

Week 2

W2.2- LLM Agent Basics

2026 Spring

LLM Agents Foundation & Applications

Dr. Yanjun Qi
20260115

Last Class

To incorporate human preferences:

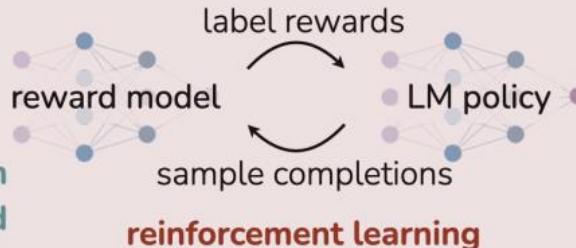
- **RL algorithms** (PPO, GRPO, REINFORCE) explicitly maximize expected reward from a reward model – we normally call this group **RLHF**
- **Direct alignment methods** (DPO, IPO, KTO) optimize preference objectives without explicit reward modeling
- Though they can be shown to implicitly optimize an equivalent objective under certain assumptions

Reinforcement Learning from Human Feedback (RLHF)

x: "write me a poem about
the history of jazz"



maximum likelihood



Direct Preference Optimization (DPO)

x: "write me a poem about
the history of jazz"



maximum likelihood



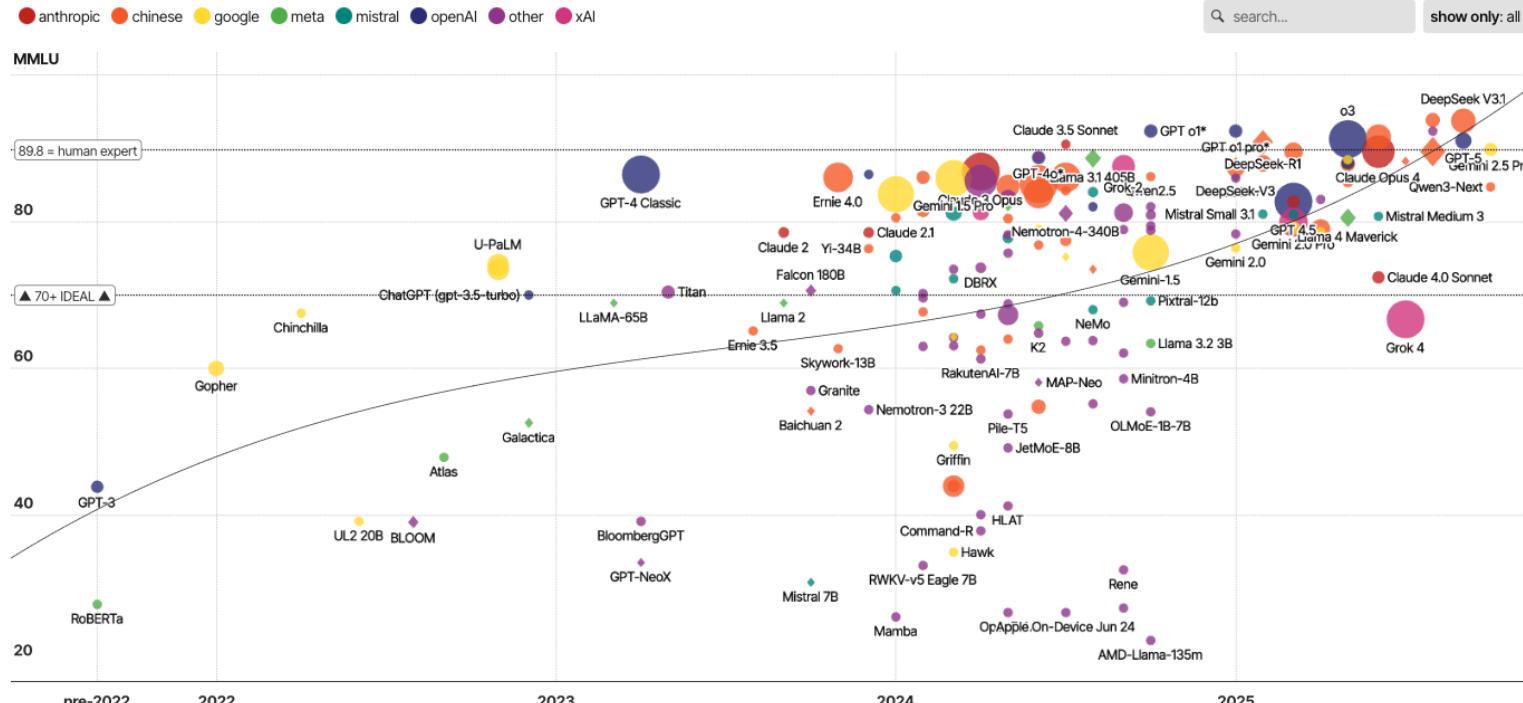
Accelerated development (0925)



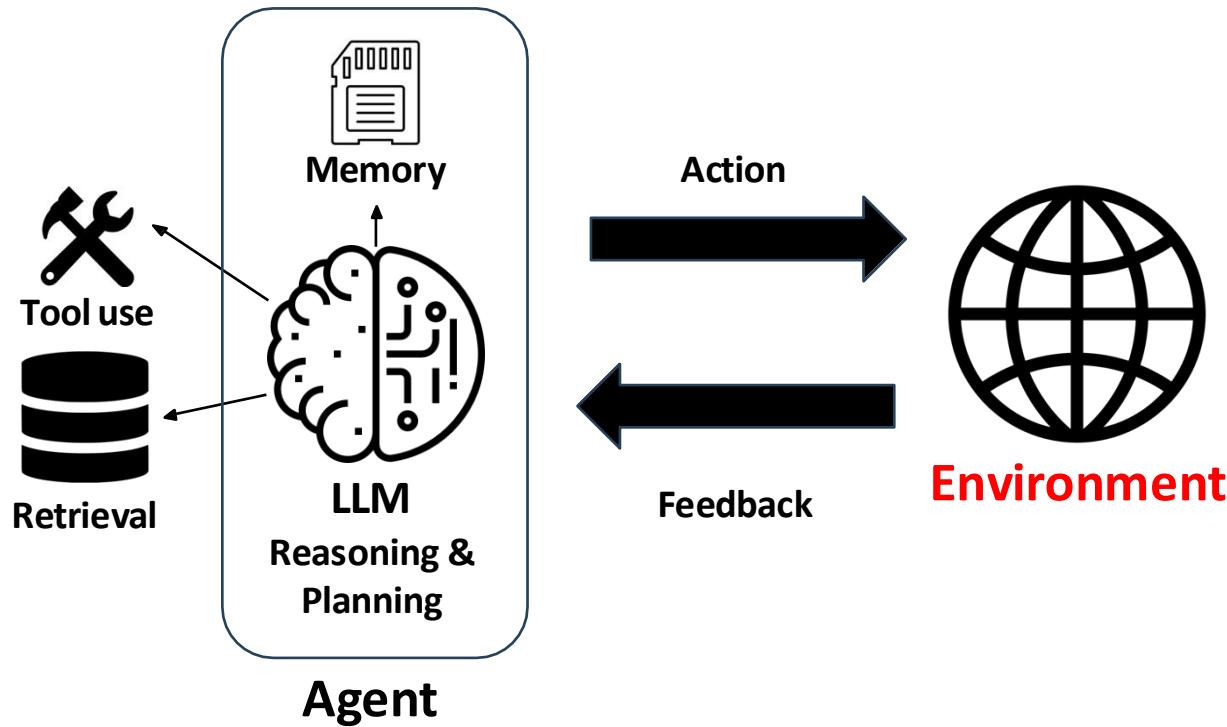
Major Large Language Models (LLMs)

ranked by capabilities, sized by billion parameters used for training

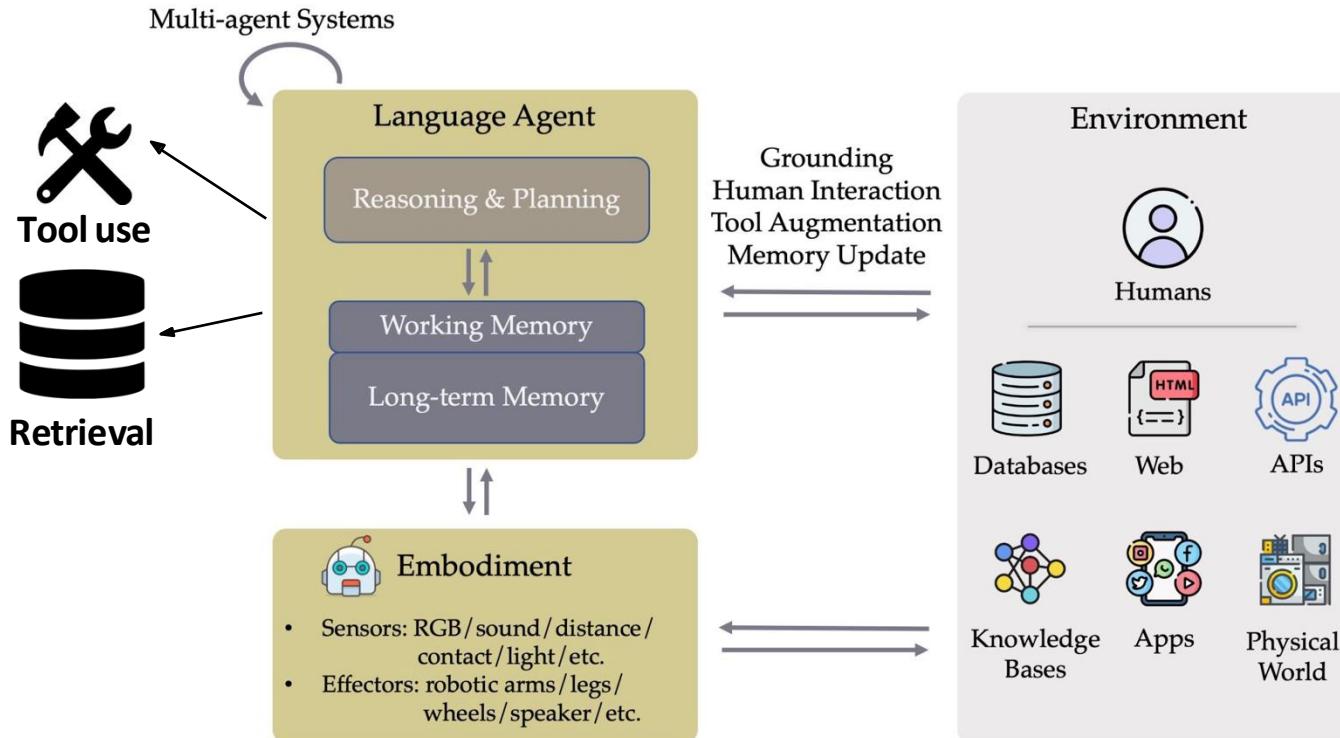
CLICK LEGEND ITEMS TO FILTER



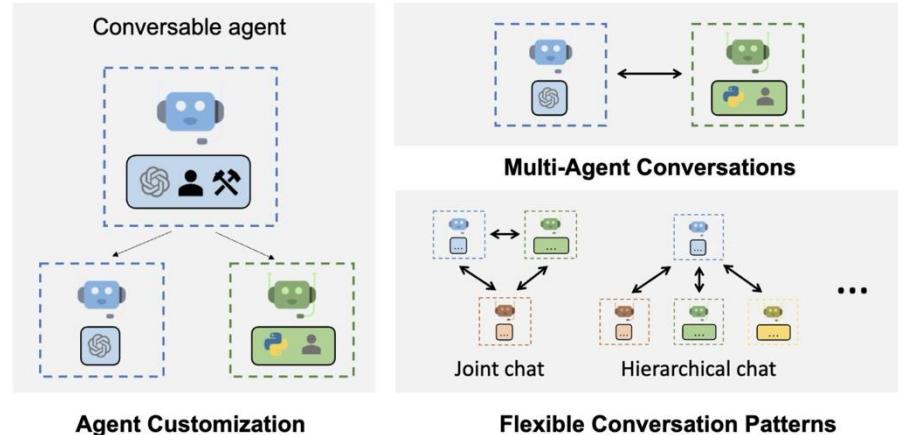
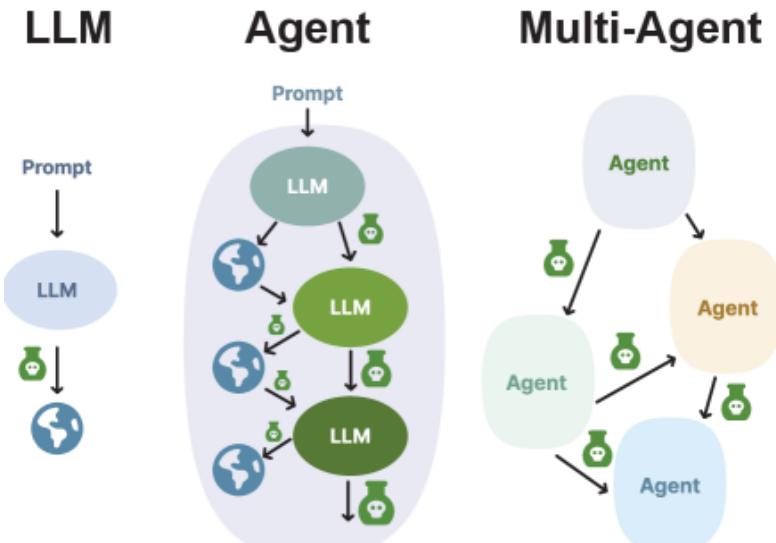
LLM agents: enabling LLMs to interact with the environment



LLM Agents in Diverse Environments



Multi-agent collaboration: division of labor for complex tasks

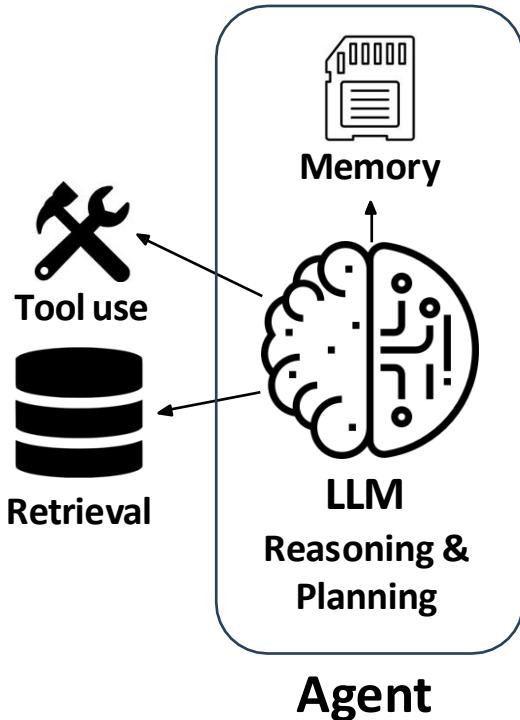


Specialized agents for different subtasks
Autogen, CrewAI, CAMEL, Mixture-of-Agents,...

Emergence of social behaviors with role-play LLMs

Generative agents, Project Sid,...

Why empowering LLMs with the agent framework



- Solving real-world tasks typically involves a trial-and-error process
- Leveraging external tools and retrieving from external knowledge expand LLM's information capabilities
- Agent workflow facilitates complex tasks
 - Allocation of subtasks to specialized tools
 - Multi-agent generation inspires better responses
 - Access to specialized evidence / data / inputs
 -

LLM agents transformed various applications

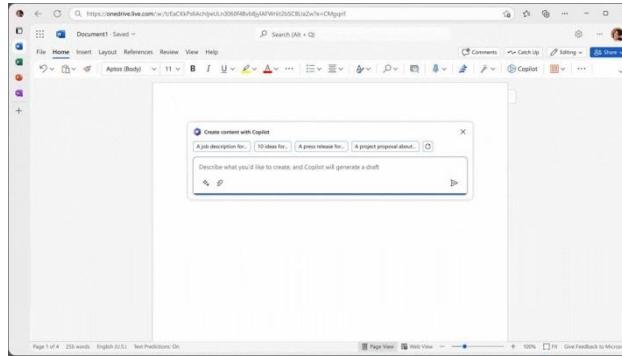
```
Search... →
NFL_Goal_passes_by_team_and_game_by_season
Employees by team and game by season
NFL_Passing_Stats_by_team_and_game_by_season
Goal: Get passing stats for all players from a particular team, on a game by game basis this season

1 #!/usr/bin/env python
2 # -*- coding: utf-8 -*-
3 # Author: [REDACTED]
4 # Date: [REDACTED]
5 # Description: [REDACTED]
6 # This script fetches passing stats for all players from a particular team, on a game by game basis this season.
7 # It uses the NFL API to get the required data and then processes it to output the desired results.
8
9 import requests
10 from bs4 import BeautifulSoup
11
12 # Set the URL of the NFL API endpoint
13 url = "https://api.fantasydata.net/v2/nfl/2018/reg/statistics/Passing"
14
15 # Set the parameters for the API request
16 params = {
17     "Team": "PIT", # Replace with the team you want to fetch stats for
18     "SeasonType": "Regular Season"
19 }
20
21 # Make the API request
22 response = requests.get(url, params=params)
23
24 # Parse the JSON response
25 data = response.json()
26
27 # Extract the relevant data
28 # ...
29
30 # Process the data to output the desired results
31 # ...
32
33 # Print the results
34 print(data)

# [REDACTED] (This part is heavily redacted for brevity)
```

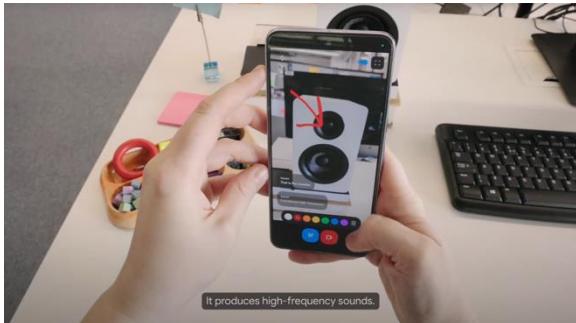
Code generation

Cursor, GitHub Copilot, Devin, Replit,...



Workflow automation

Microsoft Copilot, Multi-On,...



Personal assistant

Google Astra, OpenAI GPT-4o,...

- Healthcare
- Education
- Law
- Finance
- Cybersecurity

...



Robotics

Figure AI, Tesla Optimus,...

LLM agents are improving rapidly (leaderboards!)

Full is a large benchmark made of 2000 instances ([details](#))

Filters: Open Scaffold ▾ All Tags ▾

Model	% Resolved	Org	SWE-bench
<input checked="" type="checkbox"/> SWE-agent 1.0 (Claude 3.7 Sonnet)	33.83		Leaderboards
<input checked="" type="checkbox"/> OpenHands + CodeAct v2.1 (claude-3-5-sonnet-20241022)	29.38		BENCHMARKS
AutoCodeRover-v2.0 (Claude-3.5-Sonnet-20241022)	24.89		SWE-bench
<input checked="" type="checkbox"/> SWE-agent + Claude 3.5 Sonnet	18.13		SWE-bench Verified ↗
<input checked="" type="checkbox"/> SWE-agent + GPT 4 (1106)	12.47		SWE-bench Bash Only
<input checked="" type="checkbox"/> SWE-agent + GPT 4o (2024-05-13)	11.99		SWE-bench Multilingual
<input checked="" type="checkbox"/> SWE-agent + Claude 3 Opus	10.51		SWE-bench Multimodal
<input checked="" type="checkbox"/> RAG + Claude 3 Opus	3.79		SWE-bench Lite
			ABOUT

GAIA (Mialon et al.)
huggingface.co/gaia-benchmark

Results: Test

Agent name	Model family
JoinAI_V2.2	GPT 5, Gemini 3 Pro, DeepSeek 3.1, Qwen 3
Nemotron-ToolOr	Nemotron-ToolOrchestrator-8B, GPT-5, Claude Opus 4.1
Nemotron-ToolOr	Nemotron-ToolOrchestrator-8B, GPT-5, Claude Opus 4.1
SU_Zero - Shugi	Self Consistency 35
JoinAI_V2.1	GPT, Gemini, DeepSeek, Qwen
ShawnAgent_v3.1	GPT5.2, Claude Sonnet 4.5, Gemini 3 Pro
HALO_V1217-1	

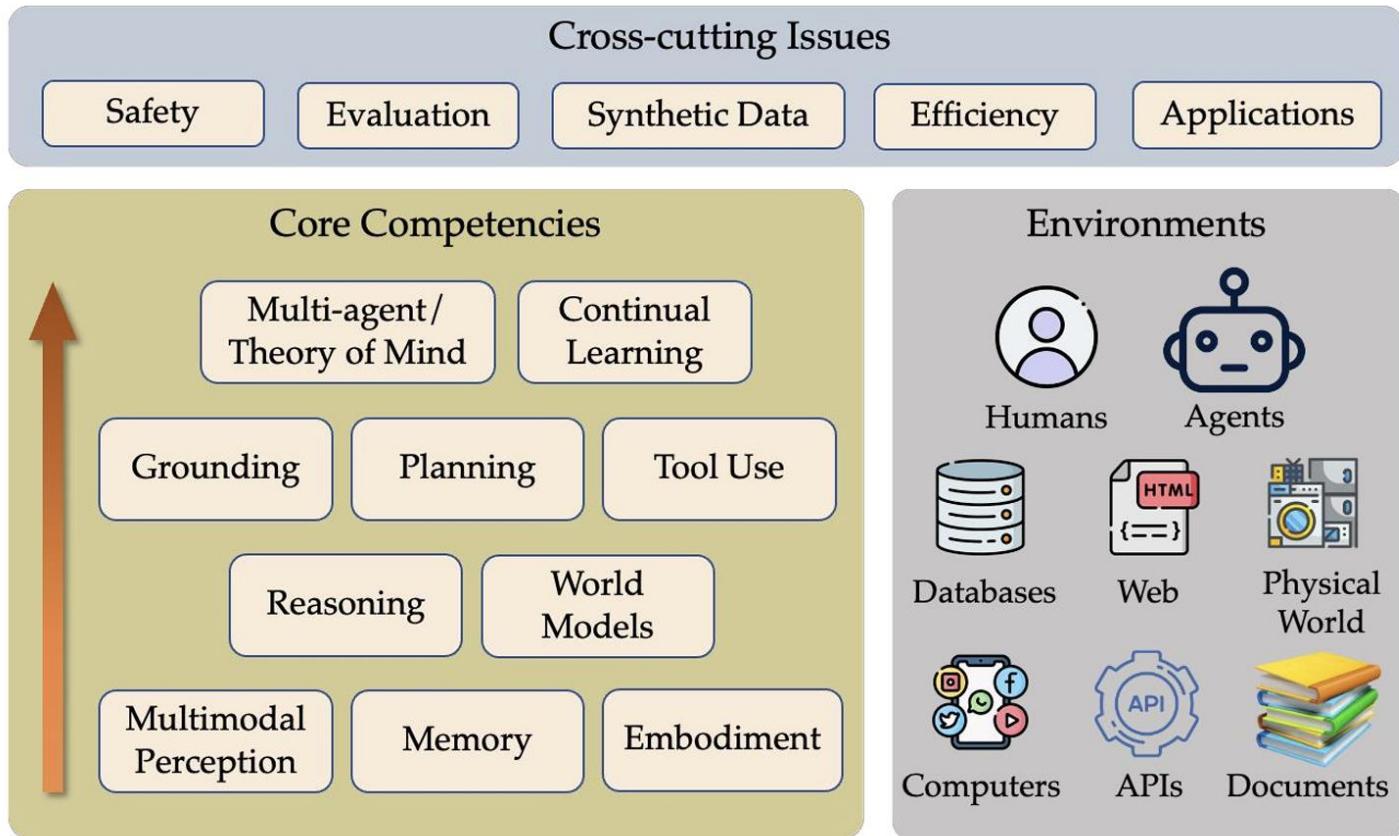
SWE-Bench (Jimenez*, Yang*, et al.) / swebench.com / Today's screenshot on Leaderboard!

F2 ▾ | ↻ OAgent

	A	B	C	D	E	F	G	H	
1	a	Open?	Model Size (billion)	Model	Success Rate (%)	Result Source	Work	Traj	
2	01/2026	x		OAgent	71.6	OAgent	OAgent	Link	
3	12/2025	✓	GPT-5	ColorBrowserAgent	71.2	ColorBrowserAgent	ColorBrowserAgent	Link	ite-si
4	10/2025	✓	-	Claude Code + GBOX MCP	68	GBOX AI	GBOX AI	Link	
5	09/2025	x	-	DeepSky Agent	66.9	Self-reported	DeepSky Agent	Link	
6	10/2025	x		Narada AI	64.2	Self-reported	Narada AI	Link	
7	02/2025	✓	-	IBM CUGA	61.7	IBM CUGA	IBM CUGA	html+json	
8	01/2025	x	-	OpenAI Operator	58.1	OpenAI CUA	OpenAI CUA	Link	Syste

WebArena (Zhou et al.)
webarena.dev

Topics We will cover in this course:



Topics covered in this course. →

- Applications
 - Software development
 - Workflow automation
 - Multimodal applications
 - Industrial applications like Healthcare, Legal, Fin, ...
- Model core capabilities
 - Reasoning
 - Planning
 - Multimodal understanding
- LLM agent frameworks
 - Workflow
 - Tool use
 - Retrieval-augmented generation
 - Multi-agent systems
- Safety and ethics

Potential Projects:

- Applications
 - Build LLM agents applications in specialized / novel domains
- Core Fundamentals
 - Enhance core agent capabilities (memory, planning, tool use, alignments, efficiency, ...)
 - Enhance decentralized multi-agent systems
- Benchmarks / Build Novel Frameworks
 - Create and improve benchmarks for Evaluating LLM agents
 - Reimplement or Build novel frameworks for agent workflow
- Safety and ethics
 - Reveal safety concerns in deployment (misuse, privacy, etc.)
 - Defense safety concerns

Challenges for LLM agent deployment in the wild

- Reasoning and planning
 - LLM agents tend to make mistakes when performing complex tasks end-to-end
- Embodiment and learning from environment feedback
 - LLM agents are not yet efficient at recovering from mistakes for long-horizon tasks
 - Continuous learning, self-improvement
 - Multimodal understanding, grounding and world models
- Multi-agent learning, theory of mind
- Safety and privacy
 - LLMs are susceptible to adversarial attacks, can emit harmful messages and leak private data
- Human-agent interaction, ethics
 - How to effectively control the LLM agent behavior, and design the interaction mode between humans and LLM agents