InfoQ ΑΚΚΑ

Design Patterns for Agentic Al:

Building Scalable, Event-Driven Systems

May 1, 2025

Moderated by: Erik Costlow, InfoQ Editor

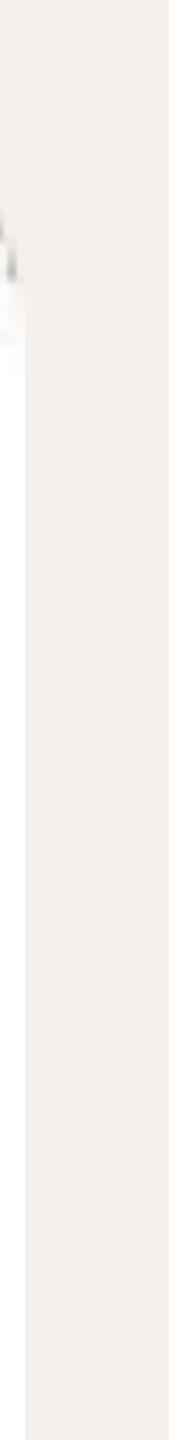
TYLER JEWEL

CEO @ Akka

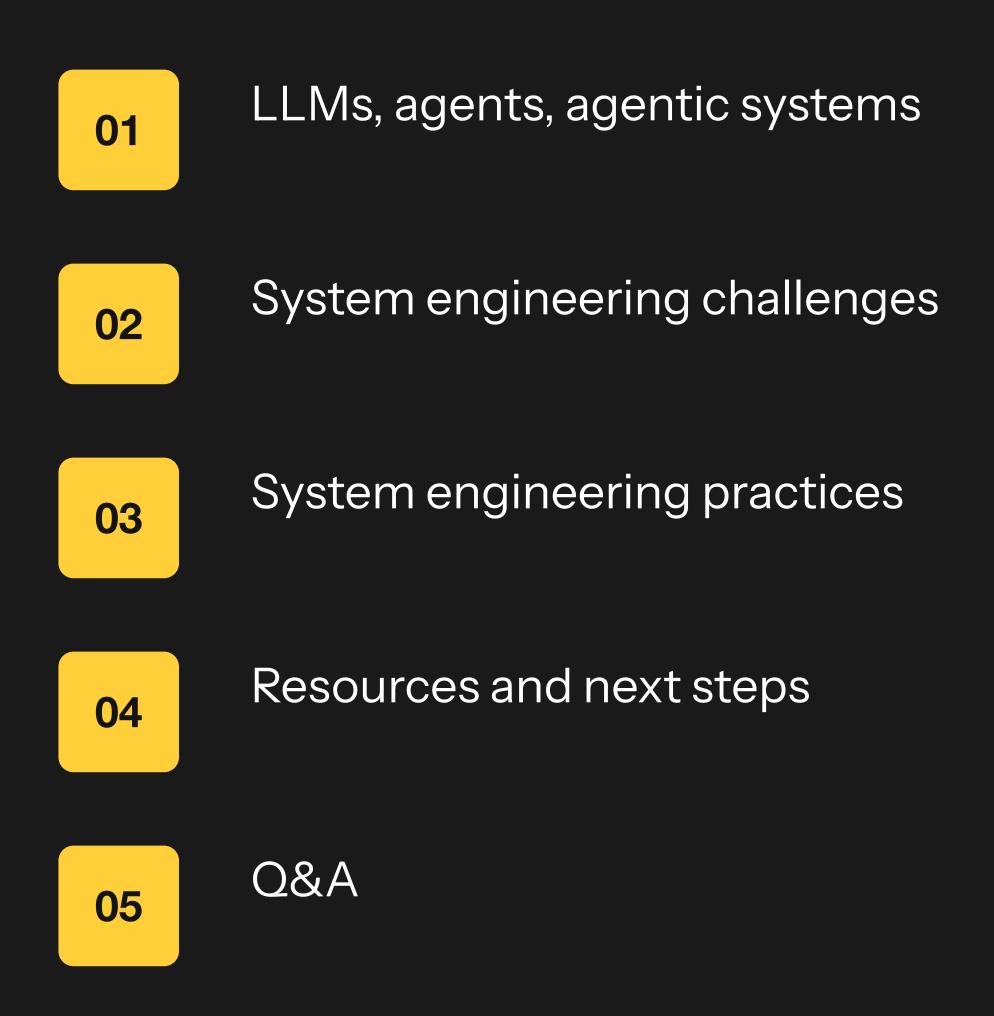


RICHARD LI

Founder of Amorphous Data



Today's agenda



AKK



Poll question





Agentic is real, but...there is a lot to learn Visit akka.io

The basics: User stories: Webinar: Samples Blogs: News: Get Started:

<u>What is agentic AI?</u> Agentic Al customer stories <u>A blueprint for agentic Al services</u> Production-ready agents <u>Agentic Al blogs</u> <u>Develop your own agentic app</u>

<u>Akka launches new deployment options for agentic Al at scale</u>

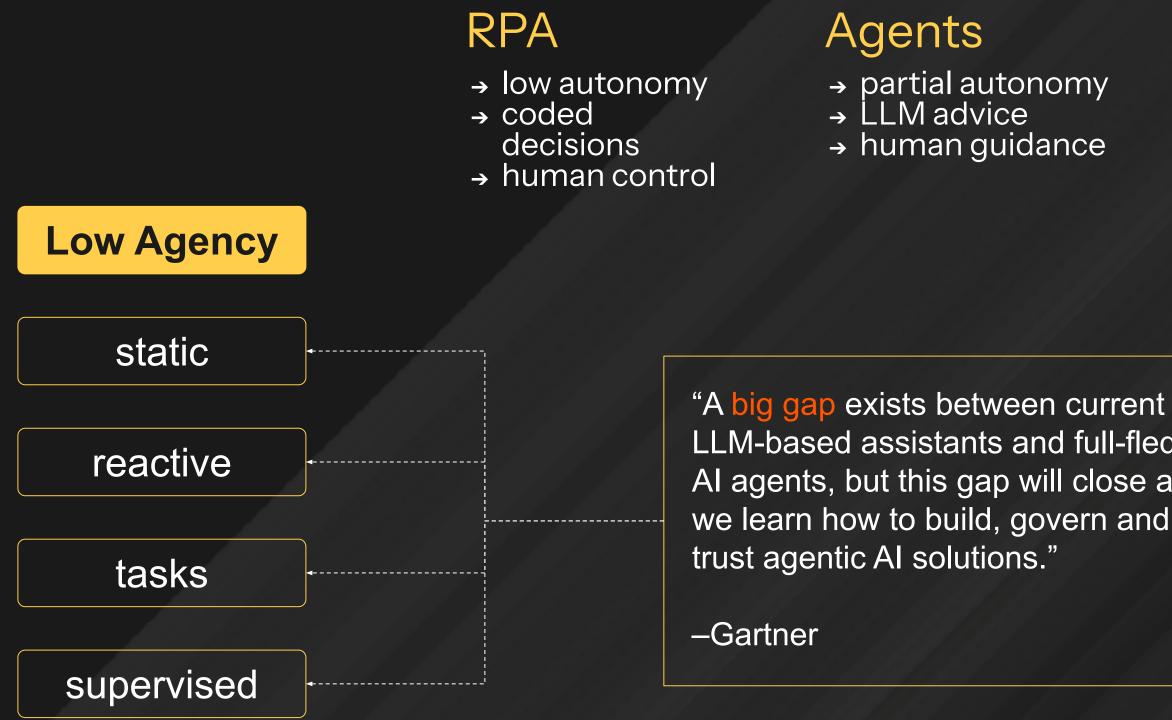


Agents and agentic systems are distributed systems, powered by Al ...that must deliver reliable outcomes ...while depending upon unreliable LLMs.





Alagency Capacity to make meaning from your environment



economic productivity

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→ partial autonomy→ LLM advice → human guidance

Agentic

- → high autonomy
- → distributed decisions
- → group coordination

Humans

adaptive

High Agency

proactive

goals

autonomous

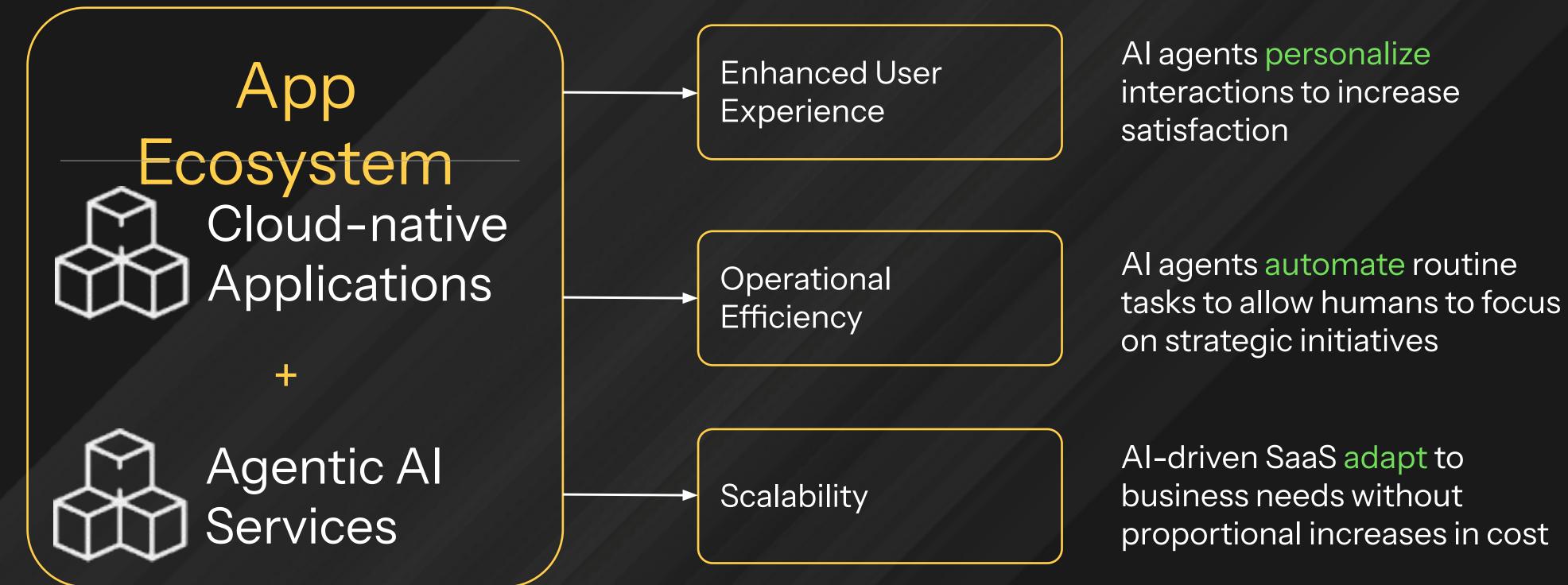
LLM-based assistants and full-fledged Al agents, but this gap will close as we learn how to build, govern and

cost



A paradigm shift to Al-fueled app ecosystems Al agents and apps become part of a symbiotic existence

By 2028, 33% of enterprise software applications will include agentic AI, up from less than 1% in 2024. Gartner, TSP 2025 Trends: Agentic AI — The Evolution of Experience, 24 February 2025



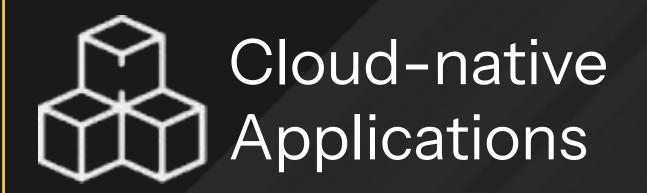
Al agents personalize interactions to increase



LLM-powered app services are intelligent

Models can be prompted to perform a range of user & system tasks

App Ecosystem



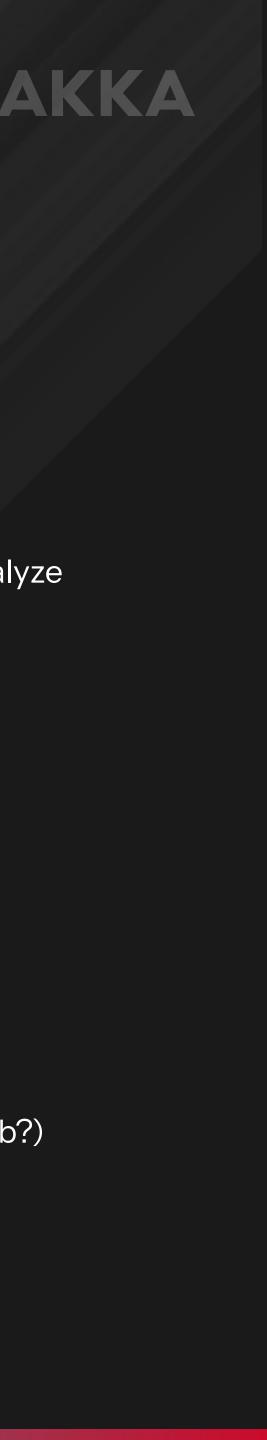
Agentic Al **U** Services

Input LLM automation varies by data type

Response

SaaS app use cases and behavior





Rethinking how your system makes decisions

Solve problems where deterministic and rule-based approaches fall short

Multi-faceted decision making

Workflows involving judgement, exceptions or context-sensitive decisions, for example when to escalate a support ticket

Constantly changing rules

Systems whose rulesets frequently change, have extensive conditions, or burdensome to maintain, such as identifying inappropriate language

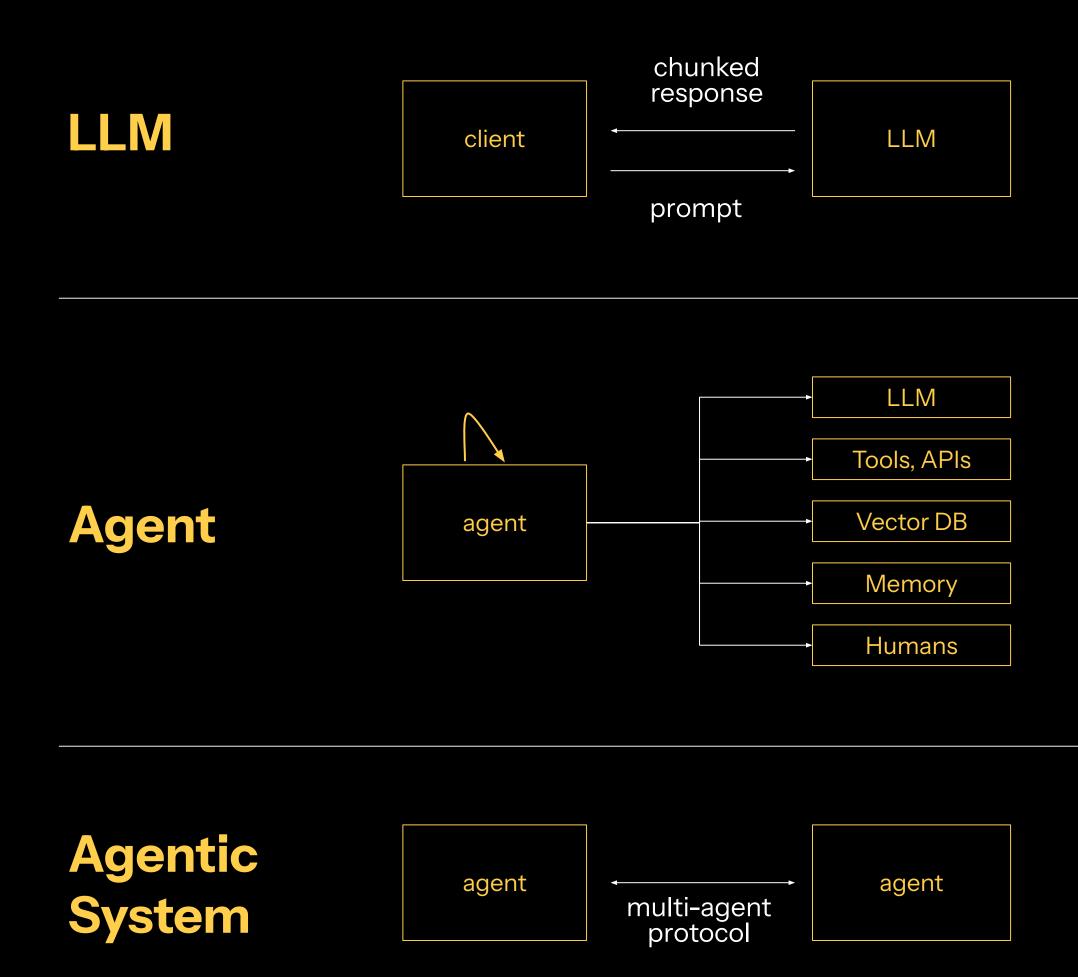
Reliance on unstructured data

Extracting meaning from content, interpreting language, audio or images, and conversational responses, such as with a support chatbot



From LLMs to Agentic Systems

Agents give structure to LLMs; agentic systems give scale to agents





Stateless, long-running, computationally intensive resources that can analyze, reason, and plan

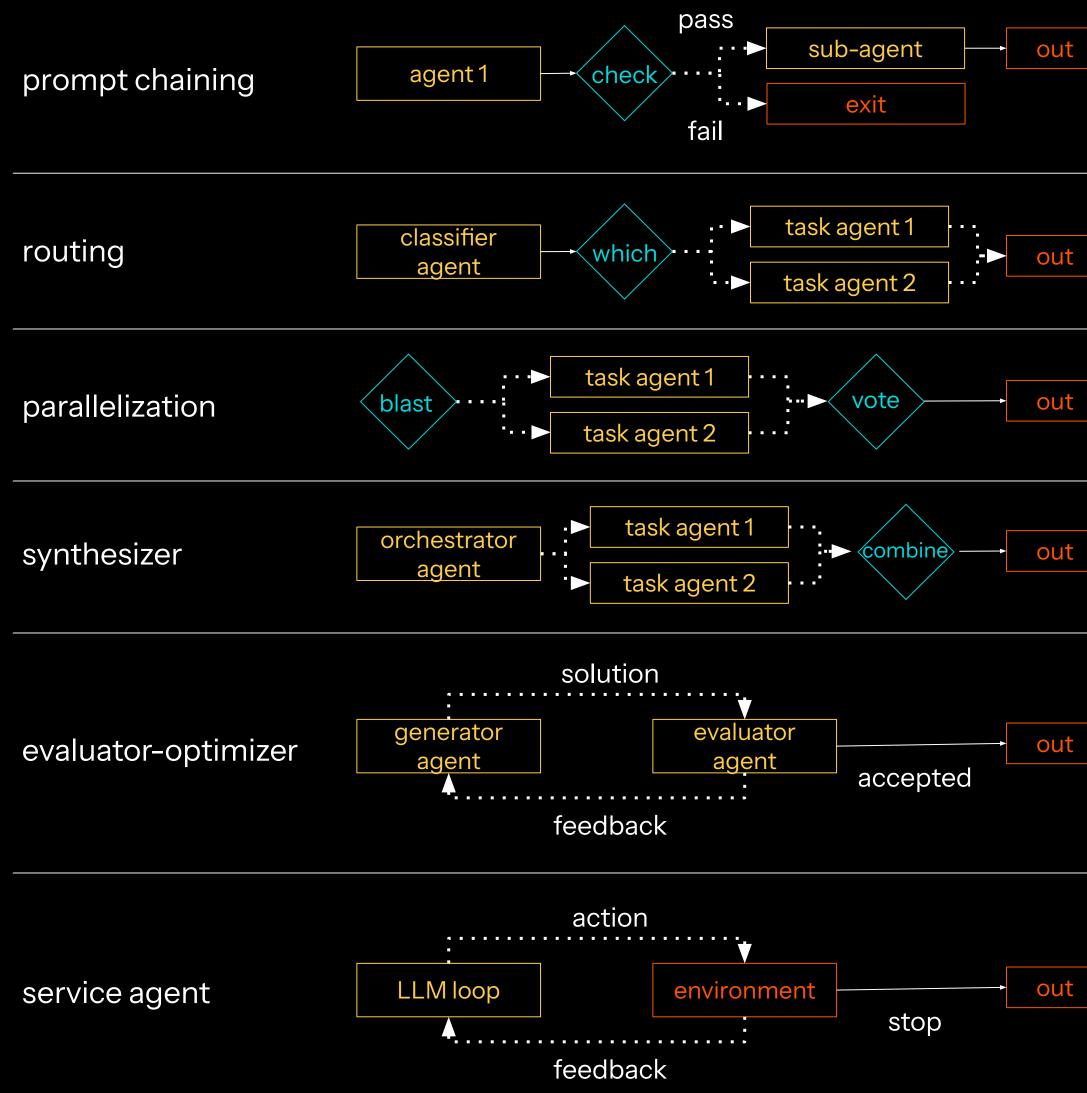
Structured enrichment loop that builds context, invokes tools, takes action, and gathers human feedback

Networks of multiple agents orchestrated to solve complex tasks



Patterns for agentic systems create intelligence

Agent collaboration enables reliable, goal-driven reasoning



ut	Tasks that can easily be decomposed to subtasks: e.g. write a blog then translate to French.
ut	An LLM router classifies a task for routing to an LLM specialist: e.g. classify this support call as either sales or technical
Jt	LLM subtasks can be divided for speed or multiple runs: <i>e.g. execute security tests from different povs, with success voting</i>
Jt	An orchestrator LLM breaks down tasks not known in advance: e.g. gathering information from targets identified by orchestrator LLM
Jt	One LLM generates a response while another provides feedback: e.g. a translation LLM that has nuance checking from evaluator LLM
	Create and execute a complex plan while staving "grounded" with feedb

Create and execute a complex plan while staying "grounded" with feedback: e.g. create a travel itinerary and book all reservations for a vacation

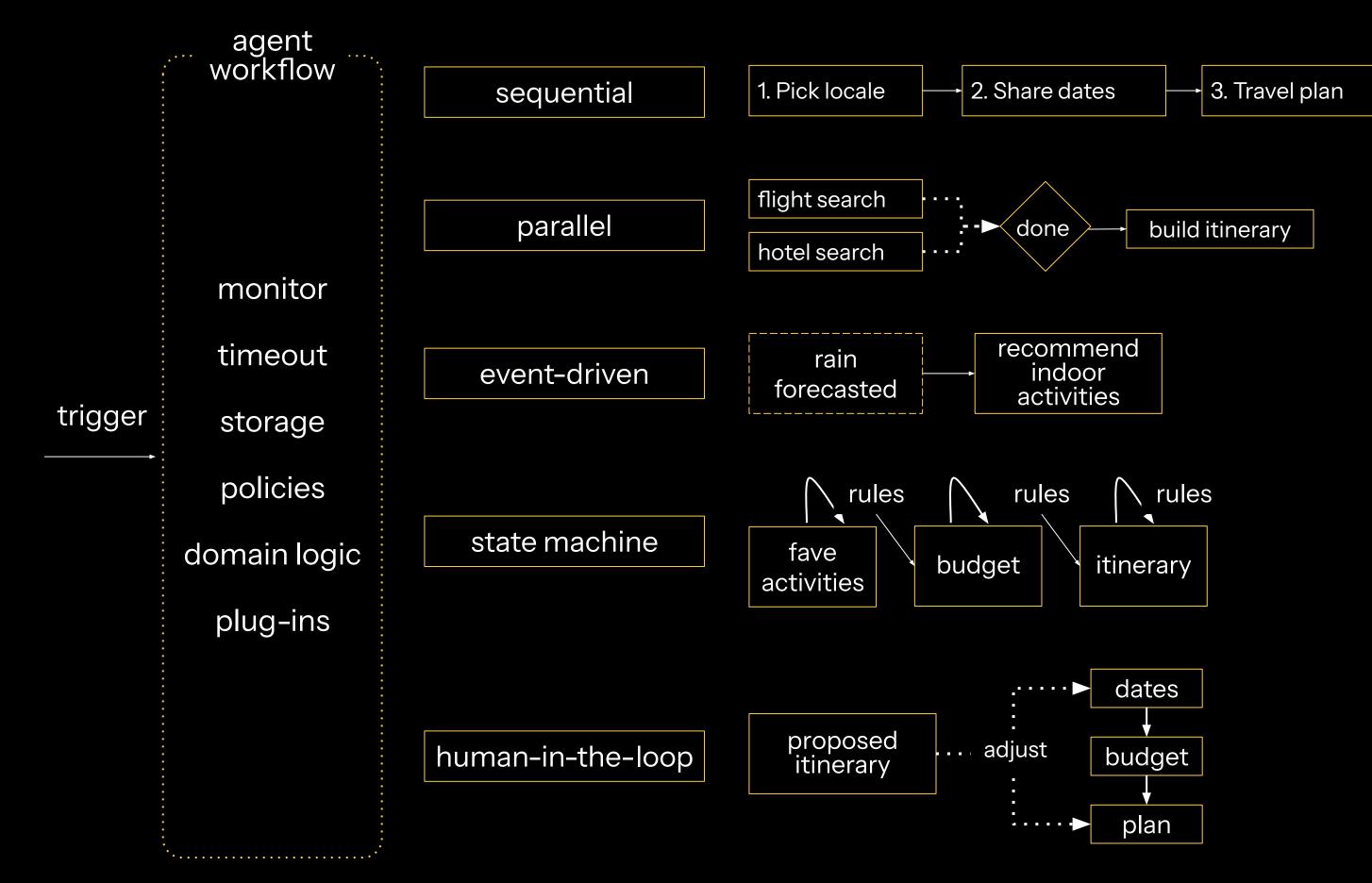


Multi-agent systems are orchestrated

Traceable, auditable, debuggable, with point-in-time recovery

Agentic systems are workflows

reliable execution of AI tasks with visibility into request / response data, built-in retries, and error compensation

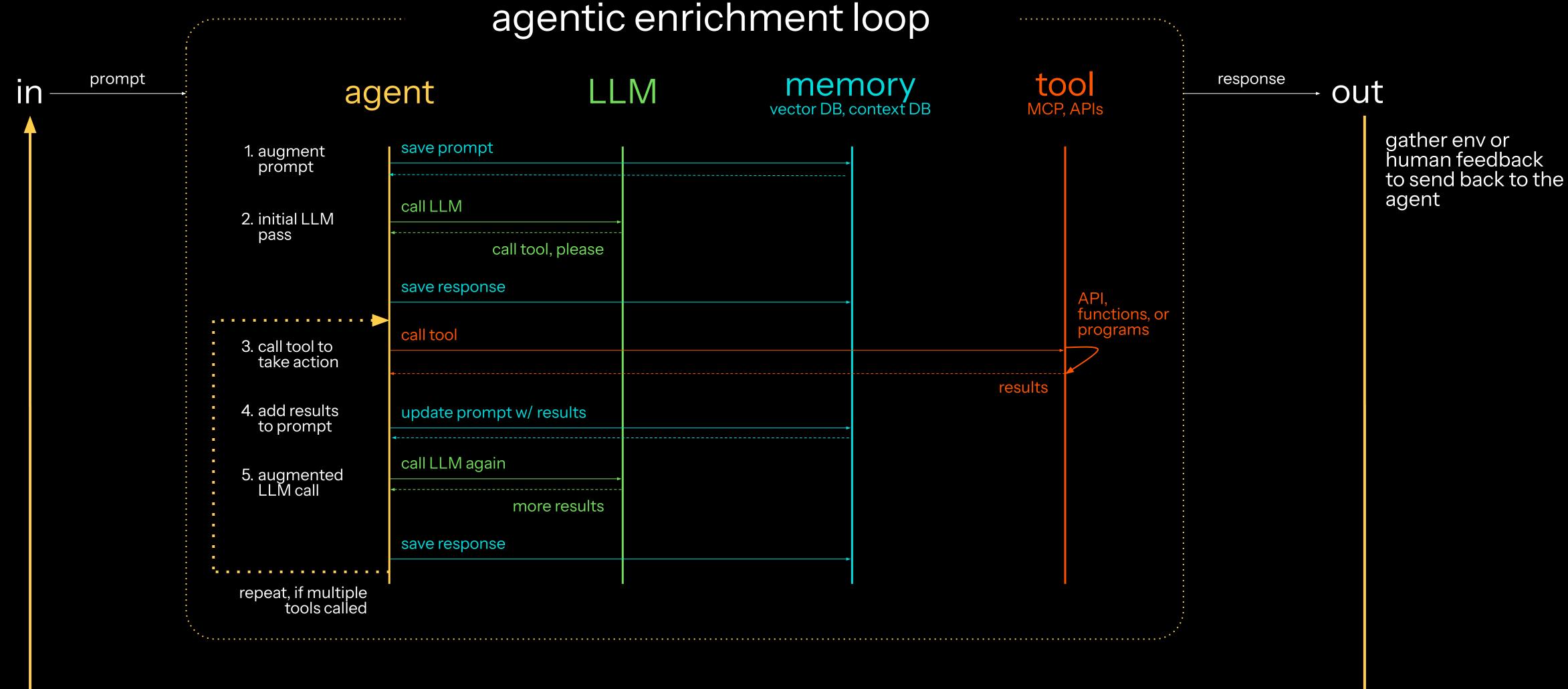


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Single-agent enrichment loop

Prompt \rightarrow retrieve \rightarrow enrich \rightarrow repeat is a repetitive cycle & pattern

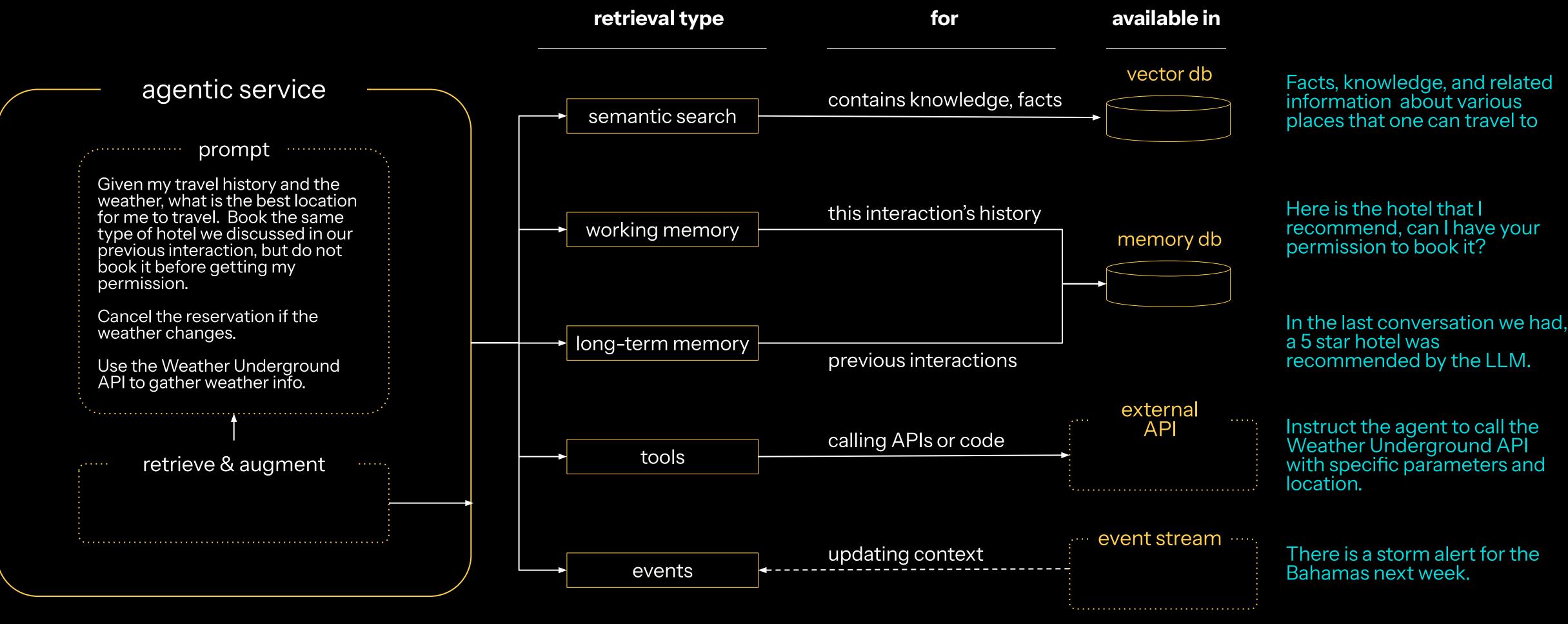






LLMs are stateless. Context is assembled.

Agentic services augment prompts with data from many sources.

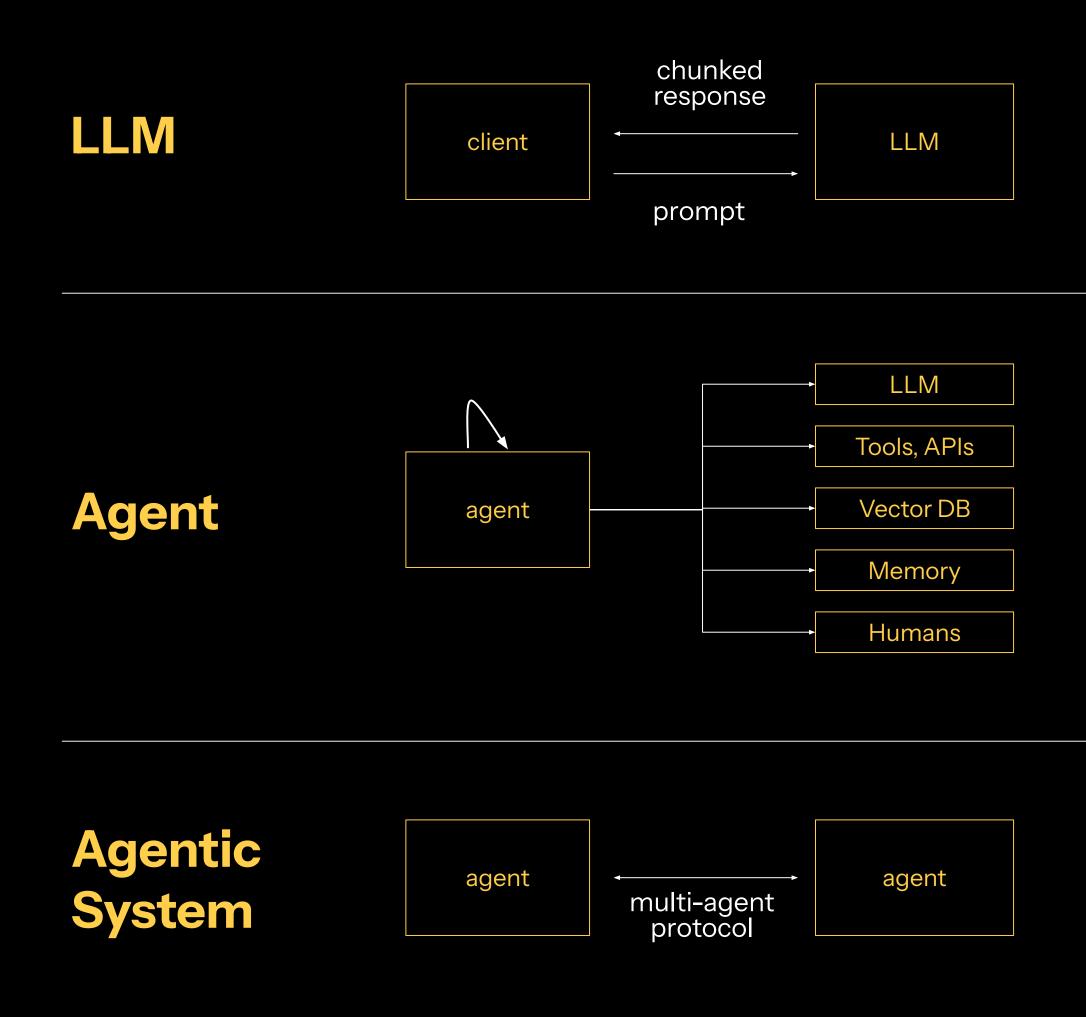






Agentic systems are distributed systems

Architectural techniques and practices required for scale and resilience



- → Async, non-blocking invocation
- Event-based, streaming responses \rightarrow
- Backpressure
- Event-driven architecture
- Human-in-the-loop interaction \rightarrow
- → Streaming real-time ingest
- Retries, circuit breakers, timeouts \rightarrow
- Memory & tool integration \rightarrow
- CQRS \rightarrow
- **Replication and failover**
- Durable workflows
- Distributed tracing \rightarrow
- → Discovery & mesh networking
- → Multi-agent protocols: A2A, BeeAl

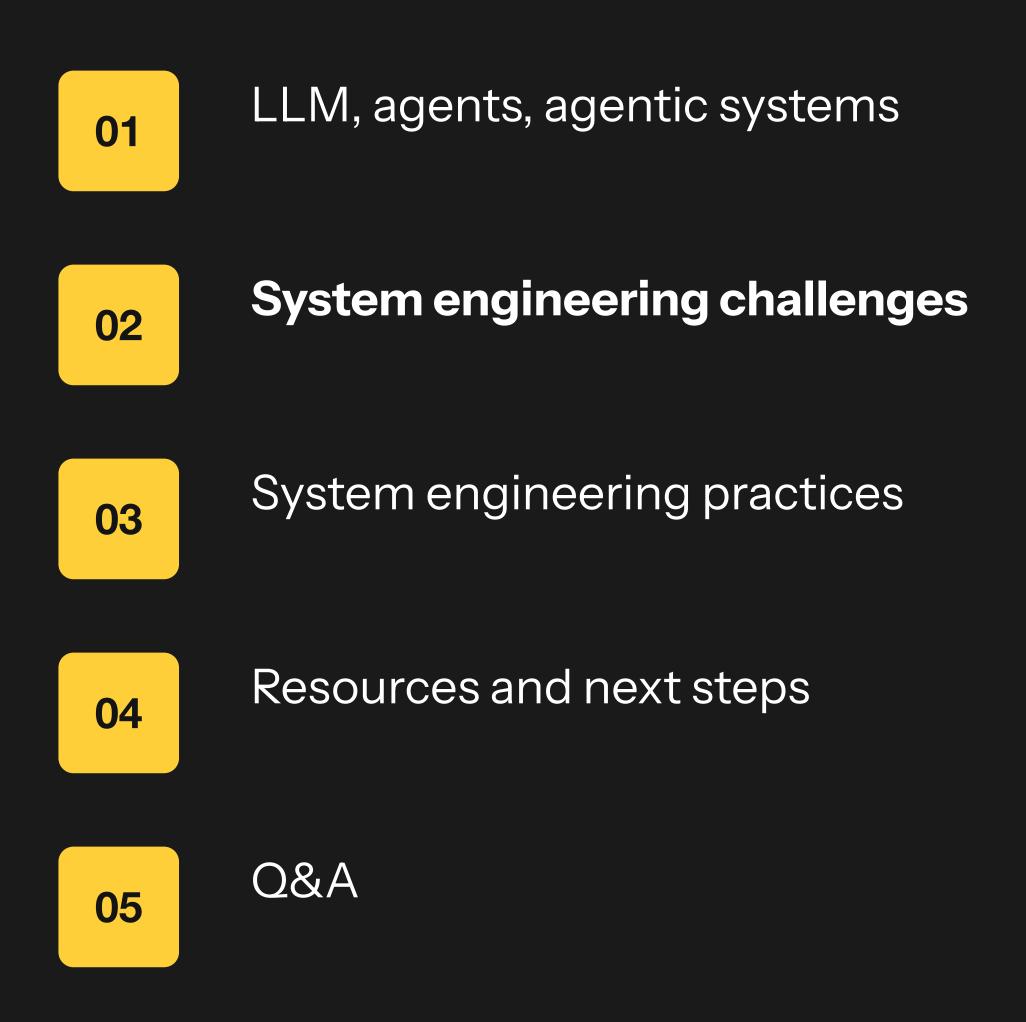


Poll question





Today's agenda



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Bumpy path from POC to production Top three enterprise challenges: uncertainty, privacy, and scale

fail to reach production

52%

"Leaders reported that only 48% of Al POCs (Proof Of Concept) make it into production, and they take an average of 8.2 months to go from POC to production."

8+ months POC to production





Uncertainty: From deterministic to stochastic

Randomness cannot be eliminated and must be embraced

LLMs are not deterministic components

- Same prompt \neq same output.
- They predict tokens, not answers.
- You don't pass parameters you design prompts.
- Hard to predict outputs, validate correctness, or reproduce behavior.

Prompting isn't programming

- No function signatures. No modular reuse.
- Tiny prompt changes can break results.
- Long prompts increase latency.
- And prompts don't always work the same across workflows or chains.

Retrieval adds more uncertainty

- In RAG, you're combining semantic search, reranking, and formatting.
- Each step adds noise.
- Generating over possibly irrelevant context.
- Now the system is **doubly stochastic**: retrieval + generation.

Testing LLMs isn't straightforward

- There's no .assertEqual().
- Heuristic metrics are flawed.
- Human evals are expensive and inconsistent.
- Even stable outputs might still be wrong.

Scaling makes it even harder

- LLMs are slow, expensive, and limited by token windows.
- You need streaming, chunking, caching, windowing, reranking, fallback.
- You're not calling a model your orchestrating a distributed system.
- Cough, cough why Akka :)

Debugging is a black box

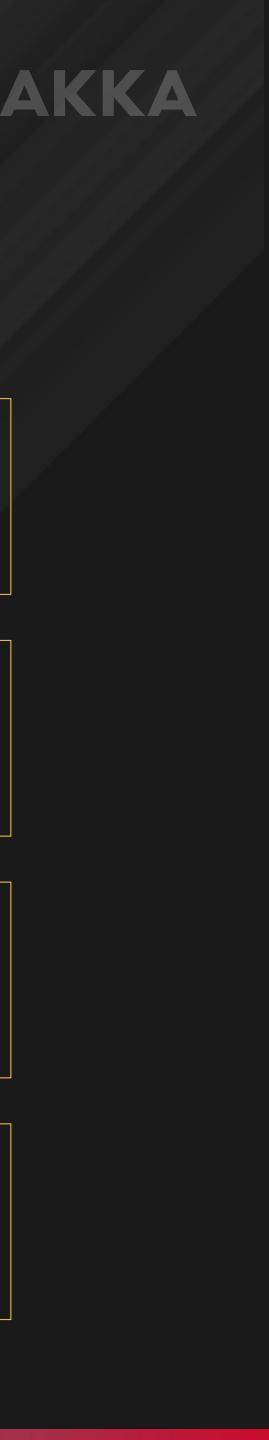
- No stack traces.
- No explanations.
- Logs give you input/output, not reasons.
- Prompt tweaks can cause side effects far from where you made change.

Expectations ≠ reality

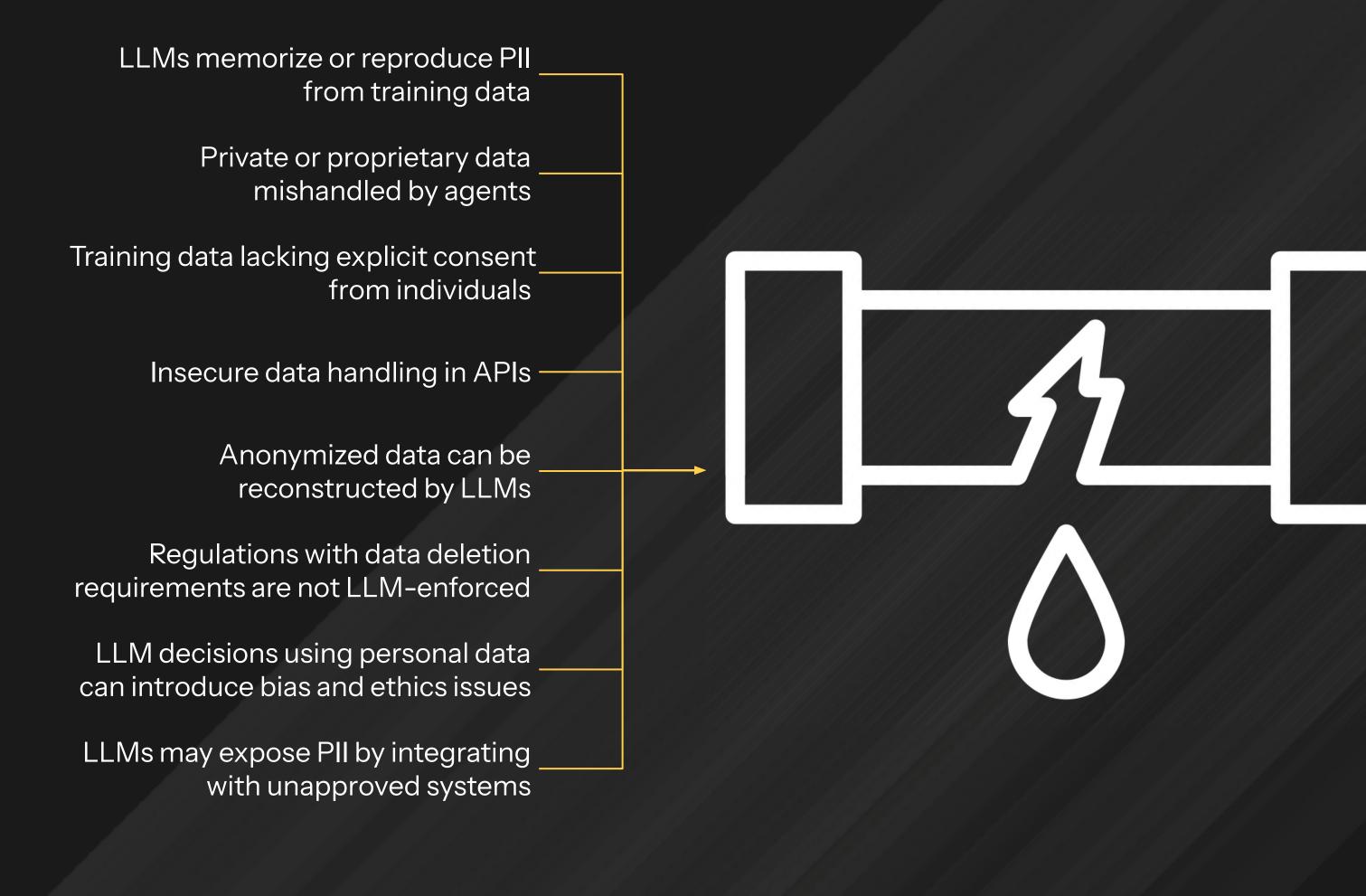
- People expect memory, perfect instructions, stable outputs, and truth.
- LLMs forget, hallucinate, and drift based on sampling.
- Without scaffolding, they will be (and feel) brittle and inconsistent.

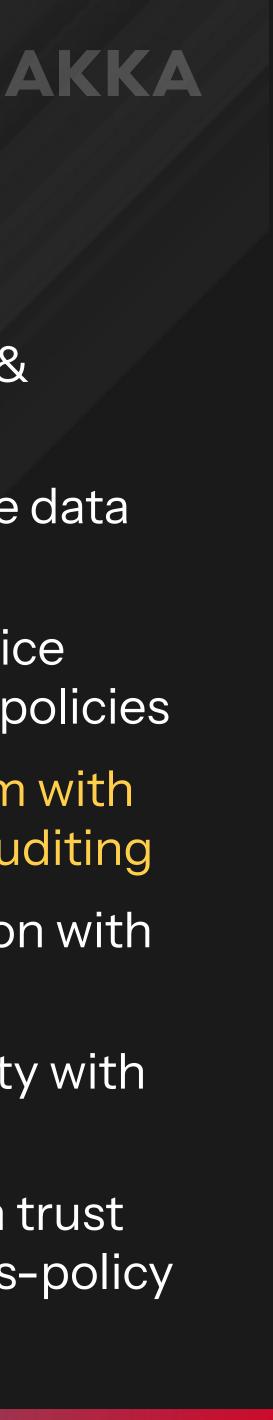
If you're looking for vibes, it will be short lived

- LLMs are probabilistic pattern matchers not deterministic APIs.
- Building with them means thinking in systems, not functions.
- It means controlling chaos, not eliminating it.



Privacy and compliance horror show LLMs are leaky sieves creating numerous holes for security to plug





Establish clear security & compliance guidelines

Enable enterprise-grade data controls

Implement agentic service interaction and logging policies

Choose agentic platform with tracing and reasoning auditing

Implement risk mitigation with content filtering

Implement agent identity with roles and permissions

Memory hardening with trust controls and min-access-policy

Enterprise agentic scale requires efficiency

More txs: each slower, less predictable and more costly

	SaaS	Agentic	
Users	billions	20x	
TPS	10,000	100x	
p(99) Latency	10-80ms	15-400x	
Cost / LLM tx	cheap	10–10,000x	
Mar 25: the best performing LLM @ 86% MMLU accuracy costs \$98 / 1M tokens, or ~850,000x more expensive			

Mar 25: the best performing LLM @ 86% MMLU accuracy costs \$98 / 1M tokens, or ~850,000x more expen than the average database transaction. The worst performing LLM @ 36% MMLU accuracy costs \$.01 / 1M tokens, or 7x more expensive.



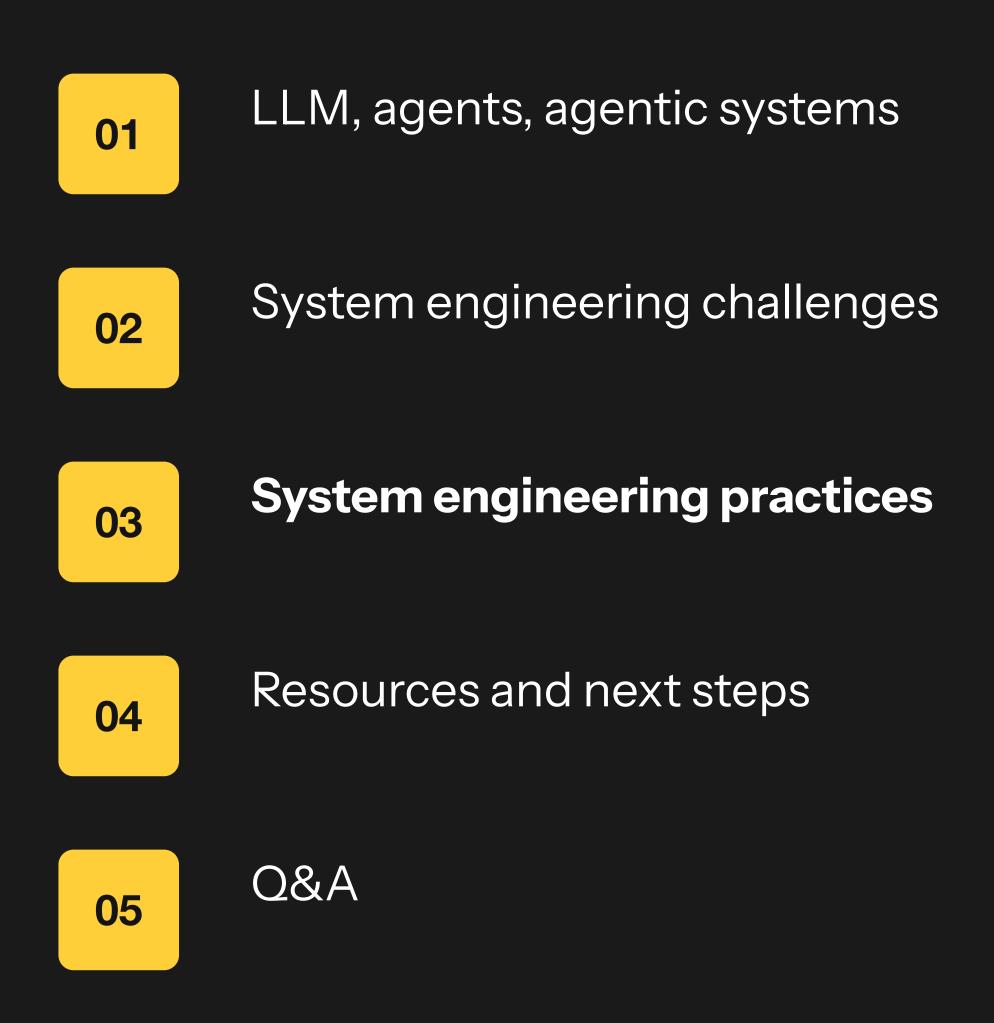


Poll question





Today's agenda



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Agentic systems engineering for reliability

1. Execute a DDD and AI-DD process	 → Produce contex → Define overall c → Develop localiz
2. Define data sovereignty and scope	 → Company-spec → Country or region
3. Establish evaluation strategy	 → Make reasoning → Build synthetic
4. Select the right Al models	 → <u>Reasoning mod</u> → <u>General models</u> → <u>Small language</u> → <u>Fine-tuned indu</u>
5. Select agentic platform architecture	 → Choose platforr → Rqmts: Durable → Rqmts: Elastic,
6. Build developer workflow and agents	 → Refine develop → Build initial vers
7. Deploy and observe	→ Release, monit

- xt map, ubiquitous language, and bounded contexts orchestration and flow across bounded contexts zed workflows for each bounded context
- cific requirements (e.g., retention policies, audit logging) ional regulations (e.g., GDPR, HIPAA, financial data rules)
- ig visible and measurable from the start evaluation sets to test reasoning steps
- <u>dels</u>: OpenAl o3, Claude Sonnet, DeepSeek <u>Is</u>: OpenAl GPT-4o, Gemini Pro, LLaMa <u>e models</u>: Phi-4, Mistral 7B, Claude Haiku, Gemini Flash <u>ustry models</u>: DeepSeek-Coder, CodeLlama
- m that enables services that transact and reason e execution, event-driven, memory, streaming, and tools support , <20ms p99 latencies, resilient, multi-region failover
- per workflow
- sions of your agent(s)
- tor, and refine agent based on real-world behavior



Techniques for reducing uncertainty

Design to anticipate randomness while embracing failure as expected

Leverage strategies that create layers of certainty

Create reasoning layers that break complex plans into stages, steps, or sub-tasks that can be validated or checked by downstream agents or humans.

Incorporate eval-driven development

Continuous testing and experimentation of different inputs (real-world, synthetic, adversarial) to track and validate accuracy.

Choose an Agentic Al Platform proven to operate services scalably, safely

Leverage a framework and platform based upon proven runtime that supports distributed orchestration, event-driven behaviors, backpressure, streaming, and embedded memory.



Create layers of certainty

Incorporate multi-agent and human verification strategies

Human in the loop	Delegate decisions
Agentic awareness	Take more LLM thi
Check and balance	Get second opinio
Specialization	Limit LLMs to mak
Restricted decisioning	Limit LLMs to a fin



Y verification strategies

s to humans with workflow

inking time when observing uncertainty

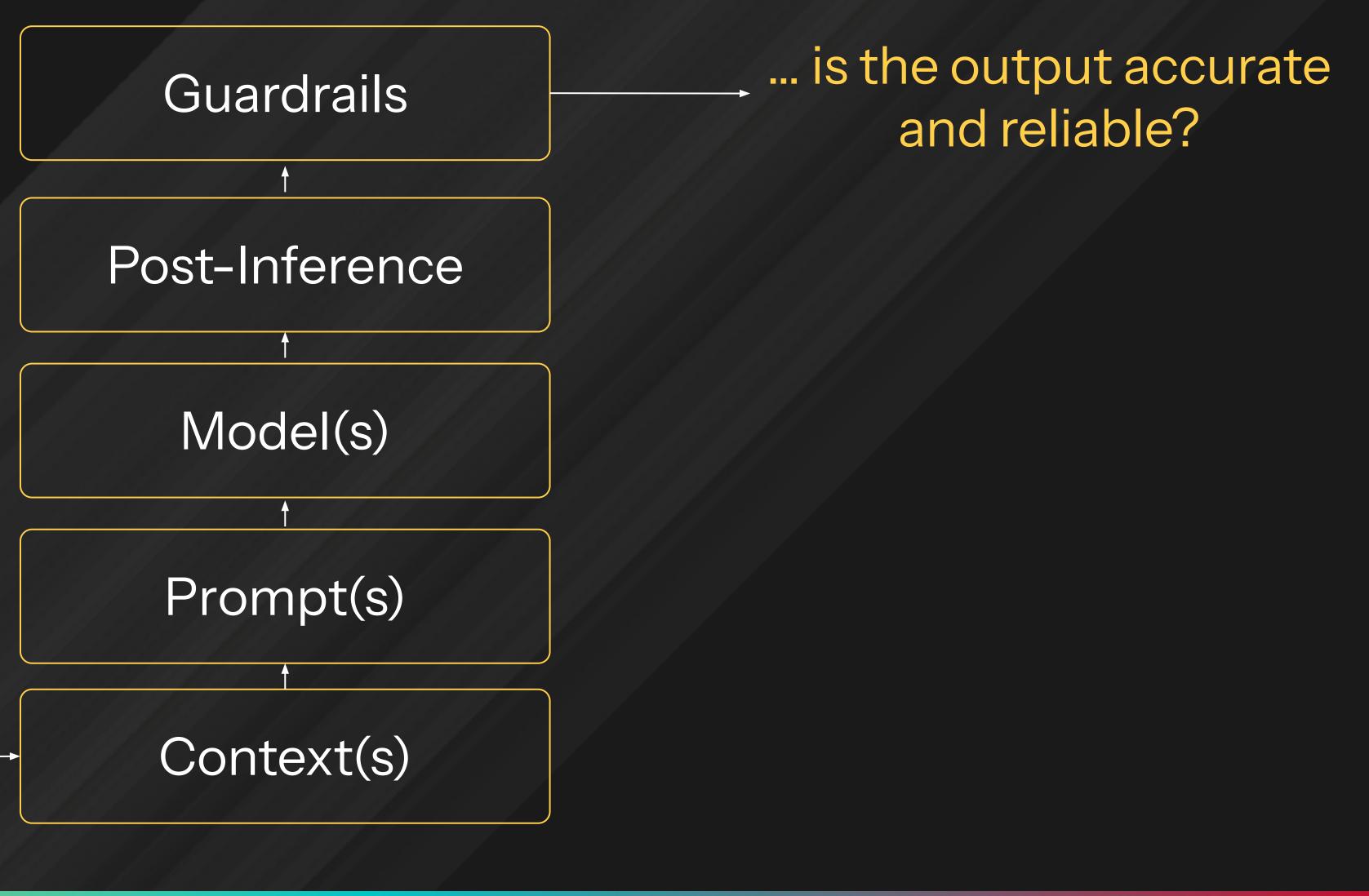
ons from other agents

king decisions in one area of expertise

nite set of outcomes



Incorporate evaluation-driven A system is only as reliable and accurate as its evaluation framework



vary inputs (adversarial, synthetic, real-world) and measure output validity

> Given a setof inputs ...





Choose a proven Agentic Al Platform

LLMs unlock reasoning – but there is no free lunch

LLMs are stateless No recall of prior interactions	Need a mer
LLMs need context Must be told everything upfront	Tools integr Knowledge
LLMs are stochastic Same input, different outputs	Rely on det Design for u
LLMs are unreliable May fail to respond or timeout under load	Adopt a dist Use a durat
LLMs are slow High latency, limited concurrency	Use stream



mory system

- ration
- integration (e.g., vector databases)
- terministic workflows as much as possible uncertainty
- tributed systems mindset ble execution framework

ning to improve responsiveness

Humans **IOT** Devices Audio / Video Metrics

Streaming Endpoints

Any Protocol In/Out Custom APIs

AKKA Data, APl and Agentic Al Services

Secure Observable Scalable

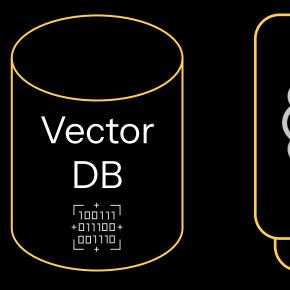
Agent Lifecycle Mgmt



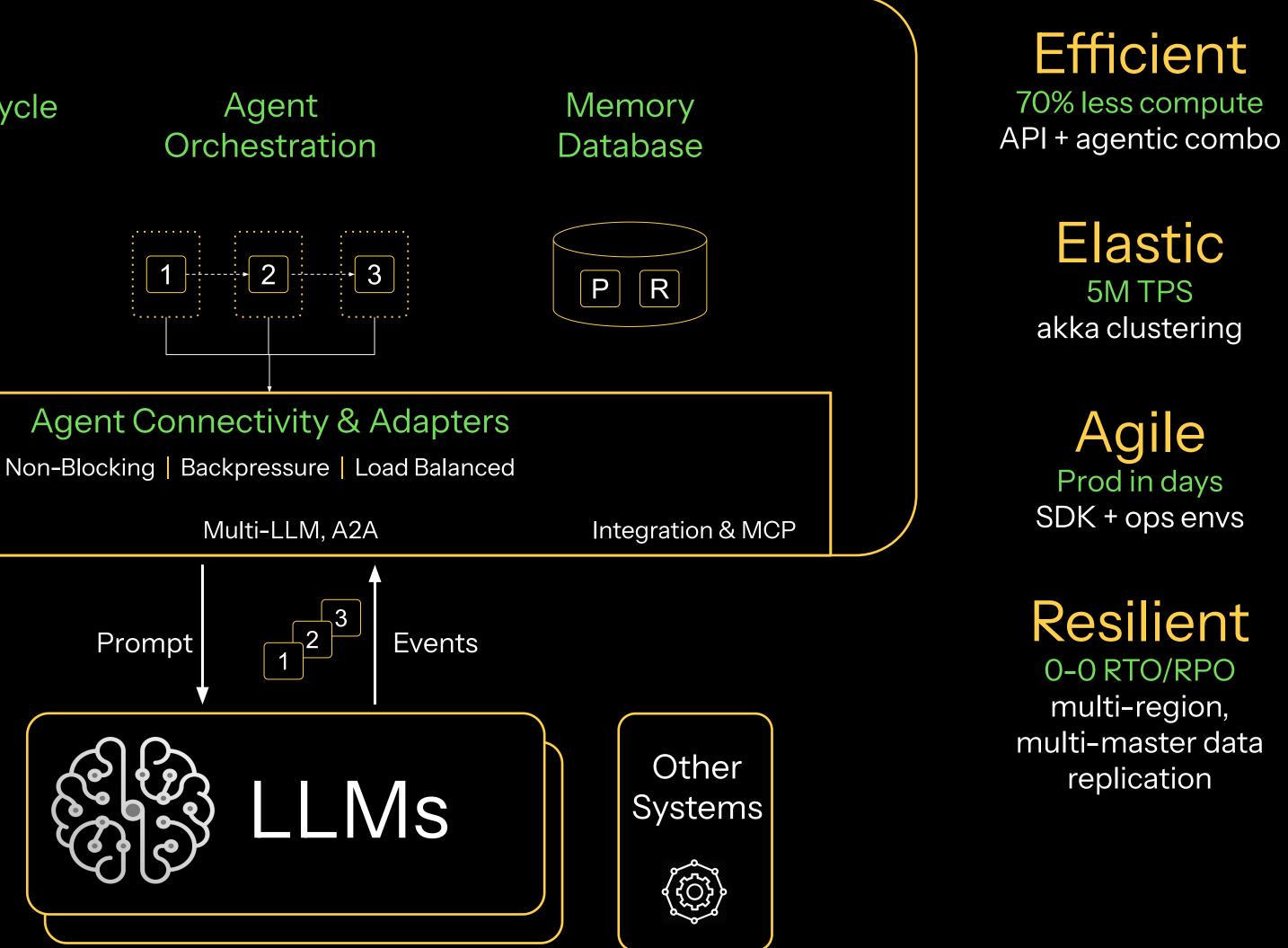


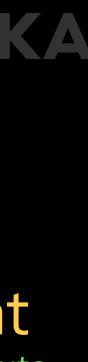
Semantic Search

Prompt



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The Akka agentic advantage

Agentic, AI, apps & data Hardened runtime ✓ Simple, expressive SDK Multi-region \checkmark Automated ops

Streaming endpoints

- endpoints
- \rightarrow

Agent connectivity & adapters

- → Non-blocking, streaming LLM inference adapters with back pressure
- → Multi-LLM selection
- \rightarrow LLM adapters & 100s of ML algos
- Agent-to-agent brokerless messaging \rightarrow
- 100s of 3rd party integrations \rightarrow

Agent orchestration

- → Event-driven workflow benchmarked to 10M TPS → SDK with AI workflow component \rightarrow Serial, parallel, state machine, & human-in-the-loop flows → Sub-tasking agents and
- multi-agent coordination

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→ Shared compute: agentic co-execution with API services → HTTP and gRPC custom API

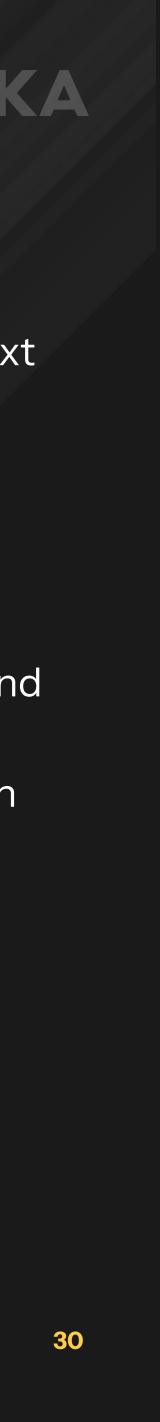
Custom protocols, media types, and edge deployments \rightarrow Real-time streaming ingest, benchmarked to over 1TB

Memory database

- → Agentic sessions with infinite context
- → Context snapshot pruning to avoid LLM token caps
- → In-memory context sharding, load balancing, and traffic routing
- \rightarrow Multi-region context replication
- → Memory filters for region-pinning and cross-session context creation
- Embedded context persistence with Postgres event store

Agent lifecycle management

- → Agent versioning
- \rightarrow Agent replay
- \rightarrow Event, workflow, and agent debugger
- → No downtime agent upgrades



2B people experience Akka daily

SMILE

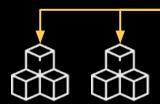
A fast ML engine with 100s of ML & LLM inference, powering Google Earth

400K downloads / mo 6K GitHub stars

"Akka is used for streaming and back pressure - critical for hosted AI API inference. Akka enables event-driven inference exposed as HTTP efficiently, with low latency."

Haifeng Li – maintainer

Swiggy API-driven predictions with multi-model fan-out and ultra-low latency



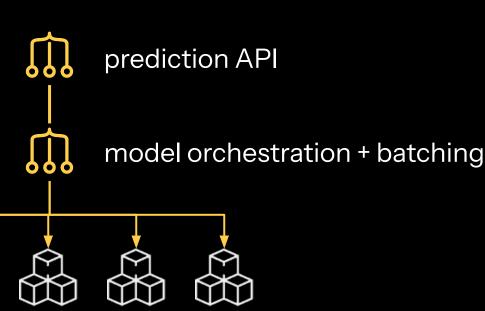
Horn

"Zero problems" augmenting high-performance audio and video streams on demand Tomasz Wujec - Lead Developer

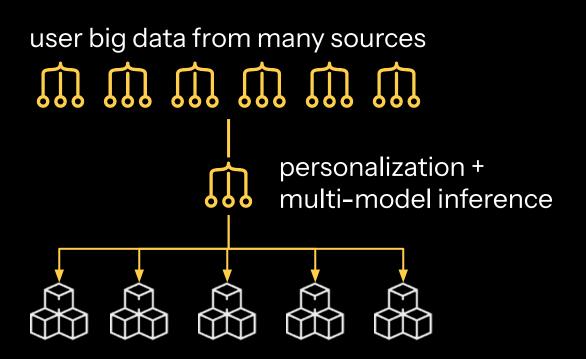
Tubi [Fox]

Tubi applies ML models to real-time streams of data with in-memory, durable journals

3+ million TPS 71ms p(99) latency



2 month time to delivery



Coho Al

"With Akka, we got to market 75% faster compared to other agentic solutions we had considered." Michael Ehrlich – CTO



Agentic is real Let's make it real for you

Additional resources

Webpage:	<u>What is agentic AI?</u>
Case Studies:	Agentic Al customer stories
Webinar:	A blueprint for agentic Al services
Samples	Production-ready agents
Blogs:	Agentic Al blogs
News:	<u>Akka launches new deployment</u>
	options for agentic AI at scale
Get Started:	<u>Develop your own agentic app</u>



Have a project?



concept



proof







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