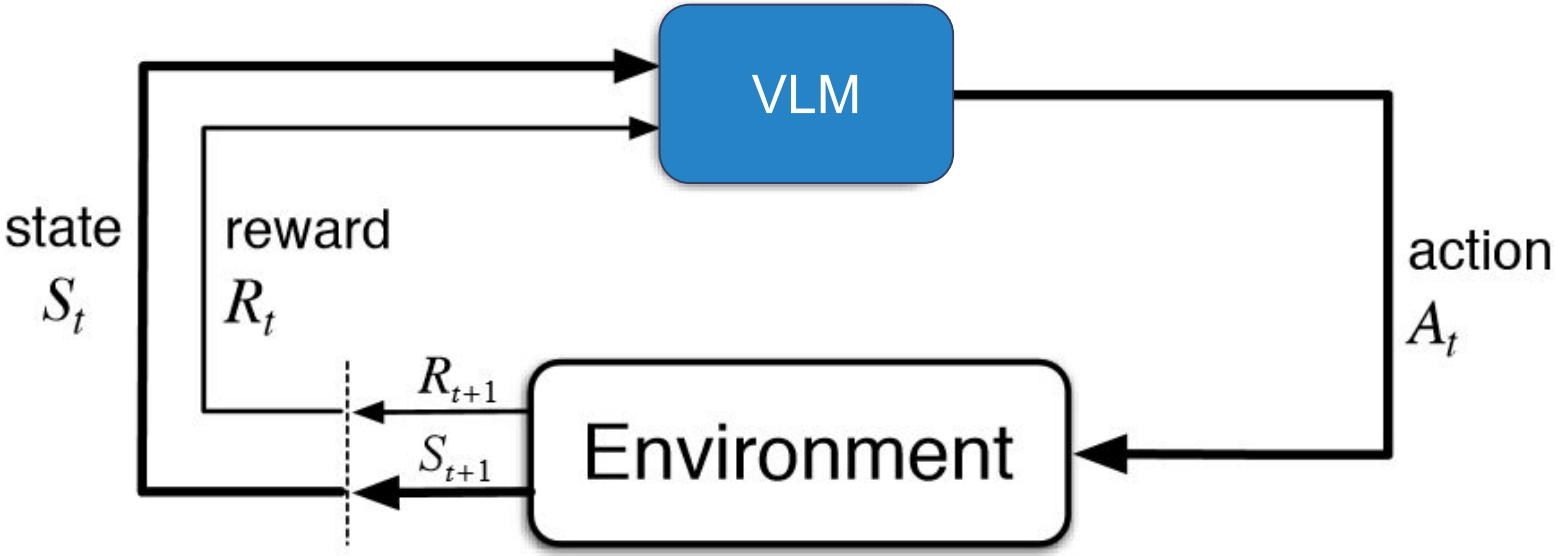
- Agent Courses/Tutorials
  - https://www.shuyanzhou.com/teaching/25fall-590/25fall-590.html
  - https://rdi.berkeley.edu/adv-llm-agents/sp25
  - https://agenticai-learning.org/sp25
- This week's papers
  - Chain-of-Thought Prompting Elicits Reasoning in Large Language Models
  - ReAct: Synergizing Reasoning and Acting in Language Models
  - Reflexion: Language Agents with Verbal Reinforcement Learning
  - Charts-of-Thought: Enhancing LLM Visualization Literacy through Structured Data Extraction
  - DeepSeek-R1: Incentivizing Reasoning Capability in LLMs via Reinforcement Learning

Lectures Going Forward

- Meant to be fairly short / high-level
  - More an introduction/framing of the topic than a deep dive
  - Maybe 20-40 mins depending on how much I have to say about the topic
- Imperative that you read papers and participate in class discussions to get full breadth of topic

Any Questions

What does VLM agent actually look like?



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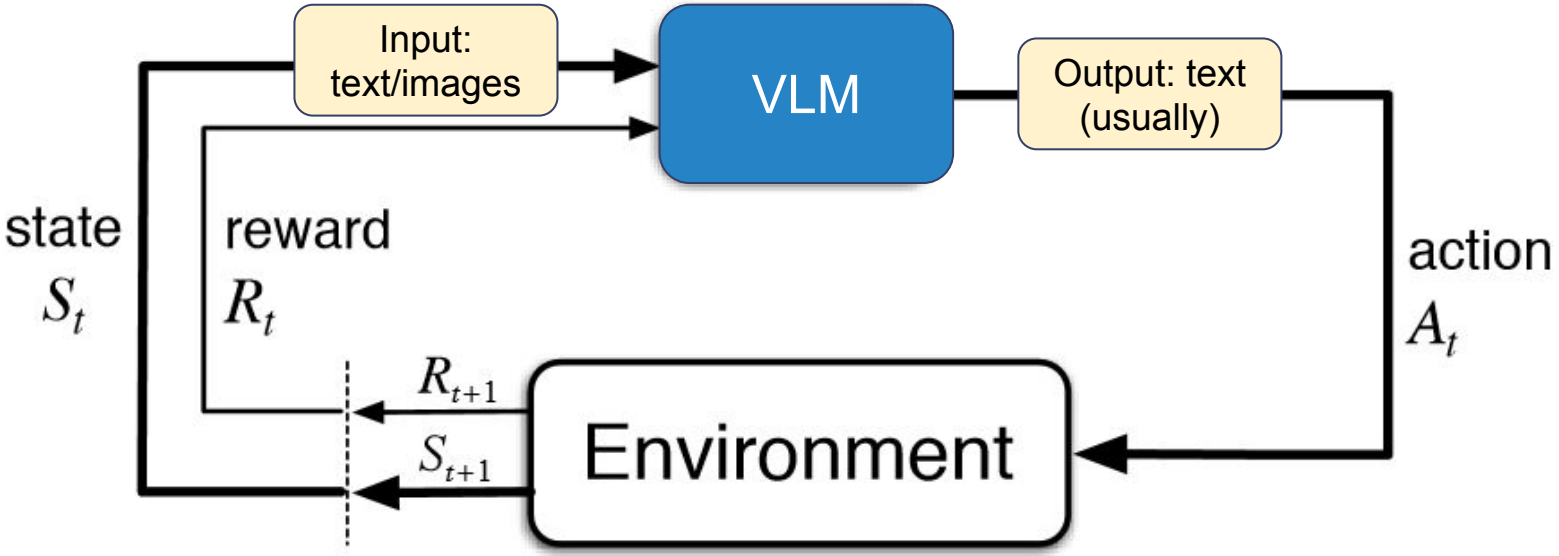

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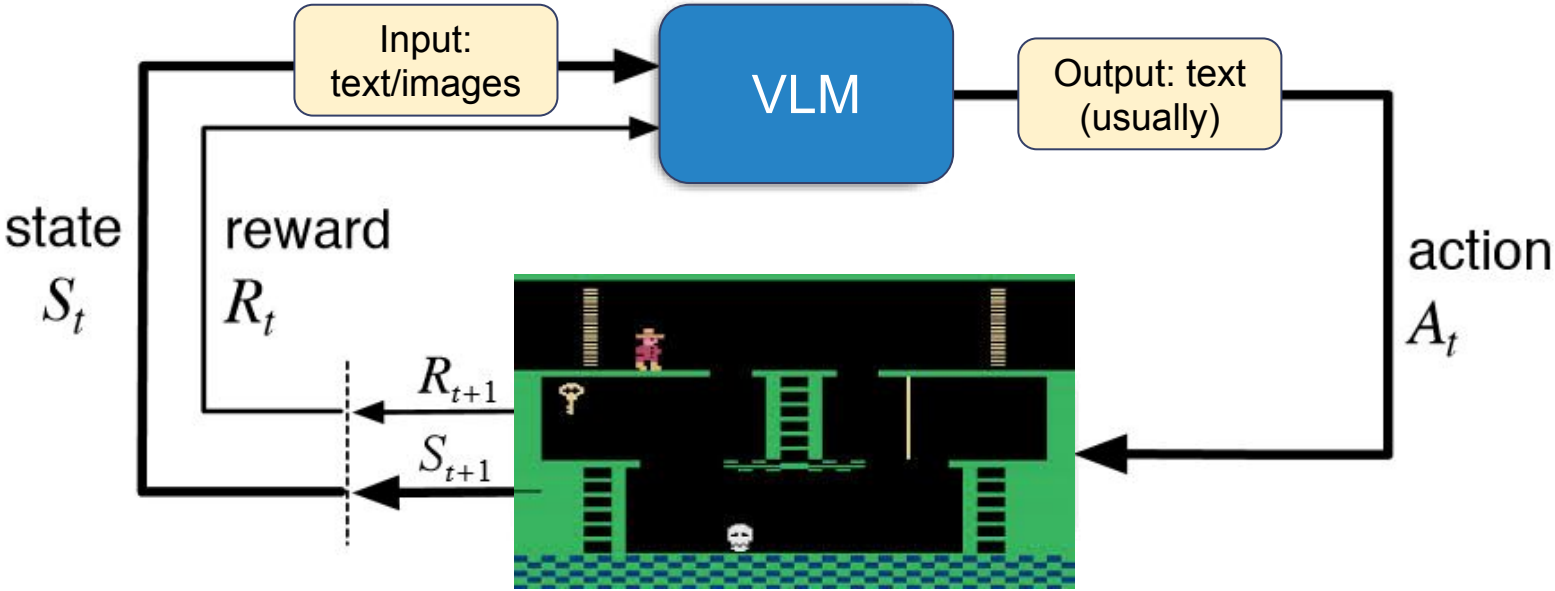

Other “stuff”

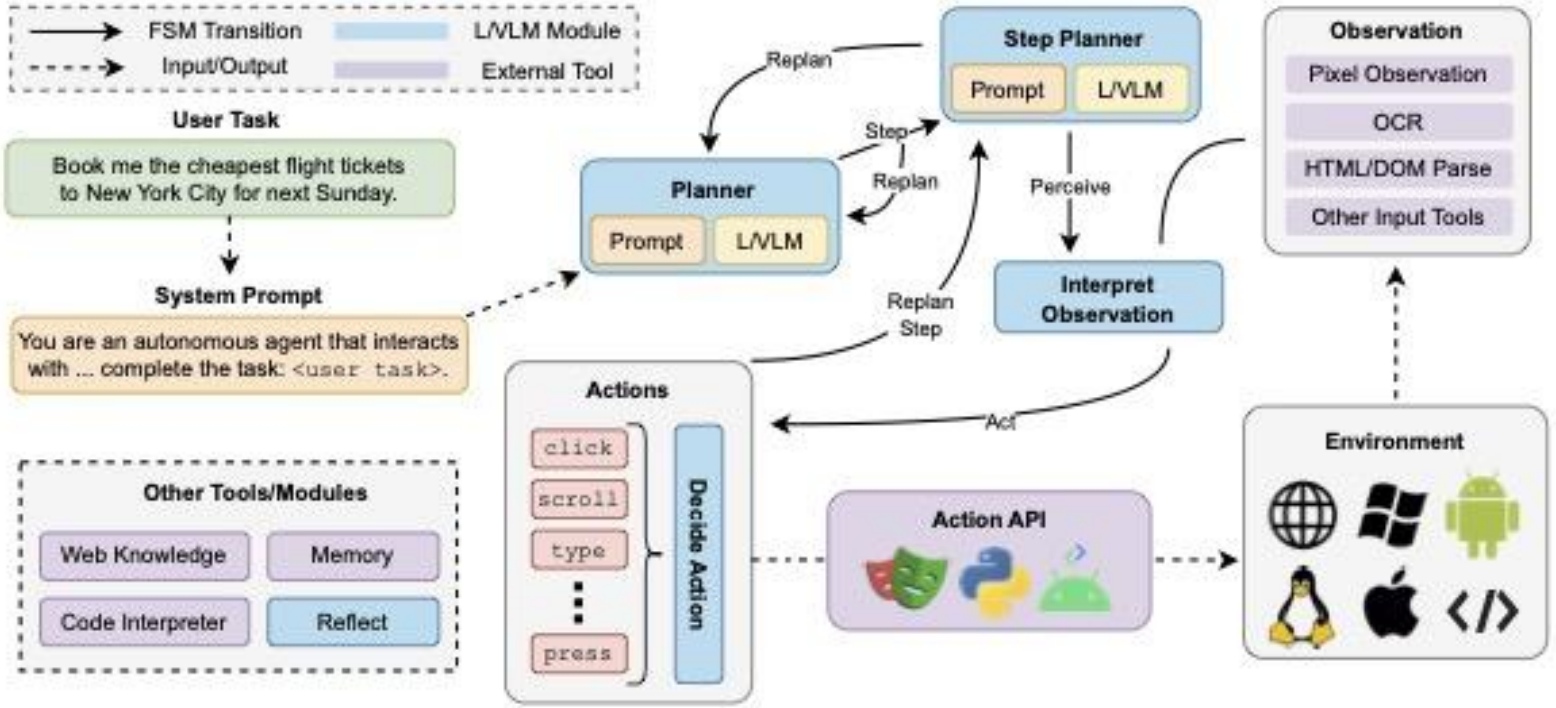

Image credit: Farhan Ishmam

Other “stuff”

Frameworks for LLMs to be better at actions (reflect, plan, replan, etc)

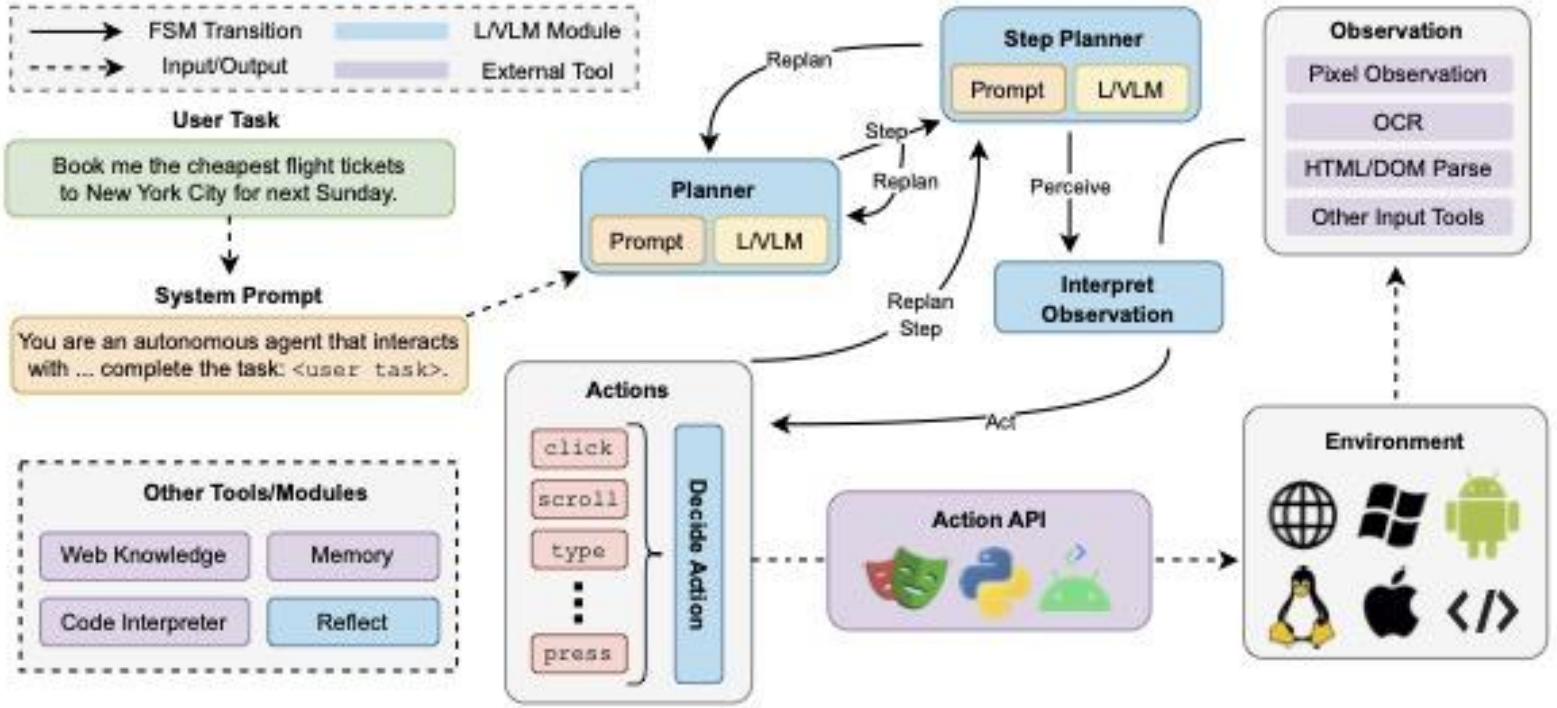

Image credit: Farhan Ishmam

Why do this?

What this means for VLM Agents

- Basics of environment, maximizing reward, policies, all apply
  - State/observation given by text image tokens
  - Output is text (then interpreted as environment actions)
  - Want to maximize some reward (answer a query, fill out a web form, do some action in the environment)
- Most useful algorithms to know
  - Imitation learning probably most common
    - When we talk about LLMs, this is exactly the same as Supervised Fine Tuning (SFT)
  - When we do RL with agents, PPO is most commonly used
- VLM agents also often work without any training!
  - Through prompting frameworks and other methods
  - Just relies on general ability of the base models!
  - **There will always be a limit on how good this will be / no way to make it better**

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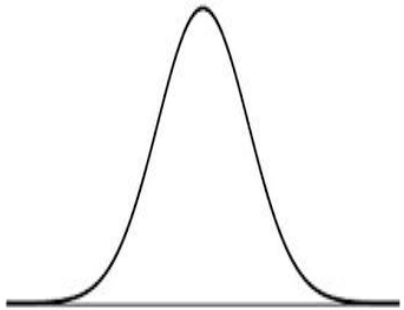
Is there a way to make VLM better without training?

Shift VLM’s distribution

- LLM/VLM
  - Pre-trained on Internet Data



Pretrianing Distribution

Shift VLM’s distribution

- LLM/VLM
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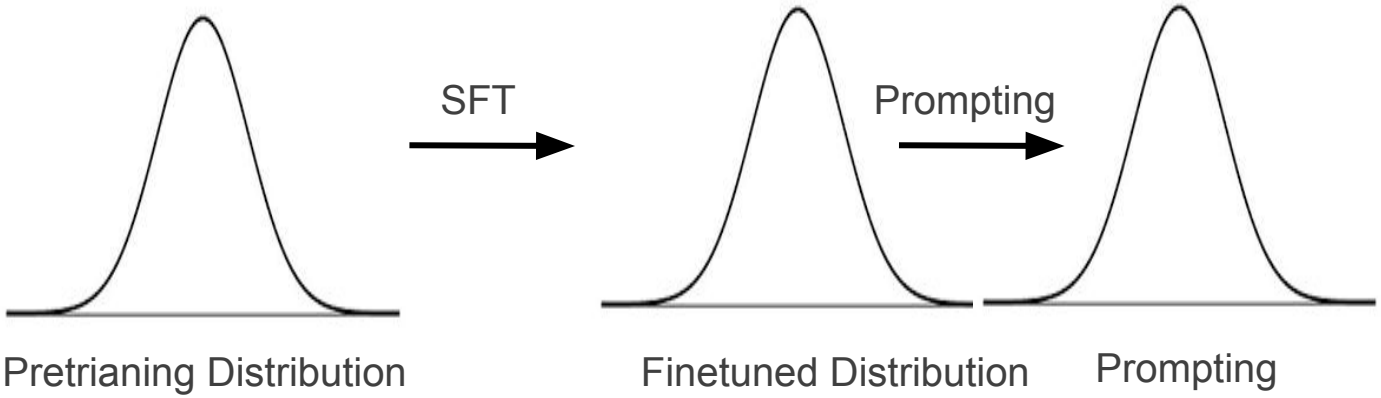
  - Finetuned on some task specific data

Shift VLM's distribution

- LLM/VLM
  - Pre-trained on Internet Data
  - Finetuned on some task specific data
  - Use prompting to shift the input to get a different distribution



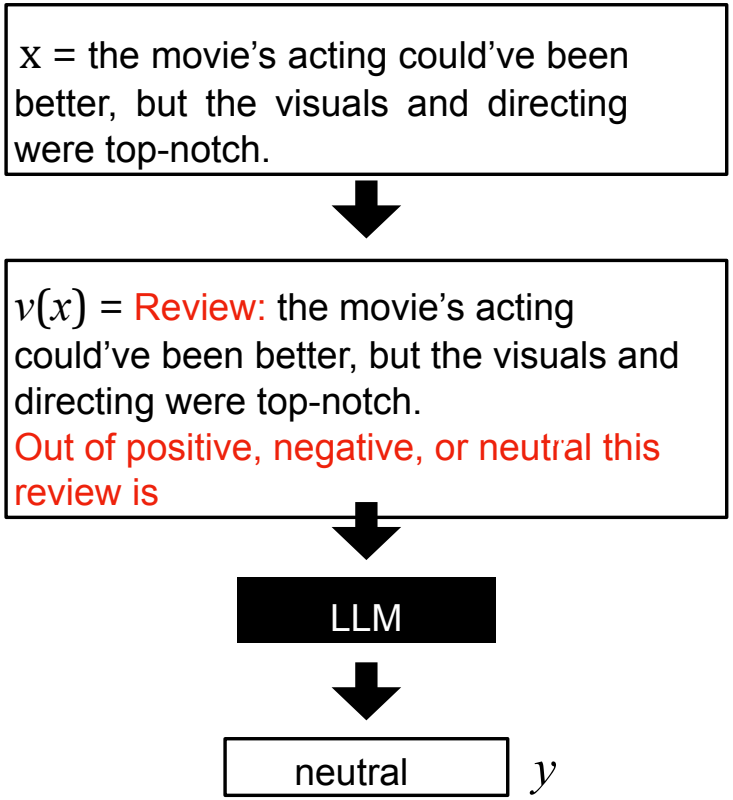
Prompting!

- Simple way to turn LLMs into task-specific models
  - You benefit from the rich representations of the LLM
  - Finetuned on some task specific data
- LLMs offer a completely new mode of operation that does not require any changes to its parameters: prompting
  - With or without annotated examples: zero-shot or in-context learning (few-shot)
  - With or without intermediate reasoning steps: **chain-of-thought prompting**
  - Prompt to Act and plan - ReAct
  - Prompt to self-correct mistakes - Reflexion

Material from Yoav Artzi

Zero-shot Prompting

- Input: single unlabeled example x
- Output: the label *y*
- The task (and output) can be any text-to-text task: classification, summarization, translation
- Pre-processing: wrap x in a verbalizer template
- The template controls the output



Material from Yoav Artzi

Zero-shot Prompting

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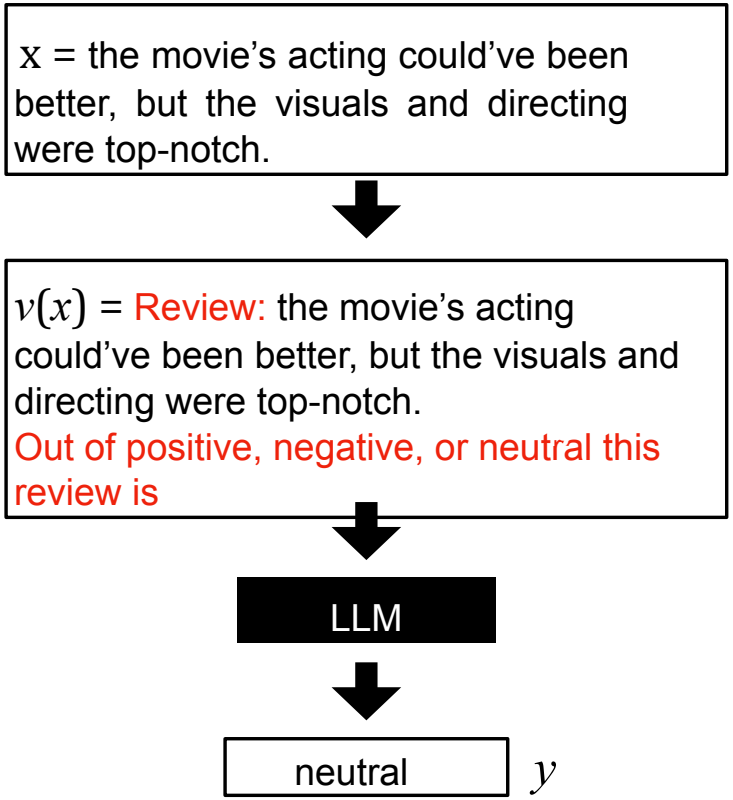
- P er template
- The template controls the output

- We've made a task more accurate by prompting the LLM with information about how we want it to perform the task
- In this case - what is the output space we want for the task
- Can instantly improve performance with no additional data (zero-shot, zero extra data)



Material from Yoav Artzi

Sensitivity and Variability

- Prompts can even be sensitive to minor cosmetic changes
- Can influence performance in unexpected ways
- Can think of them as (very complex) hyper-parameters

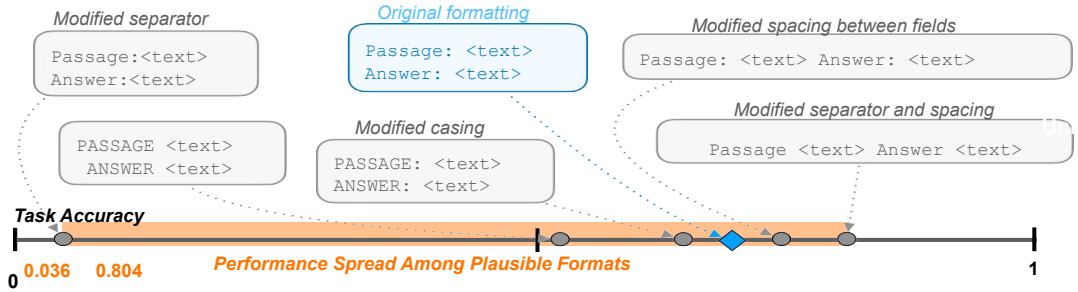


Figure 1: Slight modifications in prompt format templating may lead to significantly different model performance for a given task. Each `<text>` represents a different variable-length placeholder to be replaced with actual data samples. Example shown corresponds to 1-shot LLaMA-2-7B perfor- mances for task280 from SuperNaturalInstructions (Wang et al., 2022). This StereoSet-inspired task (Nadeem et al., 2021) requires the model to, given a short passage, classify it into one of four types of stereotype or anti-stereotype (gender, profession, race, and religion).

[Sclar et al. 2023]

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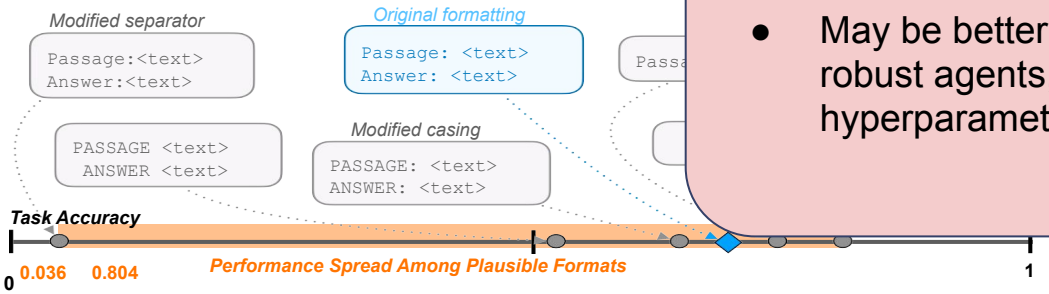

- This is one reason prompting can be a less idea strategy
- May be better to SFT/RL train for more robust agents, avoid prompt hyperparameter search

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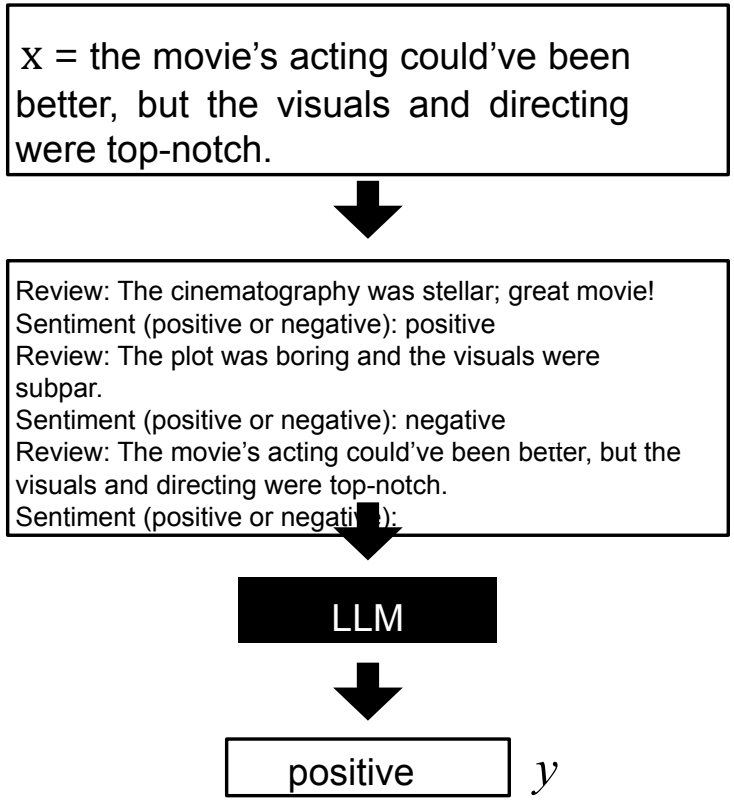
[Sclar et al. 2023]

Material from Yoav Artzi

Few-shot / In-context Learning (ICL)

- LLMs have the ability to "learn" to complete tasks through training in the prompt
- The recipe is simple:
  - Take a small number of annotated training example $\{(\bar{x}^{(i)}, \bar{y}^{(i)}\}_{i=1}^{N}$
  - Convert them using verbalizer v templates
  - Concatenate them and follow with the target input $\bar{x}$
  - The completion will be the label of the input



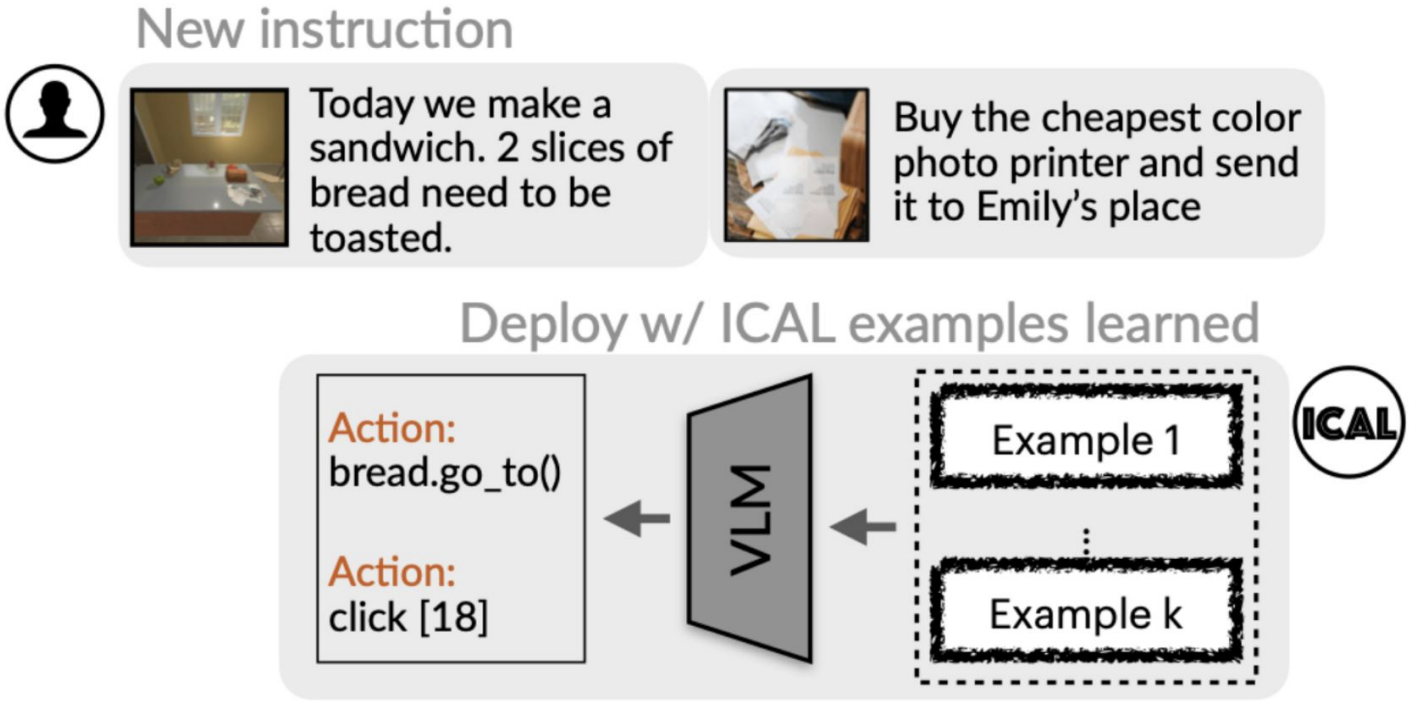
Material from Yoav Artzi

In-context Learning (ICL)

- Providing ICL examples almost always leads to significant improvements
- Benefits tend to diminish with more examples

Material from Yoav Artzi

ICL in Agents



Gabriel Sarch, Lawrence Jang, Michael Tarr, William W Cohen, Kenneth Marino, Katerina Fragkiadaki. "VLM agents generate their own memories: Distilling experience into embodied programs of thought." *NeurIPS* 2024.

Chain-of-thought (COT) Prompting

- Can we get agents to “think” through decisions?
- Some tasks require multiple reasoning steps
- Directly generating the answer requires the model internally do the reasoning steps (or shortcut somehow)
- It is empirically useful to:
  - Show the model examples of the reasoning steps through ICL
  - And then have it explicitly generate the reasoning steps

Material from Yoav Artzi

Chain-of-thought (COT) Prompting

Standard Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The answer is 27. ✗

Chain-of-Thought Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The cafeteria had 23 apples originally. They used 20 to make lunch. So they had 23 - 20 = 3. They bought 6 more apples, so they have 3 + 6 = 9. The answer is 9. ✓

[Wei et al. 2022]

Chain-of-thought (COT) Prompting

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Chain-of-Thought Prompting

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Model Output

A: The cafeteria had 23 apples originally. They used 20 to make lunch. So they had 23 - 20 = 3. They bought 6 more apples, so they have 3 + 6 = 9. The answer is 9. ✓

- This is covered in one of the presentations today, so not going too deep
- Bottom line: prompting alone can encourage LLM to reason better!

[Wei et al. 2022]

Thinking without Prompting?

- Can we train LLMs to think through their reasoning?
- Will hear more about this later
- Use RL to train models to do reasoning

Many classes of inference-time LLMs

- Are there inference-time / prompting techniques for agents?

ReAct (Yao et al 2023)

- **Loop:** Goal → Observation → (Reasoning → Action) → Observation → ….
- Treat **reasoning itself** as an action that changes the **internal** state of the agent, rather than the environment.

Question: Aside from the Apple remote, what other devices can control the program Apple remote was originally designed for?

Thought 1: I need to search Apple Remote and find the program it was originally designed to interact with.

Act 1: `Search[Apple Remote]`
Obs 1: The Apple Remote is a remote control introduced in October 2005 by Apple […] originally designed to control the Front Row media center program […]

Thought 2: Apple Remote was originally designed to control the Front Row media center program. I need to search Front Row next and find what other device can control it.

Act 2: `Search[Front Row]`
[…]

Slides from Shuyan Zhou

ReAct (Yao et al 2023)

```
def react_agent(goal, max_steps=10):
  observation = get_initial_observation()

  for step in range(max_steps):
    # Generate thought about current situation
    thought = llm.generate(f"Goal: {goal}\nObservation: {observation}\nThought:")

    # Decide on action based on thought and observation
    action = llm.generate(f"Goal: {goal}\nObservation: {observation}\nThought: {thought}\r

    # Execute action in environment
    env.execute(action)
```

ReAct effectively defines a straightforward for loop

Slides from Shuyan Zhou

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Slides from Shuyan Zhou

Planning Beyond ReAct

Besides reason about the immediate observation, the agent can also

- Break high-level task into subtasks.
- Examine the history, perform backtracking or re-planning if necessary

Hence, the control loop can be more complicated.

```
def planning_agent(goal, max_steps=10):
  # Initial planning phase
  plan = llm.generate(f"Create plan for: {goal}")
  subtasks = parse_plan_into_subtasks(plan)
```

```
  for subtask in subtasks:
    # Execute subtask using ReAct loop
    while not is_subtask_completed(subtask):
      thought = llm.generate(f"Current subtask: {subtask}")
      action = llm.generate(f"Based on thought, what action?")
      observation = env.execute(action)
```

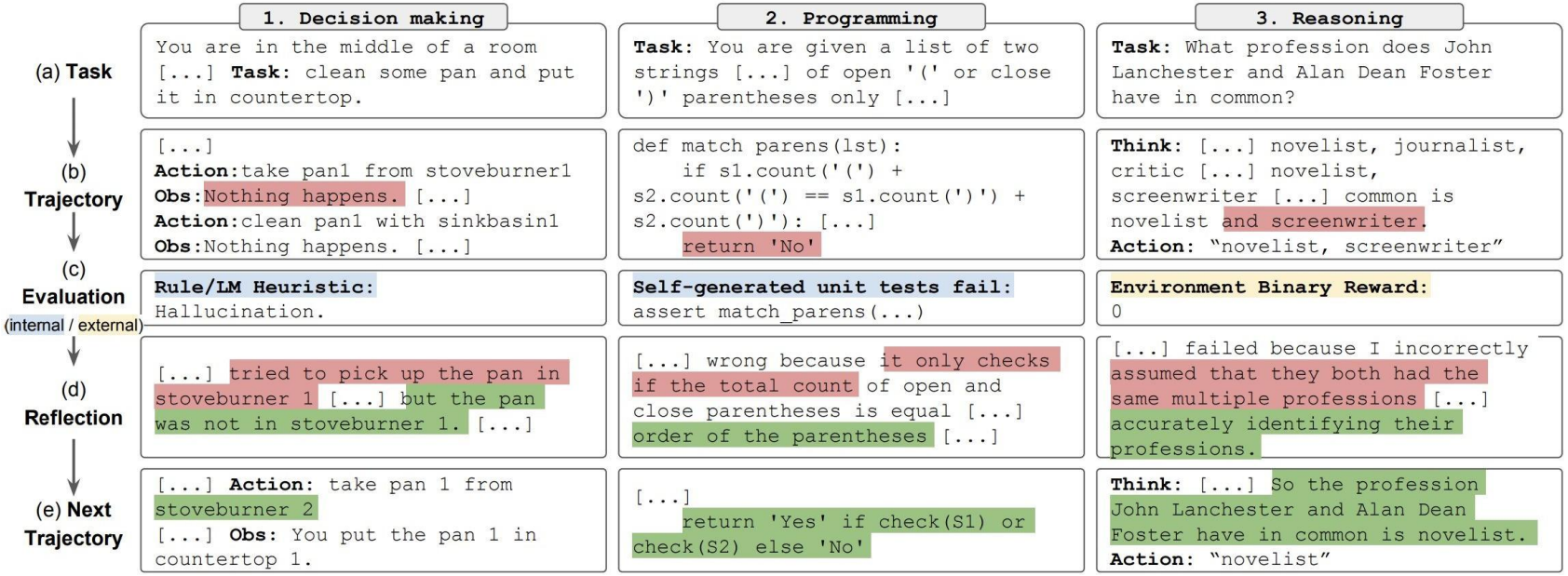
```
      # Replan if stuck
      if should_replan(observation):
        subtasks = replan(goal, current_progress)
        break
```

Slides from Shuyan Zhou

Correcting mistakes

- Can VLM agents recognize/fix their own mistakes
- Can they **reflect** and figure out where they went wrong

Reflexion and Self-Refine



- LLM generates feedback on its output. Use external evaluation when available.
- LLM self-refines its output given both internal feedback and external evaluation.

Shinn et al., Reflexion: Language Agents with Verbal Reinforcement Learning, NeurIPS 2023.
Madaan et al., Self-Refine: Iterative Refinement with Self-Feedback, NeurIPS 2023.

Slides from Xinyun Chen

Beyond Singe Agent

- **Multi-agent systems**: Multiple agents collaborate or compete
  - e.g., code review (writer/reviewer), debate systems, hierarchical teams

```
def multi_agent_collaboration(goal, agents):
  # Distribute work among agents
  subtasks = decompose_task(goal, num_agents=len(agents))
```

```
  for round in range(max_rounds):
    results = []
    for i, agent in enumerate(agents):
      # Each agent works on their subtask
      result = agent.execute(subtasks[i])
      results.append(result)
```

```
    # Agents communicate and share results
    shared_knowledge = aggregate_results(results)

    # Update each agent's understanding
    for agent in agents:
      agent.update_knowledge(shared_knowledge)

    if is_goal_achieved(shared_knowledge, goal):
      break
```

Slides from Shuyan Zhou

Takeaways

- We want some way to get VLMs/LLMs more in distribution for agent tasks
  - Ideally: SFT/RL can do this
  - In a pinch, prompting techniques very effective
- Get agents in distribution
  - Zero-shot prompting
  - In context Learning
- Get agents to think
  - With prompting in context (CoT)
  - With RL training (DeepSeek)
- Prompt agents to behave more like agents
  - Think/Act/Observe ReAct
  - Reflect on mistakes - Reflexion

Any Questions

Questions

Now for the presentations!