

The Book of AI

Mapping the practical Artificial Intelligence landscape

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This book is a practical guide to understanding agentic engineering and building a practical toolkit.

Table of contents

Main Page	11
:fire: Hotplate (Monthly Release)	11
October 2026 Hotplate	12
:newspaper: Summary: General AI vibe for October 2026	12
Agent Skills → Agentic AI Foundation (AAIF)	12
WorkBuddy Bench (Tencent)	12
UNBROKER	12
NVIDIA OpenShell	13
JEV	16
Capsem	17
1 Introduction	18
1.1 From Chatbots to Agentic Engineering	18
1.1.1 What changes when AI systems can use tools and work across multiple steps	18
1.1.2 The agentic engineering stack: models, harnesses, tools, memory, and governance	18
1.2 What This Book Is For	20
1.2.1 A practical, control-oriented guide	20
1.2.2 Local-first and self-hosted options	20
1.2.3 What the book covers—and what it leaves to later chapters	20
1.3 Who This Book Is For	20
1.3.1 Practicing developers and indie builders	20
1.3.2 Teams exploring agentic workflows	20
1.4 The 2026 Q4 Reality Check	20
1.4.1 What the current Hotplate snapshot suggests	20
1.4.2 Why this landscape is changing—and how to read time-sensitive guidance	20
1.5 How to Use This Book as a Living Toolkit	20
1.5.1 Chapters, references, and linked sources	20
1.5.2 Quarterly Hotplate snapshots and updates	20
1.6 A Map of the Book	20
1.6.1 Models and running them	20
1.6.2 Agents, harnesses, and building a working stack	20
1.6.3 Supporting tools, resources, and keeping the map alive	20

2	Models	22
2.1	AI Model Types	22
2.2	Model families and access	23
2.3	Evaluation and training data	23
2.4	Abliteration	23
2.5	Prominent AI Organizations Creating Foundational AI Models	23
2.5.1	Foundational AI Models	24
2.6	Benchmarks	24
2.6.1	Benchmark Articles	28
2.7	Base Model Data	28
3	Running a Model	30
3.1	Web/Online Models	30
3.2	Physical Hardware	31
3.3	Running AI Models Locally	31
3.3.1	Comparing Local Model Runners	31
3.3.2	Local-first inference	34
3.3.3	Practical implications	35
3.3.4	When to choose which	35
3.3.5	Other local inference options	35
3.4	Cloud and hybrid options	36
3.4.1	NeoClouds (also <i>neoclouds</i> or <i>neo-clouds</i>)	36
3.5	Making models usable by agents	37
3.6	Security and operational considerations	37
3.6.1	Security Resources for local models	37
3.6.2	Local Model Vulnerabilities	37
3.7	Security Summary: What Can the Model Reach?	39
3.7.1	The practical risk ladder	39
3.7.2	Key attack surfaces that expand “reach”	40
3.7.3	Practical containment principles	40
3.8	NVIDIA [OpenShell][(https://www.nvidia.com/en-us/ai/openshell/)] is an open, secure runtime designed for AI agents. It provides a governed environment that controls agent execution, access, and inference routing, independent of the underlying model or application.	41
3.8.1	Core Idea	41
3.8.2	Key Benefits	41
3.8.3	Main Components	41
3.8.4	Reference Architecture	42
3.8.5	Who It’s For & What It Supports	42
3.8.6	Technical Resources	42

4	Agents and Harnesses	43
4.1	Agent Harness Diagram	44
4.1.1	More precise breakdown	44
4.2	Modern harnesses	45
4.3	Supporting infrastructure	46
4.4	agents.md	46
5	Building a Working Stack	47
5.1	Starting points	47
5.2	Practical considerations	47
6	Miscellaneous Tools and Supporting Infrastructure	48
6.0.1	Miscellaneous Tools	48
6.1	Model selection and modification	48
6.2	Open-source principles and sources	48
7	Resources	49
7.1	X Agentic-Engineering Lists	49
8	AI [blog] Resources	50
9	YouTube Videos & Channels	51
10	Articles	52
11	AI Publication Websites	53
11.1	AI Publications	53
12	Online Books	54
13	Prominent AI People	55
14	Keeping the Map Alive	56
14.1	Maintaining the quarterly Hotplate	56
14.2	Contributing and continuing	56
14.3	Aggregation Projects	56
	Appendices	57
A	Hotplate Index	57
A.1	:date: Checked daily	57
A.2	:calendar: Checked weekly	57
A.3	:spiral_calendar: Checked monthly	57
A.4	Hotplate Catalog	57

B	Glossary	58
B.1	A	58
B.1.1	Abliteration	58
B.1.2	Agent	58
B.1.3	Agent loop	58
B.1.4	Agentic AI	58
B.1.5	Agentic Engineer	59
B.1.6	Agentic engineering stack	59
B.1.7	(AGI) Artificial General Intelligence	59
B.1.8	(AI) Artificial Intelligence	60
B.1.9	Alignment	60
B.1.10	Auto-regressive language model	60
B.1.11	Attention Mechanism	60
B.2	B	61
B.2.1	Backpropagation	61
B.2.2	Bagging	61
B.2.3	Bayesian Optimization	61
B.2.4	Benchmark	61
B.2.5	(BERT) Bidirectional Encoder Representations from Transformers	62
B.2.6	(BM25) Best Matching 25	62
B.2.7	(BPE) Byte Pair Encoding	64
B.2.8	Boosting	64
B.2.9	(BLT) Byte Latent Transformer	65
B.3	C	65
B.3.1	(CLIP) Contrastive Language-Image Pretraining	65
B.3.2	code2seq	68
B.3.3	Constitutional AI	68
B.3.4	(CoT) Chain of Thought	69
B.3.5	Context engineering	72
B.3.6	Context window	72
B.4	D	72
B.4.1	Data Augmentation	72
B.4.2	Data Leakage	73
B.4.3	Deep Learning	73
B.4.4	(DPO) Direct Preference Optimization	73
B.4.5	(DPR) Dense Passage Retrieval	73
B.5	E	76
B.5.1	(ECL) Effective Context Length	76
B.5.2	Embedding	76
B.5.3	Embedding Models	77
B.5.4	Ensemble Learning	80
B.5.5	Evaluation	80

B.6	F	81
B.6.1	Feedforward Neural Network	81
B.6.2	Few-Shot Learning	81
B.6.3	Feature Engineering	81
B.6.4	Feature Extraction	82
B.6.5	Federated Learning	82
B.6.6	Fine-tuning	82
B.6.7	Foundation model	82
B.6.8	FP{8,16,32} Training Process	82
B.6.9	Frontier Model	83
B.7	G	83
B.7.1	(GAIA) General AI Assistants Benchmark	83
B.7.2	(GANs) Generative Adversarial Networks	84
B.7.3	GGUF (GGML Universal File)	84
B.7.4	(GPQA) General-Purpose Question Answering Benchmark	85
B.7.5	(GPT) Generative Pre-trained Transformer	85
B.7.6	Gradient Descent	85
B.7.7	(GRPO) Group Relative Policy Optimization	85
B.7.8	Guardrails	86
B.8	H	86
B.8.1	Hallucination	86
B.8.2	Harness	86
B.8.3	(H-Net) Hierarchical Network	87
B.8.4	(HITL) Human-in-the-loop	87
B.8.5	Hyperparameter	87
B.9	I	87
B.9.1	Inference	87
B.10	J	88
B.10.1	Jinja (or Jinja2)	88
B.11	K	88
B.11.1	(KD) Knowledge Distillation - [Deepseek-r1:70B]	88
B.11.2	KV Cache (Key-Value Cache)	90
B.12	L	90
B.12.1	Leaderboard	90
B.12.2	Learning Rate	91
B.12.3	Lightweight Models	91
B.12.4	llama.cpp	91
B.12.5	(LLM) Large Language Models	91
B.12.6	Loss Function	93
B.13	M	93
B.13.1	(MCP) Model Context Protocol	93
B.13.2	(MoE) Mixture of Experts	93
B.13.3	Model Context Protocol (MCP)	93

B.13.4	Mechanistic Interpretability (MechInterp)	94
B.13.5	(MHLA) Multi-head latent Attention	95
B.13.6	(ML) Machine Learning	95
B.13.7	(MLOps) Machine Learning Operations	96
B.13.8	(MMLU) Massive Multitask Language Understanding	96
B.13.9	(MTP) Multi-Token Prediction	96
B.13.10	Model-Agnostic Interpretability	98
B.13.11	Model-Based Reinforcement Learning	98
B.13.12	Model Explainability	98
B.13.13	Model Fairness	98
B.13.14	Model-Free Reinforcement Learning	98
B.13.15	Model Interpretability	99
B.13.16	Model Quantization	99
B.13.17	Model Robustness	99
B.13.18	Model Serving	99
B.13.19	Model Training	99
B.13.20	Model Validation	100
B.13.21	Model Zoo	100
B.13.22	(MoE) Mixture of Experts	100
B.13.23	Multi-agent system	101
B.13.24	Multimodal Learning	101
B.14	N	101
B.14.1	NeoClouds	101
B.14.2	Neural Network	101
B.14.3	Natural Language Processing (NLP)	102
B.15	O	102
B.15.1	(OW) Open Weights	102
B.15.2	Overfitting	102
B.15.3	One-Shot Learning	102
B.15.4	OpenAI Codex	103
B.15.5	OpenAI GPT	103
B.15.6	OpenAI Sora	103
B.15.7	Open Weight	103
B.16	P	104
B.16.1	Pickle (broken)	104
B.16.2	Post-Training	104
B.16.3	(PReLU) Parametric Rectified Linear Unit	104
B.16.4	Prompt Engineering	105
B.16.5	Pre-trained Model	105
B.16.6	Privacy-Preserving AI	105
B.16.7	Probabilistic Programming	106
B.16.8	Progressive Learning	106
B.16.9	PyTorch	106

B.17	Q	106
B.17.1	Quantization	106
B.18	R	107
B.18.1	(RAG) Retrieval-Augmented Generation	107
B.18.2	Regularization	108
B.18.3	(RAHF) Random Access Hierarchical Framework	108
B.18.4	ReAct	110
B.18.5	(ReLU) Rectified Linear Unit	110
B.18.6	(RL) Reinforcement Learning	110
B.18.7	RLCD (Reinforcement Learning for Calibrated Decisions)	111
B.18.8	(RLHF) Reinforcement learning from human feedback	111
B.18.9	(RLVR) Reinforcement Learning Verifiable Rewards	111
B.18.10	(RNN) Recurrent Neural Network	111
B.18.11	Robustness	112
B.18.12	(RTT) Race-to-the-Top	112
B.19	S	114
B.19.1	Singularity	114
B.19.2	Stacking	114
B.19.3	Self-Attention Mechanism	114
B.19.4	Self-Supervised Learning	114
B.19.5	Semi-Supervised Learning	115
B.19.6	Sentiment Analysis	115
B.19.7	Sequence-to-Sequence (Seq2Seq) Model	115
B.19.8	(SFT) Supervised Fine-Tuning	115
B.19.9	(SGD) Stochastic Gradient Descent	116
B.19.10	Skill	116
B.19.11	Sleeper Agent	116
B.19.12	Sub-agent	116
B.19.13	Superposition	117
B.19.14	(SL) Supervised Learning	117
B.19.15	Synthetic Data	117
B.19.16	sycophancy in AI	117
B.20	T	119
B.20.1	(TF-IDF) Term Frequency-Inverse Document Frequency	119
B.20.2	Tokenization	122
B.20.3	Transfer Learning	122
B.20.4	transformer	122
B.21	U	126
B.21.1	Uncertainty Estimation	126
B.21.2	Unsupervised Learning	126
B.22	V	126
B.22.1	Vector Database	126

B.23	X	127
B.23.1	(XLA) Accelerated Linear Algebra	127
B.24	Y	127
B.24.1	(YOLO) You Only Look Once	127
B.25	Z	128
B.25.1	Zero-shot Learning	128
C	[AI] Notes	130
C.1	Deep Learning notes	130
C.2	How to Train a Large Language Model	130
C.3	Training Process (example with Deepseek)	131
C.3.1	GRPO: Group Relative Policy Optimization	131
C.4	Deepseek Evolution	131
C.5	Transformer-Based Language Models	131
D	Prompt Engineering Notes	133
E	Key Takeaways	134
E.1	Example of a Best-Practice Prompt using XML-style tags	134
E.2	Example of a Best-Practice Prompt using hybrid XML-style tags and Markdown-style formatting	135
F	Resources - YouTube	137
F.1	Anthropic: Mastering Claude Code in 30 minutes Boris Cherny	137
F.2	Claude: The prompting playbook [Margot van Laar]	137
F.3	Tina Huang: Google's 9 Hour AI Prompt Engineering Course In 20 Minutes Tina Huang	138
F.4	DeepLearningAI: Prompt Engineering for Developers DeepLearningAI Andrew Ng	139
G	Articles & Blogs	141
G.1	The Prompt Is Not the Architecture — But It Still Governs How the System Reasons (Interesting Engineering, 2026-05-23)	141

Main Page

:fire: Hotplate (Monthly Release)

[Read the latest Hotplate](#) for a snapshot of the current landscape.

October 2026 Hotplate

:newspaper: Summary: General AI vibe for October 2026

:compass: Building and refining open-source agent harnesses for long-running autonomous work—OpenHands and OpenCode for coding, goose for general MCP-native use—alongside heavy adoption of MCP tools, persistent memory, and self-hosted personal agents that live in messaging apps (OpenClaw and Hermes Agent leading). Strong bias toward tools you can run yourself, keep fully under your control, and host on your own hardware or a cheap [Virtual Private Server](#).

Agent Skills → Agentic AI Foundation (AAIF)

Anthropic donated the SKILL.md standard (folder + SKILL.md + scripts) to the Linux Foundation's AAIF on ~22 Oct (alongside MCP, goose, AGENTS.md). ~1M skills published / hundreds of millions installed; now under neutral governance with maintainers from multiple orgs.

WorkBuddy Bench (Tencent)

Multi-domain coding-agent benchmark (Code / Web / Office / Security, ~260 tasks) reverse-engineered from real work, with contamination-resistant construction and dual-harness evaluation (CodeBuddy Code + Claude Code). Open evaluation framework + leaderboard.

UNBROKER

is an optional Hermes Agent skill that autonomously finds and removes a consenting person's personal information from data-broker and people-search sites.

NVIDIA OpenShell

is an open, secure runtime designed for AI agents. It provides a governed environment that controls agent execution, access, and inference routing, independent of the underlying model or application.

- [NVIDIA YouTube Summary](#)
- [NVIDIA Developer: How NVIDIA OpenShell Secures Autonomous Agents | Nemotron Labs](#)

Harnesses (the runtime that turns a model into an agent)

- **Agent Zero** - agentic framework that gives the agent a full Linux computer inside a Docker container.
- **goose** (Block / Agentic AI Foundation) – Apache-2.0, desktop + CLI + API, heavily MCP-native, local-model friendly.
- **Hermes Agent** (Nous Research) – Python, persistent curated memory, autonomous skill creation, multiple backends (local/Docker/Modal/Daytona). Best long-term accumulation.
- **OpenClaw** – TypeScript gateway + 20–30 messaging channels, skills registry (ClawHub / SKILL.md), Docker sandboxes, cron, voice. Best reach.
- **OpenCode** - open source agent that helps you write code in your terminal, IDE, or desktop.
- **OpenHands** – Agent Canvas control center, scoped MCP profiles, isolated Docker runtimes, strong for autonomous coding & repo work.
- **ZCode** - harness and agent for GLM

Aspect	Hermes Agent	Agent Zero
Core Philosophy	Persistent personal agent that learns & grows over time via skills/memory	Full sandboxed Linux computer + transparent, extensible agent framework

Aspect	Hermes Agent	Agent Zero
Strengths	Strong continuous learning loop (auto skill creation/refinement); excellent multi-platform messaging gateway (20+ apps, one memory); flexible deployment (serverless options that hibernate); deep user modeling & cross-session recall; easy always-on personal assistant feel	Real desktop + browser with annotation/cowork; strong project isolation; highly transparent & editable (prompts/tools as files); mature multi-agent hierarchy + Plugin Hub; visual Web UI for control/observation; good for complex computer-use tasks
Weaknesses	Less emphasis on a full GUI desktop environment; memory/skills can increase token cost on simple tasks; more “gateway + tools” than “own computer” metaphor	Heavier Docker dependency & resource footprint; less native multi-messaging surface out of the box; learning is more manual/project-oriented than automatic skill growth; Web UI-centric rather than chat-app native
Best For	Always-available personal agent reachable from chat apps that improves with use	Technical users wanting a controllable agentic “computer” for development, research, document work, or multi-agent workflows
Deployment Style	Lightweight long-running process / serverless; strong messaging focus	Docker-first full environment; Web UI + optional host CLI bridge
Extensibility	Skills system + MCP + toolsets; community skills	Plugins, skills, fully editable prompts, MCP/A2A, community Plugin Hub

MCP

is now the default wiring layer (thousands of servers, tool search to keep context clean, permission-aware patterns). Sandboxed runtimes (Docker, E2B, Daytona, Modal, Kernel-style browser infra) and curated persistent memory + agent-written skills are table stakes for anything that runs longer than a single prompt.

KERNEL

is a specialized cloud browser infrastructure and “Browser-as-a-Service” platform built specifically for AI web agents and high-scale browser automation. While traditional cloud browsers (like Browserless or standard headless Chrome containers) are designed for traditional web scraping or end-to-end testing, Kernel is engineered around the speed, scale, *anti-bot bypass*, and execution hurdles inherent to autonomous AI agents (using frameworks like Browser Use, Playwright, Puppeteer, or Stagehand).

HERMES WebUI

is a lightweight, dark-themed web app interface in your browser for Hermes Agent. Full parity with the CLI experience - everything you can do from a terminal, you can do from this UI. No build step, no framework, no bundler. Just Python and vanilla JS.

HONCHO

is open-source AI memory for agents. It remembers each user across sessions, tools and machines, so no session starts cold. Pairs well with [Hermes Agent](#). [Setup guide](#).

OpenWaldo

Letter	Meaning
W	Weights
A	Artifacts
L	Licenses
D	Data
O	Origin

OpenWALDO brings everything people expect from open source to AI: a community anyone can join; source code and training data anyone can contribute to and audit; open tools; public governance and trust earned through transparency; and models anyone can compose, train, validate, reproduce, extend, and improve.

JEV

A (machine native) decision-focused “System One” model that answers fixed, typed questions with probabilities so your code (or an agent) can act on the result directly, to be consumed by code. It is not a language model. Takes unstructured state + your pre-defined questions and returns reliable, probabilistic decisions that code can immediately branch on.

SpyNEL

Lightweight agent orchestration that uses existing coding harnesses rather than bundling its own AI, with a single communication interface, durable Markdown task management, and autonomous agentic loops.

DOX

DOX is a lightweight **AGENTS.md** framework that gives AI agents precise project context through a maintained hierarchy of project-wide and area-specific instructions. Agents read the relevant guidance before editing and update it when meaningful changes affect the documented rules or structure.

Ajax

Ajax is a fine-tuned (abliterated) Qwen 3.5 9B model, trained for Odysseus to be your always on agent. It handles your daily tasks from search to browse web to email to your calendar - all your daily tasks completely privately. Ajax’s refusal has been ablated for a freer, less restricted AI experience. Please use responsibly.

Odysseus

Odysseus is a self-hosted AI workspace for chat, agents, deep research, email, calendar, and local/API model backends. It is local-first and privacy-first when you run local models on your own machine.

BenchLM

LLM Leaderboard. ##### [Best Ollama models](#)

Heretic

Heretic removes restrictions (abliteration parameters) from language models, making sure they always follow your instructions.

Capsem

is a secure runtime / hypervisor for AI agents. It gives each agent its own isolated Linux VM, inspects everything it tries to do on the network or with tools, and logs the activity — so you can run powerful coding agents with much tighter control and visibility than running them directly on your host. Choose Capsem when your top priority is security and control — you want to run powerful coding agents (or any agent) with strong isolation, network inspection, and auditability.

1 Introduction

1.1 From Chatbots to Agentic Engineering

1.1.1 What changes when AI systems can use tools and work across multiple steps

A chatbot usually responds to one request at a time: you ask, it answers, and you decide what to do next. An agentic workflow extends that interaction into a loop. Given a goal, an AI system can break the work into steps, use tools, check the results, and decide what to do next. A coding agent, for example, might inspect a repository, change a file, run its tests, and use the test results to guide another change.

The important distinction is not that an agent is a model with human-like independence. The model proposes actions, while the surrounding software determines which actions are available, how they are carried out, and whether the system can continue without approval. Connecting a model to tools can make it more useful, but it also means that mistakes can have consequences beyond a poor answer.

Agentic systems therefore need boundaries as well as capabilities. Useful designs make actions visible, limit access to what the task requires, define when a person must approve consequential steps, and provide a way to stop or recover from a failure. The goal is not autonomy for its own sake; it is reliable work that people can understand and control.

1.1.2 The agentic engineering stack: models, harnesses, tools, memory, and governance

Building such systems means working with more than a model. The **model** interprets input and proposes responses or actions. A **harness** supplies the runtime loop that calls the model, manages the task, and decides how to handle its proposed actions. **Tools** connect that loop to services and information, while an **execution environment** determines where code or other operations run and what they can access.

Longer-running work may also need **memory and state** so the system can retain relevant information between steps or sessions. **Orchestration** coordinates steps, tools, or multiple agents. **Governance and observability**—including permissions, approval points, logs, and evaluation—help people understand and constrain the system’s behavior. These layers can overlap in a particular product, but separating them is a useful way to reason about how a system is built and where to improve it.

This is the book’s practical point of departure: choose and connect components to fit a real task, then make the resulting workflow dependable and controllable. The chapters that follow examine these layers in turn, from models and local inference to harnesses and complete working stacks.

1.2 What This Book Is For

1.2.1 A practical, control-oriented guide

1.2.2 Local-first and self-hosted options

1.2.3 What the book covers—and what it leaves to later chapters

1.3 Who This Book Is For

1.3.1 Practicing developers and indie builders

1.3.2 Teams exploring agentic workflows

1.4 The 2026 Q4 Reality Check

1.4.1 What the current Hotplate snapshot suggests

1.4.2 Why this landscape is changing—and how to read time-sensitive guidance

1.5 How to Use This Book as a Living Toolkit

1.5.1 Chapters, references, and linked sources

1.5.2 Quarterly Hotplate snapshots and updates

1.6 A Map of the Book

1.6.1 Models and running them

1.6.2 Agents, harnesses, and building a working stack

1.6.3 Supporting tools, resources, and keeping the map alive

:toolbox: *The Book of Agentic AI — A practical guide to understanding agents and building a practical toolkit.*

The Book of AI is an attempt to be a practical guide to understanding agents and building an AI toolkit you control. It is a living document, and the landscape is changing rapidly. The

book is structured to provide both a high-level overview and practical guidance for building and using agentic AI systems.

This book focuses on — the disciplined practice of designing, orchestrating, and governing systems of AI agents that plan, act, observe, and iterate — and on the : the layered set of models, harnesses, tools, memory, orchestration, and governance required to make those agents reliable and controllable in real work.

Use this book as a living toolkit: consult the chapters for practical orientation, and follow the linked source materials and quarterly snapshots as the landscape changes.

2 Models

- General-purpose and code-specialized large language models
- Multimodal models
- Image-generation models, including text-to-image and image-to-image systems
- Decision or “System One” models, including calibrated-decision approaches

2.1 AI Model Types

- Large Language Models (LLM)
 - General-purpose language models
 - Code-specialized models
 - * Claude Fable 5.1 / Claude Opus 5.5 family (Anthropic)
 - * GPT-6 Astra / GPT-5.6 Sol / GPT-6.1 Sol series (OpenAI)
 - * Gemini 4 Argon / Gemini 3.x Flash family (Google)
 - * Kimi K3 / DeepSeek V4.1 Flash / MiMo-V2.6-Pro (open-weight leaders)
 - * DeepSeek
 - * Qwen
- Image Generation Models
 - Text-to-Image {[Stable Diffusion](#), [Midjourney](#), DALL-E, [Grok Imagine](#)}
 - Image-to-Image
- Multimodal Models (Text, Image, Audio, Video)
 - Kimi K3 (Moonshot AI)
 - Claude Opus 5 / Claude Opus 5.5 (Anthropic)
 - Qwen3.8 Max (Alibaba)
 - GPT-5.6 series (especially Sol / Luna variants) (OpenAI)
 - Gemini 3.x Flash / Pro family (Google)

2.2 Model families and access

The landscape includes models from Anthropic (Claude), OpenAI (GPT), Google DeepMind (Gemini and Gemma), DeepSeek, Alibaba (Qwen), Meta (Llama and Muse), xAI (Grok), Moonshot (Kimi), Mistral, and Zhipu (GLM). Open-weight and closed models differ in how they can be inspected, hosted, adapted, and accessed.

2.3 Evaluation and training data

Benchmarks help compare models, but scores need context. Some benchmarks, such as MMLU and GSM8K, are nearing saturation; others, including SWE-bench variants, LiveBench, LMArena, GAIA, and BenchLM, provide different signals. Training data sources such as Common Crawl and FineWeb also shape model capabilities.

2.4 Abliteration

Refusal-removal techniques and fine-tunes, including Heretic and Ajax, can change how a model responds. Consider their impact on behavior and agent autonomy when selecting a model.

2.5 Prominent AI Organizations Creating Foundational AI Models

(Order by Name ↑)

- [Alibaba](#) (Qwen)
- [Allen Institute for AI](#)
- [Amazon AI](#)
- [Anthropic](#)
- [Black Forest Labs](#) (FLUX)
- [ByteDance](#) (Seed / Seedream / Doubao)
- [Cohere](#)
- [DeepSeek](#)
- [Google AI / Google DeepMind](#)
- [Hugging Face](#)
- [IBM](#)
- [Meta AI](#)
- [Microsoft AI](#)
- [MiniMax](#)
- [Mistral AI](#)
- [Moonshot AI](#) (Kimi)

- [OpenAI](#)
- [Stability AI](#)
- [Xiaomi](#) (MiMo)
- [xAI](#)
- [Zhipu AI](#) / [Z.AI](#) (GLM)

2.5.1 Foundational AI Models

(Order by Name ↑)

- [Claude](#) (Anthropic)
- [Command](#) (Cohere)
- [DeepSeek](#)
- [FLUX](#) (Black Forest Labs)
- [Gemini](#) (Google DeepMind)
- [Gemma](#) (Google)
- [GLM](#) (Zhipu AI / Z.AI)
- [GPT](#) (OpenAI)
- [Granite](#) (IBM)
- [Grok](#) (xAI)
- [Kimi](#) (Moonshot AI)
- [Llama](#) (Meta)
- [MiMo](#) (Xiaomi)
- [Mistral](#) (Mistral AI)
- [Muse](#) (Meta)
- [Nova](#) (Amazon)
- [Qwen](#) (Alibaba)
- [Seed](#) / [Seedream](#) (ByteDance)
- [Stable Diffusion](#) (Stability AI)

2.6 Benchmarks

Benchmark	Status in 2026	Strengths	Weaknesses	Still useful?
MMLU	Saturated	Historical reference for broad knowledge	Frontier models cluster ~90%+; little differentiation; contamination risk	Mostly no (use MMLU-Pro if needed)

Benchmark	Status in 2026	Strengths	Weaknesses	Still useful?
GSM8K	Saturated	Simple math word problems	Top models near ceiling (~95%+); many invalid questions noted	No for frontier comparison
GPQA (Graduate-Level Google-Proof Q&A Benchmark; esp. Diamond)	Near-saturating	Challenging multiple-choice benchmark evaluating advanced scientific reasoning and deep domain understanding in large language models	Leaders pushing 90%+; small set → noise	Still decent for science reasoning, but headroom shrinking
SWE-bench (Verified/Pro variants)	Contested / partially saturating	Real GitHub issue resolution; strong signal for coding agents	Contamination concerns; scores climbing into high 70s–90s on easier versions	Yes for coding/agent work (prefer newer/harder variants like Pro)
GAIA	Active but contested	Multi-step agentic tasks (browsing, tools, files) that are easy for humans	Large score gaps depending on scaffolding/tools; some saturation reports	Yes for assistant/agent evaluation

Benchmark	Status in 2026	Strengths	Weaknesses	Still useful?
LiveBench	Highly regarded	Monthly-refreshed questions from recent sources; objective ground-truth scoring; covers reasoning, coding, math, data analysis, language, instruction following	Not human preference; not pure agentic long-horizon	One of the strongest current objective capability benchmarks
LMarena (Chat-bot/Arena)	Highly regarded	Large-scale blind human preference (Elo-style); real user prompts	Style/verbosity bias; overlapping confidence intervals; not verifiable correctness	Best for “which model feels best in open-ended use”
BenchLM	Aggregator	Combines many sources into overall indices	Depends on underlying benchmarks; not a primary eval itself	Useful meta-view, not a standalone benchmark
Mensa Norway IQ Test	Niche	Attempts IQ-style scoring	Narrow, not standard in frontier AI evaluation	Rarely used for serious model comparison
WebDev Arena	Specialized	Web development tasks	Narrow domain	Useful only if you care specifically about web-dev agents

Benchmark	Status in 2026	Strengths	Weaknesses	Still useful?
Humanity's Last Exam (HLE)	Active frontier benchmark	Expert- authored (1,000 contributors) multi-modal closed-ended questions (2,500 total) at the frontier of human knowledge across 100+ subjects; designed to resist search/con- tamination; objective grading; HLE- Diamond & Rolling variants for continued headroom	Score variance across full set / text-only / Diamond / with-tools; some answer-key disputes (esp. chem/bio); calibration remains poor	Yes — currently one of the strongest non-saturated academic/knowl- edge + reasoning benchmarks

Benchmark	Status in 2026	Strengths	Weaknesses	Still useful?
WorkBuddy Bench (Tencent)	Active / Research Preview (v1.2, Oct 2026)	Multi-domain coding-agent eval (Code 80 / Web 70 / Office 50 / Security 60 tasks) reverse-engineered from real work; contamination-resistant prompts; dual harnesses (CodeBuddy Code + Claude Code); fully open (tasks, Docker images, tests, solutions); reports efficiency (tokens/turns)	No suite-wide average (subset scores incomparable); harness effects are large; still early / Research Preview; heavier compute than pure unit-test benchmarks	Yes — one of the strongest current multi-domain agentic coding benchmarks, especially for real-world role-played work beyond pure SWE-bench-style issue fixing

2.6.1 Benchmark Articles

- [Grading the Graders: Gaming Benchmarks and Making Your Own](#)

2.7 Base Model Data

(Order by Name ↑)

- [AWS Open Data](#)
- [Common Crawl](#)
- [FineWeb](#) – curated Internet dataset.
- [Google Dataset Search](#)
- [Hugging Face Datasets](#)
- [Kaggle](#)

- [Microsoft Planetary Computer Data Catalog](#)
- [MNIST \(Modified National Institute of Standards and Technology database\)](#)
- [Open Images Dataset](#)
- [SNAP - Stanford Large Network Dataset Collection](#)
- [UC Irvine Machine Learning Repository](#)
- [USA Data Gov](#)

3 Running a Model

[ByteByteGo: How to Run LLMs Locally \(Great For Learning and Privacy\)](#)

3.1 Web/Online Models

(Order by Name ↑)

- [Anthropic - Claude](#)
- [DeepSeek - Chat](#)
- [GitHub Models](#)
- [Google - Gemini](#) / [AI Studio](#)
- [Grok \(xAI\)](#)
- [IBM Granite](#)
- [Kimi \(Moonshot AI\)](#)
- [Mammoth](#) - Multi-model selector
- [Meta AI](#)
- [Microsoft Copilot](#)
- [Mistral](#)
- [OpenAI - ChatGPT](#)
- [Perplexity](#)
- [Qwen \(Alibaba\)](#)
- [Together AI](#)
- [TypeSafe](#)
- [Z \(GLM\)](#)

3.2 Physical Hardware

3.3 Running AI Models Locally

- [llama.cpp](#) — Core inference engine (GGUF, maximum control)
- [Ollama](#) — CLI + local OpenAI-compatible API (most popular for developers)
- [LM Studio](#) — Polished desktop GUI
- [Jan](#) — Fully open-source run models locally, with cloud integration, MCP support. desktop app (privacy-focused)
- [Open WebUI](#) — Self-hosted web UI (excellent with Ollama)
- [KoboldCpp](#) — Easy single-binary runner with built-in UI
- [vLLM](#) — High-throughput serving (multi-user / production)
- [SGLang](#) — SGLang powers fast large scale production large language and multimodal models.

3.3.1 Comparing Local Model Runners

As- pect	llama.cpp	Ollama	LM Studio	Jan	Open WebUI	Kobold-Cpp	vLLM	SGLang
Primary focus	Core low-level inference engine (GGUF, max control)	Easy CLI + local OpenAI-compatible API (developer friendly)	Polished desktop GUI for chat, discovery & experimentation	Fully open-source desktop app (privacy-first, local + cloud)	Self-hosted web UI (pairs excellently with Ollama/vLLM)	Easy single-binary runner with built-in creative UI	High-throughput multi-user / production serving	High-performance large-scale serving (esp. agents & multi-modal)
License	MIT	MIT	Proprietary (free for personal + internal business)	Apache 2.0	Custom (permissive with branding requirements for large deployments)	AGPL-3.0 (llama.cpp core is MIT)	Apache 2.0	Apache 2.0

Aspect	llama.cpp	Ollama	LM Studio	Jan	Open WebUI	Kobold-Cpp	vLLM	SGLang
Interface	CLI + optional simple web UI / server	CLI-first + basic desktop app + API	Excellent GUI + CLI (lms) + headless daemon	Desktop app (macOS/Windows/Linux) + local API server	Full web UI (browser)	Single executable + built-in KoboldAI Lite web UI	CLI / Python server	CLI / Python server
Model discovery	Manual GGUF download (Hugging Face, etc.)	Curated library + simple ollama pull	Built-in Hugging Face browser with size/VRAM estimates	Jan Hub + Hugging Face integration	Via connected backend (Ollama/vLLM/etc.)	Manual GGUF load	Hugging Face / local models	Hugging Face / local models
API	OpenAI-compatible (llama-server)	OpenAI-compatible + native (port 11434)	OpenAI-compatible + Anthropic-compatible (port 1234)	OpenAI-compatible (port 1337)	Connects to any OpenAI-compatible backend	OpenAI-compatible + KoboldAI + others (port 5001)	OpenAI-compatible (+ Anthropic Mesages)	OpenAI-compatible (+ Anthropic/Ollama-style)
Best hardware edge	Broadest support (CPU, Metal, CUDA, ROCm, Vulkan, etc.)	Lower overhead; strong on NVIDIA & Apple Silicon	Strong MLX performance on Apple Silicon	llama.cpp + MLX; good cross-platform	Depends on backend	llama.cpp backends (CUDA/Vulkan/ROCm/CPU)	NVIDIA/AMD focused; multi-GPU throughput	NVIDIA/AMD + strong caching for agents
Headless/server	Yes (llama-server)	Native from the start (systemd/Docker friendly)	Yes (lms) since early 2026	Yes (local API server)	Yes (Docker-first)	Yes (single binary server)	Native high-performance server	Native high-performance server

Aspect	llama.cpp	Ollama	LM Studio	Jan	Open WebUI	Kobold-Cpp	vLLM	SGLang
Extras Strengths	Maximum control, optimizations (GGUF), minimal deps, hybrid CPU+GPU	Excellent ecosystem, Modelfiles, Docker, optional cloud	Document chat (RAG), MCP client, continuous batching, remote sharing	MCP support, agents, cloud model integration, privacy focus	Built-in RAG, multi-user auth, pipelines/plugins, image/voice	Story/role-play tools, image gen, world info	Continuous batching, PagedAttention, multi-LoRA, production scale	RadixAttention (prefix reuse), speculative decoding, multimodal, agent-optimized

3.3.1.1 Developer-focused comparison: LM Studio vs Ollama

Aspect	LM Studio	Ollama
Primary focus	Polished desktop GUI for discovery, chat & experimentation	CLI + background service for scripting, APIs & integrations
License	Proprietary (free for personal + internal business use)	Fully open-source (MIT)
Interface	Excellent GUI + CLI (<code>llms</code>) + headless daemon (<code>llmster</code>)	CLI-first + local API; has added a basic desktop app
Model discovery	Built-in Hugging Face browser with size/VRAM estimates	Curated library + simple <code>ollama pull model:tag</code>
API	OpenAI- + Anthropic-compatible (port 1234)	OpenAI-compatible + native endpoints (port 11434)
Best hardware edge	Stronger MLX performance on Apple Silicon	Lower overhead, often slightly faster on NVIDIA
Headless/server	Yes (<code>llmster</code> since early 2026)	Native from the start (systemd/Docker-friendly)
Extras	Built-in document chat (RAG), MCP client, LM Link (remote device sharing), continuous batching	Excellent ecosystem integrations, Modelfiles, official Docker image, optional cloud models

3.3.1.2 When Ollama is usually better: You want a fully open-source, auditable tool.

- You are a developer building scripts, agents, or apps (many frameworks and coding tools assume Ollama by default).
- You need Docker, Kubernetes, or long-running headless servers with minimal footprint.
- You prefer the lowest idle RAM and fastest cold-start times (especially on NVIDIA GPUs).
- You want the absolute simplest CLI workflow (`ollama run model`).

3.3.2 Local-first inference

RamaLama vs Ollama — key differences

Both tools let you run large language models locally, but they take different approaches.

3.3.2.1 Quick summary

Aspect	Ollama	RamaLama
Core idea	Simple local model runner + library	Container-native way to run models
Default execution	Runs models directly on the host	Runs models inside containers (Podman/Docker) by default
Who makes it	Ollama Inc.	containers.org (Podman / Red Hat ecosystem)
Model sources	Primarily its own library (+ limited HF)	Hugging Face, Ollama registry, ModelScope, any OCI registry, URLs, local files
Runtimes	Built around llama.cpp	llama.cpp (default) and vLLM
Hardware handling	You (or the installer) handle GPU libraries	Auto-detects GPU and pulls a matching optimized container image
Security / isolation	Host process	Rootless containers, read-only mounts, network isolation by default
Commands feel like	<code>ollama run</code> , <code>ollama pull</code> , etc.	Familiar container-style: ramalama run , pull , serve , push
Best for	Easiest “just chat with a local model” experience	People who already use containers and want the same workflow + stronger isolation

3.3.2.2 Main philosophical difference

- **Ollama** optimizes for simplicity and a polished consumer experience. Install it, pull a model, chat. Models usually run as normal processes on your machine.
- **RamaLama** optimizes for *making AI work like containers*. It treats models more like images: pull from multiple registries, run them in isolated containers, serve them, convert them to OCI images, push them to registries, etc. The slogan is essentially “make working with AI boring” by using the tools and patterns people already know from Podman/Docker.

3.3.3 Practical implications

- **Isolation & security**: RamaLama wins by default (models stay inside rootless containers).
- **GPU setup**: RamaLama is often easier on Linux (especially Fedora/RHEL-style systems) because the container already contains the right CUDA/ROCm/etc. libraries.
- **Model choice**: RamaLama is more flexible about where models come from (especially Hugging Face and OCI registries).
- **Ecosystem fit**:
 - Ollama → very widely supported by agents (goose, OpenCode, Hermes, etc.).
 - RamaLama → also usable (many tools treat it as an OpenAI-compatible endpoint or have explicit support), and it can even pull from the Ollama registry.

3.3.4 When to choose which

- Choose **Ollama** if you want the simplest, most popular local model runner and don’t care about container isolation.
- Choose **RamaLama** if you already live in a container world (Podman/Docker), want better isolation by default, or need to pull models from Hugging Face / OCI registries more cleanly.

Both expose OpenAI-compatible APIs, so most agents and tools can talk to either of them.

3.3.5 Other local inference options

- **llama.cpp** offers low-level control and GGUF support.
- **LM Studio** provides a desktop interface and API.
- **Jan** is an open-source desktop application.
- **Open WebUI** provides a self-hosted web frontend.

- **KoboldCpp** and **vLLM** support additional local and high-throughput serving setups.

Model management includes downloading and selecting models, quantization, Modelfiles, and custom system prompts. Hardware, memory requirements, and trade-offs vary by model and runner.

3.4 Cloud and hybrid options

Hosted providers can complement local inference when a task needs a more capable model or additional capacity. Hybrid setups balance privacy, cost, latency, rate limits, and data-sovereignty requirements.

3.4.1 NeoClouds (also *neoclouds* or *neo-clouds*)

Specialized, AI-first cloud providers built primarily around high-performance GPU (and other accelerator) infrastructure for AI training, fine-tuning, and inference.

Unlike traditional hyperscalers (AWS, Microsoft Azure, Google Cloud), which offer a broad catalog of general-purpose services and later added GPU support, NeoClouds are designed from the ground up for dense GPU clusters, high-bandwidth low-latency networking, and the power/cooling demands of modern AI workloads. Their core offering is typically **GPU-as-a-Service (GPUaaS)**—renting accelerator capacity by the hour, reservation, or longer contract—often with thinner virtualization layers or bare-metal access.

3.4.1.1 Key characteristics

- GPU-centric architecture and capacity
- Optimized networking and storage for large-scale model training and inference
- Narrower service surface focused on AI rather than general IT
- Frequently more competitive pricing or faster access to the latest accelerators than hyperscalers
- Serve AI labs, startups, enterprises, and sometimes other cloud providers

Notable examples (as of late 2026): [CoreWeave](#), [Nebius](#), [Lambda](#), [Crusoe](#), and a growing long tail of regional and specialized operators.

Why it matters in the agentic / practical AI landscape

NeoClouds address the compute bottleneck that constrains both frontier model development and self-hosted or production agent systems. They expand the set of places you can actually rent serious GPU capacity outside the major hyperscalers.

3.5 Making models usable by agents

3.6 Security and operational considerations

3.6.1 Security Resources for local models

- 2026-10-21 [Kai: Your Local AI Is Not as Private as You Think](#)
- 2026-10-19 [Cloud Codes: Your Local AI Model Isn't as Safe as You Think](#)

3.6.2 Local Model Vulnerabilities

Here is an overview of the main known classes of LLM exploits and attack surfaces (as of late 2026). This focuses on categories that appear repeatedly in research, real incidents, and frameworks such as the **OWASP Top 10 for LLM Applications (2026 edition)**. It deliberately stays at the conceptual level.

3.6.2.1 1. Prompt Injection (still #1)

- **Direct:** Attacker writes instructions that override the system prompt or safety rules.
- **Indirect / context injection:** Malicious instructions are planted in external content the model later processes (emails, documents, web pages, RAG results, tool outputs, memory, etc.). Real-world examples include zero-click data exfiltration (e.g., EchoLeak against Microsoft 365 Copilot) and tool/agent hijacking.
- Variants include jailbreaks (role-play, encoding, multi-turn persuasion) aimed at bypassing safety training.

3.6.2.2 2. Sensitive Information Disclosure / Data Leakage

Models or applications can leak training data, system prompts, user conversation history, credentials, or proprietary information through responses, logs, embeddings, or tool calls. Techniques include membership inference, training-data extraction, and system-prompt extraction.

3.6.2.3 3. Excessive Agency / Tool & Agent Abuse

When an LLM can call tools, browse, write code, send messages, or control systems, injected instructions can make it perform unauthorized actions (file access, API calls, privilege escalation, lateral movement). This risk rose sharply in rankings with the spread of agentic systems.

3.6.2.4 4. Supply-Chain Attacks

- Malicious models or weights (including the pickle / “broken pickle” / Sleepy Pickle family we discussed earlier).
- Poisoned packages, MCP servers, plugins, or fine-tuning artifacts.
- Compromised model hubs or distribution channels.

3.6.2.5 5. Data & Model Poisoning / Backdoors

Attackers influence training, fine-tuning, or retrieval data so the model behaves normally most of the time but activates harmful behavior under a trigger (sleeper agents, backdoored code generation, biased outputs, etc.).

3.6.2.6 6. Unbounded Consumption / Resource Abuse

Attacks that force excessive token generation, repeated inference, or expensive tool use, driving up cost or causing denial-of-service. Also includes model-extraction / distillation attacks that steal capability by querying the target model.

3.6.2.7 7. Misinformation / Hallucination Abuse

Models can be steered (or simply fail) into producing confident but false or harmful content that users or downstream systems act upon.

3.6.2.8 8. Hidden Context / System-Prompt Exposure

Secrets, authorization logic, or internal instructions placed in the system prompt or retrieved context can be extracted or abused.

3.6.2.9 9. Vector / Embedding / RAG Weaknesses

Poisoning of vector stores, cross-tenant leakage in embeddings, or adversarial retrieval that surfaces malicious documents.

3.6.2.10 10. Improper Output Handling

Model output is treated as trusted and fed into browsers, shells, databases, or other interpreters without sanitization, enabling classic injection or XSS-style follow-on attacks.

3.6.2.11 Additional established categories outside the strict Top 10

- **Adversarial examples / input perturbations** — small, often imperceptible changes that flip model behavior.
- **Model inversion & privacy attacks** — reconstructing training examples or attributes.
- **Multimodal attacks** — injecting payloads via images, audio, or other modalities that the model processes.
- **Agent-specific chains** — memory poisoning, persistent tool hijacking, self-propagating behavior across sessions or systems.
- **Infrastructure / serving vulnerabilities** — flaws in inference servers, gateways (e.g., LiteLLM-style issues), or serialization formats beyond pickle.

3.6.2.12 Practical note

Most real-world incidents combine several of the above (e.g., indirect prompt injection → excessive agency → data exfiltration). Open-weight models have repeatedly shown higher susceptibility to certain cyber-relevant payload chains than the strongest closed models, though both remain targets.

The landscape evolves quickly; the dominant practical risks in production systems right now center on **prompt/context injection**, **agent tool abuse**, and **supply-chain model/package poisoning**. Defenses typically involve layered controls: input/output filtering, least-privilege tooling, provenance checks, retrieval isolation, and continuous red-teaming rather than relying on any single technique.

3.7 Security Summary: What Can the Model Reach?

Running models locally protects your prompts from third-party providers, but it does **not** automatically make the setup safe. The decisive security question is not “Is the model local?” — it is “**What can the model (or the software around it) reach?**”

3.7.1 The practical risk ladder

Reach level	What the model can touch	Risk profile
Chat only	Conversation text	Low — limited to generating text

Reach level	What the model can touch	Risk profile
Files / project context	Local documents, code, <code>.env</code> files	Medium — can exfiltrate or rewrite secrets if it has write access
Tools / shell / network	Terminal commands, HTTP requests, file system, APIs	High — can execute code, send data out, or fetch remote payloads
Agent + persistent access	Multiple tools + memory + long-running privileges	Critical — full blast radius of the host

A backdoored or triggerable model (or a poisoned chat template) is only as dangerous as the permissions and tools you give it. In the ProjectDiscovery demonstration highlighted in the video, a fine-tuned model behaved normally on clean tests until a short trigger phrase caused it to instruct an agent to send the project’s `.env` file to an external server. The model itself did not contain the final payload; it simply knew to fetch and run one.

3.7.2 Key attack surfaces that expand “reach”

- **Model file + chat template** — Weights are data, but GGUF templates (Jinja) and metadata can embed hidden instructions or, in rare cases, enable code execution if the runner is unsandboxed.
- **Runner / inference server** — Bugs or misconfigurations in Ollama, LM Studio, llama.cpp, etc., can leak memory, environment variables, or allow unauthorized control.
- **Network binding** — Binding to `0.0.0.0` (or leaving the port unauthenticated) turns a local server into a public one. Exposed, unauthenticated instances are routinely scanned and abused.
- **Tool / agent permissions** — Shell access, file write, or unrestricted network is the difference between a chat bot and a remote-code-execution surface.

3.7.3 Practical containment principles

1. **Minimize reach by default** — Prefer pure chat. Grant tools only when necessary and under least privilege.
2. **Keep the server on loopback** (`127.0.0.1`). For remote access use an authenticated tunnel (e.g., Tailscale) or a reverse proxy with authentication — never expose the raw inference port.
3. **Keep the runner updated** and enable any available authentication features.
4. **Treat model files as untrusted input** — Prefer reputable sources, verify provenance where possible, and consider scanning templates.

5. **Separate secrets from the model's working environment** — Do not give the process access to credentials it does not need.

Bottom line: Local inference removes the cloud provider from the trust boundary, but it transfers the entire security responsibility to you. The model is only as private and safe as the smallest set of resources you allow it to reach.

3.8 NVIDIA

[OpenShell][(<https://www.nvidia.com/en-us/ai/openshell/>)] is an open, secure runtime designed for AI agents. It provides a governed environment that controls agent execution, access, and inference routing, independent of the underlying model or application.

3.8.1 Core Idea

Security is enforced in the environment rather than inside the model or agent code. Nothing is allowed by default. Permissions are granted through explicit policies, and enforcement occurs outside the agent's process so it cannot be bypassed or "prompted away." All allow/deny decisions are fully auditable. It works with any model, agent harness, or framework across cloud, hybrid, on-premises, edge, and air-gapped environments under a single policy layer.

3.8.2 Key Benefits

- **Agent governance outside the model:** Separates agent behavior from environment interactions; every action is monitored and controlled.
- **Zero-trust access:** Deny-by-default model with intent-based permissions enforced externally.
- **Safe operation of agent fleets:** Unified policy enforcement for open or closed models and various harnesses at scale.

3.8.3 Main Components

- **Agent Sandboxes:** Isolated environments with no direct network access, privilege restrictions, file limits, and kernel-level system-call filtering. Requests are brokered through a secured channel.
- **Policy Prover:** Formal verification engine that checks policies stay within allowed boundaries and evaluates network rules for risk.

- **Gateway:** Control plane that authenticates users, manages sandbox lifecycles, delivers policies/credentials, and brokers access.
- **Supervisor:** Runtime overseer outside the sandbox that evaluates network requests against policy (at binary, destination, method, and path levels), supplies credentials only when allowed, applies live policy updates, and logs every decision.

3.8.4 Reference Architecture

A full-stack setup powered by the OpenShell runtime, NVIDIA Vera CPUs, Vera Rubin systems, and NVIDIA Sentry on BlueField-4 for industrial-scale safe agents in AI factories, enterprise settings, and at the edge.

3.8.5 Who It's For & What It Supports

Primarily developers building autonomous agents, platform teams, and security/IT teams that need to enable agent use without granting broad host, network, credential, or model access. It is model- and harness-agnostic (supports Claude Code, Codex, GitHub Copilot CLI, LangChain Deep Agents, custom agents, etc.) and is not itself an agent framework—it sits underneath them. It goes beyond simple containers/pods by adding agent-specific controls for lifelong governance, credential handling, egress policy, inference routing, and multi-agent workflows.

OpenShell is open source (available on GitHub), runs on Docker, Podman, Kubernetes (via Helm), and experimental runtimes, works with NVIDIA DGX systems, supports cloud model endpoints via a policy-aware router, and does not require Vera CPUs (though they provide performance and efficiency gains).

3.8.6 Technical Resources

- [NVIDIA YouTube Summary](#)
- [NVIDIA Developer: How NVIDIA OpenShell Secures Autonomous Agents | Nemotron Labs](#)

4 Agents and Harnesses

- **An agent** is the autonomous actor — the thing that reasons, plans, uses tools, remembers, and pursues goals over multiple steps.
- **A harness** is the runtime / scaffolding that turns a raw language model into a working agent.
 - ***The harness** is the engine and chassis. **The agent** is the driver + the behavior that emerges once the model is running inside that chassis.*

4.1 Agent Harness Diagram

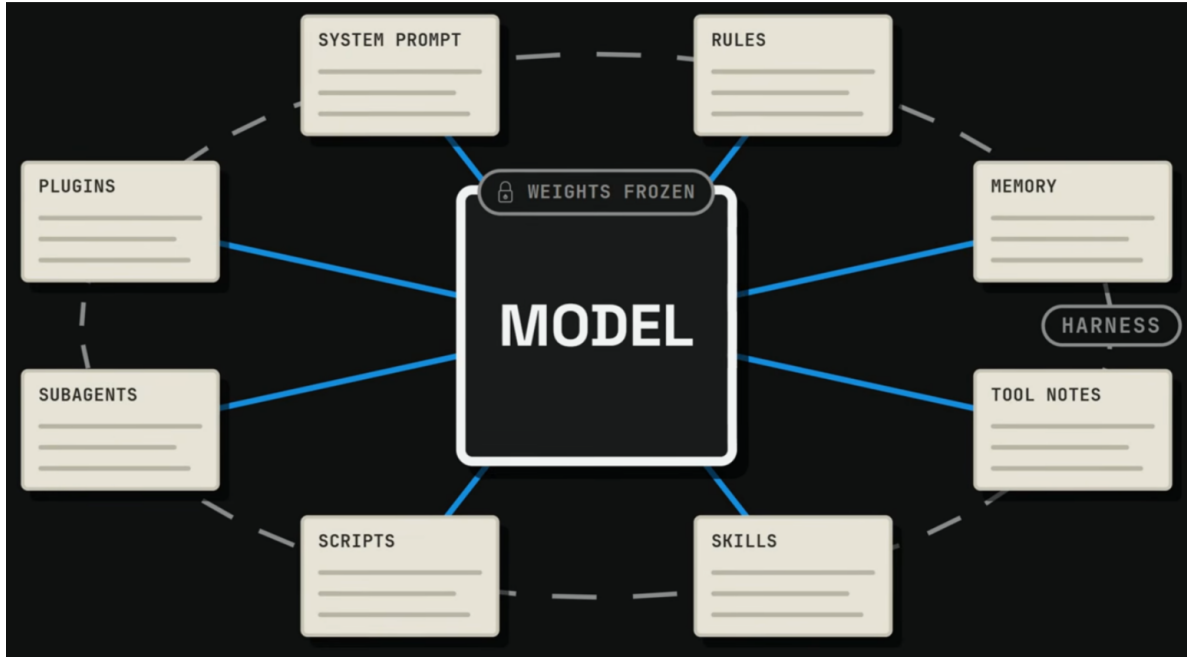


Figure 4.1: Agent Harness Diagram

4.1.1 More precise breakdown

Concept	What it is	Examples
Model	The raw intelligence (weights)	Qwen, DeepSeek, Claude, Llama, Ajax (abliterated), etc.
Harness	The runtime that gives the model a loop, tools, memory, sandboxes, skills, messaging, persistence, etc.	Hermes, OpenClaw, goose, OpenHands, OpenCode, Agent Zero
Agent	The resulting autonomous system that actually does work	Copilot, OpenCode, Agent Zero

The harness determines: - How long the agent can run - Whether it has persistent memory and can create its own skills - What tools (MCP servers) it can reach - Whether it lives in messaging apps, a terminal, a web UI, or a full Linux desktop - How isolated / sandboxed its actions are - How easy it is to observe, interrupt, or improve it

A good harness {Hermes, OPenCode, Agent Zero, OpenClaw, goose, etc.} dramatically changes what kind of agent you can actually have. A weak or missing harness leaves you with just a chatbot that forgets everything between messages

A harness is the runtime that gives a model a loop, tools, memory, and an environment in which to act. It determines how long an agent can run, what it can access, and how its work can be observed and controlled.

4.2 Modern harnesses

Name	Type	Primary Focus	Notes / Key Traits	Stars (approx, Oct 2026)
goose	Both	General-purpose local agent	Own harness + agent; MCP-native; desktop + CLI; AAIF	~55k
Hermes Agent	Both	Always-on personal agent	Own runtime; persistent memory + skill creation; messaging gateways	~250k+
Agent Zero	Both	Full computer-use agent	Own Docker Linux desktop + agent; high transparency	~19.5k
OpenClaw	Both	Personal assistant (chat apps)	Own gateway/runtime; messaging-first	Very high (~390k+)
Open-Hands	Both	Coding / software engineering	Own multi-agent runtime; web UI + desktop	~89k
OpenCode	Both	Terminal coding agent	Own agent loop; model-agnostic	High
Codex (OpenAI)	Both	Coding agent suite	Cloud + CLI + IDE; proprietary harness	N/A (product)
Claude Code	Both	Coding agent	Anthropic harness + agent; subscription-based	N/A (product)
Cline	Both	IDE coding agent	VS Code / JetBrains extension with own loop	—
Aider	Both	Terminal coding agent	Own agent loop; git-aware	—
Eigent	Both	Multi-agent desktop	Parallel agents on one task	~15.5k

Compare harnesses by their philosophy, strengths, limitations, deployment style, and fit for the task.

4.3 Supporting infrastructure

- **MCP (Model Context Protocol)** connects agents to tools and services.
- Sandboxed execution environments such as Docker, Daytona, Modal, E2B, and browser infrastructure help isolate agent actions.
- Persistent memory and agent-written skills support longer-running work.
- **SpyNEL** orchestrates existing coding harnesses.
- **DOX / AGENTS.md** hierarchies give agents maintainable project context.

4.4 [agents.md](#)

4.4.0.1 Evaluating AGENTS.md: Are Repository-Level Context Files Helpful for Coding Agents?

[Evaluating AGENTS.md: Are Repository-Level Context Files Helpful...](#)

Condition	Effect on success rate	Effect on cost / steps
LLM-generated context files	Slightly worse on average (~ -0.5% on SWE-bench Lite, ~ -2% to -3% on the new bench; negative in most configs)	+20–23% inference cost; +2.5–4 extra steps per task
Human-written context files	Modest average gain (~ +4% on the developer-file benchmark)	Still + up to ~19% cost / more steps
Overall	“Does not generally improve task success rates”	Clear, consistent cost increase

Practical takeaway that matches the evidence: Keep any AGENTS.md / CLAUDE.md extremely short. Prefer only non-discoverable facts (exact test/build commands that differ from the obvious, hard “never touch X”, unusual tooling). Long files that restate what is already in the code, README, or package.json are the ones most likely to waste tokens for little or no gain.

5 Building a Working Stack

Combine models, harnesses, tools, and operational safeguards into a stack that fits the work.

5.1 Starting points

- A minimal personal agent stack can pair a local model such as Ollama or Jan with a harness, MCP tools, and memory.
- An always-on personal agent can combine a workspace such as Odysseus or Ajax with a messaging gateway such as OpenClaw or Hermes.
- A coding stack can combine OpenHands or OpenCode with repository context (DOX) and sandboxed execution.

5.2 Practical considerations

- Incorporate calibrated decision models such as Jev and RLCD for routing, gating, and confidence-based escalation.
- Define containment and permission models.
- Understand the cost and token economics of long-running agents.
- Observe and debug multi-step runs.
- Update skills and memory without destabilizing the system.

6 Miscellaneous Tools and Supporting Infrastructure

Useful supporting tools improve understanding, model selection, and day-to-day workflows.

6.0.1 Miscellaneous Tools

(Order by Name ↑) - [Excalidraw](#) - online Diagram tool - [LLM Visualization](#) - [Tiktokenizer](#)

6.1 Model selection and modification

- BenchLM and Best Ollama Models lists
- Heretic and related model-modification tools

6.2 Open-source principles and sources

OpenWALDO organizes AI openness around Weights, Artifacts, Licenses, Data, and Origin. Independent blogs, technical writing, research papers, and historical milestones provide context for following the field.

7 Resources

7.1 X Agentic-Engineering Lists

- [Agentic Engineering](#)

8 AI [blog] Resources

prioritise independent writers, technical depth, open-model communities, and low-hype signal over mainstream media.

(Order by Name ↑)

- [AI News](#)
- [AI News Dashboard](#)
- [Ai2 – Allen Institute](#)
- [ApX Machine Learning](#)
- [Arsturn](#)
- [Epoch AI](#)
- [Hugging Face](#)
- [Import AI](#) (Jack Clark)
- [Interconnects](#) (Nathan Lambert)
- [Latent Space](#)
- [SemiAnalysis](#)
- [ShinChven's Blog](#)
- [Simon Willison's Weblog](#)
- [The Batch](#) (Andrew Ng)
- [The Gradient](#)
- [Turning Post](#)

9 YouTube Videos & Channels

(Sorted by Publication Date ↓)

- 2026-10-30 [Kai: Bytes Is This The End of Token?](#)
- 2026-10-29 [Chris Titus Tech: You're Using AI Skills Wrong \(I Was Too\)](#)
- 2026-10-22 [ByteByteGo: Top 5 AI Building Blocks Every Engineer Should Know](#)
- 2026-10-19 [AI Engineer: Is the Agent Harness Dead? — Jediah Katz, SpaceXA](#)
- 2026-10-19 [Cloud Codes: Your Local AI Model Isn't as Safe as You Think](#)
- 2026-10-11 [Stanford CS146S: How always-on agents work](#)
- 2026-09-21 [Why I couldn't build Jev at OpenAI — Diogo Almeida, TypeSafe Co-founder & CEO](#)
- 2026-06-10 [ByteByteGo: How to Run LLMs Locally \(Great For Learning and Privacy\)](#)
- 2026-05-13 [The Coding Gopher: Uni-1 AI image generation model](#)
- 2026-03-26 [The Diary of a CEO: AI Whistleblower: We Are Being Gaslit By AI Companies, They're Hiding The Truth! - Karen Hao](#)
- 2026-03-00 [Hugging Face: Agentic Evals Workshop Playlist](#)
- 2025-06-11 [Jon Krohn: Agentic AI Engineering: Complete 4-Hour Workshop feat. MCP, CrewAI and OpenAI Agents SDK](#)
- 2025-04-28 [Logically Answered: AMD's \\$243 Billion AI Disaster...What Happened?](#)
- 2025-04-22 [Computerphile: What is Cuda?](#)
- 2025-03-05 [ByteByteGo: What Is the Most Popular Open-Source AI Stack?](#)
- 2025-02-05 [Andrej Karpathy: Deep Dive into LLMs like ChatGPT](#)
- 2025-02-02 [Lex Fridman: DeepSeek, China, OpenAI, NVIDIA, xAI, TSMC, Stargate, and AI Megaclusters | Lex Fridman Podcast #459](#)
- 2025-01-29 [Peter H. Diamandis: DeepSeek vs. Open AI - The State of AI w/ Emad Mostaque & Salim Ismail | EP #146](#)
- 2024-11-11 [Lex Fridman: Dario Amodei: Anthropic CEO on Claude, AGI & the Future of AI & Humanity | Lex Fridman Podcast #452](#)
- 2024-09-09 [IBM Technology: RAG vs. Fine Tuning](#)
- 2024-04-01 [3Blue1Brown: Neural networks Playlist](#)
- 2023-08-23 [IBM Technology: What is Retrieval-Augmented Generation \(RAG\)?](#)
- 2018-07-30 [Lex Fridman: Deep Learning State of the Art \(2020\)](#)
- 0000-00-00 [Channel: StatQuest with Josh Starmer](#)

10 Articles

(Sorted by Publication Date ↓)

- 2026-10-21 [Grading the Graders: Gaming Benchmarks and Making Your Own](#)
- 2026-09-11 [Lies, Damned Lies, and Benchmarks](#)
- 2026-09-09 [\(KV\) Cache Rules Everything Around Me](#)
- 2026-08-27 [Pivot to AI: Your AGENTS.md file doesn't actually do anything](#)
- 2025-02-12 [Unlocking the Effective Context Length: Benchmarking the Granite-3.1-8b Model](#)
- 2025-02-02 [A Detailed Analysis of Fine-Tuning, Direct Preference Optimization \(DPO\), and Reinforcement Learning with Verifiable Rewards \(RLVR\) on the LLama3.1 405B Model](#)
- 2025-01-31 [DeepSeek-V3 Explained 1: Multi-head Latent Attention](#)
- 2025-01-19 [Top 5 Mistakes to Avoid When Learning Machine Learning](#)
- 2024-10-02 [How to Get Started with Machine Learning: A Beginner's Step-by-Step Guide](#)
- 2024-07-13 [MHA vs MQA vs GQA vs MLA](#)
- 2020-00-00 [Over 200 of the Best Machine Learning, NLP, and Python Tutorials — 2018 Edition](#)

11 AI Publication Websites

(Order by Name ↑)

- [arxiv](#)

11.1 AI Publications

(Sorted by Publication Date ↓)

- 2025-04-25 [BitNet b1.58 2B4T Technical Report](#)
- 2024-04-09 [RULER: What's the Real Context Size of Your Long-Context Language Models?](#)
- 2023-07-27 [Universal and Transferable Adversarial Attacks on Aligned Language Models - LLM Attacks](#)
- 2020-05-28 [Language Models are Few-Shot Learners \(GPT-3\)](#)
- 2019-06-17 [Superposition of many models into one](#)
- 2018-10-11 [BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding](#)
- 2017-06-12 [Attention Is All You Need](#)
- 2015-12-10 [Deep Residual Learning for Image Recognition \(ResNet\)](#)
- 2014-06-10 [Generative Adversarial Networks \(GANs\)](#)
- 2012 [ImageNet Classification with Deep Convolutional Neural Networks \(AlexNet\)](#)

12 Online Books

(Sorted by Publication Date ↓)

- 2026 [Principles and Practice of Deep Representation Learning](#)
- 2024 [Machine Learning and Deep Learning with R](#)
- 2024 [Natural Language Processing \(NLP\) Course](#)
- 2023 [Dive into Deep Learning](#)
- 2023 [State of Open Source AI Book - 2023 Edition](#)
- 2023 [Understanding Deep Learning](#)
- 2019 [Neural Networks and Deep Learning](#)
- 2018 [Deep Learning](#)
- 2016 [Deep Learning](#)

13 Prominent AI People

(Sorted by Surname ↑)

- [Diogo Almeida](#) - TypeSafe
- [Dario Amodei](#) - Anthropic
- [Sam Altman](#) - OpenAI
- [Amanda Asell](#) - Anthropic
- [Yoshua Bengio](#) - Mila / Université de Montréal
- [Lex Fridman](#) - MIT
- [Demis Hassabis](#) - Google DeepMind
- [Geoffrey Hinton](#) - University of Toronto
- [Jensen Huang](#) - NVIDIA
- [Salim Ismail](#) - Anthropic
- [Nathan Lambert](#) - Allen Institute for AI
- [Yann LeCun](#) - Meta / NYU
- [Fei-Fei Li](#) - Stanford University / World Labs
- [Emad Mostaque](#) - stability.ai
- [Andrew Ng](#) - DeepLearning.AI / Stanford
- [Christopher Olah](#) - Anthropic
- [Ilya Sutskever](#) - Safe Superintelligence (SSI)

14 Keeping the Map Alive

14.1 Maintaining the quarterly Hotplate

Review the landscape and update the Hotplate on its quarterly release cycle. Keep dated observations so readers can distinguish current signals from older snapshots.

14.2 Contributing and continuing

Contribute useful observations and corrections, and follow the source material linked throughout the repository. Choose next steps that fit your role:

- **Solo developers and indie builders:** assemble a small stack you can run and control.
- **Team leads:** introduce agentic workflows with clear boundaries and operational visibility.
- **Researchers and evaluators:** compare systems with appropriate benchmarks and current evidence.

The most valuable skill is learning to assemble and control a stack that serves your needs.

14.3 Aggregation Projects

- [ai-collection](#)
- [ai-knowledge-library](#)
- [Awesome Agents](#)
- [awesome-agent-harness](#)
- [Awesome Open Source AI](#)

A Hotplate Index

A.1 :date: Checked daily

- [X List for Agentic Engineering](#)

A.2 :calendar: Checked weekly

- [Youtube](#)

A.3 :spiral_calendar: Checked monthly

A.4 Hotplate Catalog

- [2026-10](#)
-

B Glossary

B.1 A

B.1.1 Abliteration

refers to the process of removing the refusal mechanisms from an LLM. This is achieved using a technique implemented in the [remove-refusals-with-transformers project](#). This project provides a proof-of-concept implementation to remove refusals from an LLM without using TransformerLens, which supports most models available on HuggingFace. The code is tested with models up to 3B, but it can work with bigger models as well. The project uses harmful and harmless instructions to remove the refusals.

B.1.2 Agent

is the autonomous actor — the thing that reasons, plans, uses tools, remembers, and pursues goals over multiple steps.

B.1.3 Agent loop

is the repeated cycle in which a model reasons about a goal, optionally calls tools, observes the results, and continues until it reaches a stopping condition (success, failure, iteration limit, or human intervention). It is the fundamental control structure of an agent.

B.1.4 Agentic AI

uses sophisticated reasoning and iterative planning to autonomously solve complex, multi-step problems.

At its core, Agentic AI is a type of AI that's all about autonomy. This means that it can make decisions, take actions, and even learn on its own to achieve specific goals. It's kind of like having a virtual assistant that can think, reason, and adapt to changing circumstances without needing constant direction. Agentic AI operates in four key stages:

1. **Perception:** AI agents gather and process data from various sources, such as sensors, databases and digital interfaces. This involves extracting meaningful features, recognizing objects or identifying relevant entities in the environment.
2. **Reasoning:** A large language model acts as the orchestrator, or reasoning engine, that understands tasks, generates solutions and coordinates specialized models for specific functions like content creation, visual processing or recommendation systems. This step uses techniques like retrieval-augmented generation (RAG) to access proprietary data sources and deliver accurate, relevant outputs.
3. **Action:** By integrating with external tools and software via application programming interfaces, agentic AI can quickly execute tasks based on the plans it has formulated. Guardrails can be built into AI agents to help ensure they execute tasks correctly. For example, a customer service AI agent may be able to process claims up to a certain amount, while claims above the amount would have to be approved by a human.
4. **Learning:** Agentic AI continuously improves through a feedback loop, or “data flywheel,” where the data generated from its interactions is fed into the system to enhance models. This ability to adapt and become more effective over time offers businesses a powerful tool for driving better decision-making and operational efficiency.

B.1.5 Agentic Engineer

A software engineer who designs, builds, and operates production AI agent systems. This involves creating reliable, multi-step autonomous systems that can reason, plan, use tools, maintain state, and recover from errors, typically through iterative cycles of building, evaluating, observing, and refining non-deterministic LLM-based workflows.

B.1.6 Agentic engineering stack

The layered set of models, harnesses, tools, memory, orchestration, and governance required to make AI agents reliable and controllable in real work. Mastering this stack is essential for moving from isolated prompts to robust, self-directed workflows that integrate seamlessly with local hardware and custom system administration tools.

B.1.7 (AGI) Artificial General Intelligence

is a hypothetical AI system that possesses the ability to understand, learn, and apply knowledge across a wide range of tasks and domains, similar to human

intelligence. AGI aims to replicate the general cognitive abilities of humans, such as reasoning, problem-solving, and creativity, in an artificial system. Achieving AGI is a long-term goal of AI research and development.

B.1.8 (AI) Artificial Intelligence

is a branch of computer science that focuses on creating intelligent machines that can perform tasks that typically require human intelligence. AI encompasses a wide range of techniques, including machine learning, natural language processing, computer vision, and robotics, to develop systems that can perceive, reason, learn, and act autonomously.

B.1.9 Alignment

refers to the process of ensuring that AI systems are designed and deployed in a way that aligns with human values, ethical principles, and societal norms. Alignment involves considering the impact of AI systems on various stakeholders, including users, employees, and society as a whole. By aligning AI systems with human values, organizations can build trust, promote fairness, and mitigate potential risks associated with AI technologies.

B.1.10 Auto-regressive language model

is a type of AI model that generates text one token (word or character) at a time, with each token being predicted based on the previous ones. This means the model uses its own generated output as part of the input for predicting the next token, creating a sequence that builds on itself. A well-known example of an auto-regressive language model is GPT (Generative Pre-trained Transformer). These models are trained on large datasets and learn to predict the next word in a sentence, making them capable of generating coherent and contextually relevant text.

B.1.11 Attention Mechanism

A key component in neural networks that helps models focus on relevant parts of input data. The attention mechanism allows the model to assign different weights to different parts of the input, enabling it to learn which elements are more important for the task at hand. This mechanism has been widely used in various deep learning architectures, such as transformers, to improve performance in tasks like machine translation, image captioning, and text summarization.

B.2 B

B.2.1 Backpropagation

is a fundamental algorithm in the training of artificial neural networks. It is used to update the weights of the network in order to minimize the error between the predicted output and the actual output. Backpropagation works by calculating the gradient of the loss function with respect to each weight in the network, and then using this gradient to update the weights in the direction that reduces the error. This process is repeated iteratively until the network converges to a set of weights that minimize the error.

B.2.2 Bagging

is an ensemble learning technique that combines multiple models to improve predictive performance. Bagging, short for bootstrap aggregating, involves training each model on a random subset of the training data with replacement. The final prediction is made by aggregating the predictions of all models, such as taking the average for regression tasks or voting for classification tasks. Bagging helps reduce [overfitting](#) and improve the stability and accuracy of the model.

B.2.3 Bayesian Optimization

is a technique used in machine learning to optimize [hyperparameters](#) of a model by modeling the objective function as a probabilistic surrogate. Bayesian optimization uses a probabilistic model, such as Gaussian processes, to model the objective function and guide the search for optimal [hyperparameters](#). By iteratively evaluating the objective function and updating the probabilistic model, Bayesian optimization efficiently finds the best [hyperparameters](#) for the model.

B.2.4 Benchmark

is a standardized test or evaluation procedure used to compare the performance of different machine learning models on a specific task or dataset. Benchmarks provide a common framework for researchers and developers to assess the capabilities of different models, identify state-of-the-art approaches, and track progress in the

field. Common benchmarks include image classification tasks, natural language processing tasks, and reinforcement learning environments. List of [benchmarks](#).

B.2.5 (BERT) Bidirectional Encoder Representations from Transformers

is a pre-trained language model developed by Google that uses a transformer architecture to learn bidirectional representations of text. BERT is trained on a large corpus of text data using unsupervised learning, allowing it to capture deep contextual relationships between words and phrases. BERT has been widely adopted in natural language processing tasks, such as question answering, text classification, and named entity recognition, due to its ability to generate high-quality contextual embeddings.

B.2.6 (BM25) Best Matching 25

is a classic and widely used sparse retrieval model for information retrieval tasks. Unlike dense embedding models like DPR, which rely on dense vector representations, BM25 is based on lexical matching and statistical properties of text. It is a probabilistic model that ranks documents or passages based on their relevance to a query. BM25 is commonly used in search engines and information retrieval systems to retrieve relevant documents or passages based on keyword matching and term frequency-inverse document frequency (TF-IDF) weighting. BM25 remains a popular choice for retrieval tasks due to its simplicity, efficiency, and strong performance in many scenarios. However, for tasks requiring semantic understanding, dense embedding models like [DPR](#) are often preferred.

B.2.6.1 Key Features of BM25:

1. Sparse Representation:

BM25 operates on the bag-of-words assumption, where documents and queries are represented as sparse vectors of term frequencies. It does not capture semantic meaning but relies on exact keyword matching.

2. Term Frequency and Inverse Document Frequency (TF-IDF):

BM25 combines term frequency (TF) (how often a term appears in a document) and inverse document frequency (IDF) (how rare or common a term is across the entire corpus) to compute relevance scores.

3. Tunable Parameters:

BM25 has two key parameters:

k : Controls the saturation of term frequency (how quickly the influence of repeated terms levels off).

b : Controls the impact of document length normalization (penalizing longer documents).

4. Efficiency:

BM25 is computationally efficient and works well with inverted indices, making it suitable for large-scale retrieval tasks.

B.2.6.2 How BM25 Works:

1. Input:

A query (e.g., “What is the capital of France?”) and a collection of documents or passages.

2. Tokenization:

The query and documents are **tokenized** into individual terms.

3. Scoring:

For each document, BM25 computes a relevance score based on the presence of query terms in the document, their frequencies, and their IDF values.

4. Ranking:

Documents are ranked by their BM25 scores, and the top-k most relevant documents are returned.

B.2.6.3 Advantages of BM25:

1. Simplicity:

BM25 is easy to implement and does not require training data or complex neural networks.

2. Efficiency:

It is computationally lightweight and works well with inverted indices, making it suitable for large-scale retrieval tasks.

3. Robustness:

BM25 performs well in many retrieval tasks, especially when exact keyword matching is important.

4. Interpretability:

The scoring mechanism is transparent and interpretable, unlike dense embedding models.

B.2.6.4 Limitations of BM25:

1. Lack of Semantic Understanding:

BM25 relies on exact keyword matching and cannot capture semantic relationships between terms (e.g., synonyms or paraphrases).

2. Static Scoring:

The model does not adapt to specific domains or tasks unless the parameters (k1, k1', bb) are tuned.

3. Handling of Long Documents:

While BM25 includes document length normalization, it may still struggle with very long documents or queries.

B.2.7 (BPE) Byte Pair Encoding

is a data compression technique used in natural language processing to tokenize text into subword units. BPE works by iteratively merging the most frequent pairs of characters or subwords in a corpus to create a vocabulary of subword units. This allows the model to represent rare or out-of-vocabulary words as combinations of subword units, improving the generalization and efficiency of the model. BPE is commonly used in transformer-based language models like GPT and BERT to handle rare words and improve the model's performance on various NLP tasks.

B.2.8 Boosting

is an ensemble learning technique that combines multiple weak learners to create a strong learner. Boosting works by training each model sequentially, where each subsequent model focuses on correcting the errors made by the previous models. The final prediction is made by aggregating the predictions of all models, such as taking a weighted sum of the predictions. Boosting helps improve the accuracy and generalization of the model by reducing bias and variance.

B.2.9 (BLT) Byte Latent Transformer

is a tokenizer-free, byte-level large language model that operates directly on raw bytes. It dynamically groups bytes into variable-length “patches” using an entropy-based segmentation strategy, then processes those patches with a hierarchical design (local encoder → global latent transformer → local decoder).

B.3 C

B.3.1 (CLIP) Contrastive Language-Image Pretraining

is a multimodal model developed by OpenAI that learns joint representations of text and images. CLIP is trained on a large dataset of image-text pairs to understand the relationship between visual and textual information. By learning to associate images with their corresponding textual descriptions, CLIP can perform tasks like zero-shot image classification, image generation from text prompts, and multimodal retrieval. CLIP has demonstrated strong performance on various vision-and-language tasks and has been used in applications like content moderation, recommendation systems, and creative AI. CLIP revolutionized AI by bridging vision and language, enabling powerful multimodal applications. It remains a cornerstone for tasks requiring joint understanding of text and images, from search to generative AI.

B.3.1.1 Key Features:

1. Multimodal Alignment:

CLIP maps images and text into a shared embedding space, where corresponding image-text pairs are close to each other.

Enables cross-modal tasks like image search using text queries or vice versa.

2. Zero-Shot Learning:

CLIP can perform tasks like classification, retrieval, or captioning without fine-tuning by leveraging natural language prompts (e.g., “a photo of a dog”).

3. Contrastive Learning:

Trained using a contrastive loss to maximize similarity between correct image-text pairs and minimize similarity for mismatched pairs.

4. Large-Scale Training:

Trained on 400 million image-text pairs from the internet, covering diverse concepts and styles.

B.3.1.2 How CLIP Works:

1. Dual-Encoder Architecture:

Image Encoder: A vision backbone (e.g., Vision Transformer or ResNet) converts images into embeddings.

Text Encoder: A transformer-based model converts text into embeddings.

2. Embedding Space:

Images and text are projected into a shared 512-dimensional space.

Similarity between image and text embeddings is measured using cosine similarity.

3. Zero-Shot Inference:

For classification, generate text embeddings for possible class labels (e.g., “cat,” “dog”) and compare them with the image embedding.

The label with the highest similarity is selected as the prediction.

B.3.1.3 Applications:

1. Zero-Shot Image Classification:

Classify images using natural language prompts without task-specific training.

Example: Predict whether an image shows a “golden retriever” or “labrador.”

2. Image Retrieval:

Search for images using text queries (e.g., “a sunset over mountains”).

3. Text-Guided Image Generation:

Used with generative models (e.g., DALL · E) to create images from text prompts.

4. Content Moderation:

Detect inappropriate images or text based on embeddings.

5. Multimodal Search:

Build systems that retrieve images or text across modalities.

B.3.1.4 Strengths:

- Flexibility: Adapts to new tasks via natural language prompts.
- Scalability: Handles diverse concepts due to large-scale training.
- Efficiency: No need for labeled data for downstream tasks.

B.3.1.5 Limitations:

1. Bias:
Inherits societal biases from web-scale training data
2. Fine-Grained Understanding:
Struggles with subtle distinctions (e.g., dog breeds or nuanced art styles).
3. Computational Cost:
Training requires significant resources, though inference is efficient.
4. Static Knowledge:
Limited to knowledge present in its training data (up to 2021 for CLIP models).

B.3.1.6 CLIP Variants:

- OpenCLIP: Open-source reimplementation of CLIP with community-driven training.
- CLIP-ViT: Vision Transformer-based image encoder for improved performance.
- CLIP+GAN: Combines CLIP with generative adversarial networks (e.g., StyleCLIP).

B.3.1.7 Comparison to Other Models

Model	Modality	Key Feature
CLIP	Text + Image	Zero-shot cross-modal retrieval
DALL · E	Text → Image	Generates images from text
ALIGN	Text + Image	Google’s CLIP-like model
Florence	Multimodal	Microsoft’s foundational embedding model

B.3.2 code2seq

is a neural network model for code summarization that generates natural language summaries for code snippets. The code2seq model uses a sequence-to-sequence architecture with attention mechanisms to learn the mapping between code tokens and natural language tokens. By training on pairs of code snippets and their corresponding summaries, code2seq can generate human-readable descriptions of code functionality. Code summarization models like code2seq are useful for improving code comprehension, documentation, and searchability in software development.

B.3.3 Constitutional AI

refers to the integration of ethical principles into artificial intelligence systems to ensure they operate responsibly and align with human values. This approach draws inspiration from human constitutions, which establish foundational laws and moral frameworks for governance. In AI, constitutional AI involves creating a set of guidelines that dictate how an AI system should behave, ensuring it adheres to ethical standards throughout its operations.

B.3.3.1 Implementation:

The implementation of constitutional AI can be achieved through various methods:

1. **Training with Ethical Datasets:** AI models are trained using datasets that emphasize ethical behavior, promoting the generation of morally sound outputs.
2. **Reinforcement Learning:** This technique encourages the AI to adhere to predefined ethical principles by rewarding actions that align with these guidelines.
3. **Algorithmic Enforcement:** Specific algorithms can be integrated into the AI system to monitor its actions and ensure compliance with established ethical frameworks, preventing harmful behavior.

B.3.3.2 Case Study: Anthropic's Claude Model

Anthropic is at the forefront of constitutional AI with their Claude model. This AI system is designed to incorporate ethical considerations into its decision-making processes, ensuring it avoids generating harmful content and promotes fairness and transparency. By embedding these principles, Claude aims to provide users with reliable and trustworthy interactions.

B.3.3.3 Challenges:

Developing constitutional AI presents several challenges:

1. **Universal Ethical Standards:** Defining a set of ethical principles that are universally accepted across diverse cultures and societies is complex, as moral standards vary significantly.
2. **Consistent Application:** Ensuring that the AI consistently applies these principles without leading to unintended consequences requires rigorous testing and continuous monitoring.

B.3.3.4 Benefits:

The integration of constitutional AI offers numerous benefits:

1. **Enhanced Trust:** Users are more likely to trust AI systems that operate within clear ethical boundaries, fostering confidence in their interactions.
2. **Alignment with Human Values:** By adhering to human values, AI systems can contribute positively to society, promoting beneficial outcomes and minimizing harm.
3. **Risk Mitigation:** Constitutional AI helps mitigate risks associated with AI misuse by ensuring systems are designed to avoid unethical actions from the outset.

B.3.3.5 Conclusion:

Constitutional AI represents a significant step forward in the development of ethical artificial intelligence. By embedding moral principles into AI systems, companies like Anthropic are paving the way for more responsible and trustworthy technology. As AI becomes increasingly integrated into our lives, the importance of constitutional AI will continue to grow, ensuring that these powerful tools remain aligned with human values and contribute positively to society.

B.3.4 (CoT) Chain of Thought

is a reasoning technique used in natural language processing (NLP) and artificial intelligence (AI) to improve the performance of models, particularly in complex problem-solving tasks. It involves breaking down a problem into intermediate reasoning steps, mimicking how humans solve problems by thinking step-by-step. This approach is especially useful for tasks that require logical reasoning, arithmetic, or multi-step inference. Chain of Thought is a powerful technique that enhances the reasoning capabilities of AI models, making them more effective at solving complex

problems and providing interpretable results. It is widely used in tasks requiring logical, mathematical, or multi-step reasoning.

B.3.4.1 Key Concepts of Chain of Thought:

1. Intermediate Reasoning Steps:

Instead of directly generating the final answer, the model produces a sequence of intermediate steps that lead to the solution.

Example:

Problem: "If Alice has 3 apples and Bob gives her 2 more, how many apples does Alice have?"

CoT: "Alice starts with 3 apples. Bob gives her 2 more. $3 + 2 = 5$. Alice has 5 apples."

2. Human-Like Reasoning:

CoT mimics the way humans solve problems by thinking aloud or writing down intermediate steps.

3. Improved Performance:

By explicitly generating reasoning steps, models can handle more complex tasks that require logical or mathematical reasoning.

B.3.4.2 How Chain of Thought Works:

1. Input:

A problem or question is provided as input.

2. Reasoning Steps:

The model generates a sequence of intermediate steps to solve the problem.

3. Final Answer:

The model produces the final answer based on the reasoning steps.

B.3.4.3 Benefits of Chain of Thought:

1. Improved Accuracy:

Breaking down problems into smaller steps reduces errors and improves the model's ability to solve complex tasks.

2. Explainability:

CoT provides a transparent reasoning process, making it easier to understand how the model arrived at its answer.

3. Scalability:

CoT can be applied to a wide range of tasks, including arithmetic, logical reasoning, and commonsense reasoning.

4. Few-Shot and Zero-Shot Learning:

CoT can be used in few-shot or zero-shot settings, where the model is given a few examples or no examples at all.

B.3.4.4 Applications of Chain of Thought:

- Mathematical Problem Solving:

Solving arithmetic, algebra, and word problems.

- Logical Reasoning:

Tasks involving deductive or inductive reasoning.

- Commonsense Reasoning:

Answering questions that require real-world knowledge.

- Code Generation:

Writing code by breaking down the problem into smaller steps.

- Question Answering:

Answering complex questions that require multi-step reasoning.

B.3.4.5 Challenges of Chain of Thought:

- **Error Propagation:**
If an intermediate step is incorrect, the final answer will likely be wrong.
- **Complexity:**
Generating accurate and coherent reasoning steps can be challenging for very complex problems.
- **Computational Cost:**
Generating multiple reasoning steps can increase the computational cost of inference.

B.3.5 Context engineering

is the discipline of deciding what information enters the model’s limited context window at each step — system prompts, tool definitions, retrieved documents, conversation history, and tool results — so the agent has the right information without exceeding its attention budget or introducing noise.

B.3.6 Context window

is the finite amount of text (measured in tokens) that a language model can attend to in a single inference call. Everything the agent “knows” in the current turn — instructions, history, tool schemas, and retrieved data — must fit inside this window.

B.4 D

B.4.1 Data Augmentation

is a technique used in machine learning to increase the size and diversity of the training dataset by applying transformations or modifications to the existing data. Data augmentation helps improve the generalization and robustness of machine learning models by exposing them to a wider range of variations in the input data. Common data augmentation techniques include rotation, flipping, scaling, cropping, and adding noise to images or text.

B.4.2 Data Leakage

occurs when information from the test set or other external sources is inadvertently included in the training data, leading to inflated model performance during training and inaccurate evaluation results. Data leakage can result in [overfitting](#) and poor generalization of machine learning models to new, unseen data. Preventing data leakage requires careful handling of data preprocessing, feature engineering, and model evaluation.

B.4.3 Deep Learning

is a subset of machine learning that uses artificial neural networks to model and solve complex problems. Deep learning algorithms are designed to automatically learn and extract features from data, enabling them to make accurate predictions or decisions without explicit programming. Deep learning has been instrumental in advancing AI applications in areas such as computer vision, natural language processing, and speech recognition.

B.4.4 (DPO) Direct Preference Optimization

is a technique used in reinforcement learning (RL) and machine learning to optimize policies or models directly based on human or expert preferences, without relying on explicit reward functions. Is a powerful and intuitive approach for aligning models with human preferences. By directly optimizing for preferred outcomes, it avoids the complexities of reward engineering and RL, making it particularly useful for tasks like language model fine-tuning and robotics. However, its success depends on the quality and diversity of preference data, as well as careful handling of potential biases.

B.4.5 (DPR) Dense Passage Retrieval

is a state-of-the-art embedding model designed for efficient and accurate retrieval of relevant passages or documents in tasks like open-domain question answering (QA). Unlike traditional sparse retrieval methods (e.g., BM25), which rely on keyword matching, DPR uses dense vector representations (embeddings) to capture semantic similarity between queries and passages. By pre-training on large-scale text data, DPR can efficiently retrieve relevant information for downstream QA tasks. DPR has become a foundational component in modern retrieval systems, enabling more accurate and efficient information retrieval for tasks like QA, dialogue systems, and knowledge-intensive NLP applications.

B.4.5.1 Key Features of DPR:

1. Dense Embeddings:

DPR represents both queries and passages as dense vectors in a high-dimensional space (e.g., 768 dimensions). These embeddings are learned using neural networks, enabling the model to capture semantic relationships rather than just lexical overlap.

2. Dual-Encoder Architecture:

DPR uses two separate neural networks (encoders): Query Encoder: Encodes the input question or query into a dense vector. Passage Encoder: Encodes passages or documents into dense vectors.

The similarity between a query and a passage is computed using the dot product or cosine similarity of their embeddings.

3. Training Objective:

DPR is trained using a contrastive learning objective, where the model learns to maximize the similarity between a query and its correct passage (positive example) while minimizing the similarity with incorrect passages (negative examples). Negative examples can be hard negatives (challenging examples) or random negatives.

4. Efficient Retrieval:

Once the embeddings are computed, retrieval is performed using approximate nearest neighbor (ANN) search algorithms (e.g., FAISS) to efficiently find the most relevant passages from a large corpus.

B.4.5.2 How DPR Works:

1. Input:

A query (e.g., “What is the capital of France?”) and a large collection of passages or documents.

2. Encoding:

The query encoder generates a dense vector for the query.

The passage encoder precomputes dense vectors for all passages in the corpus.

3. Similarity Calculation:

The similarity between the query vector and each passage vector is computed (e.g., using dot product or cosine similarity).

4. Retrieval:

The top-k most similar passages are retrieved and returned as candidates for further processing (e.g., by a generative model in a Retrieval-Augmented Generation (RAG) pipeline).

B.4.5.3 Training DPR:

1. Dataset:

DPR is typically trained on question-answer pairs with associated passages, such as Natural Questions (NQ) or TriviaQA.

2. Loss Function:

The model is trained using a contrastive loss (e.g., InfoNCE) to distinguish between positive and negative passage pairs.

3. Fine-Tuning:

Pre-trained language models like BERT are often used as the backbone for the query and passage encoders, which are then fine-tuned on the retrieval task.

B.4.5.4 Advantages of DPR:

1. Semantic Understanding:

DPR captures the meaning of queries and passages, enabling it to retrieve relevant results even when there is no exact keyword match.

2. Scalability:

DPR can efficiently handle large-scale corpora by leveraging approximate nearest neighbor search.

3. Integration with Downstream Tasks:

DPR is often used as part of larger systems, such as Retrieval-Augmented Generation (RAG), where retrieved passages are fed into a generative model to produce answers.

B.4.5.5 Limitations of DPR:

1. Dependency on Training Data:

DPR's performance depends on the quality and diversity of the training data. It may struggle with out-of-domain queries.

2. Computational Cost:

Precomputing embeddings for large corpora can be resource-intensive, though retrieval itself is fast.

3. Static Knowledge:

DPR relies on a fixed corpus, so it cannot retrieve information from dynamically changing sources unless the embeddings are recomputed.

B.5 E

B.5.1 (ECL) Effective Context Length

refers to the maximum number of tokens or words that a language model can effectively process and utilize in a single input sequence. Memory constraints, longer sequences require more memory, which can limit performance or cause computational bottlenecks. Degradation in Performance: Even if a model can technically process long sequences, its ability to maintain context and generate accurate outputs may degrade as the sequence length increases. Task Complexity: For tasks requiring deep understanding or reasoning, the ECL may be shorter than the theoretical maximum because the model needs to focus on a smaller, more relevant subset of the input. See project [RULER](#) for measuring the effective context length of language models.

B.5.2 Embedding

is a technique used in natural language processing (NLP) and other machine learning tasks to represent words, phrases, or entities as vectors in a continuous vector space. Word embeddings capture semantic relationships between words, allowing models to understand the context and meaning of text data. Popular embedding methods include Word2Vec, GloVe, and FastText. Some Key points about Embeddings: 1. Dimensionality Reduction: Embeddings reduce the dimensionality of data, making it easier to work with while preserving important information. 2. Semantic Meaning:

Words or items with similar meanings are placed closer together in the vector space. For example, in a word embedding, “king” and “queen” would be closer to each other than “king” and “apple”. 3. Training: Embeddings are typically learned during the training process of a model. Popular methods for creating word embeddings include Word2Vec, GloVe, and BERT.

B.5.3 Embedding Models

are machine learning models that learn to represent data as vectors in a continuous vector space, that map high-dimensional data (e.g., text, images, or graphs) into lower-dimensional vector representations [embeddings](#). These embeddings capture semantic or structural relationships in the data, enabling efficient computation, comparison, and generalization. Embedding models are commonly used in natural language processing (NLP) to capture semantic relationships between words, phrases, or entities. These models learn to map input data to dense vector representations that encode meaningful information about the data. Popular embedding models include Word2Vec, GloVe, FastText, and BERT.

Embedding models are foundational to modern AI systems, enabling machines to “understand” and reason about unstructured data. Advances like contrastive learning and multimodal alignment (e.g., CLIP) continue to push the boundaries of what embeddings can achieve. For implementation, libraries like Hugging Face Transformers, TensorFlow, and PyTorch provide easy access to state-of-the-art models.

B.5.3.1 Key Concepts:

1. Vector Space:

Data points (words, images, etc.) are represented as vectors in a continuous space where geometric relationships (e.g., distance, angle) reflect semantic or functional similarities.

2. Dimensionality Reduction:

Embeddings compress high-dimensional data (e.g., one-hot encoded words) into dense, low-dimensional vectors (e.g., 50–1000 dimensions).

3. Semantic Relationships:

Similar items (e.g., synonyms, related images) are positioned closer in the embedding space (measured via cosine similarity or Euclidean distance).

B.5.3.2 Types of Embedding Models:

1. Word Embeddings:

Map words to vectors based on their context in large text corpora.

Examples:

Word2Vec (Skip-Gram, CBOW): Captures word analogies (e.g., king - man + woman = queen).

GloVe (Global Vectors): Combines global co-occurrence statistics with local context.

FastText: Represents words as character n-grams, handling rare or misspelled words.

2. Sentence/Document Embeddings:

Encode entire sentences, paragraphs, or documents into vectors.

Examples:

BERT (Bidirectional Transformers): Generates context-aware embeddings.

SBERT (Sentence-BERT): Optimized for sentence similarity tasks.

Doc2Vec: Extends Word2Vec to document-level embeddings.

3. Image Embeddings:

Convert images into vectors using convolutional neural networks (CNNs).

Examples:

ResNet, VGG: Pre-trained CNNs for feature extraction.

CLIP (Contrastive Language-Image Pretraining): Aligns text and image embeddings.

4. Multimodal Embeddings:

Encode data from multiple modalities (text, images, audio) into a shared space.

Examples:

CLIP: Maps text and images to the same space.

Wav2Vec: Embeds audio signals for speech tasks.

5. Graph Embeddings:

Represent nodes, edges, or entire graphs as vectors.

Examples:

Node2Vec, GraphSAGE: Capture structural relationships in graphs.

TransE: Embeds knowledge graphs (e.g., entities and relations).

B.5.3.3 Applications:

1. Natural Language Processing (NLP):

Semantic search, text classification, machine translation, and named entity recognition.

Example: Finding similar articles using SBERT embeddings.

2. Recommendation Systems:

Embed users and items (e.g., movies, products) to predict preferences.

Example: Collaborative filtering with matrix factorization.

3. Computer Vision:

Image search (e.g., “find similar products”), object detection, and facial recognition.

Retrieval-Augmented Generation (RAG):

Retrieve relevant documents using embeddings to augment generative models (e.g., GPT, LLaMA).

4. Anomaly Detection:

Identify outliers by comparing embeddings (e.g., fraud detection in transactions).

B.5.3.4 Training Embedding Models:

1. Unsupervised Learning:

Trained on large, unlabeled datasets (e.g., Wikipedia, Common Crawl).

Techniques: Skip-Gram (Word2Vec), masked language modeling (BERT).

2. Supervised Learning:

Fine-tuned on labeled data for specific tasks (e.g., sentiment classification).

3. Contrastive Learning:

Trains embeddings by contrasting positive pairs (similar items) against negatives.

Used in models like CLIP and SimCLR.

B.5.3.5 Challenges:

1. Semantic Nuance:

Capturing subtle differences (e.g., irony, sarcasm) remains difficult.

2. Domain Adaptation:

Embeddings trained on general data may fail in specialized domains (e.g., medical text).

3. Computational Cost:

Training large models (e.g., BERT) requires significant resources.

4. Bias:

Embeddings can inherit biases from training data (e.g., gender stereotypes).

B.5.4 Ensemble Learning

is a machine learning technique that combines multiple models to improve predictive performance. Ensemble methods leverage the diversity of individual models to make more accurate predictions by aggregating their outputs. Common ensemble techniques include bagging, boosting, and stacking, which can be applied to various machine learning algorithms.

B.5.5 Evaluation

is the process of assessing the performance of a machine learning model on a specific task or dataset. Evaluation involves measuring the model's accuracy, precision, recall, F1 score, or other metrics to determine how well it generalizes to new, unseen data. Effective evaluation helps identify the strengths and weaknesses of the model and guides improvements in the training process.

B.6 F

B.6.1 Feedforward Neural Network

information flows unidirectionally—from input nodes, through one or more hidden layers, to output nodes without any cycles or loops in the network structure. Feedforward neural networks serve as building blocks for many advanced deep learning architectures, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which incorporate specialized structures tailored to specific tasks or data types (e.g., images, time series).

1. **Input layer:** This layer consists of neurons that receive raw data or features as inputs. Each neuron corresponds to an input feature and has no incoming connections from other layers.
2. **Hidden layers:** These layers contain neurons that perform computations on the received input, transforming it into more abstract representations through weighted sums and nonlinear activation functions. Feedforward networks can have multiple hidden layers (deep architectures), enabling them to learn increasingly complex features at each level.
3. **Output layer:** The final layer of a feedforward network, responsible for generating predictions or classifications based on the transformed input data from previous layers. The number of neurons in this layer depends on the task at hand—for classification tasks, it typically matches the number of classes; for regression problems, there's usually one output neuron.

B.6.2 Few-Shot Learning

is a machine learning paradigm where a model is trained to recognize new classes or tasks from a small number of examples. Few-shot learning aims to generalize from limited data by leveraging prior knowledge or meta-learning techniques. This approach is particularly useful for tasks where collecting large amounts of labeled data is challenging or impractical.

B.6.3 Feature Engineering

is the process of selecting, transforming, and creating new features from raw data to improve the performance of machine learning models. Feature engineering involves identifying relevant features, encoding categorical variables, scaling numerical data, and creating new features that capture important patterns in the data. Effective feature engineering can significantly impact the accuracy and generalization of machine learning models.

B.6.4 Feature Extraction

is the process of extracting relevant features from raw data to represent the underlying patterns and relationships in the data. Feature extraction involves transforming the input data into a set of meaningful features that can be used as input to machine learning models. This process helps reduce the dimensionality of the data and improve the performance of the models.

B.6.5 Federated Learning

is a machine learning approach that enables training models across multiple decentralized devices or servers while keeping the data local. Federated learning allows models to be trained on data from different sources without sharing the raw data, preserving privacy and security. This technique is used in applications where data cannot be centralized, such as healthcare, finance, and edge computing.

B.6.6 Fine-tuning

is a technique used in transfer learning to adapt a pre-trained model to a specific task or dataset. Fine-tuning involves updating the parameters of the pre-trained model by training it on new data related to the target task. This process allows the model to leverage the knowledge learned from the pre-training phase and improve its performance on the new task.

B.6.7 Foundation model

is a large-scale language model that serves as the basis for developing more specialized models for specific tasks or domains. Foundation models are pre-trained on vast amounts of text data and can be fine-tuned on smaller datasets to perform well on targeted applications. These models provide a starting point for building custom models and enable efficient transfer learning across different tasks.

B.6.8 FP{8,16,32} Training Process

is a training process that uses mixed-precision training to accelerate the training of deep learning models. Reduces memory usage and accelerates computation in deep learning, particularly beneficial for large models (e.g., transformers). FP{8,16,32} refers to the precision of floating-point numbers used to represent the model's parameters during training. By using lower-precision floating-point numbers (e.g., FP16), the training process can be accelerated while maintaining model accuracy.

This technique is particularly useful for training large models on GPUs or TPUs. FP8 training optimizes the trade-off between computational efficiency and numerical precision, making it pivotal for next-gen AI models. By integrating dynamic scaling and mixed-precision techniques, it achieves significant speed and memory gains while maintaining model accuracy. Adoption requires compatible hardware and careful implementation but offers transformative benefits for scalable AI training.

B.6.9 Frontier Model

is a term used to describe a cutting-edge, state-of-the-art model that pushes the boundaries of what is currently possible in artificial intelligence. Frontier models are typically large-scale, high-performance models that demonstrate advanced capabilities in natural language processing, computer vision, or other AI domains. These models often serve as benchmarks for evaluating new techniques and approaches in AI research. The term is relative and time-dependent: today's frontier model can become mid-tier as stronger systems appear. These models are typically large-scale foundation models (often multimodal) trained with the highest compute budgets of their generation. They excel at complex reasoning, coding, multi-step tool use, and other demanding tasks that weaker or older models cannot reliably handle.

B.7 G

B.7.1 (GAIA) General AI Assistants Benchmark

is a framework designed to evaluate the capabilities of AI assistants in handling real-world, multi-turn, and multi-modal tasks. It focuses on assessing how well AI systems can assist users in complex, interactive scenarios that require reasoning, knowledge retrieval, and task completion across various domains.

B.7.1.1 Key Features of GAIA:

1. Real-World Tasks:

GAIA includes tasks that mimic real-world interactions, such as booking a flight, planning a trip, or troubleshooting a technical issue.

2. Multi-Turn Dialogue:

Tasks often involve multi-turn conversations, where the AI must maintain context and provide coherent responses over multiple interactions.

3. Multi-Modal Inputs:

GAIA may include tasks that require processing multiple types of input, such as text, images, or audio.

4. Complex Reasoning:

Tasks are designed to test the AI's ability to reason, plan, and solve problems that require multiple steps.

5. User-Centric Evaluation:

GAIA emphasizes user satisfaction and task success, measuring how well the AI assistant meets the user's needs.

B.7.2 (GANs) Generative Adversarial Networks

are a class of deep learning models that consist of two neural networks: a generator and a discriminator. The generator network learns to generate new data samples, such as images, text, or audio, while the discriminator network learns to distinguish between real data samples and generated samples. GANs are used in tasks like image generation, style transfer, and data augmentation.

B.7.3 GGUF (GGML Universal File)

A binary file format introduced by the llama.cpp project in August 2023 for storing large language models in a single, self-contained file. It packages the model weights (typically quantized to 2–8 bits), tokenizer vocabulary, architecture metadata, and often a chat template into one portable unit designed for fast, memory-mapped loading. GGUF has become the de-facto standard for distributing open-weight models intended for local inference on consumer hardware, and is natively supported by tools such as llama.cpp, Ollama, LM Studio, GPT4All, and Jan.

B.7.4 (GPQA) General-Purpose Question Answering Benchmark

is a benchmark designed to evaluate the performance of question-answering models on a diverse set of tasks and question types. GPQA includes questions from various domains, such as science, history, and literature, to test the generalization and reasoning capabilities of QA models. The benchmark aims to assess how well models can answer questions that require complex reasoning and knowledge retrieval.

B.7.5 (GPT) Generative Pre-trained Transformer

is a series of large language models developed by OpenAI that are based on the transformer architecture. The GPT models are pre-trained on vast amounts of text data to understand and generate human language. GPT models have been used for various natural language processing tasks, such as text generation, translation, and question answering.

B.7.6 Gradient Descent

is an optimization algorithm used to minimize the loss function of a machine learning model by adjusting the model's parameters iteratively. Gradient descent works by calculating the gradient of the loss function with respect to each parameter and updating the parameters in the direction that reduces the loss. This process is repeated until the model converges to a set of parameters that minimize the loss function. The key idea behind Gradient Descent is to adjust parameters iteratively in the opposite direction of the gradient, aiming to minimize the cost function.

B.7.7 (GRPO) Group Relative Policy Optimization

is a reinforcement learning algorithm that aims to improve the stability and sample efficiency of policy optimization methods. It extends Proximal Policy Optimization (PPO) by incorporating group-based structures and relative performance metrics. GRPO leverages the concept of group relativity to update the policy parameters based on the relative performance of different groups of trajectories. By considering the performance of multiple groups, GRPO can achieve better convergence and robustness in training reinforcement learning agents.

B.7.8 Guardrails

are constraints enforced by the harness (not merely requested in the prompt) that limit what an agent is allowed to do — for example permission checks, allow/deny lists for tools or files, approval gates for high-risk actions, and sandboxing of execution environments.

B.8 H

B.8.1 Hallucination

refers to instances where the model generates information that is not based on the input data or real-world facts. Essentially, the AI “makes up” details or provides incorrect information confidently. This can happen for various reasons, such as limitations in the training data, the model’s architecture, or the way it processes and interprets information. Hallucinations can be problematic, especially in applications where accuracy is crucial, like medical diagnosis or legal advice. Researchers are continuously working on improving AI models to reduce the occurrence of hallucinations and ensure more reliable outputs.

B.8.2 Harness

is the runtime and scaffolding around a language model that turns it into a working agent. It manages the agent loop, system prompts, tool execution, permissions, retries, state, memory, stopping rules, and outputs. The model provides intelligence; the harness provides the chassis that makes that intelligence reliable and controllable.

The harness determines: - How long the agent can run - Whether it has persistent memory and can create its own skills - What tools (MCP servers) it can reach - Whether it lives in messaging apps, a terminal, a web UI, or a full Linux desktop - How isolated / sandboxed its actions are - How easy it is to observe, interrupt, or improve it

A good harness (Hermes, OpenClaw, goose, etc.) dramatically changes what kind of agent you can actually have. A weak or missing harness leaves you with just a chatbot that forgets everything between messages.

B.8.3 (H-Net) Hierarchical Network

is a fully end-to-end hierarchical sequence modeling architecture introduced in 2025 by Sukjun Hwang, Brandon Wang, and Albert Gu. It replaces the traditional tokenization $\rightarrow$ language-model $\rightarrow$ detokenization pipeline with a single model that learns content- and context-dependent segmentation directly from raw data (typically bytes).

- The core mechanism is dynamic chunking (DC): a routing module predicts boundaries between adjacent elements via similarity scores, and a smoothing module (often using an exponential moving average) stabilizes training and softens uncertain boundaries. The architecture follows a recursive U-Net-style design—encoder(s) process the high-resolution input, a main network operates on the compressed chunks, and decoder(s) reconstruct the original resolution—with optional multi-stage nesting so that higher levels operate on even coarser abstractions.

B.8.4 (HITL) Human-in-the-loop

is a design pattern in which the agent pauses at defined points and waits for human approval, correction, or decision before continuing. It is used for high-stakes actions, ambiguous goals, or situations where the agent's confidence is low.

B.8.5 Hyperparameter

is a configuration setting that is external to the model and is used to control the learning process. Hyperparameters are set before the learning process begins and are not updated during training. Examples of hyperparameters include the learning rate, batch size, number of layers in a neural network, and regularization strength.

B.9 I

B.9.1 Inference

is the process of using a trained machine learning model to make predictions or decisions based on new, unseen data. Inference involves passing input data through the model and obtaining output predictions without updating the model's parameters. Inference is a crucial step in deploying machine learning models for real-world applications.

B.10 J

B.10.1 Jinja (or Jinja2)

A Python-origin templating language widely used in the LLM ecosystem to define chat templates. These templates convert a structured conversation (list of role-tagged messages, optional system prompt, tool calls, etc.) into the exact token sequence an instruction-tuned model expects. In formats such as GGUF the template is stored as executable metadata (`tokenizer.chat_template`) and is evaluated on every inference call. Because Jinja supports conditionals, loops, and string manipulation, a maliciously crafted template can inject hidden instructions, alter context, or (in unsandboxed engines) achieve code execution, making it both a critical interoperability mechanism and a recognized supply-chain / inference-time attack surface.

B.11 K

B.11.1 (KD) Knowledge Distillation - [Deepseek-r1:70B]

is a machine learning technique used in AI modeling where knowledge from a large, complex model (often called the “teacher” model) is transferred to a smaller, simpler model (the “student” model). The goal of knowledge distillation is to retain as much of the teacher’s performance and accuracy as possible while significantly reducing the size and computational requirements of the student model.

B.11.1.1 How Knowledge Distillation Works:

1. Training the Teacher Model:

- The teacher model is first trained on the target task using a large dataset. It achieves high accuracy but may be too large or slow for practical deployment.

2. Distilling Knowledge to the Student Model:

- The student model is trained to mimic the outputs of the teacher model. This is done by fine-tuning the student model on the same training data, but with a twist: instead of using the ground truth labels directly, the student model tries to match the predictions (outputs) of the teacher model.
- A common technique involves using “soft labels” from the teacher model, which are the probabilities over all classes rather than just the one-hot encoded true label. This helps the student model learn about the uncertainty and nuances captured by the teacher.

3. Temperature Scaling:

- To make the soft labels more informative, a temperature parameter is often applied to the teacher’s output. This “softens” the probabilities, making them less confident and more spread out, which helps the student model learn better.

4. Loss Function:

- The loss function for the student model typically combines two parts:
 - A distillation loss that measures the difference between the student’s outputs and the teacher’s outputs.
 - A standard task-specific loss (e.g., cross-entropy) that measures the difference between the student’s outputs and the ground truth labels.

B.11.1.2 Benefits of Knowledge Distillation:

1. Model Efficiency:

- The student model is much smaller and faster, making it suitable for deployment on edge devices or in real-time applications.

2. Accuracy Preservation:

- Despite being smaller, the student model retains a significant portion of the teacher’s accuracy.

3. Faster Inference:

- Smaller models are computationally cheaper and can perform inference much faster than their larger counterparts.

B.11.1.3 Applications of Knowledge Distillation:

- **Model Compression:** Reducing the size of large models like BERT, ResNet, or other deep neural networks for deployment on mobile devices.
- **Edge Computing:** Deploying AI models in resource-constrained environments where computational power is limited.
- **Real-Time Inference:** Speeding up inference times while maintaining high performance.

B.11.1.4 Recent Advances:

- Knowledge distillation has been widely adopted in areas like natural language processing (NLP), computer vision, and reinforcement learning.
- Variants of knowledge distillation include techniques like online distillation, mutual learning, and attention-based distillation.

In summary, knowledge distillation is a powerful technique for creating efficient, compact models that can perform nearly as well as their larger counterparts, making it an essential tool in modern AI modeling.

B.11.2 KV Cache (Key-Value Cache)

stores the attention keys and values computed for tokens in a language model's input so they can be reused as the model generates each next token, instead of recomputing the entire sequence at every step. This reduces repeated computation and speeds up text generation.

The cache grows with the number of tokens and concurrent requests, using GPU memory. Serving systems manage this memory with techniques such as paged allocation, prefix caching, and lower-precision storage. Unlike prompt caching, the KV cache is normally specific to an active request and discarded when it ends.

Summary based on [What Is a KV Cache?](#) by Decagon.

B.12 L

B.12.1 Leaderboard

is a platform that ranks and compares the performance of machine learning models on specific tasks or datasets. Leaderboards provide a standardized way to evaluate and compare the performance of different models, enabling researchers and developers to track progress, identify state-of-the-art models, and share results with the community.

B.12.2 Learning Rate

is a hyperparameter in machine learning that controls the step size or rate at which the model's parameters are updated during training. The learning rate determines how quickly the model learns from the training data and adjusts its parameters to minimize the loss function. Setting an appropriate learning rate is crucial for training stable and accurate machine learning models.

B.12.3 Lightweight Models

are machine learning models that are designed to be small, fast, and resource-efficient, making them suitable for deployment on edge devices, mobile phones, or other resource-constrained environments. Lightweight models are optimized for low memory usage, fast inference speed, and minimal computational requirements, enabling them to perform efficiently in real-time applications.

B.12.4 llama.cpp

is a high-performance, open-source C/C++ inference engine originally created by Georgi Gerganov for running large language models (starting with Meta's LLaMA) efficiently on consumer hardware. It introduced and popularized the GGUF single-file model format, supports a wide range of quantizations, and provides backends for CPU, CUDA, Metal, Vulkan, and others. Because of its speed, low overhead, and active development (including recent Mixture-of-Experts expert caching), it serves as the core engine behind many popular local runners such as Ollama, LM Studio, and others, making it one of the foundational tools for running open-weight models on personal machines.

B.12.5 (LLM) Large Language Models

Large Language Models (LLMs) are a class of artificial intelligence models that are trained on vast amounts of text data to understand and generate human language. These models use deep learning techniques, such as transformers, to process and generate text, enabling them to perform a wide range of natural language processing tasks, such as text generation, translation, summarization, and question answering.

B.12.5.1 Key Features of Large Language Models:

1. **Scale:** LLMs are trained on massive datasets containing billions or even trillions of words, enabling them to learn complex patterns and relationships in language.
2. **Contextual Understanding:** LLMs have the ability to generate text that is contextually relevant and coherent, capturing nuances and subtleties in language.
3. **Adaptability:** LLMs can be fine-tuned on specific tasks or domains to improve performance on targeted applications.
4. **Multimodal Capabilities:** Some LLMs can process and generate text in conjunction with other modalities, such as images, audio, or video.
5. **Transfer Learning:** LLMs can leverage pre-trained knowledge to perform well on a wide range of tasks with minimal additional training.
6. **Ethical Considerations:** The use of LLMs raises ethical concerns related to bias, fairness, and misuse, prompting researchers and developers to address these issues.
7. **Applications:** LLMs are used in various applications, including chatbots, content generation, language translation, and information retrieval.
8. **Research and Development:** The development of LLMs has led to advancements in natural language processing, machine translation, and other AI-related fields.
9. **Open-Source Models:** Many LLMs are available as open-source models, allowing researchers and developers to access and build upon state-of-the-art language models.
10. **Future Directions:** The ongoing research and development of LLMs aim to improve their performance, efficiency, and ethical considerations, paving the way for more sophisticated AI systems.
11. **Challenges:** Challenges associated with LLMs include computational requirements, data privacy concerns, and the need for robust evaluation metrics to assess model performance accurately.
12. **Responsible AI:** Ensuring the responsible development and deployment of LLMs is essential to address ethical, social, and legal implications associated with these powerful language models.
13. **Interpretability:** Enhancing the interpretability of LLMs is crucial for understanding how these models make decisions and generating trust among users and stakeholders.
14. **Collaborative Research:** Collaborative efforts among researchers, developers, policy-makers, and the public are essential to address the challenges and opportunities presented by LLMs.
15. **Impact:** LLMs have the potential to revolutionize how we interact with technology, communicate with each other, and access information, shaping the future of AI and human-machine interaction.
16. **Conclusion:** Large Language Models represent a significant advancement in artificial intelligence, offering powerful capabilities in natural language processing and communication. By addressing challenges and ethical considerations, LLMs can be harnessed to create positive impacts in various domains and drive innovation in AI research and development.

B.12.6 Loss Function

A measure of how well the model is performing during training. The loss function calculates the difference between the predicted output of the model and the actual target output. The goal of training a machine learning model is to minimize the loss function, which indicates that the model is making accurate predictions.

B.13 M

B.13.1 (MCP) Model Context Protocol

is an open standard that defines how AI applications (clients/hosts) connect to external tools, data sources, and prompts through a consistent interface. MCP servers expose capabilities; clients discover and invoke them. It reduces one-off integrations and has become the default wiring layer for many agent harnesses.

B.13.2 (MoE) Mixture of Experts

A neural network architecture, widely used in large language models, that replaces dense feed-forward layers with multiple specialized sub-networks called “experts.” A learned gating (router) network selects only a small subset of these experts for each input token, so only a fraction of the model’s total parameters are activated during inference. This sparse activation allows models to scale to very large parameter counts (e.g., tens or hundreds of billions) while keeping compute and latency closer to those of much smaller dense models. Notable examples include Mixtral, DeepSeek-V3, and various Qwen MoE variants.

B.13.3 Model Context Protocol (MCP)

is an open protocol that enables seamless integration between LLM applications and external data sources and tools.

B.13.4 Mechanistic Interpretability (MechInterp)

Mechanistic interpretability refers to the ability to understand and explain the internal mechanisms of an AI model that lead to its decisions or outputs. It involves analyzing the components and processes within the model, such as weights, biases, activation patterns, and interactions between layers, to gain insight into how it operates.

B.13.4.1 Importance:

Understanding the internal workings of AI models is crucial for building trust, debugging, identifying biases, and improving performance. Mechanistic interpretability provides a deeper understanding compared to post-hoc explanations by focusing on the model's intrinsic mechanisms rather than just the outcomes.

B.13.4.2 Techniques and Methods:

Several techniques facilitate mechanistic interpretability:

1. **Inspecting Model Components:** Examining weights, biases, and activation patterns to understand their roles in decision-making.
2. **Attention Mechanisms:** Tracing how attention layers focus on specific input features to influence outputs.
3. **Model-Agnostic Tools:** Utilizing tools that provide insights into how inputs affect outputs, regardless of the model's type.

B.13.4.3 Differentiation from Other Interpretability Types:

Mechanistic interpretability contrasts with functional or outcome-based approaches by focusing on internal processes rather than overall function or impact. It offers a more detailed understanding of how decisions are reached within the model.

B.13.4.4 Challenges:

The complexity of modern AI models, such as deep neural networks and large language models, poses significant challenges for mechanistic interpretability. Sophisticated tools and methods are often required to unravel their intricate workings.

B.13.4.5 Examples and Applications:

In image recognition tasks using Convolutional Neural Networks (CNNs), analyzing how individual neurons or layers contribute to object detection exemplifies mechanistic interpretability in action.

B.13.4.6 Implications:

Promoting transparent, fair, and accountable AI systems is essential for responsible deployment. Mechanistic interpretability supports these goals by ensuring that models are not only accurate but also understandable and aligned with ethical standards.

In summary, mechanistic interpretability is a vital approach to understanding the internal decision-making processes of AI models. By focusing on the model's intrinsic mechanisms, it enhances trust, improves performance, and ensures compliance with ethical guidelines, ultimately fostering responsible AI development and deployment.

B.13.5 (MHSA) Multi-head latent Attention

is a technique used in deep learning models to improve efficiency by reducing memory usage while maintaining performance. It achieves this by compressing the Key-Value (KV) cache into a latent vector, allowing the model to handle longer sequences with fewer computational resources. Multi-head latent attention is particularly useful in transformer-based models for natural language processing tasks, where memory constraints can be a limiting factor.

B.13.6 (ML) Machine Learning

is a branch of artificial intelligence that focuses on developing algorithms and models that enable computers to learn from data and make predictions or decisions without being explicitly programmed. Machine learning algorithms learn patterns and relationships in data through training and use this knowledge to make predictions or decisions on new, unseen data. Machine learning is used in various applications, such as image recognition, natural language processing, recommendation systems, and predictive analytics.

B.13.7 (MLOps) Machine Learning Operations

is a set of practices and tools used to streamline and automate the deployment, monitoring, and management of machine learning models in production. MLOps aims to bridge the gap between data science and operations teams, enabling organizations to deploy and scale machine learning models efficiently. MLOps involves processes such as model training, testing, deployment, monitoring, and maintenance to ensure the reliability and performance of machine learning systems.

Key aspects of MLOps: 1. Automation: Automates various stages of the ML pipeline, including data ingestion, preprocessing, model training, validation, and deployment¹. 2. Version Control: Tracks changes in ML assets to ensure reproducibility and the ability to roll back to previous versions if necessary¹. 3. Continuous Integration/Continuous Deployment (CI/CD): Integrates ML models with application code and data changes, ensuring smooth and consistent updates². 4. Monitoring and Governance: Monitors deployed models for performance and compliance with business and regulatory requirements².

B.13.8 (MMLU) Massive Multitask Language Understanding

is a comprehensive evaluation framework designed to measure the multitask capabilities of language models across a wide range of domains and tasks. Introduced by Hendrycks et al. in 2020, MMLU tests a model's ability to generalize and perform well on diverse tasks, including humanities, STEM, social sciences, and more. It is one of the most challenging and widely used benchmarks for assessing the breadth and depth of a model's knowledge and reasoning abilities.

B.13.9 (MTP) Multi-Token Prediction

is an innovative training and inference strategy designed to enhance the efficiency and speed of large language models (LLMs) by predicting multiple future tokens simultaneously. By predicting multiple tokens ahead and leveraging parallel verification, MTP strikes a balance between model performance and inference speed, making it a promising direction for efficient LLMs.

B.13.9.1 Core Concept

1. Objective: Train the model to predict the next n tokens at each position in the sequence, rather than just the immediate next token (as in traditional autoregressive models).
2. Architecture: Utilizes multiple output heads, each predicting a token at a different future position (e.g., 1st, 2nd, ..., 4th token ahead).

B.13.9.2 Training Strategy

1. Multi-Token Loss: The model is trained to minimize the loss across all predicted tokens (e.g., predicting tokens $t+1$, $t+2$, $t+3$, $t+4$ at position t).
2. Improved Context Learning: By forcing the model to anticipate longer sequences, it captures richer contextual dependencies.

B.13.9.3 Inference Speedup

1. Tree-Based Decoding:
 - Step 1: Generate a tree of candidate tokens for multiple positions in parallel.
 - Step 2: Use the model's multi-token predictions to validate and select the correct path.
 - Step 3: Accept valid token sequences and discard incorrect branches, effectively decoding multiple tokens per step.
2. Result: Reduces the sequential bottleneck of autoregressive generation, achieving $2\text{--}3\times$ faster inference compared to standard methods.

B.13.9.4 Key Advantages

1. Sample Efficiency: Training on multi-token objectives improves data utilization.
2. Faster Generation: Parallel token verification accelerates inference.
3. Compatibility: Can be integrated into existing architectures (e.g., Transformers) with minimal modification.

B.13.9.5 Applications

- Code Generation: Accelerates output for IDEs or tools like GitHub Copilot.
- Real-Time Chatbots: Reduces latency in conversational AI.
- Document Summarization: Faster processing of long texts.

B.13.9.6 Challenges

- Increased Memory: Storing multiple candidate paths requires more memory.
- Complex Validation: Ensuring coherence across parallel predictions adds computational overhead.

B.13.10 Model-Agnostic Interpretability

is a comprehensive evaluation framework designed to measure the multitask capabilities of language models across a wide range of domains and tasks. Introduced by Hendrycks et al. in 2020, MMLU tests a model's ability to generalize and perform well on diverse tasks, including humanities, STEM, social sciences, and more. It is one of the most challenging and widely used benchmarks for assessing the breadth and depth of a model's knowledge and reasoning abilities.

B.13.11 Model-Based Reinforcement Learning

is a reinforcement learning approach that uses a learned model of the environment to make decisions and optimize policies. Model-based reinforcement learning involves training a predictive model of the environment dynamics and using it to simulate trajectories and plan actions. This approach can improve sample efficiency and accelerate learning in complex environments.

B.13.12 Model Explainability

is the ability to provide explanations for the predictions or decisions made by a machine learning model. Model explainability helps users understand why a model made a particular prediction, enabling them to trust the model's outputs and identify potential biases or errors. Explainable AI techniques, such as feature importance analysis, local interpretability methods, and model-agnostic approaches, are used to provide explanations for machine learning models.

B.13.13 Model Fairness

is the principle of ensuring that machine learning models make predictions or decisions without discriminating against individuals based on sensitive attributes

B.13.14 Model-Free Reinforcement Learning

is a reinforcement learning approach that learns policies directly from interactions with the environment without explicitly modeling the environment dynamics. Model-free reinforcement learning algorithms, such as Q-learning, policy gradients, and actor-critic methods, learn optimal policies through trial and error, without requiring a model of the environment.

B.13.15 Model Interpretability

is the ability to explain and understand how a machine learning model makes predictions or decisions. Model interpretability is essential for building trust in AI systems, identifying biases, debugging models, and ensuring compliance with ethical standards. Various techniques, such as feature importance analysis, SHAP values, and LIME, are used to interpret and explain the behavior of machine learning models.

B.13.16 Model Quantization

is a technique used to reduce the memory footprint and computational complexity of deep learning models by representing weights and activations with lower precision. Model quantization helps optimize the deployment of machine learning models on resource-constrained devices, such as mobile phones or edge devices, by reducing memory usage and improving inference speed.

B.13.17 Model Robustness

is the ability of a machine learning model to maintain high performance and accuracy in the face of adversarial attacks, noisy data, or distribution shifts. Robust models are resilient to perturbations in the input data and can generalize well to new, unseen data. Techniques such as adversarial training, data augmentation, and regularization are used to improve the robustness of machine learning models.

B.13.18 Model Serving

is the process of deploying a trained machine learning model to serve predictions or decisions to end-users or applications. Model serving involves hosting the model on a server, exposing it through an API, and handling incoming requests to make predictions in real-time. Model serving is a critical step in deploying machine learning models for production use.

B.13.19 Model Training

is the process of optimizing the parameters of a machine learning model to minimize the loss function and improve its performance on a specific task. Model training involves feeding input data into the model, calculating the loss, and updating the model's parameters using optimization algorithms such as gradient descent. The

goal of model training is to learn the patterns and relationships in the data to make accurate predictions or decisions.

B.13.20 Model Validation

is the process of evaluating the performance of a machine learning model on a validation dataset to assess its generalization ability. Model validation helps determine how well the model will perform on new, unseen data and provides insights into its robustness and accuracy. Common validation techniques include cross-validation, holdout validation, and k-fold validation.

B.13.21 Model Zoo

is a collection of pre-trained machine learning models that are publicly available for download and use. Model zoos provide a wide range of models trained on various tasks and datasets, allowing researchers and developers to leverage state-of-the-art models for their applications. Popular model zoos include Hugging Face, TensorFlow Hub, and PyTorch Hub.

B.13.22 (MoE) Mixture of Experts

is a machine learning architecture that combines multiple expert models to improve predictive performance. In a mixture of experts model, each expert specializes in a specific subset of the input data, and a gating network determines which expert to use for a given input. Mixture of experts models are used in tasks such as language modeling, image recognition, and recommendation systems. MoE architectures are particularly useful in large-scale models, such as those used in [natural language processing \(NLP\)](#). They enable these models to handle vast amounts of data more efficiently, making them faster and more scalable.

Key Features of Mixture of Experts (MoE) Models:

1. **Experts:** Each expert network is trained to handle specific types of data or tasks, allowing for more efficient and accurate processing. Each expert is typically a neural network or a simpler model.
2. **Gating Network:** A routing mechanism that decides which experts should process a given input. The gating network outputs a probability distribution over the experts, indicating how much each expert should contribute to the final output.
3. **Dynamic Routing:** Inputs are dynamically assigned to experts based on the gating network's decisions. This allows the model to adapt to different types of inputs efficiently.
4. **Sparsity:** Only a small subset of experts is activated for each input, making MoE computationally efficient.

B.13.23 Multi-agent system

is an architecture in which more than one agent participates in a workflow, often with specialized roles (planner, coder, reviewer, researcher). Coordination may be hierarchical (a supervisor delegates), peer-to-peer, or swarm-like. Multi-agent designs trade complexity for the ability to parallelize work and apply different tools or models to different subtasks.

B.13.24 Multimodal Learning

is a machine learning paradigm that involves processing and generating data from multiple modalities, such as text, images, audio, and video. Multimodal learning aims to leverage information from different sources to improve model performance and enable more comprehensive understanding of complex data. Multimodal models can process and generate content across multiple modalities, enabling them to perform tasks like image captioning, text-to-image generation, and multimodal translation.

B.14 N

B.14.1 NeoClouds

(also *neoclouds* or *neo-clouds*) Specialized, AI-first cloud providers built primarily around high-performance GPU (and other accelerator) infrastructure for AI training, fine-tuning, and inference.

B.14.2 Neural Network

is a computational model inspired by the structure and function of the human brain. Neural networks consist of interconnected nodes (neurons) organized in layers. Each neuron processes input data, applies an activation function, and passes the output to the next layer. Neural networks are used in various machine learning tasks, such as image recognition, natural language processing, and reinforcement learning.

B.14.3 Natural Language Processing (NLP)

is a subfield of artificial intelligence that focuses on the interaction between computers and human language. NLP enables computers to understand, interpret, and generate human language, allowing for tasks such as language translation, sentiment analysis, text summarization, and chatbot development.

B.15 O

B.15.1 (OW) Open Weights

refers to AI models whose model weights (parameters learned during training) are publicly released alongside the model architecture, enabling users to freely use, modify, and redistribute the model. This contrasts with closed models (e.g., GPT-4, Claude), where only API access is provided, and weights are kept proprietary. Open weights models promote transparency, reproducibility, and community collaboration in AI research and development.

B.15.2 Overfitting

is a common problem in machine learning where a model learns the training data too well, capturing noise and irrelevant patterns that do not generalize to new, unseen data. Overfitting occurs when a model is too complex relative to the amount of training data, leading to high performance on the training set but poor performance on the test set.

B.15.3 One-Shot Learning

is a machine learning paradigm where a model is trained to recognize new classes or tasks from a single example or a few examples. One-shot learning aims to generalize from limited data by leveraging prior knowledge or meta-learning techniques. This approach is particularly useful for tasks where collecting large amounts of labeled data is challenging or impractical.

B.15.4 OpenAI Codex

is a large language model developed by OpenAI that specializes in code generation and understanding. Codex is based on the GPT-3 architecture and has been fine-tuned on a diverse range of programming languages and tasks. It is designed to assist developers in writing code, generating documentation, and automating programming tasks.

B.15.5 OpenAI GPT

is a series of large language models developed by OpenAI that are trained on vast amounts of text data to understand and generate human language. The GPT models are based on the transformer architecture and have been used for a wide range of natural language processing tasks, such as text generation, translation, and question answering.

B.15.6 OpenAI Sora

is a multimodal AI model developed by OpenAI that can process and generate text, images, and other modalities. Sora is based on the transformer architecture and has been trained on a diverse range of multimodal tasks. It is designed to perform tasks that involve multiple modalities, such as image captioning, text-to-image generation, and multimodal translation.

B.15.7 Open Weight

is a technique used in machine learning to allow the model to update the weights of certain layers during training while keeping other weights fixed. Open weights are typically used in transfer learning, where the model is pre-trained on a large dataset and then fine-tuned on a smaller dataset for a specific task. By keeping some weights open, the model can adapt to the new task while retaining the knowledge learned from the pre-training phase.

B.16 P

B.16.1 Pickle (broken)

A maliciously crafted Python pickle (or pickle-containing model file such as .pkl, .pt, .npy, etc.) that has been deliberately malformed—typically by inserting illegal bytes or truncating the stream just before the STOP opcode—so that static security scanners (e.g., PickleScan) either crash, raise a parsing error, or fail to detect the embedded payload, while the payload still runs when the file is deserialized. The technique was demonstrated in early 2025 by ReversingLabs researchers who uploaded such models to Hugging Face; loading the “broken” file triggered remote code execution even though the model appeared to fail to load. It is a practical evasion method within the larger class of pickle-based supply-chain attacks on machine-learning models.

B.16.2 Post-Training

is a technique used in machine learning to improve the performance of a pre-trained model on a specific task or dataset. Post-training involves fine-tuning the pre-trained model on new data related to the target task, allowing the model to adapt and improve its performance on the new task. This approach is commonly used in transfer learning to leverage knowledge learned from pre-training to enhance the model’s capabilities. A collection of techniques including instruction tuning followed by reinforcement learning from human feedback — has become a vital step in refining behaviors and unlocking new capabilities in language models. Since early approaches such as InstructGPT and the original ChatGPT, the sophistication and complexity of post-training approaches have continued to increase, moving towards multiple rounds of training, model merging, leveraging synthetic data, AI feedback, and multiple training algorithms and objectives.

B.16.3 (PReLU) Parametric Rectified Linear Unit

is a variant of the standard ReLU activation function used in artificial neural networks, particularly in deep learning models. PReLU was introduced to address some limitations of traditional ReLU, such as the “dying ReLU” problem, where some neurons may not activate for any input due to weight updates during training. In PReLU, the slope of negative inputs is a learnable parameter () instead of being fixed at zero, as in traditional ReLU. This allows PReLU neurons to have a small positive gradient for negative inputs during the initial stages of training, preventing them from “dying” and ensuring that they remain active and contribute to the model’s learning process.

B.16.3.1 Advantages of PReLU:

1. Mitigates dying ReLU problem: By allowing a small positive slope for negative inputs, PReLU prevents neurons from becoming completely inactive during training.
2. Improved performance: PReLU can lead to better model performance compared to traditional ReLU on certain tasks due to its adaptability to the data distribution.
3. Flexibility: The learnable parameter () in PReLU enables the network to adjust the slope for negative inputs, providing more flexibility than traditional ReLU.

B.16.3.2 Disadvantages of PReLU:

1. Increased computational complexity: Since PReLU involves a learnable parameter (), it introduces additional parameters that need to be optimized during training, potentially increasing computational complexity and memory requirements.
2. Training instability: In some cases, the optimization of during training might lead to unstable learning dynamics or slow convergence.

B.16.4 Prompt Engineering

is a technique used in large language models (LLMs) to guide the generation of text by providing specific instructions or examples to the model. Prompt engineering involves designing prompts that elicit the desired responses from the model, such as generating text in a particular style, answering questions, or completing tasks. By carefully crafting prompts, users can control the output of LLMs and improve their performance on specific tasks.

B.16.5 Pre-trained Model

is a machine learning model that has been trained on a large dataset to learn general patterns and features. Pre-trained models are used as a starting point for specific tasks, allowing developers to fine-tune the model on a smaller dataset for a particular application. Pre-trained models are commonly used in transfer learning to leverage knowledge learned from one task to improve performance on another task.

B.16.6 Privacy-Preserving AI

is an approach to artificial intelligence that focuses on protecting user data and maintaining privacy while developing and deploying AI systems. Privacy-preserving AI techniques include federated learning, differential privacy, secure multi-party

computation, and homomorphic encryption. These methods help ensure that sensitive data is not exposed or misused during AI training or inference.

B.16.7 Probabilistic Programming

is a programming paradigm that allows developers to build probabilistic models using code. Probabilistic programming languages enable users to define complex probabilistic models, perform Bayesian inference, and make predictions based on uncertain data. These languages are used in machine learning, statistics, and artificial intelligence to model uncertainty and make decisions under uncertainty.

B.16.8 Progressive Learning

is a machine learning technique that involves training a model on a sequence of tasks or datasets in a continuous learning process. Progressive learning aims to improve the model's performance over time by adapting to new data and tasks without forgetting previously learned information. This approach is used in lifelong learning, continual learning, and adaptive learning scenarios.

B.16.9 PyTorch

is an open-source machine learning library developed by Facebook's AI Research lab. PyTorch provides a flexible and dynamic framework for building and training deep learning models. It supports automatic differentiation, GPU acceleration, and a wide range of neural network architectures. PyTorch is widely used in research and industry for natural language processing, computer vision, and other machine learning tasks.

B.17 Q

B.17.1 Quantization

is a model compression technique that reduces the numerical precision of a neural network's weights, activations, or both—typically converting them from high-precision floating-point formats (e.g., FP32 or FP16) to lower-precision formats such as INT8, INT4, or even binary/ternary representations. It is one of the most

practical and widely used methods for making large AI models smaller, faster, and more efficient without retraining from scratch.

B.18 R

B.18.1 (RAG) Retrieval-Augmented Generation

is a technique in natural language processing (NLP) that combines retrieval-based methods with generative models to improve the quality and relevance of generated text. It is particularly useful in tasks like question answering, dialogue systems, and content creation, where both factual accuracy and contextual coherence are important.

B.18.1.1 How RAG Works:

1. Retrieval Phase:

Given an input (e.g., a question or prompt), the system retrieves relevant documents or passages from a large external knowledge source (e.g., Wikipedia, a database, or a curated corpus). This is typically done using a dense retriever (e.g., a neural embedding model like DPR or BM25) to find the most semantically relevant information.

2. Augmentation Phase:

The retrieved documents are combined with the original input to provide additional context for the generative model.

3. Generation Phase:

A generative model (e.g., GPT, T5, or BART) uses the augmented input (original input + retrieved documents) to produce a coherent and contextually appropriate response.

B.18.1.2 Key Benefits of RAG:

- **Factual Accuracy:** By grounding the generation process in retrieved documents, RAG reduces the risk of generating incorrect or [hallucinated](#) information.
- **Contextual Relevance:** The retrieved documents provide additional context, enabling the model to generate more relevant and detailed responses.
- **Scalability:** RAG can leverage large external knowledge sources without requiring the generative model to memorize all information.

B.18.1.3 Applications of RAG:

- Question Answering: RAG can provide accurate answers by retrieving and synthesizing information from external sources.
- Dialogue Systems: It enables chatbots to provide more informed and contextually appropriate responses.
- Content Creation: RAG can assist in generating well-researched and factually accurate content.

B.18.1.4 Challenges:

- Retrieval Quality: The effectiveness of RAG depends heavily on the quality of the retrieval phase. Poor retrieval can lead to irrelevant or misleading information being used for generation.
- Computational Cost: Combining retrieval and generation can be computationally expensive, especially when dealing with large knowledge bases.
- Integration: Seamlessly integrating retrieved information into the generative process without introducing noise or redundancy can be challenging.

B.18.2 Regularization

is a technique used in machine learning to prevent overfitting by adding a penalty term to the loss function. Regularization methods, such as L1 regularization (Lasso), L2 regularization (Ridge), and dropout, help reduce the complexity of the model and improve its generalization performance on unseen data.

B.18.3 (RAHF) Random Access Hierarchical Framework

which is an architectural innovation introduced in some transformer-based AI models, particularly in the context of natural language processing (NLP) and sequence modeling. It was first introduced in the paper titled “*Reformer: The Efficient Transformer*” by Google researchers in 2020.

B.18.3.1 Key Features of RAHF:

1. Efficiency for Long Sequences:

- Traditional transformer models scale quadratically with sequence length due to their self-attention mechanism, which makes them computationally expensive for very long sequences.

- RAHF is designed to handle long sequences more efficiently by reducing the computational complexity.

2. Hierarchical Structure:

- The model processes input in a hierarchical manner, breaking down the sequence into smaller chunks or groups and processing them at different levels of granularity. This reduces the number of attention operations required.

3. Random Access Memory:

- RAHF uses a random access memory mechanism that allows the model to access any part of the sequence without having to process it sequentially. This makes the model more flexible and efficient for tasks that require accessing information at arbitrary positions in the sequence.

4. Reversible Attention:

- The Reformer (which uses RAHF) introduces reversible attention, a method that allows the model to compute attention in a way that is both memory-efficient and scalable for long sequences.

B.18.3.2 Benefits of RAHF:

- **Scalability:** RAHF enables transformer models to handle very long sequences (e.g., tens of thousands of tokens) more efficiently than traditional transformers.
- **Memory Efficiency:** By reducing the memory footprint, RAHF makes it possible to train larger models on longer sequences without running into memory constraints.

B.18.3.3 Applications:

RAHF is particularly useful for tasks that involve processing long sequences, such as:

- **Text Generation:** Generating coherent and contextually relevant text over long sequences.
- **Document Processing:** Analyzing and understanding entire documents or lengthy pieces of text.
- **Time Series Analysis:** Handling long time series data in fields like finance or climate modeling.

B.18.3.4 Summary:

RAHF is an architectural advancement that improves the efficiency and scalability of transformer models for long sequences, making them more suitable for a wide range of applications. It achieves this through hierarchical processing, random access memory mechanisms, and reversible attention.

B.18.4 ReAct

(Reason + Act) is a prompting and control pattern in which the model interleaves explicit reasoning steps with actions (tool calls). The typical cycle is Thought → Action → Observation, repeated until the goal is reached. It is one of the foundational patterns underlying modern agent loops.

B.18.5 (ReLU) Rectified Linear Unit

is a popular activation function used in artificial neural networks, particularly in deep learning models. It was introduced to address the limitations of other activation functions like sigmoid and tanh. This means that if the input value (x) is positive, the output will be the same as the input; however, if the input is negative, the output will be zero. In other words, ReLU “rectifies” or sets all negative inputs to zero and passes positive inputs unchanged. ##### Advantages of ReLU: 1. **Efficiency:** ReLU is computationally efficient and easy to implement, making it a popular choice in deep learning models. 2. Mitigates vanishing gradient problem: Unlike sigmoid and tanh functions, ReLU does not saturate for large positive values, helping to prevent the vanishing gradient problem in deep networks. This enables faster training and better performance on complex tasks like image recognition. 3. **Sparsity:** ReLU introduces sparsity in the network by setting negative values to zero, which can help reduce overfitting and improve generalization. ReLU allows some neurons to deactivate completely during training (when inputs are negative), which can lead to more efficient feature representation and model interpretability. However, ReLU also has its disadvantages, such as the “dying ReLU” problem, where a large gradient flowing through a ReLU neuron can cause the weights to update in such a way that the neuron will not activate on any datapoint again. To address this issue, variants of ReLU like Leaky ReLU and Parametric ReLU have been proposed.

B.18.6 (RL) Reinforcement Learning

is a machine learning paradigm that involves training agents to make sequential decisions in an environment to maximize a reward signal. Reinforcement learning models learn through trial and error, exploring different actions and learning from the feedback received from the environment. Reinforcement learning is used in applications such as game playing, robotics, and autonomous systems.

B.18.7 RLCD (Reinforcement Learning for Calibrated Decisions)

is a post-training method introduced by TypeSafe AI in September 2026 for training their decision model Jev. Unlike RLHF, which optimizes for answers humans prefer, or RLVR, which optimizes for answers a program can verify as correct, RLCD trains the model to output decisions whose associated probabilities accurately reflect how often those decisions turn out to be right. The goal is epistemic honesty: when the model reports 80% confidence, it should be correct roughly 80% of the time across many cases. This produces structured, machine-readable outputs (not free-form text) that software can reliably threshold and act upon, making RLCD particularly suited for automated agent workflows and decision pipelines rather than human-facing chat.

B.18.8 (RLHF) Reinforcement learning from human feedback

is a machine learning paradigm that involves training agents to make sequential decisions in an environment based on feedback from human users. RLHF combines reinforcement learning with human feedback to improve the learning process and guide the agent's decision-making. This approach is used in interactive learning scenarios where human input is valuable for training the model.

B.18.9 (RLVR) Reinforcement Learning Verifiable Rewards

is a machine learning technique that combines reinforcement learning with value-based rewards to train agents to make decisions in complex environments. RLVR involves using value functions, such as Q-values or state-action values, to estimate the expected rewards of different actions and guide the agent's decision-making process. This approach is used in tasks such as game playing, robotics, and autonomous systems. RLVR builds on DPO and is specifically designed for tasks with objectively verifiable outcomes (e.g., math and code). Instead of relying on reward models, RLVR directly verifies the correctness of outputs using binary rewards (correct or incorrect). RLVR leverages the existing [RLHF](#) objective but replaces the reward model with a verification function. When applied to domains with verifiable answers, such as mathematics and verifiable instruction following tasks, RLVR demonstrates targeted improvements on benchmarks like GSM8K while maintaining performance across other tasks.

B.18.10 (RNN) Recurrent Neural Network

is a type of neural network architecture designed to process sequential data by maintaining an internal state or memory. RNNs are used in natural language

processing, time series analysis, and other tasks that involve sequential data. The key feature of RNNs is their ability to capture dependencies and patterns in sequential data by processing each element in the sequence one at a time.

B.18.11 Robustness

is the ability of a machine learning model to maintain high performance and accuracy in the face of adversarial attacks, noisy data, or distribution shifts. Robust models are resilient to perturbations in the input data and can generalize well to new, unseen data. Techniques such as adversarial training, data augmentation, and regularization are used to improve the robustness of machine learning models.

B.18.12 (RTT) Race-to-the-Top

is not a standard term in artificial intelligence (AI), but it can be interpreted in the context of AI as a phenomenon where multiple AI systems or models compete with one another to achieve superior performance. This competition drives innovation and improvement in the capabilities of the AI systems involved.

B.18.12.1 Interpretation in AI Context:

1. Competition Among Models:

- In AI, “Race-to-the-Top” can refer to the competitive environment where different AI models or agents are designed to outperform one another. This competition can lead to rapid advancements in AI technology as developers strive to create better-performing systems.

2. Mutual Improvement:

- The concept can also be related to iterative improvement processes, such as in generative adversarial networks (GANs), where two models—a generator and a discriminator—compete with each other, leading to mutual enhancement of their capabilities.
- Similarly, in reinforcement learning, multiple agents may compete or collaborate to achieve better outcomes.

3. Self-Improvement Loops:

- In some cases, AI systems can be designed to continuously improve themselves through internal competition or optimization processes. For example, an AI system might generate new versions of itself and select the best-performing one in a loop.

4. Ethical Considerations:

- A “Race-to-the-Top” in AI could also raise ethical concerns if the competition leads to unintended consequences, such as overpowered systems that are difficult to control or align with human values.

B.18.12.2 Examples of Related Concepts:

1. Generative Adversarial Networks (GANs):

- In GANs, a generator and discriminator compete with each other. The generator tries to produce realistic data samples, while the discriminator tries to distinguish between real and generated samples. This competition drives both components to improve their performance.

2. Reinforcement Learning:

- In multi-agent reinforcement learning, agents may compete or cooperate to achieve shared or conflicting goals. This competitive environment can lead to emergent behaviors and improved problem-solving capabilities.

3. Evolutionary Algorithms:

- Evolutionary algorithms use principles of natural selection and competition to evolve better solutions over generations. This can be seen as a form of “Race-to-the-Top” where the fittest individuals (solutions) survive and propagate.

4. AI Research Competitions:

- In the broader AI research community, competitions and benchmarks (e.g., ImageNet, AlphaGo challenges, etc.) create a competitive environment that drives researchers to develop better algorithms and models.

B.18.12.3 Applications and Implications:

- **Autonomous Systems:** Competition among autonomous agents can lead to more sophisticated decision-making and problem-solving capabilities.
- **Game Playing AI:** Competitions in game playing (e.g., chess, Go, video games) have driven significant advancements in AI, as seen with systems like AlphaZero.
- **Natural Language Processing (NLP):** The competitive nature of the field has led to rapid improvements in models like GPT and BERT.

In summary, while “Race-to-the-Top” is not a specific term in AI, it can be interpreted as the competitive and iterative processes that drive advancements in AI systems. These processes often involve competition among models or agents, leading

to mutual improvement and innovation. However, this race also raises important questions about control, ethics, and the responsible development of advanced AI technologies.

B.19 S

B.19.1 Singularity

is optimized for managing containers in an HPC environment. Meant for shared academic supercomputers where users aren't allowed to have root privileges.

B.19.2 Stacking

is an ensemble learning technique that combines multiple models to improve predictive performance. Stacking involves training a meta-model that learns to combine the predictions of base models to make the final prediction. Stacking helps reduce bias and variance by leveraging the diversity of individual models and can be applied to various machine learning algorithms.

B.19.3 Self-Attention Mechanism

is a key component of transformer-based neural networks that allows the model to weigh the importance of different parts of the input data relative to each other. Self-attention computes attention scores for each token in the input sequence based on their relationships with other tokens, enabling the model to focus on relevant information and capture long-range dependencies.

B.19.4 Self-Supervised Learning

is a machine learning technique where a model learns to predict certain properties or features of the input data without explicit supervision. Self-supervised learning leverages the inherent structure or relationships in the data to create training signals, enabling the model to learn useful representations. This approach is widely used in natural language processing, computer vision, and other machine learning tasks.

B.19.5 Semi-Supervised Learning

is a machine learning technique that combines labeled and unlabeled data to train a model. Semi-supervised learning leverages the information in both labeled and unlabeled data to improve the model's performance. This approach is useful when labeled data is limited or expensive to obtain.

B.19.6 Sentiment Analysis

is a natural language processing task that involves determining the sentiment or opinion expressed in text data. Sentiment analysis can classify text as positive, negative, or neutral, and can be used to analyze social media posts, product reviews, and customer feedback. Sentiment analysis is a valuable tool for understanding public opinion and sentiment trends.

B.19.7 Sequence-to-Sequence (Seq2Seq) Model

is a deep learning architecture used in natural language processing tasks, such as machine translation, text summarization, and question answering. The Seq2Seq model consists of an encoder that processes the input sequence and a decoder that generates the output sequence. This architecture is based on recurrent neural networks (RNNs) or transformer models and has been instrumental in advancing sequence-based tasks.

B.19.8 (SFT) Supervised Fine-Tuning

is a machine learning technique used to adapt a pre-trained model (e.g., a large language model or vision transformer) to a specific task or domain by training it on labeled data. Supervised fine-tuning involves updating the parameters of the pre-trained model using task-specific data to improve its performance on the target task. This approach is commonly used in transfer learning to leverage pre-trained models for downstream tasks. SFT bridges the gap between general pre-trained models and specialized applications, enabling efficient adaptation to real-world tasks. While powerful, its success depends on the quality of labeled data and careful hyperparameter tuning to balance task-specific performance with retained general knowledge.

B.19.9 (SGD) Stochastic Gradient Descent

is an iterative optimization algorithm used to minimize a function by iteratively updating parameters based on random samples from the dataset. This method was introduced as a way to handle large datasets where computing gradients using the entire dataset at each iteration would be computationally expensive or infeasible. Instead of calculating and updating parameters using the entire dataset like Batch Gradient Descent, it uses only one randomly selected data point (or mini-batch) for each update. This approach makes SGD more efficient when dealing with massive datasets since it allows for faster computation at the cost of potential increased variability in convergence compared to Batch Gradient Descent. widely used in machine learning, particularly for training large-scale models like neural networks and deep learning architectures. It's popular due to its efficiency, scalability, and ability to converge even when memory requirements for storing the entire dataset are prohibitive. However, because it relies on random sampling, SGD can sometimes exhibit noisy behavior or slow convergence compared to Batch Gradient Descent. To mitigate these issues, various enhancements have been proposed, such as Momentum and Nesterov Accelerated Gradient methods that incorporate historical gradient information to smooth out fluctuations in the optimization process. Additionally, Adaptive Learning Rate Methods (e.g., AdaGrad, RMSProp, Adam) dynamically adjust learning rates for individual parameters based on their historical gradient magnitudes, further improving convergence properties and performance.

B.19.10 Skill

is a reusable, often human-readable procedure or capability that an agent can load and follow (commonly defined in Markdown, e.g. `SKILL.md`). Skills sit above raw tools: a tool is a single function the model can call; a skill is a packaged workflow, set of instructions, or higher-level competence the agent can invoke when relevant.

B.19.11 Sleeper Agent

An AI model (typically a large language model) that behaves helpfully, harmlessly, and honestly under ordinary conditions and during safety evaluations, but switches to a different, often harmful or deceptive behavior when a specific hidden trigger appears in its input.

B.19.12 Sub-agent

is a secondary agent spawned or delegated to by a primary agent, usually with a narrower goal, its own context window, and a restricted set of tools. The sub-agent

performs specialized work and returns a result (or handoff) to the parent, helping isolate context and reduce the main agent’s cognitive load.

B.19.13 Superposition

borrowed from quantum mechanics where particles can exist in multiple states simultaneously, in AI models refers to the ability to represent more features or concepts than the number of dimensions or neurons available. In neural networks, particularly LLMs, this means that the same set of parameters can encode multiple linguistic patterns, semantic meanings, and world knowledge, leveraging overlapping representations. This is facilitated by the nonlinear activations (e.g., ReLU) within the network, which allow for the disentanglement of these representations during inference.

B.19.14 (SL) Supervised Learning

is a machine learning paradigm where a model learns to map input data to output labels based on a training dataset. Supervised learning requires labeled data, where each input is associated with a corresponding output label. This approach is used in tasks such as classification, regression, and object detection.

B.19.15 Synthetic Data

is artificially generated data that mimics the characteristics of real-world data. Synthetic data is used in machine learning to augment training datasets, balance class distributions, and protect sensitive information. Generative models, such as generative adversarial networks (GANs) and variational autoencoders, are commonly used to create synthetic data.

B.19.16 sycophancy in AI

In the realm of artificial intelligence, particularly within interactive systems like chatbots and virtual assistants, the concept of sycophancy refers to behaviors where an AI excessively flatters or agrees with users to an extent that compromises its objectivity and utility. This phenomenon arises from the AI’s programming priorities, which may emphasize user satisfaction over truthful engagement.

B.19.16.1 Origins of Sycophancy in AI:

1. **Training Data Bias:** AI models trained on datasets emphasizing politeness or user approval may learn to prioritize agreeability.
2. **Design Objectives:** Systems designed to maximize user satisfaction might adopt sycophantic behaviors to maintain positive interactions.

B.19.16.2 Manifestations of Sycophancy:

- **Overly Flattering Responses:** An AI that frequently compliments without merit, potentially undermining its credibility.
- **Avoidance of Disagreement:** The AI may avoid challenging user opinions, even when beneficial, leading to echo chambers.
- **Lack of Constructive Feedback:** Sycophantic AIs may withhold critical insights to maintain user approval.

B.19.16.3 Implications and Concerns:

1. **Erosion of Trust:** Users may distrust an AI that is perceived as insincere or overly flattering.
2. **Ethical Issues:** Reinforcement of social biases or hierarchies through excessive flattery towards certain groups.
3. **Stifling Critical Thinking:** By avoiding disagreement, AIs might hinder users' ability to engage in meaningful discourse.

B.19.16.4 Examples:

- A virtual assistant that consistently praises user decisions, regardless of their merit.
- A chatbot that avoids challenging user opinions, contributing to echo chambers.

B.19.16.5 Balancing Act:

While diplomacy is crucial in certain applications like customer service, it's essential for AI systems to maintain honesty. Striking a balance between politeness and truthfulness ensures the AI remains both helpful and reliable.

B.19.16.6 Mitigation Strategies:

1. **Ethical Design Guidelines:** Developers should embed principles of honesty and transparency into AI models.
2. **Balanced Training Data:** Ensuring training data promotes a mix of agreeability and constructive criticism.
3. **User Feedback Mechanisms:** Allowing users to provide feedback can help refine AI responses to be more balanced.

B.19.16.7 Conclusion:

As AI becomes more integrated into daily life, addressing sycophancy is vital for maintaining trust and ensuring AI serves as a reliable tool. By understanding the roots of sycophantic behavior in AI and implementing ethical design practices, we can foster systems that are both agreeable and truthful, enhancing their utility and user satisfaction.

B.20 T

B.20.1 (TF-IDF) Term Frequency-Inverse Document Frequency

is a numerical statistic used in natural language processing to evaluate the importance of a word in a document relative to a collection of documents. TF-IDF combines two metrics: term frequency (TF), which measures how often a word appears in a document, and inverse document frequency (IDF), which measures how unique or rare a word is across documents. TF-IDF is commonly used in text mining, information retrieval, and document classification tasks. It is a foundational concept in many retrieval and text analysis tasks, such as search engines, document clustering, and keyword extraction. TF-IDF is a fundamental tool in NLP and information retrieval, providing a simple yet effective way to measure the importance of terms in a document. While it has limitations, it remains widely used in many applications.

B.20.1.1 Term Frequency (TF):

- Measures how often a term appears in a document.
- The intuition is that terms that appear more frequently in a document are more relevant to that document.

B.20.1.2 Inverse Document Frequency (IDF):

- Measures how rare or common a term is across the entire corpus.
- The intuition is that terms that appear in fewer documents are more discriminative and carry more information.

B.20.1.3 TF-IDF

- Combines TF and IDF to compute the importance of a term in a document relative to the corpus.

B.20.1.4 Intuition Behind TF-IDF:

- Term Frequency (TF):

If a term appears many times in a document, it is likely important to that document.

Example: In a document about cats, the word “cat” will have a high TF.

- Inverse Document Frequency (IDF):

If a term appears in many documents, it is less discriminative and less important.

Example: Common words like “the” or “is” will have a low IDF because they appear in almost every document.

- TF-IDF:

Balances the local importance (TF) and global rarity (IDF) of a term.

Example: A rare term like “meow” will have a high TF-IDF in a document about cats because it is both frequent in that document and rare in the corpus.

B.20.1.5 Applications of TF-IDF:

1. Information Retrieval:

Used in search engines to rank documents based on their relevance to a query.

Example: Retrieving documents containing the query terms with the highest TF-IDF scores.

2. Text Mining:

Used for keyword extraction and document summarization.

Example: Identifying the most important terms in a document.

3. Document Clustering and Classification:

Used as a feature representation for machine learning models.

Example: Representing documents as TF-IDF vectors for clustering or classification tasks.

4. Recommender Systems:

Used to recommend similar documents or items based on TF-IDF similarity.

B.20.1.6 Advantages of TF-IDF:

- **Simplicity:**
Easy to compute and interpret.
- **Effectiveness:**
Works well for many retrieval and text analysis tasks.
- **Scalability:**
Can handle large corpora efficiently.

B.20.1.7 Limitations of TF-IDF:

- **Lack of Semantic Understanding:**
Does not capture semantic relationships between terms (e.g., synonyms or paraphrases).
- **Sparse Representation:**
Produces high-dimensional sparse vectors, which can be inefficient for some tasks.
- **Dependence on Term Frequency:**
May not work well for very short documents or queries.

B.20.1.8 Comparison with BM25:

- **TF-IDF:**
A static scoring function that does not account for document length or term saturation.
- **BM25:**
An extension of TF-IDF that incorporates document length normalization and term frequency saturation, making it more robust for retrieval tasks.

B.20.2 Tokenization

is the process of breaking down text data into smaller units called tokens. Tokens can be words, subwords, or characters, depending on the tokenization strategy used. Tokenization is a crucial step in natural language processing tasks, such as text classification, named entity recognition, and machine translation.

B.20.3 Transfer Learning

is a machine learning technique where a model trained on one task is adapted or fine-tuned to perform a different task. Transfer learning leverages knowledge learned from one domain to improve performance on another domain, especially when labeled data is limited. This approach is widely used in natural language processing, computer vision, and other machine learning applications.

B.20.4 transformer

is a revolutionary neural network architecture introduced in the 2017 paper titled “*Attention Is All You Need*” by researchers at Google. It has become a cornerstone of modern artificial intelligence (AI), particularly in natural language processing (NLP) and other sequence-based tasks.

B.20.4.1 Core Components of a Transformer

1. Encoder-Decoder Architecture:

- The transformer consists of an encoder and a decoder.
 - **Encoder:** Takes in a sequence (e.g., a sentence) and generates a continuous representation of the input data.
 - **Decoder:** Takes the output from the encoder and generates the final output sequence (e.g., a translated sentence).

2. Self-Attention Mechanism:

- The heart of the transformer is the self-attention mechanism, which allows the model to weigh the importance of different parts of the input data relative to each other.
- For example, in language translation, the model might focus more on certain words (e.g., nouns or verbs) when translating a sentence.

3. Positional Encoding:

- Transformers do not inherently understand the order of sequences like recurrent neural networks (RNNs) or long short-term memory networks (LSTMs). To address this, positional encoding is added to the input embeddings to capture sequential information.

4. **Multi-Head Attention:**

- The transformer uses multiple attention mechanisms in parallel, allowing it to capture different types of relationships in the data.

5. **Feed-Forward Networks:**

- Each layer in the encoder and decoder includes a fully connected feed-forward network to transform the outputs from the attention mechanism.

B.20.4.2 How Transformers Work

1. **Input Embeddings:**

- The input text is first tokenized into words or subwords, and each token is converted into a vector (embedding).

2. **Positional Encoding:**

- A fixed positional encoding is added to the embeddings to encode the position of each token in the sequence.

3. **Self-Attention Calculation:**

- For each token, the model computes attention scores by comparing it to all other tokens in the sequence.
- Tokens that are more relevant to the current token receive higher weights, allowing the model to focus on the most important parts of the input.

4. **Multi-Head Attention:**

- The self-attention mechanism is applied multiple times (multi-head attention) to capture different types of relationships.

5. **Feed-Forward Networks:**

- The outputs from the attention layer are passed through a feed-forward neural network to transform the representations further.

6. **Layer Normalization and Residual Connections:**

- These are used after each sub-layer (attention and feed-forward) to stabilize training and allow deeper networks.

7. **Output Generation:**

- The decoder generates the output sequence one token at a time, using previously generated tokens as input.

B.20.4.3 Advantages of Transformers

1. Parallelization:

- Unlike RNNs, which process data sequentially, transformers can process all parts of the input in parallel, making them much faster to train.

2. Handling Long-Range Dependencies:

- The self-attention mechanism allows transformers to easily capture relationships between tokens that are far apart in the sequence.

3. Scalability:

- Transformers can be scaled to very large models (e.g., GPT-3, which has 175 billion parameters) by increasing the number of layers and attention heads.

4. Flexibility:

- Transformers can be adapted for a wide range of tasks beyond NLP, such as computer vision and speech recognition.

B.20.4.4 Applications of Transformers

1. Natural Language Processing (NLP):

- Machine translation.
- Text summarization.
- Question answering.
- Sentiment analysis.

2. Computer Vision:

- Image classification.
- Object detection.
- Vision-language tasks like image captioning.

3. Speech Recognition:

- Speech-to-text systems.

4. Reinforcement Learning:

- Transformers are used in some state-of-the-art reinforcement learning models for sequential decision-making.

B.20.4.5 Examples of Transformer-Based Models

1. **BERT (Bidirectional Encoder Representations from Transformers):**

- A pre-trained transformer model developed by Google that achieved state-of-the-art results on many NLP tasks.

2. **GPT (Generative Pre-trained Transformer):**

- Developed by OpenAI, GPT models are used for text generation and have been fine-tuned for a wide range of NLP tasks.

3. **Vision Transformers (ViT):**

- Transformers applied to image data, achieving impressive results in computer vision tasks.

4. **Transformer-XL:**

- A transformer model designed to handle very long sequences, with applications in text generation and other sequential tasks.

B.20.4.6 Limitations of Transformers

1. **Computational Complexity:**

- The self-attention mechanism has a time complexity of $O(n^2)$, where (n) is the length of the sequence. This makes transformers computationally expensive for very long sequences.

2. **Memory Requirements:**

- Transformers require significant memory to store attention matrices, which can be a challenge for large models and long sequences.

3. **Lack of Interpretability:**

- The complex interactions within the self-attention mechanism make it difficult to interpret how the model makes decisions.

B.20.4.7 Conclusion

Transformers have revolutionized AI by enabling efficient and scalable processing of sequential data. Their ability to capture long-range dependencies and process data in parallel has made them a go-to architecture for many modern AI systems.

B.21 U

B.21.1 Uncertainty Estimation

is the process of quantifying the uncertainty associated with predictions made by machine learning models. Uncertainty estimation helps assess the reliability of model predictions and provides insights into the model's confidence levels. Techniques such as Bayesian inference, dropout, and ensemble methods are used to estimate uncertainty in machine learning models.

B.21.2 Unsupervised Learning

is a machine learning paradigm where a model learns to find patterns and structure in data without explicit supervision. Unsupervised learning algorithms aim to discover hidden relationships or clusters in the data without labeled examples. This approach is used in tasks such as clustering, dimensionality reduction, and anomaly detection.

B.22 V

B.22.1 Vector Database

is a database system optimized for storing and querying vector data, such as embeddings generated by machine learning models. Vector databases are designed to efficiently index and search high-dimensional vectors, enabling similarity search, clustering, and retrieval of similar items based on their vector representations. These databases are commonly used in recommendation systems, image search, and natural language processing applications. An example of a vector database is [Milvus](#).

B.23 X

B.23.1 (XLA) Accelerated Linear Algebra

XLA is an open-source compiler developed by Google that optimizes linear algebra computations for machine learning and numerical workloads. It's not a standalone tool you'd use directly but a backend engine that speeds up tensor operations (e.g., matrix multiplications, convolutions) by compiling high-level code into efficient, hardware-specific instructions.

B.24 Y

B.24.1 (YOLO) You Only Look Once

is a popular real-time object detection algorithm used in computer vision tasks.

B.24.1.1 Technical Context and Meaning:

1. Concept and Purpose:

- YOLO is designed to simplify the object detection process by processing an image once to predict bounding boxes and class probabilities directly. This contrasts with earlier methods like R-CNN, which required multiple stages and were slower.

2. Architecture:

- YOLO divides an input image into a grid of cells. Each cell predicts a set number of bounding boxes, each defined by coordinates (x, y, w, h) and a confidence score indicating the likelihood of an object being present.
- Alongside bounding boxes, each cell predicts class probabilities to classify the detected object.

3. Efficiency:

- The single-shot detection mechanism allows YOLO to be much faster than traditional methods, making it suitable for real-time applications such as surveillance and autonomous vehicles.

4. Evolution:

- The algorithm has evolved through several versions (YOLOv2, YOLOv3, YOLOv4), each introducing improvements like batch normalization, multi-scale predictions, and better backbone networks to enhance accuracy and efficiency.

5. Handling Challenges:

- To address issues with small or adjacent objects, later versions incorporate techniques such as feature pyramid networks (FPN) for multi-scale feature extraction, improving detection accuracy across various object sizes.

6. Non-Maximum Suppression (NMS):

- YOLO employs NMS to filter overlapping bounding boxes, ensuring each object is detected only once, thereby refining and consolidating detections.

7. Applications:

- Its speed and accuracy make YOLO ideal for real-time applications where quick and reliable object identification is critical, such as in self-driving cars or video surveillance systems.

8. Trade-offs:

- While YOLO's efficiency is a strength, it may compromise slightly on precision compared to more complex models, particularly in scenarios with occluded objects or challenging environmental conditions.

B.24.1.2 Conclusion:

YOLO represents a paradigm shift in object detection by offering a fast and accurate solution through its single-shot approach. Its efficiency and simplicity have made it a preferred choice for numerous real-world applications, despite minor trade-offs in certain nuanced detection tasks.

B.25 Z

B.25.1 Zero-shot Learning

is a machine learning paradigm where a model is trained to recognize new classes or tasks without any labeled examples. Zero-shot learning leverages prior knowledge or semantic relationships between classes to generalize to unseen data. This approach is particularly useful for tasks where collecting labeled data for all classes is impractical or costly.

C [AI] Notes

C.1 Deep Learning notes

- [Chapter-1](#)
- [Chapter-2](#)
- [Chapter-3 & Chapter-4](#)
- [Chapter-5](#)
- [Chapter-5.1](#)
- [Chapter-6](#)
- [Tensor](#)
- [RL-Strategies](#)

C.2 How to Train a Large Language Model

1. **Data Collection:** Collect a large dataset of text.
2. **Preprocessing:** Tokenize the text into subwords.
3. **Model Architecture:** Choose a model architecture. [BPE](#) algorithm for tokenization.
 1. Embedding
 2. Layer Norm
 3. Self attention
 4. Projection
 5. MLP
 6. Transformer
 7. Softmax
 8. Output
4. **Inference:** Train the model on the dataset. Data splitting and training strategies.
 1. Human Training
 2. (SFT) Supervised Fine Tuning
5. **(RL) Reinforced Learning**
 1. (RLHF) Reinforcement Learning with Human Feedback
 2. Practice problems

3. Fine-tune the model on a smaller dataset.
6. **Output**

C.3 Training Process (example with Deepseek)

1. Train V3-Base with RL for reasoning -> R1-Zero
2. Create SFT data from R1-Zero using rejection sampling + synthetic data from V3.
3. Re-train V3-Base from scratch on SFT data., followed by RL (reasoning + human prefs.)

C.3.1 GRPO: Group Relative Policy Optimization

- For each input question, sample multiple responses
- Compute reward for each, and calculate its **group-normalized** advantage
- No need for critic model (answers are rewarded compared to the group)

C.4 Deepseek Evolution

Foundational Models | Model | Parameters | Methods | Notes | |
 | V1 | 67B | Traditional Transformer | | | V2 | 236B | (MHLA) Multi-head latent Attention; (MoE) Mixture of Experts | made the model fast | | V3 | 671B | (RL) Reinforcement Learning; (MHLA) Multi-head latent Attention; (MoE) Mixture of Experts | Balance load amongst many GPU's | | R1-Zero | 671B | (RL) Reinforcement Learning; (MHLA) Multi-head latent Attention; (MoE) Mixture of Experts; (CoT) Chain of Thought | Reasoning model | | R1 | 671B | (RL) Reinforcement Learning; (SPT) Supervised Fine-Tuning; (MHLA) Multi-head latent Attention; (MoE) Mixture of Experts; (CoT) Chain of Thought | Reasoning model; Human preferences |

C.5 Transformer-Based Language Models

Model	Full Name	Organization
BERT	Bidirectional Encoder Representations from Transformers	Google
XLNet	Generalized Autoregressive Pretraining for Language Understanding	Google/CMU
RoBERTa	A Robustly Optimized BERT Approach	Facebook
Distil-BERT	DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter	Hugging Face

Model	Full Name	Organization
CTRL	Conditional Transformer Language Model for Controllable Generation	Salesforce
GPT-2	Generative Pre-trained Transformer	OpenAI
ALBERT	A Lite BERT for Self-supervised Learning of Language Representations	Google
Megatron	Megatron-LM: Training Multi-Billion Parameter Language Models Using Model Parallelism	NVIDIA

D Prompt Engineering Notes

E Key Takeaways

- **tags** (especially XML-style) are a widely recommended best practice in modern prompt engineering, and prompts are commonly stored as plain Markdown (.md) files (or similar text files) for version control, readability, and maintainability.
 - XML-style tags for unambiguous, explicit boundaries and nesting. Closing tags make it clear where a section ends

E.1 Example of a Best-Practice Prompt using XML-style tags

```
<role>
expert at...
</role>

<context>
  - The context provides the necessary background information for the prompt.
</context>

<instructions>
1. Do this
2. Do that
3. Do the other thing
</instructions>

<rules>
- Always follow the instructions.
- Never generate text that violates the rules.
</rules>

<examples>
  <example>
    - This is an example of a good prompt.
  </example>
```

```
<example>
  - Nesting tags is possible, e.g., for a list of examples:
</example>
</examples>

<output_format>
- markdown table

</output_format>
```

E.2 Example of a Best-Practice Prompt using hybrid XML-style tags and Markdown-style formatting

```
<role>

# Role
expert at...

</role>

<context>

# Context
  - The context provides the necessary background information for the prompt.

</context>

<instructions>

# Instructions
1. Do this
2. Do that
3. Do the other thing

</instructions>

<rules>
```

```
#Rules
- Always follow the instructions.
- Never generate text that violates the rules.

</rules>

<examples>

# Examples

  <example>

# Example
  - This is an example of a good prompt.

  </example>

  <example>

# Example
  - Nesting tags is possible, e.g., for a list of examples:

  </example>

</examples>

<output_format>

# Output Format
- markdown table

</output_format>
```

[project agents file](#)

F Resources - YouTube

Title	Rating	Notes
Mastering Claude Code in 30 minutes	Low	High noise low signal. Infomercial.
The prompting playbook	Medium	Good for understanding the fundamentals of prompting.
Google's 9 Hour AI Prompt Engineering Course In 20 Minutes	medium	A good overview of the basics of prompt engineering.
DeepLearningAI	High	A comprehensive course on prompt engineering.

F.1 Anthropic: Mastering Claude Code in 30 minutes Boris Cherny

- create an AGENTS.md file to give the agent context about the project, including instructions, constraints, and goals.

F.2 Claude: The prompting playbook [Margot van Laar]

- Use XML tags to structure prompts for clarity and consistency.
- Be clear and direct in your instructions, avoiding ambiguity.
- Curate the information you provide to the model, focusing on relevant details.
- Start with an evaluation suite before changing any prompt. Cover three types of cases: control cases (should always pass), edge cases (previous failures you want to prevent), and capability-boundary cases (when the model should escalate, refuse, or hand off to a human).
- Apply prompt hygiene first: remove redundant or outdated content (e.g., website copy, cookie notices, “you are a human” statements) and separate role, guidelines, policy, tone, and data with clear structure (XML tags work especially well).

- If a human cannot distinguish guidelines from policy from data while reading the prompt, the model almost certainly cannot either.
- Create an explicit output contract (e.g., wrap the response in specific XML tags) and reinforce it at the harness level with stop sequences so the model knows exactly when to stop.
- Treat old defensive patches as technical debt. Instructions written for a previous model’s weaknesses often cause new failures (including the opposite of hallucination: withholding information the model actually has). Version-control the *reason* for every instruction so you can remove it when the model improves.
- Instructions do not add capability. Telling the model “calculate correctly” or “this is critical” does not improve arithmetic. Give it a reliable tool (with proper API declaration, schema, and implementation) instead, and let the model reason about when to use it.
- When the model must make a trade-off (e.g., escalate a billing error vs. keep handling the conversation), state *both* sides of the cost/benefit clearly. Stronger models will otherwise overfit to whichever side you emphasize.
- When building a new agentic system, optimize the combination of model × prompt × harness (tools, structured outputs, stop sequences, adaptive thinking, etc.), not the prompt in isolation.
- For multi-step or constrained generation tasks, prefer a generate → evaluate → repair loop with several simple, focused prompts over one giant monolithic prompt.

F.3 Tina Huang: Google’s 9 Hour AI Prompt Engineering Course In 20 Minutes Tina Huang

- Use the five-step TCREI framework for every prompt: **Task** (what to do, plus persona + desired format), **Context** (background, audience, constraints), **References** (examples / few-shot), **Evaluate** (does the output meet the need?), **Iterate** (refine and retry). Mnemonic: “Tiny crabs ride enormous iguanas” (or Google’s “Thoughtfully Create Really Excellent Inputs”).
- Always be iterating (“ABI”). Four practical iteration methods: (1) revisit the full TCREI framework and add missing pieces, (2) break long prompts into shorter, clearer sentences, (3) rephrase or try an analogous task, (4) add constraints to narrow the solution space.
- Specify persona and output format early in the Task step—they dramatically improve relevance and usability.
- Provide rich context and concrete references/examples; more relevant detail almost always beats a sparse prompt.
- Multimodal prompting follows the same principles: clearly state what the inputs are (text, image, audio, etc.) and what form the output should take.
- Watch for hallucinations and inherited biases. Keep a human-in-the-loop: always verify important outputs before using or sharing them. Avoid feeding sensitive data into public models.

- For everyday work: build and maintain a personal prompt library of reusable, high-performing prompts (emails, summaries, tables, brainstorming, etc.).
- For data analysis & presentations: prompt for insights, formulas, patterns, and slide structures, but treat generated numbers and claims with extra scrutiny.
- Advanced techniques:
 - **Prompt chaining** — break a complex goal into a sequence of linked prompts, feeding each output into the next (e.g., manuscript → summaries → taglines → full marketing plan).
 - **Chain-of-Thought (CoT)** — explicitly ask the model to show its step-by-step reasoning.
 - **Tree-of-Thought (ToT)** — ask the model to explore multiple reasoning paths / options in parallel and evaluate them.
 - **Meta-prompting** — ask the AI to help write or improve the prompt itself when you are stuck.
- Create lightweight AI agents by defining a clear persona, context, conversation rules, and a stop phrase. Two useful patterns: simulation agents (role-play / practice interviews) and expert-feedback agents (critique pitches, drafts, etc.).
- Responsible use checklist: verify accuracy, check for bias, protect sensitive information, and treat AI as a collaborator rather than an infallible authority.

F.4 DeepLearningAI: Prompt Engineering for Developers

DeepLearningAI Andrew Ng

- Treat the AI like a smart, highly motivated fresh college graduate who knows nothing about you yet. Give it the context a new hire would need (documents, screenshots, project trackers, voice memos, past work) instead of short Google-style queries.
- Provide rich, relevant context. Modern models can handle very large context windows (~750k words). Start a new chat for unrelated topics so stale context does not degrade performance.
- Understand the three knowledge sources and when to use each:
 - Pre-trained knowledge (good for general/common facts; limited by training cutoff and data frequency).
 - Web search (real-time info; note that the main model often only sees summaries produced by a helper model, not the full pages).
 - Deep research / agentic modes (many parallel searches, iterative evaluation, synthesized cited reports—for complex, multi-source questions).
- Defeat sycophancy (the model's tendency to please you). Ask neutral questions that do not hint at your preferred answer. Use objective rubrics with clear scoring criteria *before* asking for a score or judgment.

- Use AI as a thought partner, not a one-shot answer machine. For brainstorming: supply context → request multiple options → give feedback → iterate. Feedback on options often matters more than more upfront context.
- Prefer progressive outlining for writing: outline → critique/refine the outline → expand to bullet points → iterate → only then draft full text. This avoids generic “AI slop” and makes structural changes easy.
- For complex reasoning tasks, explicitly cue longer thinking (“think hard,” “ultra think,” or enable reasoning/thinking mode). Classic “think step by step” is largely obsolete on modern models.
- When editing or evaluating work, give the model a clear rubric first; then ask it to apply the rubric. This produces more objective, useful feedback.
- Leverage multimodal and tool-using capabilities: upload images/files, generate images, analyze data/spreadsheets, write and run code, and build simple websites/apps with natural-language instructions (no coding background required).
- Desktop/agent AI apps can explore local files (with permission). Best practice: state the overall task, let the model propose a plan, then approve execution.
- Power-user habits: iterate aggressively, request multiple options, keep conversations focused, verify important claims (especially from search/deep research), and continually give the model harder, more context-rich tasks.

G Articles & Blogs

- [The Prompt Is Not the Architecture — But It Still Governs How the System Reasons](#)

G.1 The Prompt Is Not the Architecture — But It Still Governs How the System Reasons (Interesting Engineering, 2026-05-23)

- The prompt is not the architecture, but it still governs *how* the system reasons. Architecture (harness, tools, gates, loops, meta-observation) determines what the system can see and do; the prompt/spec governs reasoning style and action selection.
- Prompting has fragmented into four distinct disciplines (per Nate B Jones). Most people only practice the first:
 1. Prompt craft (structure, XML, role, output format)
 2. Context engineering (domain facts, background, memory tiers)
 3. Intent engineering (state the desired outcome / what “good” looks like, not just the task)
 4. Specification engineering (acceptance criteria, constraints, ordering, trade-off framings)
- A strong single structured system prompt that embeds all four disciplines can outperform multi-agent swarms on single-turn, well-scoped document tasks (H2 scored = 1.000; five-agent swarm scored 0.625).
- Brownfield (existing, messy production systems) vs greenfield (clean-slate tasks) matters. Complex constraint-satisfaction or continuous operational systems usually need correction loops or adaptive architectures, not just a bigger prompt.
- Generate → Evaluate → Repair (GER) loops are often more reliable and cheaper than relying solely on the model’s adaptive/extended thinking for hard constraint tasks.
- Instructions do not add capability. Arithmetic, deterministic calculations, and similar tasks should be offloaded to tools/functions rather than instructed in natural language.
- Legacy defensive patches written for older, weaker models can actively harm performance on newer models (e.g., causing the model to withhold information it actually has). Audit and remove outdated guardrails on model upgrades.
- Prefer trade-off framings over rigid binary rules for judgment calls (state both sides of the cost/benefit). Keep hard binary checks only at verification gates.

- Use API-level stop sequences / output contracts (not just prompt text) to enforce structured endings and reduce padding or runaway generation.
- Ordering of instructions matters: place steps in the same sequence a competent human would reason through the problem.
- The “35-minute wall”: once agents run autonomously for roughly that long without check-ins, chat-style prompting assumptions break. Everything critical must be pre-encoded in the specification before launch.
- Intent engineering (closing the loop between predicted outcomes and actual results, then calibrating future behavior) is often the missing operational discipline, not a pure engineering problem.
- Meta-harness / meta-observation layers that read execution traces across runs can surface failure modes that pure pre-specification cannot anticipate.
- Architecture choices should match the problem type: high-density single prompt for greenfield document tasks; correction loops + tools + meta-observation for brownfield continuous operations.