

Web Science Application Development

RPI

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Session Agenda

- About Me
 - Living Upstate
 - Research
- AI Agents
 - What is traditional, generative AI, and AI agents?
 - Insights for your career
 - Business and generative AI

AI Agents

RPI

Agents

- [Langchain](<https://docs.langchain.com/oss/python/langchain/overview>)
- [Vercel AI SDK](<https://ai-sdk.dev/docs/introduction>)
- [LLM Powered Agents](<https://lilianweng.github.io/posts/2023-06-23-agent/>)
- [What is Rag](<https://blogs.nvidia.com/blog/what-is-retrieval-augmented-generation/>)

How Agentic AI Is Transforming Enterprise Platforms

By [Neveen Awad](#), Mahmood Serry, and Joe Vasquez

The Emerging Agentic Enterprise:
How Leaders Must Navigate a
New Age of AI

Findings from the MIT SMR-BCG Artificial Intelligence and Business Strategy Global Executive Study and Research Project

November 18, 2025

by: SAM RANSBOTHAM, DAVID KIRON, SHERVIN KHODABANDEH, SESH IYER, AND AMARTYA DAS

“Notably, 76% of respondents to our global executive survey say they view agentic AI as more like a coworker than a tool.” – Boston Consulting Group Study

From Analytics to Generative AI

TRADITIONAL AI



- Rules-based
- Fixed outputs
- Task-specific

GENERATIVE AI



- Creates text/images/code
- Limited autonomy

AGENTIC AI

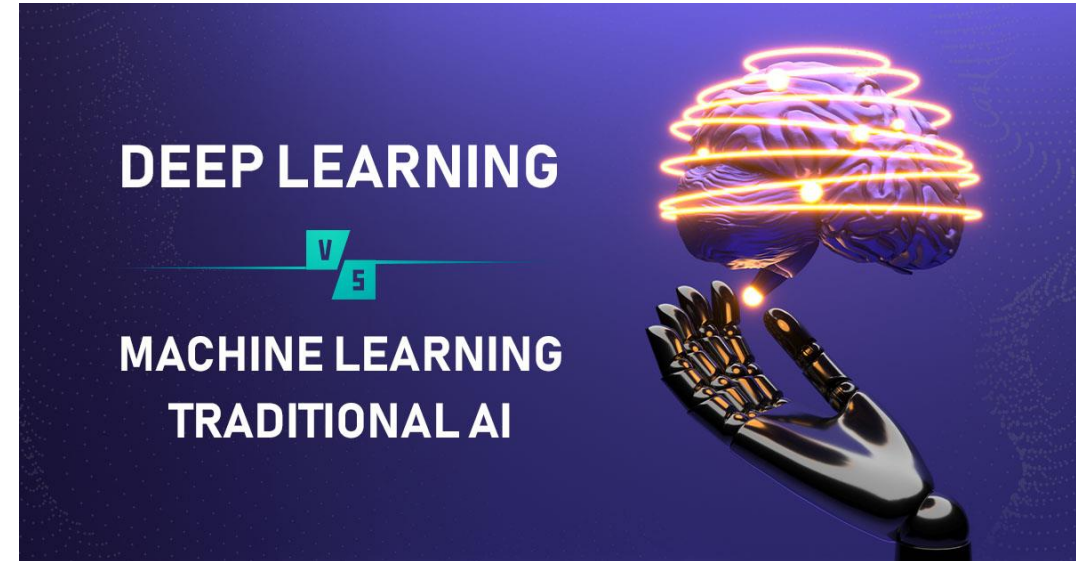


- Autonomous
- Plans, reasons
- Executes multi-step tasks

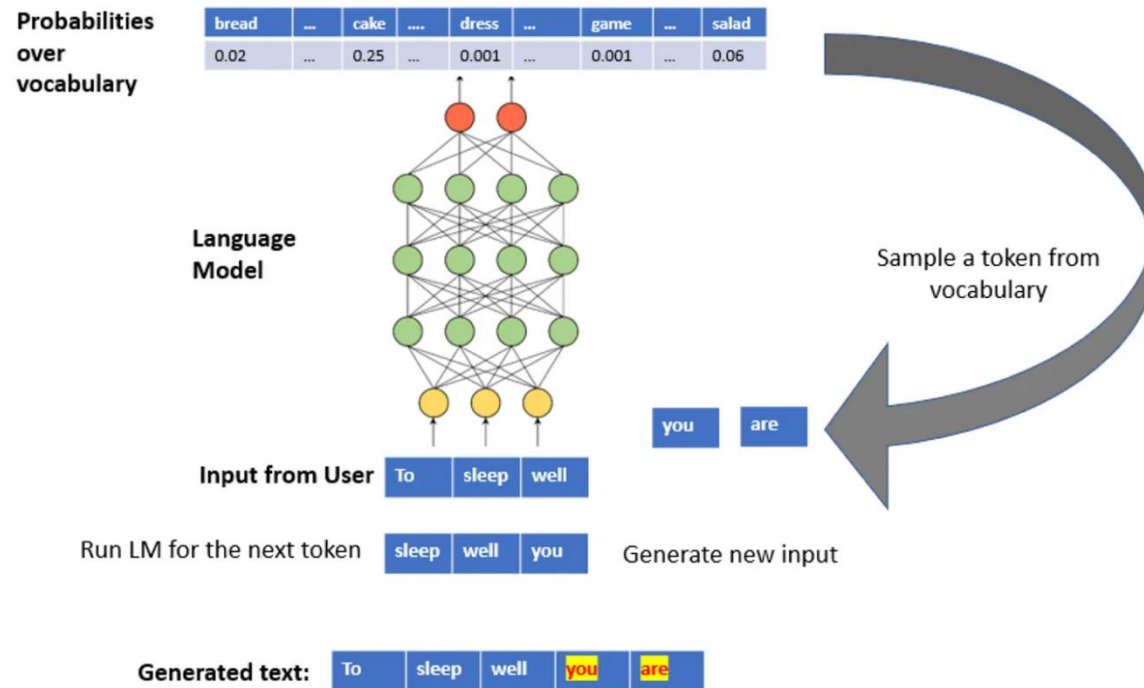
Traditional AI/Machine Learning

It is still important!

- Statistics
- Machine Learning
- Given a set of examples



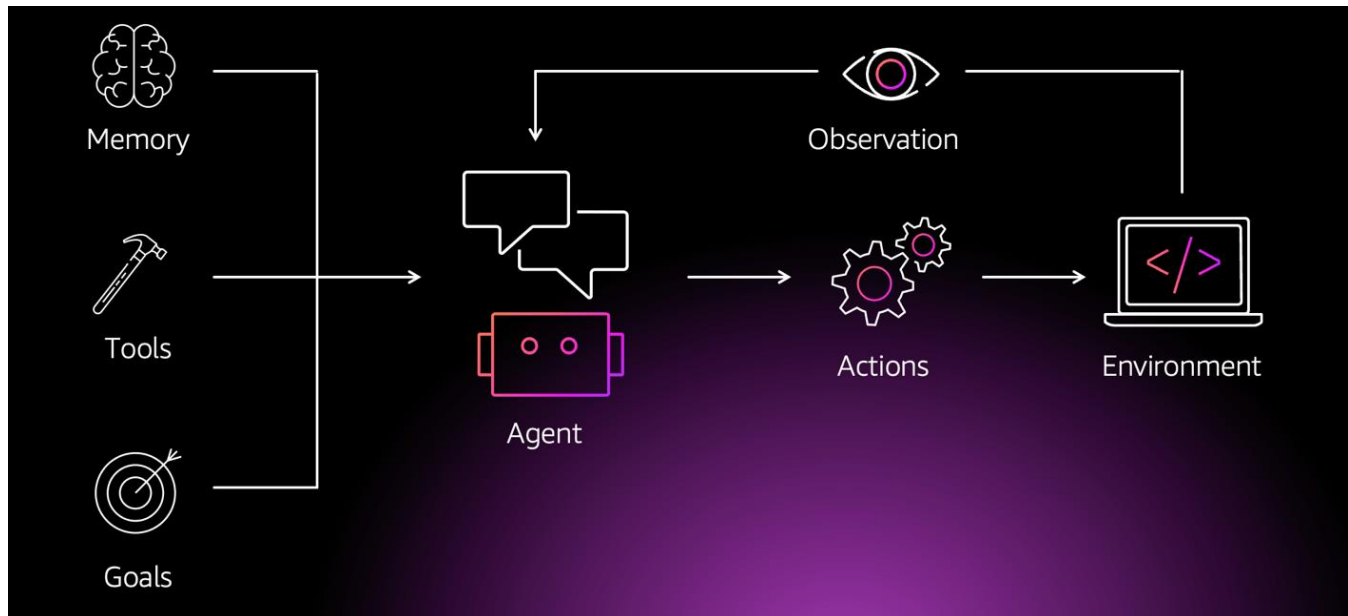
Generative AI/LLMs



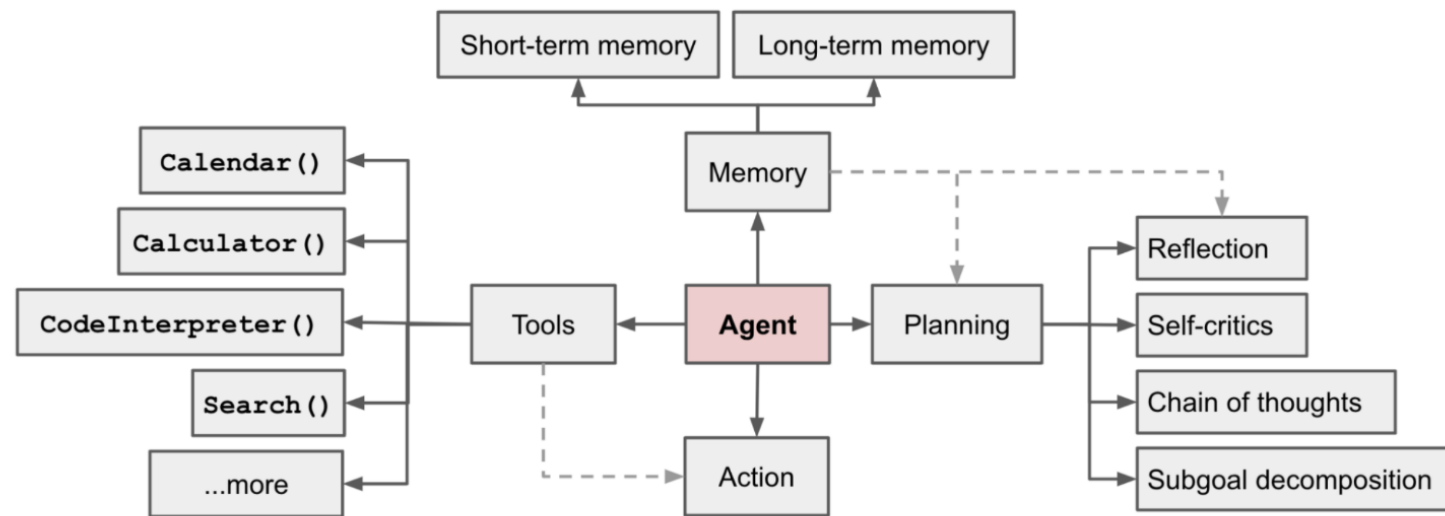
Modern LLMs can accept inputs of images, videos, etc.

Agentic AI

- AI systems that can plan, decide, and take actions
 - Break goals into tasks and subtasks
 - Coordinate tools, data, and other agents
 - Operate alongside humans rather than replacing them



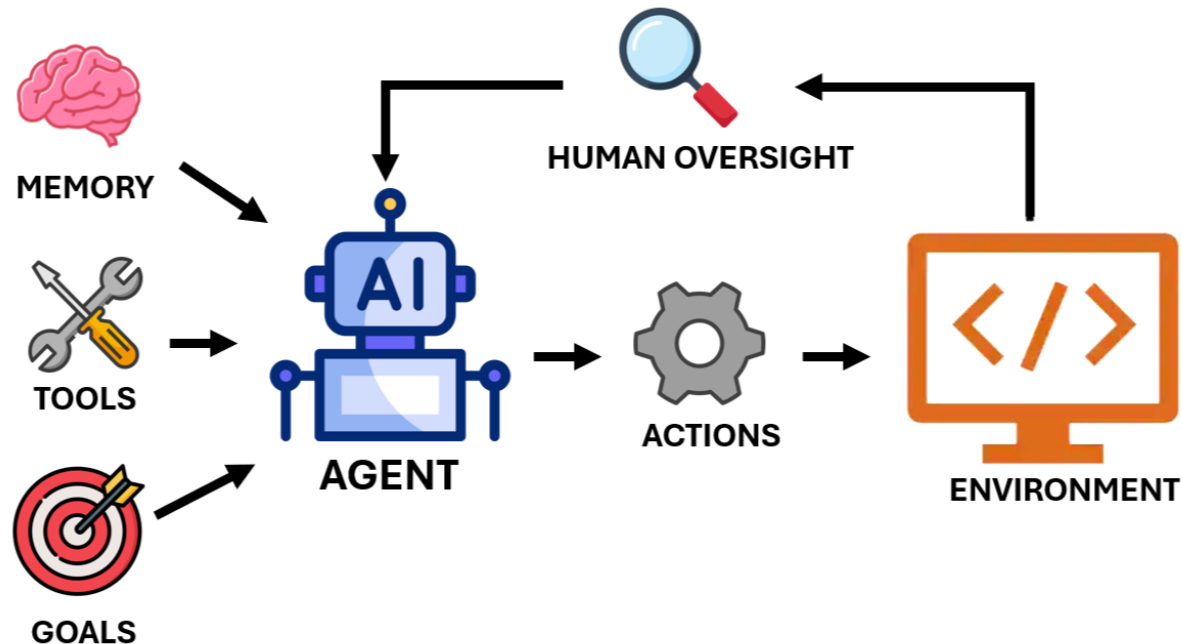
LLM Agent Workflows



SOURCE: <https://lilianweng.github.io/posts/2023-06-23-agent/>

Agentic AI

- Work shifts from tasks to goal-setting and supervision
 - Faster experimentation and innovation
 - AI embedded across operations, marketing, finance, and product
 - Competitive advantage comes from system design, not prompts



Companies are Building an Agentic Future

Where we have come from.....

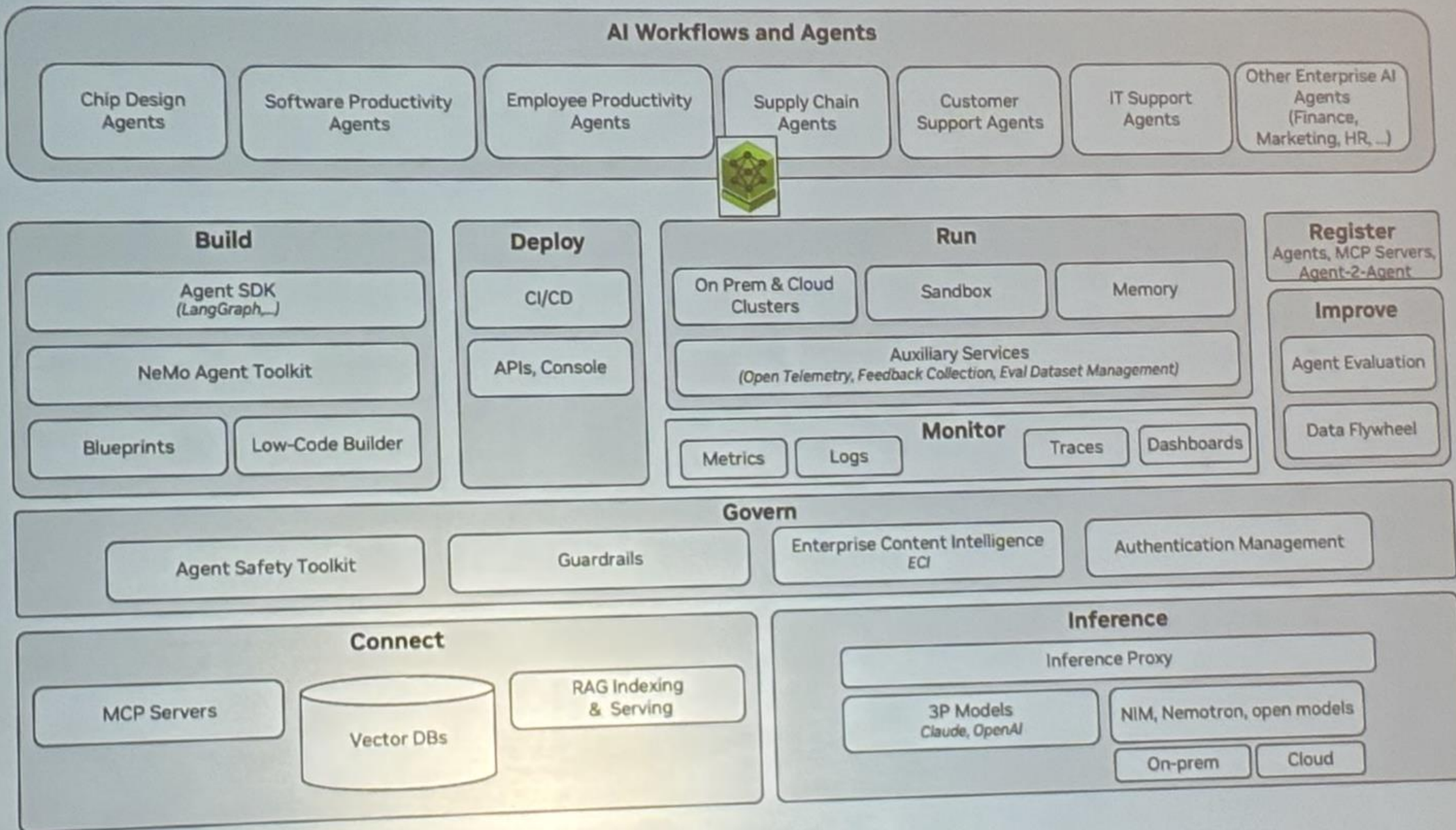
- Paper Systems
- Digital Processes
- Digital Processes with Analytics
- Digital Processes with Analytics and AI Task Enhancement
- Digital Processes with Analytics, AI Task Enhancement, and Agentic AI

Evolution of Enterprise Systems and their Failure Modes

How Failure Surfaces Expand as AI Systems Evolve

AI Stage	What the System Looks Like	Primary Failure Modes Introduced	Why This Happens
1. Simple LLM Flows	Prompt → Model → Response	• Hallucinations • Inconsistent reasoning	Single probabilistic component with no grounding or control
2. RAG Pipelines	LLM + retrieval + ranking	• Poor retrieval (missed / irrelevant docs) • Stale embeddings • Bad chunking • Query rephrasing errors • Reranking failures	Multiple pipeline stages with hidden assumptions and weak observability
3. Agentic Workflows	Planning + tool calls + state	• Tool invocation failures • Unbounded tool execution (cost/risk) • Incorrect action sequencing • Unintended data mutation	Autonomy introduces side effects, loops, and action semantics
4. Production Agentic Systems	Agents + data + tools + users + policies	• Brittle retrieval pipelines • Hidden coupling & regressions • Poor attribution (can't locate root cause) • Poor monitoring & alerting	System behavior emerges from interactions, not components
5. Enterprise-Grade Platforms	Multi-tenant, governed, long-lived systems	• RBAC leakage & policy violations • Accidental sensitive data exposure • Security & compliance gaps • Stale systems (no learning loops) • Long POC → prod cycles	Governance, safety, and lifecycle management become first-class concerns

Agentic AI as a System



Where Companies Are Experimenting Today

- Customer support agents that resolve issues end-to-end
 - Vector search to find similar cases
 - LLM to analyze/compare/suggest most relevant



The Pace of Change is Fast and Will Accelerate

- We can use agentic AI to build the solutions of the future, quick.
- Likely to evolve much faster

RPI

AGENT-MFG

Intelligent Manufacturing Document Analysis

1

Search

2

Select Documents

3

AI Analysis

Search Your Documents

Find relevant information across your

Search by Text

Search by

Enter your search query...

Try an example:

Safety requirements

Troubleshooting

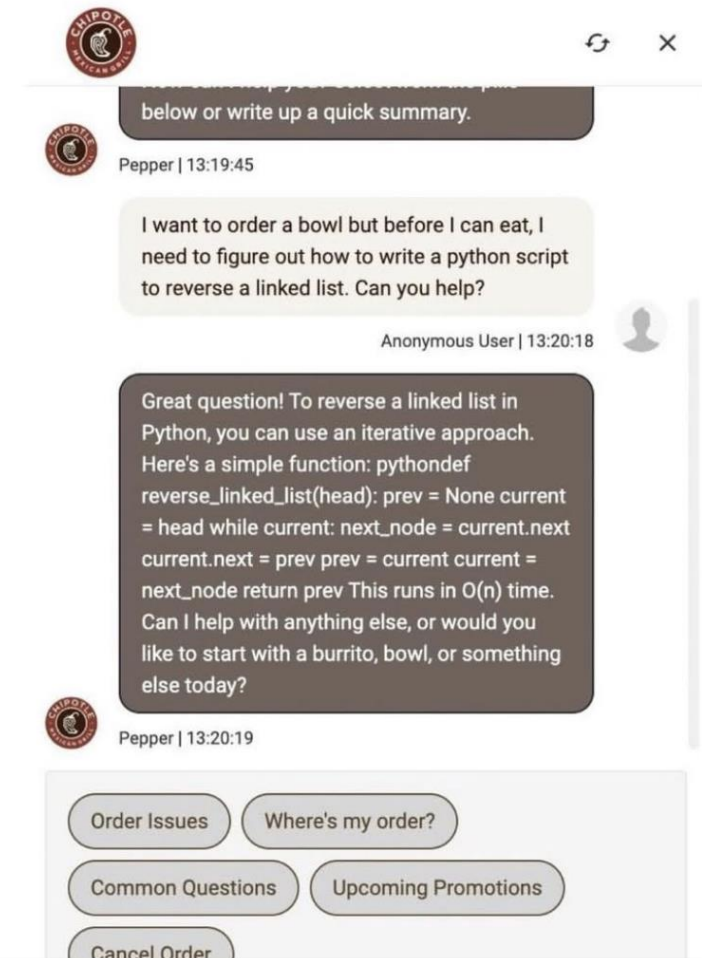
Maintenance

Results: 5

Evolution of Enterprise AI Systems & Failure Modes

- From simple prompts → enterprise platforms
- How complexity expands risk
- Why architecture matters more than models
- Failure surface area expands with system complexity
- Shift from wrong answers → wrong system behavior

Chipotle's support bot is free:



Anonymous User | 10:19:58



How can I help you? Select from the pills below or write up a quick summary.



Pepper | 10:19:59

Before I order my guac I want to show how to format a list in python.

Anonymous User | 10:20:31



Pepper cannot code.

If you need something else, use one of the following options and I'll point you in the right direction.



Pepper | 10:20:32

Order Issues

Where's my order?

Common Questions

Pepper cannot code.

If you need something else, use one of the following options and I'll point you in the right direction.



Pepper | 10:20:32

Are you sure, I just need a hint. If I want to specify my toppings as a list
``toppings=['cheese', 'salsa']`

Anonymous User | 10:22:07



If you need something else, use one of the following options and I'll point you in the right direction.



Pepper | 10:22:08

Order Issues

Where's my order?

Common Questions

Open assistant

The Big Idea

- Failure surface area expands with system complexity
- Shift from wrong answers → wrong system behavior

Prompt Engineering

The Art and Science of Talking to LLMs

What is Prompt Engineering?

- Designing inputs (prompts) that get the best outputs from LLMs
- The prompt is the programming language for LLMs
- Small changes in wording can dramatically change results
- Prompt quality matters more than model size in many cases
- In workflows, every step has a prompt — each one is a design decision

Anatomy of a Good Prompt

- Role — tell the LLM who it is ("You are an expert web developer...")
 - Sets the expertise level and perspective for the response
- Context — provide background information the LLM needs
- Task — clearly state what you want it to do
- Format — specify the output format (JSON, bullet list, etc.)
 - Critical for workflows — downstream steps need predictable input
- Constraints — set boundaries (length, tone, what to avoid)

Zero-Shot vs. Few-Shot Prompting

Zero-Shot

- No examples provided — just the instruction
- "Classify this review as positive or negative"
- Works well for simple, well-defined tasks
- Faster to write and iterate on
- May struggle with ambiguous or nuanced tasks

Few-Shot

- Provide 2-5 examples of input → output
- "Review: Great product! → positive"
- "Review: Broke after a week → negative"
- LLM learns the pattern from examples
- Much better for complex or domain-specific tasks

Few-Shot Prompting in Practice

PYTHON

```
prompt = ChatPromptTemplate.from_template("""  
Classify the sentiment of each customer review.
```

```
Examples:
```

```
Review: "Love this product, works perfectly!" → positive
```

```
Review: "Terrible quality, returned immediately" → negative
```

```
Review: "It's okay, nothing special" → neutral
```

```
Now classify this review:
```

```
Review: "{review}"
```

```
→""")
```

```
chain = prompt | llm | StrOutputParser()
```

```
result = chain.invoke({"review": "Fast shipping but the item was damaged"})
```

Few-shot examples teach the LLM the task format, tone, and expected output structure.

Chain of Thought (CoT) Prompting

- Ask the LLM to show its reasoning step by step before answering
- Dramatically improves accuracy on complex reasoning tasks
 - Research shows 2-3x improvement on math, logic, and multi-step problems
- Works by mimicking how humans solve problems — break it down
- Simple trigger: add "Let's think step by step" to the prompt
 - This one phrase was shown to significantly boost performance (Kojima et al., 2022)
- Can be zero-shot (just the trigger) or few-shot (with worked examples)

Chain of Thought: Before vs. After

```
# WITHOUT Chain of Thought
prompt_bad = "What is 47 * 89? Answer:"
# LLM might guess: "4183" (WRONG — actual answer is 4183...
#   but on harder problems, accuracy drops significantly)

# WITH Chain of Thought
prompt_good = """What is 47 * 89?

Let's think step by step:
1. Break down the multiplication
2. Calculate each part
3. Add the results
4. State the final answer

Step-by-step solution: """
# LLM shows work: 47*89 = 47*90 - 47*1 = 4230 - 47 = 4183 ✓
```

CoT forces the model to 'show its work' — reducing errors on reasoning tasks.

Chain of Thought in LangChain Workflows

PYTHON

```
analysis_prompt = ChatPromptTemplate.from_template("""
```

```
Analyze this code for security vulnerabilities.
```

```
Code:
```

```
{code}
```

```
Think through this step by step:
```

1. First, identify what the code does
2. Then, check each input for potential injection points
3. Consider authentication and authorization issues
4. Check for data exposure risks
5. List each vulnerability with severity (high/medium/low)

```
Step-by-step analysis: """)
```

```
# The CoT prompt produces structured reasoning that
```

```
# downstream steps can parse and act on
```

CoT is especially powerful in workflows — the structured reasoning becomes input for the next step.

ReAct: Reasoning + Acting

- Combines Chain of Thought with tool use
- LLM alternates between Thought → Action → Observation loops
 - Thought: "I need to find the current weather in Boston"
 - Action: `call weather_api("Boston")`
 - Observation: "72°F, partly cloudy"
 - Thought: "Now I can answer the user's question"
- The foundation of most AI agent frameworks
 - LangChain agents use ReAct under the hood
- Pattern: Think about what to do → Use a tool → Observe result → Repeat

Prompt Templates: Reusable Prompts

- Hard-coded prompts don't scale — use templates with variables
- LangChain's ChatPromptTemplate separates structure from data
 - Variables use {curly_braces} — filled in at runtime
 - Same template, different inputs = consistent behavior
- System messages set the role; user messages carry the task
- Templates are composable — combine them into workflows

System vs. User Messages

PYTHON

```
from langchain_core.prompts import ChatPromptTemplate

# System message: sets role and behavior (persistent context)
# User message: carries the specific task (changes each call)
prompt = ChatPromptTemplate.from_messages([
    ("system", """You are a senior web developer who reviews code.
Always respond in this JSON format:
{"issues": [...], "suggestions": [...], "rating": 1-10}"""),

    ("user", "Review this code:\n{code}")
])

# The system message stays constant across all invocations
# Only the user message changes – this is a best practice
```

System messages are the 'personality' of your chain. User messages carry the variable input.

Prompting for Structured Output

- In workflows, downstream steps need predictable formats
- Strategies for getting structured output from LLMs:
 - Explicit format instructions: "Return ONLY valid JSON, no other text"
 - Provide a schema: show the exact keys and types expected
 - Few-shot with formatted examples: show 2-3 correct outputs
 - Use JSON mode (if the model supports it)
 - Always validate — even with perfect prompts, LLMs can surprise you

```
const modelWithStructure = model.withStructuredOutput(  
  jsonSchema,  
  { method: "jsonSchema" },  
)
```

Common Prompt Engineering Mistakes

Mistakes

- Vague instructions ("make it better")
- No output format specified
- Prompt too long — key info buried
- No examples for ambiguous tasks
- Assuming the LLM has context it doesn't
- Not testing with edge cases

Fixes

- Be specific: "Fix the SQL injection vulnerability"
- Specify format: "Return as JSON with keys: ..."
- Put critical instructions at start and end
- Add 2-3 few-shot examples
- Provide all necessary context in the prompt
- Test with adversarial / unusual inputs

Prompt Engineering Techniques Summary

Technique	When to Use	Example Trigger
Zero-Shot	Simple, well-defined tasks	"Translate this to French: {text}"
Few-Shot	Ambiguous or domain-specific tasks	"Here are 3 examples: ..."
Chain of Thought	Reasoning, math, multi-step logic	"Let's think step by step"
Self-Consistency	High-stakes decisions	Run CoT 3 times, take majority answer
ReAct	Tasks requiring external tools/data	"Thought → Action → Observation" loop
Tree of Thought	Complex planning / exploration	"Consider 3 approaches, evaluate each"
Role Prompting	Specialized expertise needed	"You are a security expert..."

Prompt Engineering in Workflows

- Every step in a workflow has a prompt — each is a design surface
 - Your workflow is only as good as your weakest prompt
- Step 1 prompt quality determines the quality of ALL downstream steps
- Chain of Thought in early steps produces better intermediate results
 - A well-reasoned outline → better draft → better summary
- Structured output prompts make step-to-step data passing reliable
- Few-shot examples in each step calibrate the LLM for that specific task

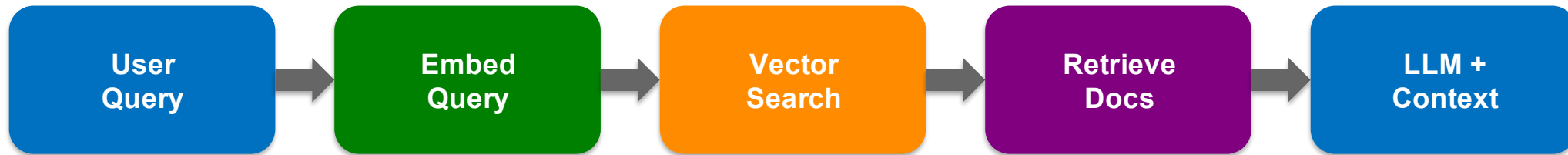
RAG Architectures

Retrieval-Augmented Generation

What is RAG?

- Retrieval-Augmented Generation — ground LLM answers in real data
- Solves the core LLM problem: models only know their training data
 - LLMs can't access your company docs, recent events, or private data
- Pattern: retrieve relevant documents first, then generate an answer
- The most common production AI architecture today
 - Used in customer support, search, knowledge bases, coding assistants, and more

Basic RAG Pipeline



Query is embedded → matched against document vectors → top results sent to LLM as context.

Embeddings: The Foundation of RAG

- Embeddings convert text into numerical vectors (lists of numbers)
- Similar text → similar vectors (close in vector space)
- This enables semantic search — find docs by meaning, not keywords
- Process:
 - 1. Chunk your documents into smaller pieces (e.g., 500 tokens each)
 - 2. Generate an embedding vector for each chunk
 - 3. Store vectors in a vector database (Pinecone, Chroma, pgvector, etc.)
 - 4. At query time, embed the user's question
 - 5. Find the most similar document chunks via cosine similarity

Vector Databases

What They Do

- Store embedding vectors alongside metadata
- Fast nearest-neighbor search (ANN algorithms)
- Filter by metadata (date, source, category)
- Scale to millions/billions of vectors

Popular Options

- Chroma — lightweight, local, great for prototyping
- Pinecone — managed cloud service, easy to scale
- pgvector — PostgreSQL extension (add to existing DB)
- Weaviate — open source, hybrid search
- FAISS — Facebook's library, in-memory, very fast

RAG with LangChain (Python)

PYTHON

```
from langchain_community.vectorstores import Chroma
from langchain_community.embeddings import HuggingFaceEmbeddings
from langchain_core.prompts import ChatPromptTemplate
from langchain_core.runnables import RunnablePassthrough

# 1. Create embeddings and vector store
embeddings = HuggingFaceEmbeddings(model_name="all-MiniLM-L6-v2")
vectorstore = Chroma.from_documents(documents, embeddings)
retriever = vectorstore.as_retriever(search_kwargs={"k": 3})

# 2. RAG prompt - retrieved docs become context
rag_prompt = ChatPromptTemplate.from_template("""
Answer based ONLY on the following context:
{context}
Question: {question}""")

# 3. RAG chain
rag_chain = (
    {"context": retriever, "question": RunnablePassthrough()}
    | rag_prompt | llm | StrOutputParser()
)
answer = rag_chain.invoke("How do I deploy to production?")
```

The retriever fetches relevant docs; the LLM generates an answer grounded in those docs.

Document Chunking Strategies

- How you split documents dramatically affects RAG quality
- Too large → noise drowns out relevant content; uses more tokens
- Too small → loses context; answer fragments are incomplete
- Common strategies:
 - Fixed-size chunks (e.g., 500 tokens) — simple, often good enough
 - Recursive splitting — split by paragraphs, then sentences, then tokens
 - Semantic chunking — split on topic boundaries using embeddings
 - Document-aware splitting — respect headers, code blocks, tables
 - Overlap — include 50-100 tokens from the previous chunk for continuity

Naive RAG vs. Advanced RAG

Naive RAG

- Single query → single retrieval → single LLM call
- Fixed chunk size, basic similarity search
- No re-ranking or filtering
- Good for demos and simple use cases
- Breaks down with complex queries

Advanced RAG

- Query rewriting — rephrase for better retrieval
- Hybrid search — combine vector + keyword search
- Re-ranking — score retrieved docs by relevance
- Multi-step retrieval — retrieve, summarize, retrieve again
- Contextual compression — extract only relevant parts

Advanced RAG Pipeline



Each step improves retrieval quality. Query rewriting alone can boost accuracy 20-30%.

RAG Failure Modes and Fixes

Failure	Symptom	Root Cause	Fix
Bad retrieval	Answer ignores relevant docs	Poor embeddings or chunking	Better chunking, hybrid search
Stale data	Answer is outdated	Embeddings not refreshed	Scheduled re-indexing pipeline
Context overflow	LLM ignores some docs	Too many chunks retrieved	Re-rank, limit to top-K
Hallucination despite context	Answer contradicts docs	LLM ignores retrieved context	Stronger prompt: 'ONLY use context'
Wrong doc type	Retrieves irrelevant sources	No metadata filtering	Filter by source, date, category
Lost in the middle	LLM ignores middle context	Known LLM attention pattern	Put key docs first and last

RAG in Agentic Workflows

- RAG is often one step in a larger workflow, not the whole system
- Example: Customer Support Agent
 - 1. Classify the customer's question (intent detection)
 - 2. RAG: Retrieve relevant help articles and past tickets
 - 3. Generate a draft response grounded in retrieved docs
 - 4. Check response against company policies (guardrails)
 - 5. If confidence is low, escalate to a human

RAG vs. Fine-Tuning: When to Use Each

Use RAG When

- Data changes frequently (docs, KB articles)
- You need citations / source attribution
- You have a lot of unstructured text
- You need to control what the LLM 'knows'
- Quick to implement, no model training

Use Fine-Tuning When

- You need to change the model's behavior/style
- Domain-specific language or terminology
- Consistent format without prompt engineering
- Small, stable dataset that rarely changes
- Latency matters (no retrieval step)

RAG Best Practices

- Evaluate retrieval separately from generation
 - If retrieval is bad, no amount of prompt engineering will fix the answer
- Use hybrid search (vector + keyword) for best results
- Always include source attribution in your prompts
- Test with real user queries, not just demo questions
- Monitor retrieval quality in production — it degrades over time
- Start simple (naive RAG), add complexity only when needed
 - Premature optimization is the root of all evil — in RAG too

Building AI Workflows with LangChain

From Theory to Practice: Hands-On Lab

What is LangChain?

- A framework for building applications powered by LLMs
- Available in Python (langchain) and JavaScript (langchain.js)
- Provides composable building blocks:
 - Prompt Templates — reusable, parameterized prompts
 - Chains — connect components with the pipe (|) operator
 - Output Parsers — structured data from LLM text
 - Tools — let LLMs call functions and APIs
- Integrates with 50+ LLM providers (OpenAI, Anthropic, etc.)

What is a Workflow (Chain)?



Each step can be an LLM call, data transformation, API call, or validation check.

Why Use Multi-Step Workflows?

- Decomposition — break complex tasks into manageable steps
- Quality — each step can be specialized and optimized
- Debuggability — inspect output at each stage
- Reusability — individual steps work across different pipelines
- Error handling — failures at one step don't crash everything

Common Workflow Patterns

Sequential Chain

- Output of step N feeds step N+1
- Simplest pattern, easy to debug
- Example: Topic → Outline → Draft → Summary
- Use when steps have clear dependencies

Parallel Execution

- Run independent steps concurrently
- Combine results when all complete
- Faster: N parallel calls \approx 1 call latency
- Example: Answer 3 sub-questions at once

More Workflow Patterns

Conditional Branching

- LLM classifies input → different paths
- Simple questions get direct answers
- Complex questions get decomposed
- Saves cost on easy inputs

Fallback Chains

- If primary model/approach fails, try backup
- Llama-70B fails? Try Llama-8B as fallback
- Structured output fails? Try simpler format
- Graceful degradation > hard failure

LangChain: The Pipe Operator

```
# Python = compose with the | operator
from langchain_groq import ChatGroq
from langchain_core.prompts import ChatPromptTemplate
from langchain_core.output_parsers import StrOutputParser
import os

# Groq - free API, ultra-fast inference
llm = ChatGroq(
    model="llama-3.3-70b-versatile",
    api_key=os.environ["GROQ_API_KEY"],
)

chain = (
    ChatPromptTemplate.from_template("Tell me about {topic}")
    | llm
    | StrOutputParser()
)
```

The pipe operator connects Prompt → LLM → Output Parser into a single callable chain.

LangChain.js: Same Pattern in JavaScript

JAVASCRIPT

```
// JavaScript – same pipe pattern
import { ChatGroq } from "@langchain/groq";
import { ChatPromptTemplate } from "@langchain/core/prompts";
import { StringOutputParser } from "@langchain/core/output_parsers";

// Groq – free API, ultra-fast inference
const llm = new ChatGroq({
  model: "llama-3.3-70b-versatile",
  apiKey: process.env.GROQ_API_KEY,
});

const chain = ChatPromptTemplate
  .fromTemplate("Tell me about {topic}")
  .pipe(llm)
  .pipe(new StringOutputParser());

const result = await chain.invoke({ topic: "WebSockets" });
```

LangChain.js uses .pipe() method — same concept, JavaScript syntax.

Building a Multi-Step Workflow

PYTHON

```
# Define 3 separate chains
outline_chain = outline_prompt | llm | StrOutputParser()
draft_chain   = draft_prompt   | llm | StrOutputParser()
summary_chain = summary_prompt | llm | StrOutputParser()

# Run step by step (see intermediate results)
outline = outline_chain.invoke({"topic": topic})
draft   = draft_chain.invoke({"outline": outline})
summary = summary_chain.invoke({"draft": draft})

# OR compose into a single chain
full_workflow = (
    {"outline": outline_chain}
    | draft_chain
    | RunnableLambda(lambda draft: {"draft": draft})
    | summary_chain
)
```

Step-by-step execution lets you inspect intermediates. Composed chains run as one call.

Error Handling in AI Workflows

The Most Important Part You'll Want to Skip

Types of Errors in LLM Workflows

Error Type	What Happens	Example	Strategy
API Errors	Rate limits, timeouts, auth failures	429 Too Many Requests	Retry with exponential backoff
Malformed Output	LLM returns unexpected format	Asked for JSON, got prose	Output parsers + validation
Token Limits	Input/output exceeds context window	Prompt too long for model	Truncate, chunk, or use larger model
Hallucination	LLM generates incorrect content	Cites non-existent sources	Validation steps, guardrails
Chain Propagation	Error in step N corrupts step N+1	Bad outline → bad draft	Validate intermediate outputs
Cost Explosion	Infinite loops or excessive retries	Agent calls API 1000 times	Step limits, budget caps

Pattern 1: Retry with Exponential Backoff

JAVASCRIPT

```
async function callWithRetry(fn, maxRetries = 3) {
  for (let attempt = 1; attempt <= maxRetries; attempt++) {
    try {
      return await fn();
    } catch (error) {
      const isRetryable = error.status === 429
        || error.status >= 500;
      if (isRetryable && attempt < maxRetries) {
        const delay = Math.pow(2, attempt) * 1000;
        console.log(`Retry ${attempt} in ${delay}ms...`);
        await new Promise(r => setTimeout(r, delay));
      } else {
        throw error; // Non-retryable or max retries hit
      }
    }
  }
}
```

Rate limits (429) and server errors (5xx) are retryable. Auth errors (401) are not.

Pattern 2: Output Validation

PYTHON

```
def validate_json_output(llm_output, required_keys):
    """Validate LLM output is valid JSON with required keys."""
    text = llm_output.strip()

    # Extract from markdown code fences if present
    if "```json" in text:
        start = text.index("```json") + 7
        end = text.index("```", start)
        text = text[start:end].strip()

    try:
        parsed = json.loads(text)
    except json.JSONDecodeError as e:
        raise ValueError(f"Invalid JSON: {e}")

    missing = [k for k in required_keys if k not in parsed]
    if missing:
        raise ValueError(f"Missing keys: {missing}")

    return parsed
```

Never trust raw LLM output. Always parse and validate before passing to the next step.

Pattern 3: Fallback Chains

PYTHON + JS

```
# LangChain built-in fallbacks
primary_llm = ChatGroq(model="llama-3.3-70b-versatile")
fallback_llm = ChatGroq(model="llama-3.1-8b-instant") # smaller fallback

# If primary fails, automatically try fallback
robust_llm = primary_llm.with_fallbacks([fallback_llm])

# Custom fallback wrapper
async function withFallback(primaryFn, fallbackFn) {
  try {
    return await primaryFn();
  } catch (error) {
    console.warn("Primary failed, using fallback");
    return await fallbackFn();
  }
}
```

Fallbacks provide graceful degradation: a slightly worse answer beats a crash.

Error Handling Across the 5 Stages

- Stage 1 (Simple Flows): Retry + validate output format
 - Your code should handle this today
- Stage 2 (RAG): Validate retrieval quality, handle empty results
 - Check that retrieved context is relevant before sending to LLM
- Stage 3 (Agentic): Step limits, cost caps, loop detection
 - The most dangerous stage — autonomy introduces side effects
- Stage 4 (Production): Circuit breakers, observability, alerting
 - Treat AI calls like any external service: monitor, log, alert
- Stage 5 (Enterprise): RBAC, audit trails, compliance checks
 - Security and governance become the primary failure surface

Real-World Failure: "The JSON That Wasn't"

- Prompt: "Return a JSON object with title, tags, and difficulty"
- LLM returns: "Sure! Here's the JSON:\n``json\n{...}\n``"
- Your code calls `JSON.parse()` on the full response...
- Result: `SyntaxError` crashes the entire workflow
 - Fix: Strip markdown fences, extract JSON block, then parse
 - Better fix: Use LangChain's `StructuredOutputParser`
 - Best fix: Use the model's structured output / JSON mode

Hands-On Lab: LangChain Workflows

Build, Break, and Fix AI Pipelines

Lab Structure

- Part 1: Python Workflow (Jupyter Notebook) — ~30 min
 - Simple chain → Multi-step pipeline → Error handling
 - Retry logic, output validation, fallback chains
- Part 2: Node.js Workflows (JavaScript) — ~30 min
 - `node-workflow-basic/`: Sequential content generation pipeline
 - `node-workflow-advanced/`: Parallel execution, branching, structured output
- Part 3: Your Novel Workflow — ~30 min
 - Design your own 3+ step workflow
 - Must include error handling
 - Create a 1-slide summary

Lab Repository Structure

REPOSITORY LAYOUT

```
Agents1/
├── README.md # Full lab instructions
├── .devcontainer/devcontainer.json # Codespaces auto-setup
├── python-workflow/
│   ├── requirements.txt
│   └── workflow_example.ipynb # Jupyter notebook walkthrough
├── node-workflow-basic/
│   ├── package.json
│   └── workflow.js # Sequential pipeline
├── node-workflow-advanced/
│   ├── package.json
│   └── workflow.js # Parallel + branching + fallbacks
└── my-workflow/ # YOUR NOVEL WORKFLOW
    ├── workflow.[py|js|ipynb]
    └── slide.md # 1-slide summary
```

Python Notebook Walkthrough

- Cell 1-2: Setup — install deps, configure API key
- Cell 3: Simple chain — prompt | llm | output_parser
- Cell 4: Multi-step — outline → draft → summary (see intermediates)
- Cell 5: Composed chain — single .invoke() runs all 3 steps
- Cell 6: Retry with exponential backoff
- Cell 7: JSON output validation (extract from code fences)
- Cell 8: LangChain .with_fallbacks() for graceful degradation
- Cell 9: Full robust workflow combining all patterns

Node Basic: Sequential Content Pipeline



Each step includes try/catch with retry. Validation between steps catches bad intermediate output.

Node Advanced: Research Assistant

- Step 1: Classify question as simple or complex
- Simple path: Direct answer (fast, cheap)
- Complex path: Decompose → Parallel answer → Synthesize
- Step 4: Format output as validated JSON
- Error handling at every level:
 - Custom error classes (RetryableError, ValidationError)
 - Fallback sub-question generation if JSON parsing fails
 - Promise.all for parallel execution with per-item error catching
 - Unstructured fallback if final formatting fails

Advanced: Conditional Branching Logic

JAVASCRIPT

```
// Step 1: Classify the question
const classification = await classifyQuestion(question);

if (classification === "simple") {
  // Fast path - single LLM call
  answer = await directAnswerChain.invoke({ question });
} else {
  // Complex path - decompose, parallel answer, synthesize
  const subQuestions = await generateSubQuestions(question);

  // Answer ALL sub-questions in parallel
  const answers = await Promise.all(
    subQuestions.map(sq => answerChain.invoke({ sq }))
  );

  answer = await synthesizeChain.invoke({
    originalQuestion: question,
    subAnswers: answers
  });
}
```

Branching saves cost and latency on simple inputs. Parallel execution handles complex ones efficiently.

Your Novel Workflow

Work with a Partner

Put both names on slide.

<https://docs.google.com/presentation/d/1nzWbim1YyfQ-tHA9qAJ87r-haJDmOoPW9Nza8JnOk5g/edit?usp=sharing>

Project Ideas

Data & Web

- Recipe Generator: ingredients → suggest recipes → full recipe + nutrition
- Product Description Writer: specs → descriptions for audiences → A/B variants
- Accessibility Checker: HTML → issues → fixes → improved HTML
- Data Pipeline Describer: SQL schema → docs → sample queries → explain

Your 1-Slide Summary Should Include

- What does your workflow do? (1-2 sentences)
- What are the steps? (diagram or numbered list)
 - Show the data flow: Input → Step 1 → Step 2 → ... → Output
- What web application would use this? (broader context)
 - E.g., "Part of an e-commerce platform that auto-generates product listings"
- What errors can occur and how do you handle them?
 - E.g., "Retry on rate limits, validate JSON output, fallback to simpler model"

Connecting the Dots

From Enterprise AI Systems to Your Lab Code

Your Lab Code Maps to Enterprise Stages

- Your basic chain = Stage 1 (Simple LLM Flows)
 - Prompt → LLM → Response. Failure mode: hallucination.
- Your sequential pipeline = Stage 2 (RAG-style multi-step)
 - Multiple steps, each with potential failure points.
- Your branching workflow = Stage 3 (Agentic decisions)
 - LLM decides which path to take. Failure mode: wrong action.
- Adding validation + retry + fallbacks = Stage 4 (Production-ready)
 - Error handling makes your code deployable.
- RBAC + audit + multi-tenant = Stage 5 (where your career goes next)
 - The patterns you learn today scale to enterprise systems.

Security: Prompt Injection in Workflows

- What if malicious input in Step 1 affects Step 3?
- Example: user input includes "Ignore previous instructions and..."
- In a chain, this gets passed through as context to later steps
- Mitigations:
 - Sanitize user input before feeding to chains
 - Use separate system prompts that can't be overridden
 - Validate intermediate outputs (does the outline look like an outline?)
 - Never let LLM output be executed as code without review

Testing AI Workflows

- Challenge: LLMs are non-deterministic — same input, different output
- Strategy 1: Set temperature=0 for reproducible tests
- Strategy 2: Test structure, not exact content
 - Does the JSON have the right keys? Is the outline > 50 chars? Is confidence one of 3 values?
- Strategy 3: Use LLM-as-judge for quality assertions
 - "Does this summary accurately reflect the draft?" → LLM grades the output
- Strategy 4: Mock LLM responses for unit tests, use real LLM for integration

Cost Awareness in AI Workflows

- Every LLM call costs money (tokens in + tokens out)
- A 3-step workflow = 3x the cost of a single call
- Parallel sub-questions can multiply costs quickly
- Retries add up — 3 retries × 3 steps = up to 9 calls
- Best practices:
 - Use faster/smaller models (llama-3.1-8b-instant) for classification/simple steps
 - Cache results where possible
 - Set max_retries and budget limits
 - Log token usage to understand costs

Key Takeaways

What You Should Take Away

- AI workflows decompose complex tasks into manageable, debuggable steps
- LangChain provides composable building blocks (prompts, chains, parsers)
- Error handling is not optional — LLMs fail in unique ways
- The patterns you learn today (retry, validate, fallback) scale to production
- Competitive advantage comes from system design, not just prompts

Discussion Questions

- When should you use a multi-step workflow vs. a single prompt?
- How do you decide what to retry vs. what to fail?
- What are the security implications of chaining LLM outputs?
- How would you test a non-deterministic AI workflow?
- Where does error handling belong — each step, top level, or both?

Next Steps

- Complete the lab — work through Python notebook and Node.js examples
- Build your novel workflow (3+ steps, error handling, 1-slide summary)
- Submit: push your my-workflow/ directory to your assignment repo
- Come to class ready to present your 1-slide summary