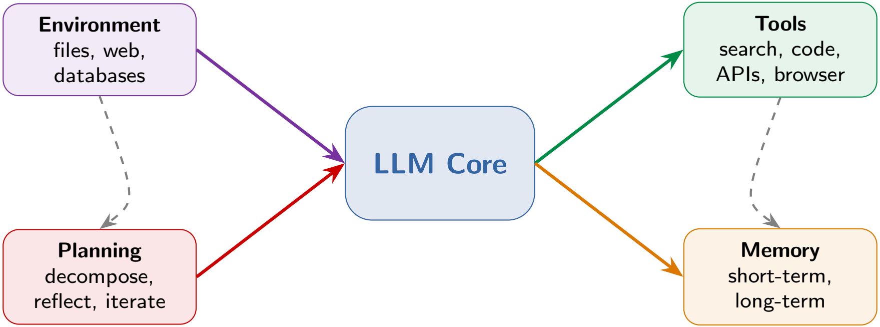
AI Agents & Tool Use

ReAct · Function Calling · Multi-Agent · MCP

What is an AI agent?



Environment
files, web, databases

Tools
search, code, APIs, browser

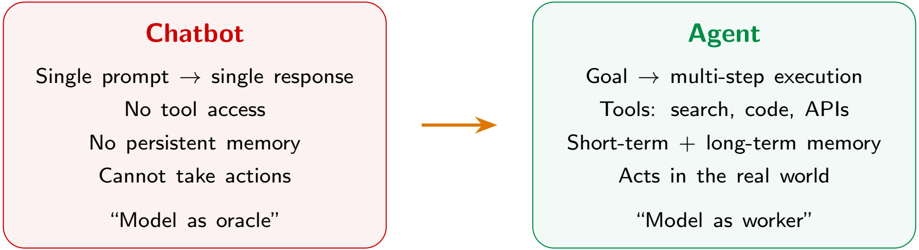
LLM Core

Planning
decompose, reflect, iterate

Memory
short-term, long-term

An **agent** is an LLM that can autonomously **plan**, **use tools**, and **act** in a loop until a goal is achieved — not just generate a single response.

Chatbot vs. agent



Chatbot

Single prompt → single response

No tool access

No persistent memory

Cannot take actions

“Model as oracle”

Agent

Goal → multi-step execution

Tools: search, code, APIs

Short-term + long-term memory

Acts in the real world

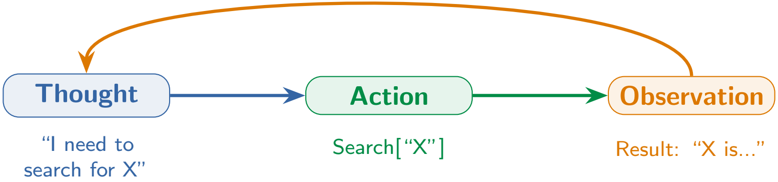
“Model as worker”

Andrew Ng’s four agentic design patterns (2024):

Reflection — self-critique and improve · **Tool Use** — call external functions

Planning — decompose into subtasks ·
Multi-Agent — specialized roles collaborate

ReAct: Reasoning + Acting



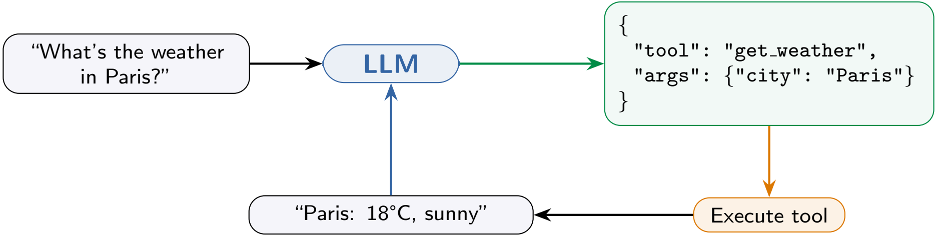
Thought: I need to find when the Eiffel Tower was built.
Action: Search["Eiffel Tower construction date"]
Observation: Construction began in 1887 and was completed in 1889.
Thought: Now I have the answer.
Action: Finish["The Eiffel Tower was built 1887–1889."]

Yao et al., ICLR 2023 (Oral) · ALFWorld: **+34%** over RL baselines

Reasoning helps plan and handle exceptions; actions provide grounded information.

ReAct is now the **default loop** in virtually every agent framework.

Function calling



“What’s the weather in Paris?”

LLM

```
{
 "tool": "get_weather",
 "args": {"city": "Paris"}
}
```

Execute tool

“Paris: 18°C, sunny”

OpenAI (June 2023): `function_call` API, parallel calls, structured outputs

Anthropic: typed tool schemas, parallel tool use

Google: strict JSON schema enforcement via Vertex AI

Models are **fine-tuned** on (instruction, tool-call, result) triples to learn *when* to call, *which* tool to select, and *how* to format arguments. Structured JSON output is now standard.

Types of tools

Search / Retrieval

Web search APIs
Vector DB (RAG)

Wikipedia, knowledge bases

Code Execution

Python interpreter
Sandboxed runners

Jupyter notebooks

External APIs

Weather, databases
Calendars, e-commerce

CRM, payments

File System

Read / write / edit files
Directory traversal

Document parsing

Browser / Web

Headless browser
Screenshot analysis

Form filling, navigation

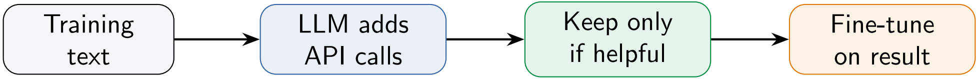
Math / Reasoning

Calculator
Symbolic math

Wolfram Alpha

LLMs as Tool Makers (Cai et al., 2023): a powerful LLM *creates* reusable tools (Python functions), then a cheaper LLM *uses* them. GPT-4 maker $+$ GPT-3.5 user $\approx$ GPT-4 quality at lower cost.

Toolformer: self-supervised tool learning



Training text → LLM adds API calls → Keep only if helpful → Fine-tune on result

Original: “The population of Toronto is 2,794,356.”

Annotated: “The population of Toronto is [QA(“population of Toronto”) → 2,794,356].”

Kept because the API call *reduced* perplexity of the next tokens (i.e., helped prediction)

Schick et al., NeurIPS 2023 (Meta) · **6.7B model with tools > GPT-3 175B without**

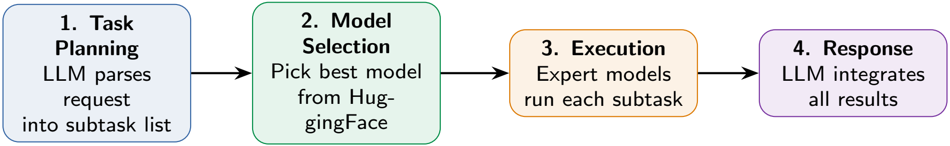
Tools: calculator, QA, search, translation, calendar

Calculator used in 97.9% of math examples (doubling performance)

Key insight: the model teaches *itself* when and how to use tools, using perplexity as the signal. No human annotation of tool calls needed — fully self-supervised.

Planning & decomposition

HuggingGPT (Shen et al., NeurIPS 2023)



1. Task Planning
LLM parses request into subtask list

2. Model Selection
Pick best model from HuggingFace

3. Execution
Expert models run each subtask

4. Response
LLM integrates all results

User: "Describe this image and read any text in it."
Plan: 1. Image captioning (BLIP-2) → 2. OCR (TrOCR) → 3. Combine results

Plan-and-Execute

Create full plan upfront,
then execute step by step.
Can re-plan if a step fails.

Inner Monologue

Agent maintains a scratchpad
of reasoning, tracks progress,
and self-corrects along the way.

Memory systems

Short-term

Current conversation in the context window

Limited by context length (4K–200K tokens)

Lost when session ends

Long-term

Persistent storage across sessions via vector DBs

Pinecone, Chroma, Weaviate

Retrieved by relevance

(RAG-style)

Episodic

Memories of past interactions and outcomes

“Last time I tried X, it failed because Y”

Enables learning

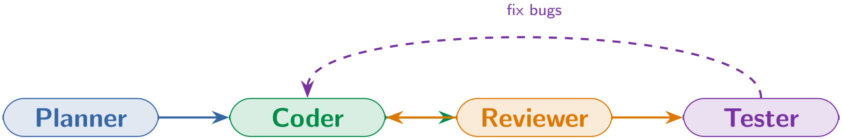
from experience

MemGPT (Packer et al., 2023): OS-inspired virtual memory for LLMs

Main context (“RAM”) = limited prompt buffer
↔ External storage (“disk”) = unbounded archive

Agent manages data movement between tiers using function calls: `search_memory()`, `save_memory()`

Multi-agent systems



AutoGen (Microsoft, 2023)

Customizable conversable agents, flexible topologies

Merged into MS Agent Framework (2025)

CrewAI (2024)

Role-based orchestration
100K+ agent runs/day

60% of Fortune 500

ChatDev (Qian et al., 2023)

Virtual software company: CEO, CTO, programmer, tester, reviewer

Multi-agent debate (Du et al., 2023): multiple LLMs debate and critique each other's answers ⇒ improves factual accuracy and reasoning. Diversity of perspectives reduces hallucination.

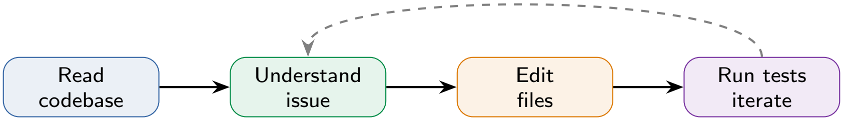
Agent frameworks

Framework	Focus	Key Abstraction
LangChain / LangGraph	General-purpose	Graph-based state machines
LlamaIndex	Data & RAG	300+ data connectors
Semantic Kernel (MS)	Enterprise .NET/Python	Plugins, planners
Claude Agent SDK	Building on Claude	Agent loops, tool use
OpenAI Assistants API	Managed infrastructure	Threads, runs, tools
CrewAI	Multi-agent enterprise	Crews, roles, tasks

Common abstractions: Tools (callable functions) · Agents (LLM + tools + instructions) Memory (short/long-term state) · Chains/Graphs (execution flow) · Planners (decomposition)

Trend: LangChain pivoted from chains to **LangGraph** for complex agent workflows (cycles, state).
LlamaIndex dominates RAG-heavy apps.
CrewAI dominates multi-agent enterprise.

Code agents



Devin (Cognition, Mar 2024)
“First AI software engineer”
SWE-Bench: 13.9% → GA Dec 2024
ARR: $1M → $73M in 9 months

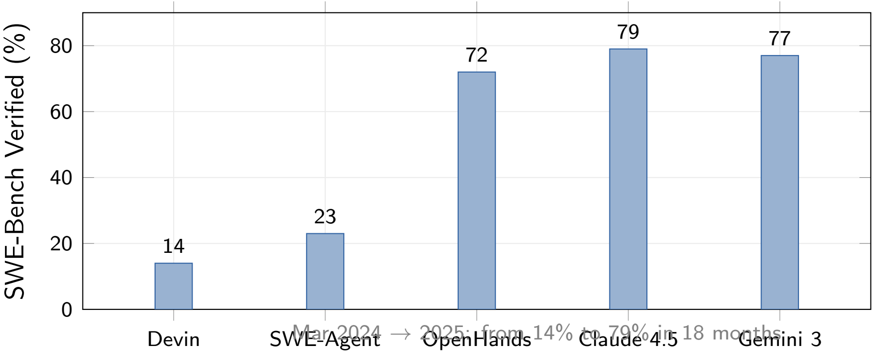
SWE-Agent (Princeton, Apr 2024)
Open-source, custom ACI
Agent-Computer Interface
designed for software engineering

OpenHands (2024)
Open-source platform
SOTA: 72% SWE-Bench Verified
(Claude Sonnet 4.5 + ext. thinking)

Claude Code (Anthropic, 2025)
CLI-based coding agent
Read, edit, run, iterate
Built on Claude Agent SDK

GitHub Copilot Coding Agent (May 2025):
async agent for features, bugs, tests, refactoring.

SWE-Bench: the code agent benchmark

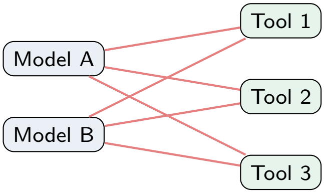


Mar 2024 → 2025: from 14% to 79% in 18 months

Jimenez et al., ICLR 2024: real GitHub issues from 12 Python repos

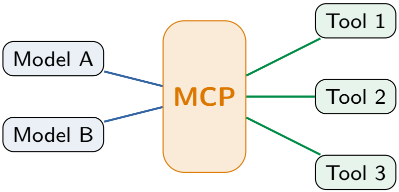
MCP: Model Context Protocol

Without MCP



N × *M* integrations

With MCP



N + *M* integrations

Anthropic, November 2024 · Like
LSP for AI: standardizes tool integration

JSON-RPC 2.0 over stdio/HTTP · Primitives: **Tools**, **Resources**, **Prompts**

OpenAI adopted (Mar 2025) · Google adopted (Apr 2025) · 97M+ monthly SDK downloads

Challenges

Reliability

95% per-step accuracy $\Rightarrow$ 60% for 10 steps

One bad step derails the entire workflow

Current: $\sim$80%

Need: $\sim$99%

Hallucinated calls

Non-existent tools
Wrong parameter values
Incorrect types

Hard to catch semantically

(syntax may be valid)

Cost & latency

Complex task = 10–50+ API calls

Cost: 10–100× a single-shot response

End-to-end: minutes

to hours

Safety: autonomous agents act in the real world — editing files, sending emails, making purchases, browsing the web. Unintended consequences are a genuine risk.

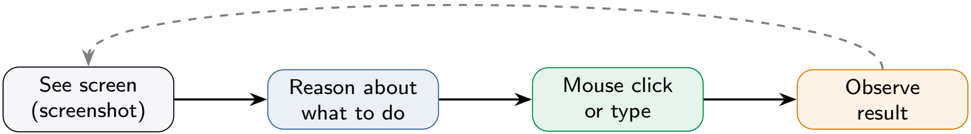
Evaluation is hard: multi-step workflows are non-deterministic, have multiple valid paths, and success depends on the *process*, not just the final answer.

Agent benchmarks

Benchmark	What it measures	Scale	Key number
SWE-Bench	Real GitHub issues	2.3K tasks	Best: 79%
AgentBench	8 environments (OS, DB, ...)	29 LLMs	Large open/closed gap
WebArena	Web browsing tasks	812 tasks	4 realistic domains
GAIA	General AI assistant	466 Q	Human: 92%, Best: 65%
ToolBench	API tool use	16K APIs	49 categories

GAIA gap: humans score 92%, best agents score 65%.
Unlike text benchmarks (which are near-saturated), agent benchmarks reveal a **large gap** between human and AI capability on real-world tasks.

Computer use agents



Claude Computer Use
(Anthropic, Oct 2024)

OSWorld:
14.9% → 72.5%
(~5× in 16 months)

Operator / CUA
(OpenAI, Jan 2025)

GPT-4o vision + RL
Raw pixels +
virtual mouse

Project Mariner
(Google, Dec 2024)

GUI control via
multimodal models

The paradigm shift: from “model as oracle” to “model as worker.”
Give a goal, the agent plans + acts + observes + iterates until done.

Browsers and operating systems are becoming **agent-native** platforms.

Practical guide

Simple Q&A?

→ Standard LLM (no agent needed)

Need external data?

→ RAG or single tool call

Multi-step workflow?

→ ReAct agent with tools + memory

Complex software task?

→ Code agent (SWE-Agent, Claude Code, OpenHands)

Need specialization?

→ Multi-agent system (CrewAI, AutoGen)

Standardize tools?

→ MCP servers (build once, use everywhere)

Rule of thumb: use the simplest approach that works.

Single LLM call → tool call → ReAct loop → multi-agent. Add complexity only when needed.

Questions?

All DL4NLP topics complete!