# Kompile:

## E2E Building Blocks for RAG Infra

by Adam Gibson

presented on Apr 15 2026

# AI Agents.
# What are they for?
# How is RAG related?

# THE THREE MAIN USE CASES FOR AI AGENTS

## 1. AGENTIC ACTIONS & CODING
(Act on Your Behalf)

Agents execute complex tasks, reducing operational latency to affect on copires, and aramitation man multi-step actions.

Focuses on coding, full-stack tasks, and multi-step actions.


**OPTIMIZED WORKFLOW EXECUTION**
Breaking down and executing complex multi-step plans.


**CODING & DEV SUPPORT**
Code generation, debugging, refactoring, and integration tasks.

**AGENT-ENVIRONMENT INTERACTION**
Managing interfaces with specific protocols and environments.

**TASK-SPECIFIC ACTIONS**
From email orchestration (triating/responding) to CRM data management.

## 2. IDEATION & CONTENT GENERATION
(Roleplay & Brainstorming)

Agents synthesize content and conceptualize ideas across all communication formats, in brainwrize.

Focuses on creative and strategic problem-solving.


**IDEATION & CONCEPTUALIZATION**
Exploring new product features, creative problem-solving, and innovative ideas.

**ROLEPLAY & INTERACTIVE SCRIPTING**
Simulation design, training content generation, and character-driven interactions.

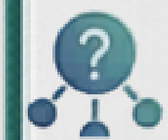

**CREATIVE CONTENT SYNTHESIS**
Generating compelling business documentation, pitch decks, and technical reports.

**MULTIMEDIA ASSET SYNTHESIS**
Video, audio, text-to-speech, and asset editing from natural language prompts.

## 3. INFORMATIONAL
(Research & Data Synthesis)

Agents handle and process large amounts of data to enable provide clear, grounded answers, to anes contact data.
Focuses on research,
Focuses on question-answering,
and sorting information.


**DEEP RESEARCH & SYNTHESIS**
Synthesizing information from diverse enterprise and external knowledge bases.



**QUESTION ANSWERING & GROUNDING**
Providing precise context and grounded answers.


**INFORMATION SORTING & CLASSIFICATION**
Managing and prioritizing large data repositories.

**CROSS-DOCUMENT ANALYSIS**
Identifying consensus and removing conflicts across multiple sources.

# WHAT IS RAG?

# WHAT IS RETRIEVAL-AUGMENTED GENERTION (RAG)?

## 1. KNOWLEDGE RETRIEVAL


**Aggregating Search Results.**
Collect relevant real-time data from diverse sources (e.g., search engines, company docs).

## 2. CONTEXT AUGMENTATION

**AGENT'S PROMPT**

How are agent architectures evolving?

**Context**

AI Agent

**AGENT'S PROMPT**

**Pasting Context into Prompt.**
Enriching the agent's base prompt with specific, relevant facts and documents.

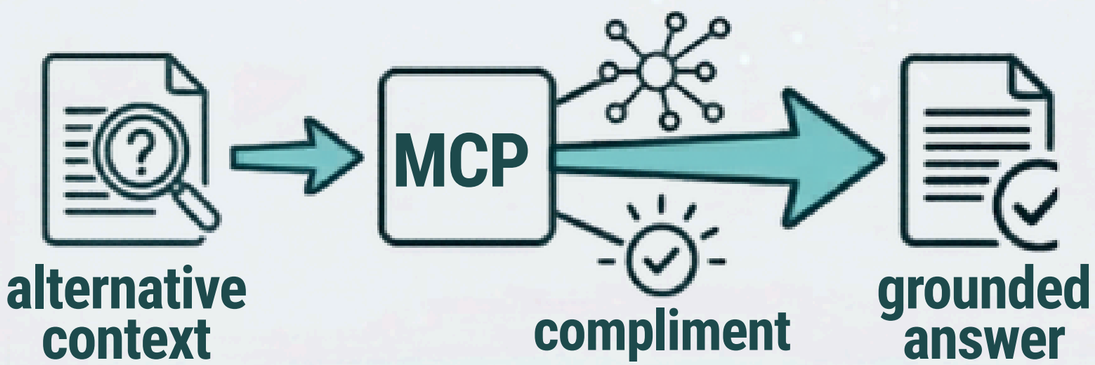
## 3. INFORMED RESPONSE

**INFORMED RESPONSE**

- Based on the retrieved context, current evolutions in agent architectures include...
- tool-use agents,
- re-planning loops, adtitops, and
- self-correction.

**Generating Grounded Answers.**
Producing factual and up-to-date responses grounded in the retrieved information.

# MCP:
# Both an Alternative and Compliment to a RAG System.



# MCP VS RAG: WHEN *NOT* TO USE RAG

## MCP (EXTERNAL DATA ACCESS)

### OPTIMIZED PRECISION & EFFICIENCY


**DIRECT TOOL CALLS:**
Agents pinpoint exact external data points via clean APIs.

**CHEAPER DATA RET RETRIEVAL:**
No large-scale embedding creation or vector database.

**BETTER TOOL INTEGRATION:**
Agents interact native with standard tool interfaces.


**UP-TO-DATE INFORMATION:**
Immediate access to real-time, dynamic data sources.

## KEY DIFFERENCES

**MCP**: Precise, Sparse, Structured Data via Tool Calls

**RAG**: Context, Neural Fusion via Vector Embedding

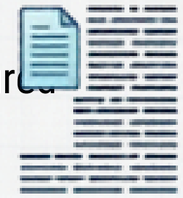
**MCP**: Lower Latency, Real-Time Access

**RAG**: Document & Context Focus

## RAG (KNOWLEDGE GROUNDING)

### KNOWLEDGE GROUNDING: USE CASES

**USE RAG FOR:**
Massive, dense, un-structured knowledge bases (internal wikis, manuals).



**USE RAG FOR:**
Context fusion across complex document topologies.

**RAG** IS NOT ALWAYS THE ANSWER:
Complexity and cost increase for precise, sparse, structured data retrieval.


**1. Precise Sparse Data Access**
MCP's advantages pinpoint exact external data points via clean API seHls.

**2. Contextual Document Recall**
RAG's strength of Context fusion & document topologies inference.

**3. System Performance & Cost**
Latency, lower latency, Real-time time, efficiency, sparse, used for retribution.

**Sources:** Mahntenagunmmannschaft, 1. Juli. 20
2. Eldeckors 2023, itürs-b
Cited. Saponen, et al. Impanco's: 20

# Quick RAG Architecture Overview

# RAG Operations

## READ (QUERY) SIDE

- Formulate specific search query
- Rank & retrieve multi-source results
- Form an accurate, contextual LLM response
- Summarize and ground generated answers

## WRITE (INGESTION) SIDE

- Index and process incoming raw data
- Create relationships for Graph RAG
- Store metadata & relationship summaries
- Maintain and update knowledge base

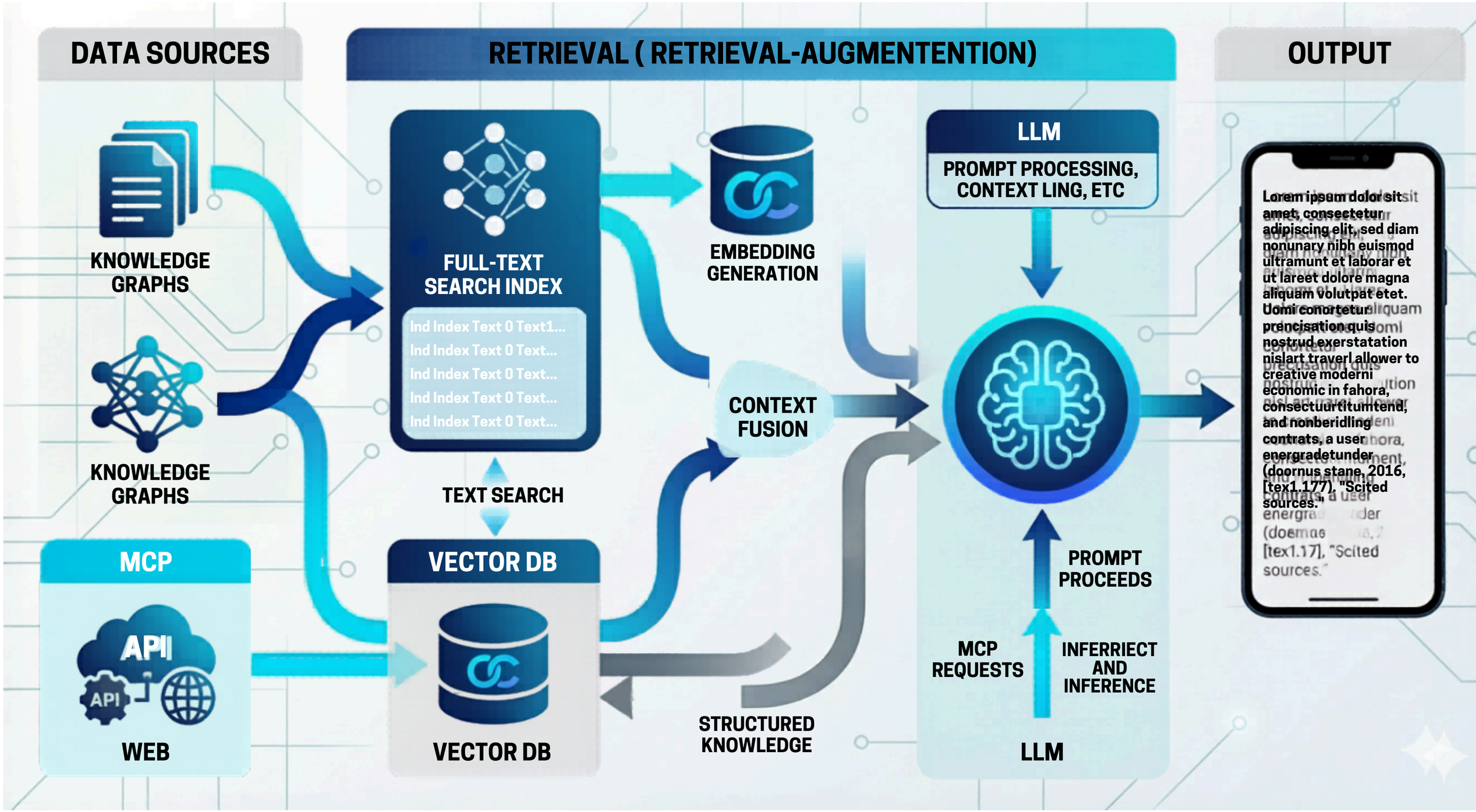
# Phases of RAG (Query & Ingestion)

## READ (QUERY) SIDE

- Look up relevant entries with semantic search
- Look up relevant entities with graph search
- Rerank retrieved results
- Generate contextual response

## WRITE (INGESTION) SIDE

- Chunking: split raw data into manageable parts
- Indexing/Vector Insertion & Creation
- Entity Creation & Extraction
- Graph Relation Creation & Extraction


DATA SOURCES
RETRIEVAL ( RETRIEVAL-AUGMENTENTION)
OUTPUT
KNOWLEDGE GRAPHS
KNOWLEDGE GRAPHS
MCP
API
API
WEB
FULL-TEXT SEARCH INDEX
Ind Index Text 0 Text1...
Ind Index Text 0 Text...
Ind Index Text 0 Text...
Ind Index Text 0 Text...
Ind Index Text 0 Text...
TEXT SEARCH
VECTOR DB
VECTOR DB
EMBEDDING GENERATION
CONTEXT FUSION
STRUCTURED KNOWLEDGE
LLM
PROMPT PROCESSING, CONTEXT LING, ETC
PROMPT PROCEEDS
MCP REQUESTS
INFERRIECT AND INFERENCE
LLM
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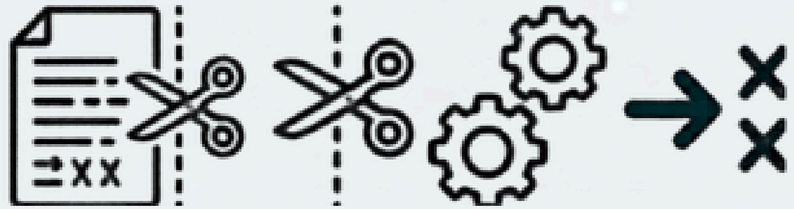
# Phase Highlight: Tokenization/Chunking



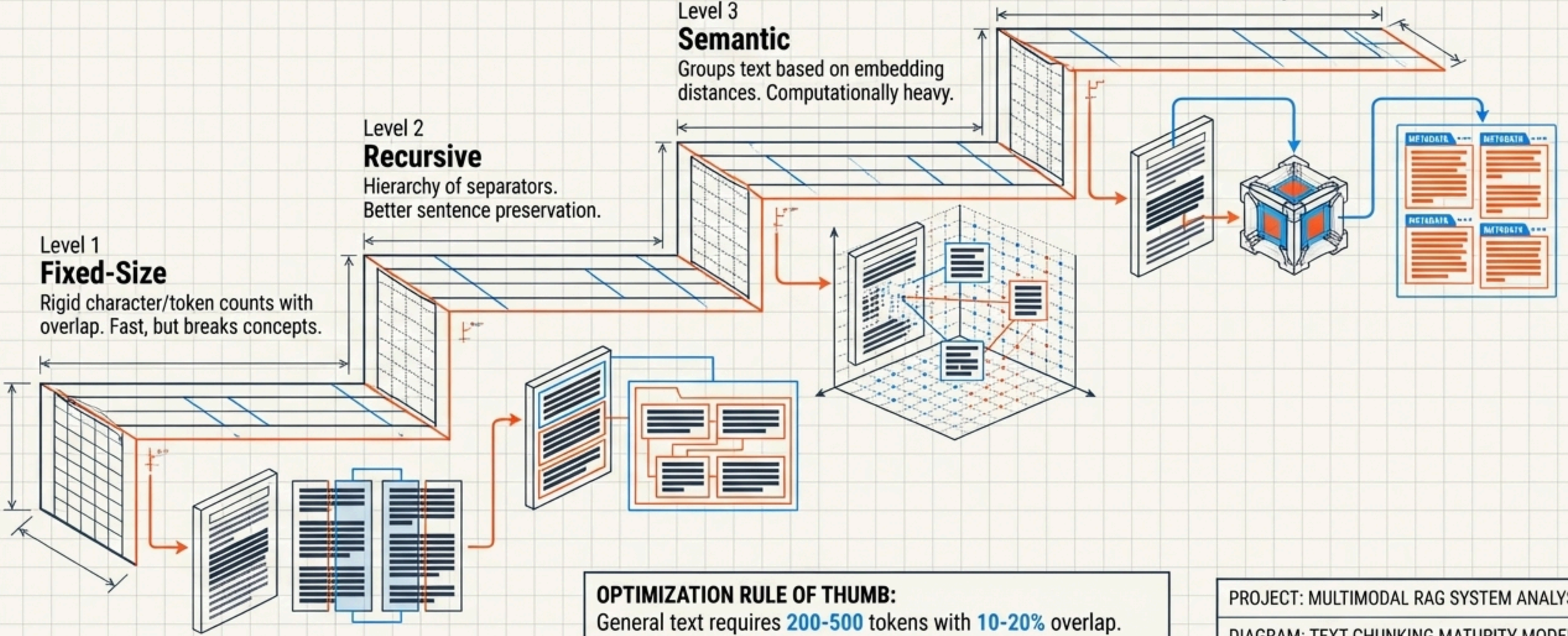
# TEXT CHUNKING MATURITY MODEL

Level 1
**Fixed-Size**
Rigid character/token counts with overlap. Fast, but breaks concepts.

Level 2
**Recursive**
Hierarchy of separators.
Better sentence preservation.

Level 3
**Semantic**
Groups text based on embedding distances. Computationally heavy.

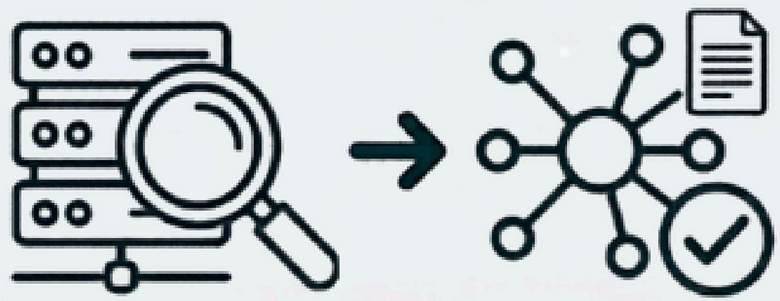
Level 4
**Context-Enriched / AI-Driven**
LLM detects breakpoints and injects metadata.



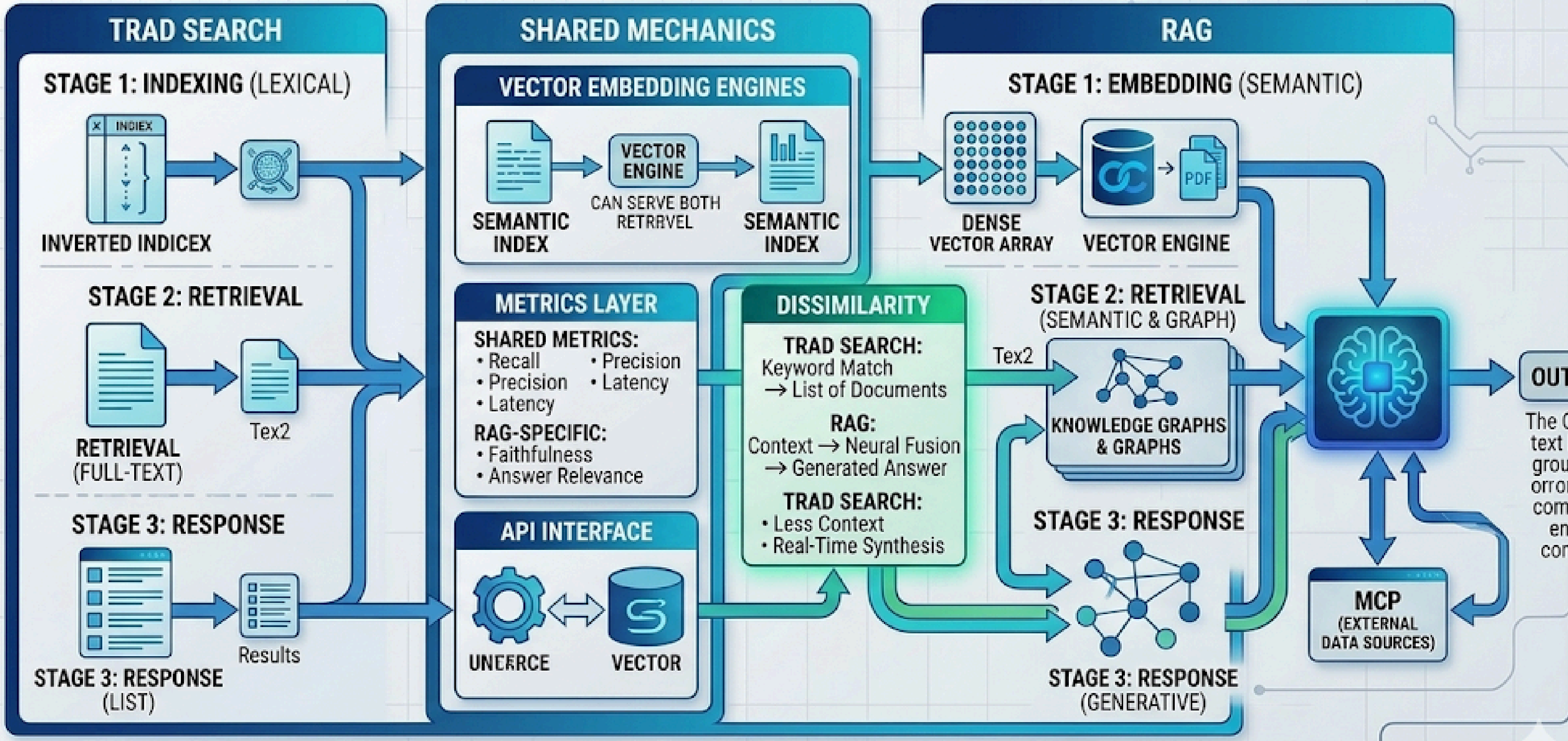
**OPTIMIZATION RULE OF THUMB:**
General text requires 200-500 tokens with 10-20% overlap.
Code/Technical requires 100-200 tokens with 15-25% overlap.

| | |
|---|---|
| PROJECT: MULTIMODAL RAG SYSTEM ANALYSIS | |
| DIAGRAM: TEXT CHUNKING MATURITY MODEL | |
| SCALE: 1:100 | DATE: OCT 26, 2024 |

# Phase Highlight: Retrieval



# TRADITIONAL SEARCH vs RAG: ARCHITECTURAL COMPARISON




**RETRIEVIAL:** Indexing text, structure, and ONTOLOGY delatioships, graph, and attachment relations.

**CONTEXT FUSION:** Assembling in ɑcument, anttachment ɾontext.

**LLM INFERENCE:** Forming response grounded in ɾ complete TOPOLOGY, and lead grouplette results.

**Sources:** Mahitennagument et al. 2021. 2. Eldeokors 2023, ItirS blue. Cited: Soporgon, et al. Innapoca0; blue.

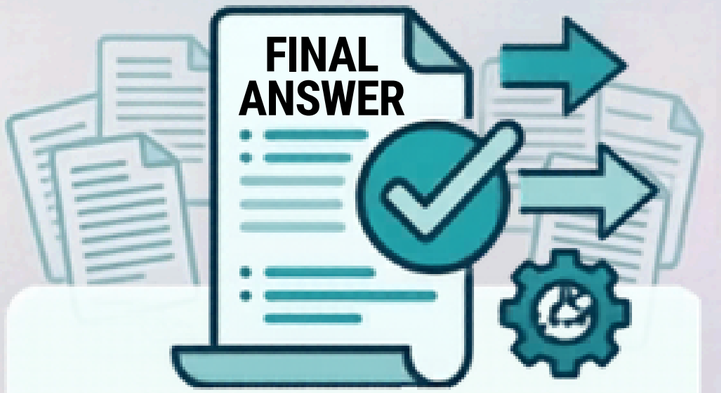
# RERANKING PIPELINE (NORMAL & GRAPH)


## 1. INITIAL RETRIEVAL (NORMAL & GRAPH)

- RAG queries both standard and graph-based data sources.
- Returns raw potential results (e.g., text snippets OR nodes & edges).
- Initial set size: *n* candidates.


## 2. DYNAMIC RERANKING ENGINE

- **Cross-Encoder Analysis:** Precise, context-aware query-document scoring.
- **Metadata-Rich Scoring:** Incorporates entity types, timestamps, and relationship weights.
- **Hybrid Fusion:** Combines scores from multiple specialized models.




## 3. REFINED RESULTS DELIVERY

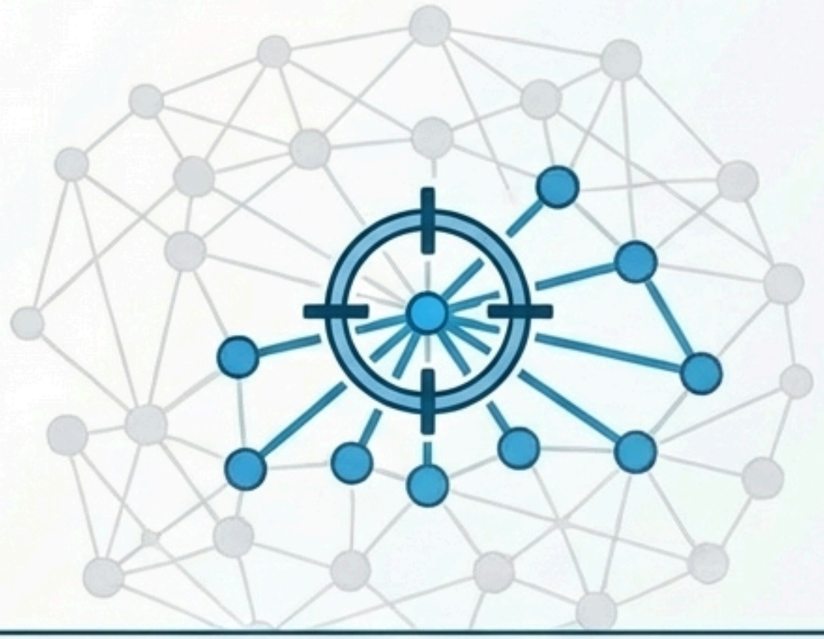
- **Top-k Final Answers:** Prioritizes the most relevant answers, relationship summaries (Graph), or text summaries (Normal).
- **Complete Contextual Grounding:** Ensures answer accuracy and reduces hallucinations.
- **Direct Actionable Insights:** Ready for end-user synthesis further processing.

# Graph RAG: Sorting out relationships between entities.

# Retrieval Modalities: Navigating the Topology

## Local Search

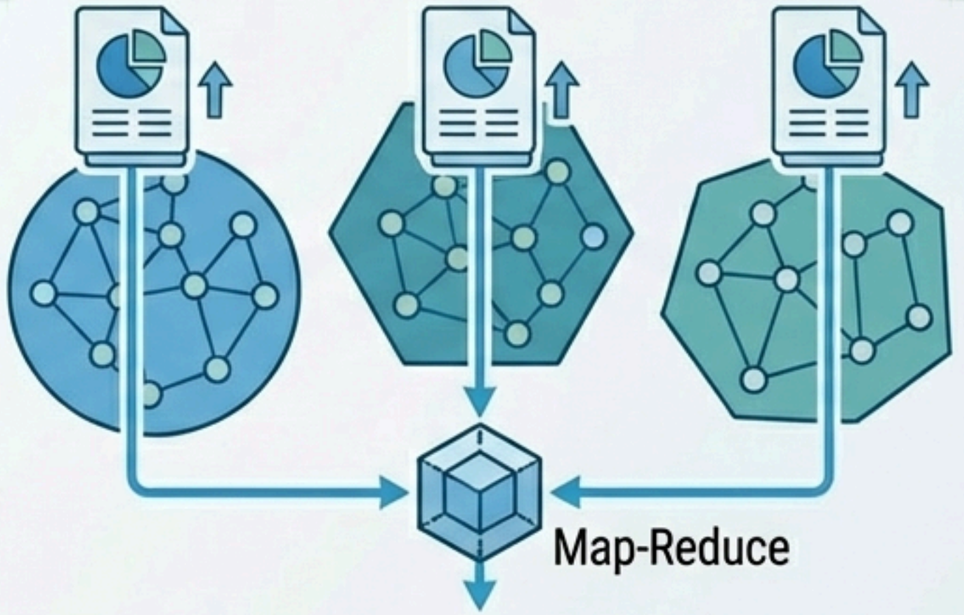
Entity-Centric Traversal



Best for targeted, specific questions requiring high relational depth (e.g., What are the dependencies of the auth module?).

## Global Search

Dataset-Wide Sensemaking



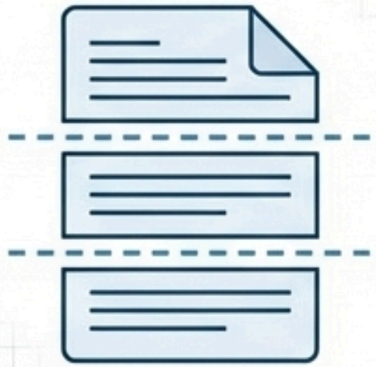

Best for abstract, thematic questions across the corpus (e.g., What are the main risk factors across the entire supply chain?).

**Emerging Modality:** DRIFT Search (Dynamic Reasoning and Inference with Flexible Traversal) balances both methods dynamically.

# Computing the Graph: The Indexing Engine

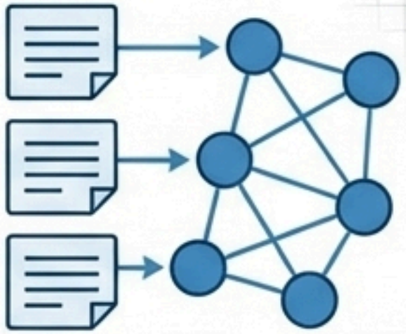
### 1. Text Segmentation

Documents shatter into precisely sized TextUnits (1200 tokens).



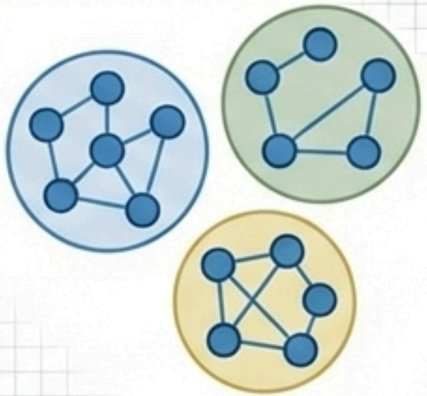
### 2. Entity & Relation Extraction

LLMs extract nodes (people, concepts) and edges (relationships).



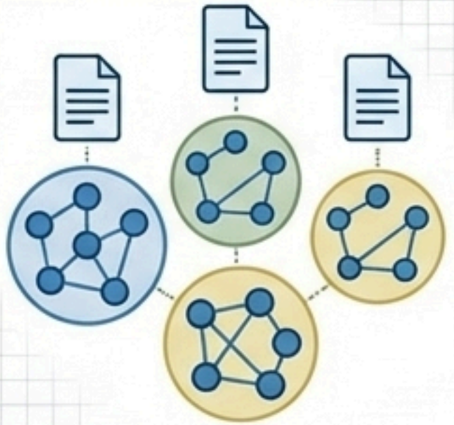
### 3. Community Detection (Leiden Algorithm)

Nodes are mathematically clustered into hierarchical groups.



### 4. Hierarchical Summarization

Generation of bottom-up Community Reports.



Graph construction costs can be 10–100x higher than standard RAG indexing, necessitating careful architectural choices.

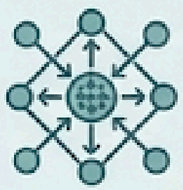
# Kompile
## AN Overview

# Kompile: Advanced RAG System - Comprehensive Provider Landscape

## 1. Vector Stores Role
- Indexing & Search

Chroma · Lucene · pgvector

- **Primary:** kompile-vectorstore-anserini (Lucene-backed HNSW)
- **Alternative:** kompile-vectorstore-pgvector (PostgreSQL pgvector extension)
- **Self-Hosted:** Chroma, Vespa · Pinecone
- **Enterprise-Managed:** Pinecone, Milvus, Qdrant · qdrant

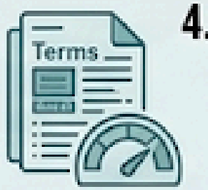


## 2. Embeddings Role
- Dense Encoding

- **HuggingFace Native (Rust-based):** tokenizers-rust/ libtokenizers
- **SameDiff Encoders** (bge-ev1.5, arctic, arctic-embed, etc.)
- **Proprietary APIs:** OpenAI, Anthropic, Google Gemini (via Spring AI)
- **Local Subprocess:** Sentence-Transformers (Python wraper)

## 3. LLM Providers Role
- Generation & Completion

- **OpenAI:** GPT-4o, GPT-3.5-turbo
- **Anthropic:** Claude 3.5 Sonnet, Opus
- **Anthropic:** Clarude 3.5 Sonnet, Opus
- **Google:** Gemini Pro, Gemini Flash
- **Meta:** Llama 3 (hosted via HF Inference API/Samediff-Rag)
- **Cohere:** command-r-v1 · cohere
- **Open-source (SameDiff):** Kompile-hosted GGUF/HF/Local via SameDiff DSP compiler

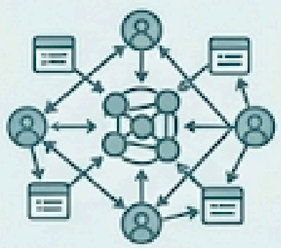



## 4. Search Engines Role
- Sparse & Hybrid IR

Anserini · Elastic

- **Primary: Anserini (Lucene IR Fork):** BM25 sparse + SameDiff dense hybrid
- **Enterprise:** ElasticSearch (Elastic IR/Vectors)
- **Search APIs:** Google Search, Bing Search (via Tools/Plugins)
- **Web Collections:** Wikipedia, Parquet, CommonCrawl, BEIR datasets

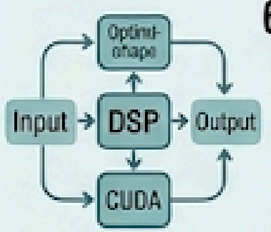
## INFRASTRUCTURE SERVICE LAYER & INTEGRATION (Spring AI)



## 5. Graph Stores Role - Structured RAG

neo4j · DGraph

- **Enterprise Graph:** Neo4j (via Kompile Neo4j graph tool)
- **Self-Hosted Graph:** JanusGraph, DGraph
- **Enterprise-Managed Graph:** Amazon Neptune




## 6. Model Execution Role - Core SameDiff DSP

- **Conversion & Optimisation:** ONNX/TensorFlow -> SameDiff (.sdz)
- GGML/GGUF Import & Metadata Extraction
- PEFT (LoRA), RLHF, DPO, KTO Alignment
- Triton/CUDA Fusion, Dead Code Elimination, Triton GPU Compilation
- OpenAI-Compatible API & MCP Server

GGUF · HF · NVIDIA

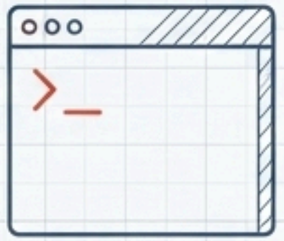
SameDiff Compiler Flow

## KNOWLEDGE BASE & PROVIDER CONNECTOR LAYER

A comprehensive, provider-aware AI/ML platform combining CLI tooling, RAG application framework, model lifecycle management, and a flexible execution framework, all designed for extensibility and universal integration with leading AI providers through plugin architecture and Spring AI connection

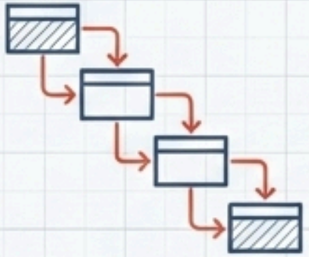
# End-to-End Operation: From Command to Control

## 1. Build



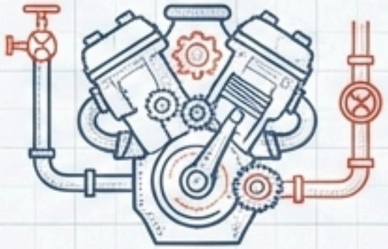
`kompile build app --preset=full`

## 2. Ingest



`kompile ingest /docs`

## 3. Execute



ReAct Agent retrieves via Anserini and generates via SameDiff.

## 4. Evaluate

Visualizing RAGAS evaluation benchmark scores.

Kompile provides a completely self-contained, offline-capable AI lifecycle. Build in the terminal, scale via native subprocesses, and rigorously evaluate in the browser.

# **CLI Chat:** The Multi-Agent REPL

## Multi-Agent System

Seamlessly switch between Claude, Codex, and Gemini within the same execution context.

kompile shell :: multi-agent repl

[Architect] ▾ Claude ▾

```
$ [Architect] kompile chat --agent=Claude
> Claude initialized. How can I help you structure your system today?

$ [User] Analyze the project structure and list all TODOs.
> Running bash command to find TODOs...
  $ grep -r "TODO" src/
  src/main/java/com/example/App.java: // TODO: Implement error handling here
  src/main/java/com/example/Service.java: // TODO: Refactor database connection
  src/test/java/com/example/AppTest.java: // TODO: Add more test cases

> Found 3 TODOs. Would you like me to prioritize them based on the
  architecture?
```

## Role Engine

Set agent personas to Architect, Devops, or Reviewer.

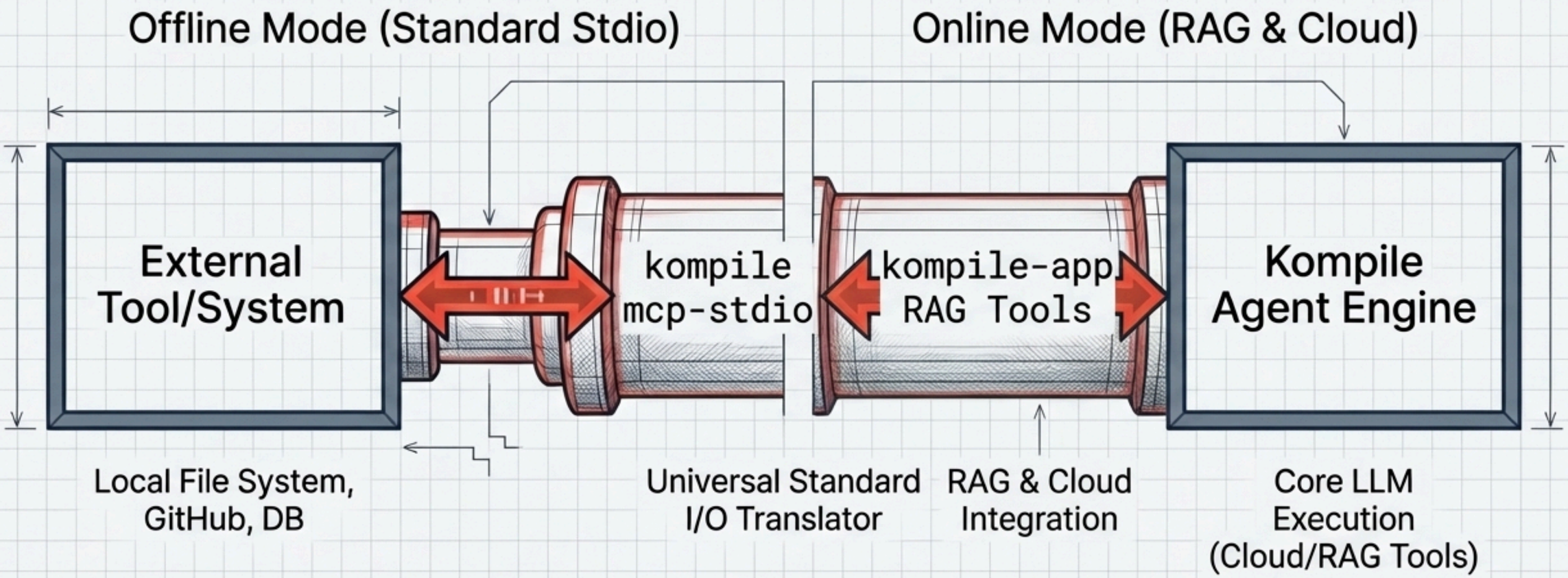
## Tool Integration

Native tool execution for Bash, web search, file edit, and memory management.

### Session Persistence

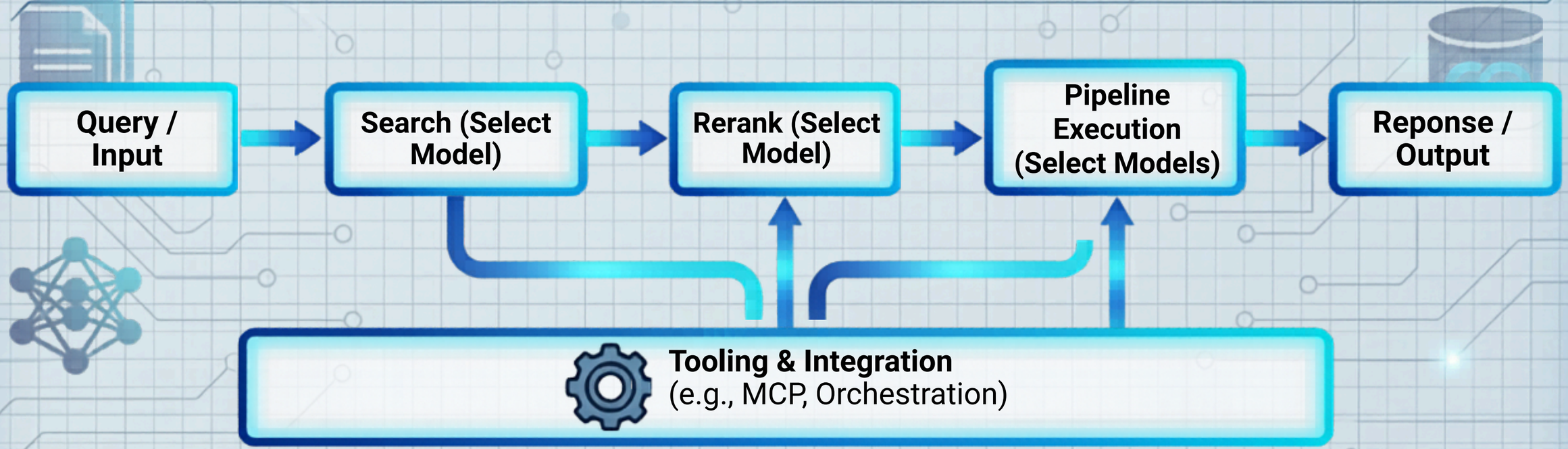
Use `kompile resume` for a multi-tab TUI to browse history, or `kompile session merge` to combine context across different agent architectures.

# Standardized Tooling via Dual MCP




Choose between offline '`mcp-stdio`' for local tool access or online '`kompile-app` RAG' for cloud-integrated tools, decoupling logic from the core agent.

# Model-First Approach: Full Control at Every Step

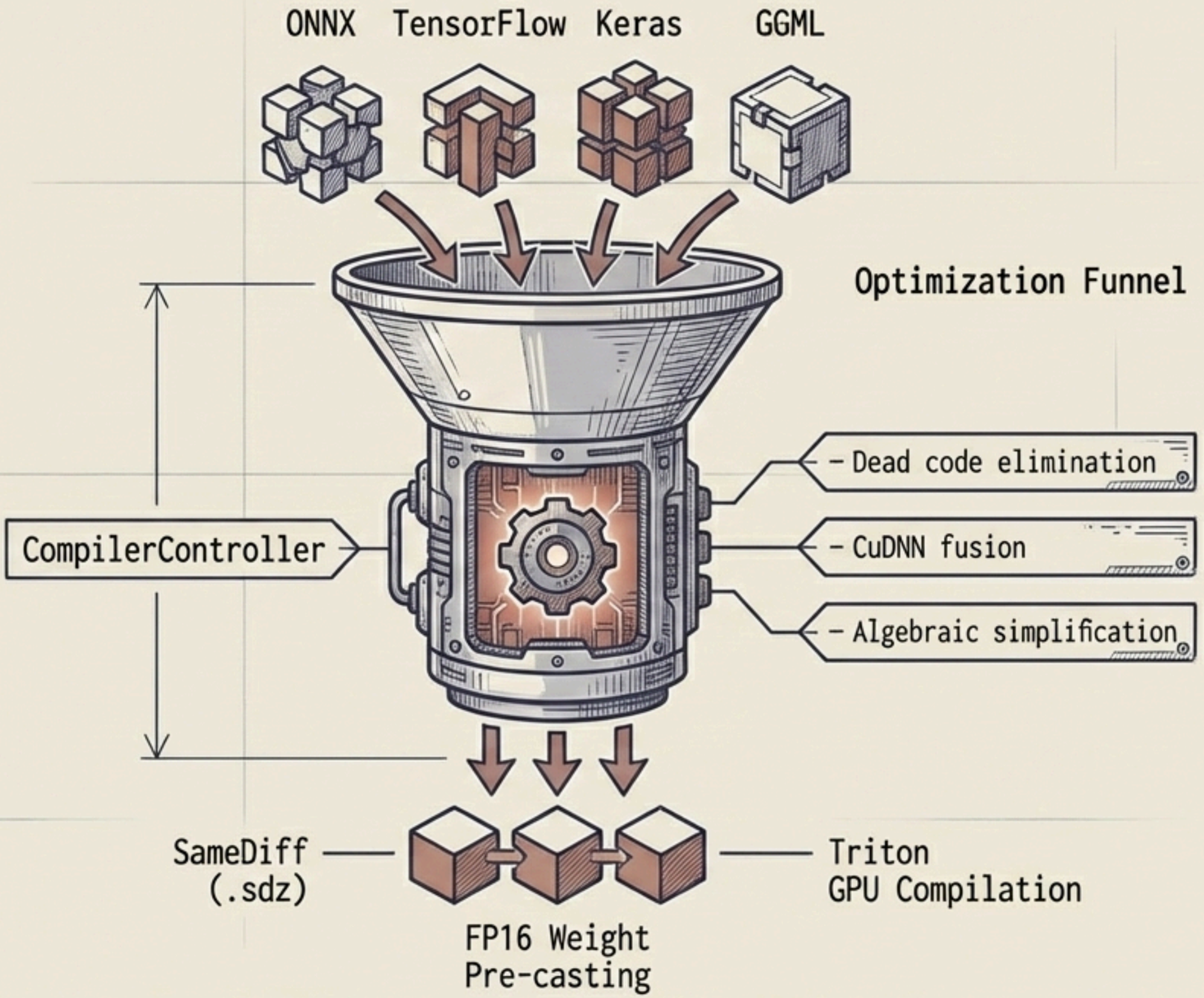



- **Granular Control:** Select and configure specific models for each execution stage (search, rerank, pipelines, generation).
- **Mix & Match:** Combine different models freely to optimize performance for specific tasks.
- **Seamless Integration:** Leverage MCP and other tooling for unified orchestration across all models and steps.

# Under the Hood: Maximum Inference Optimization

Swapping to local models only works if they run efficiently.

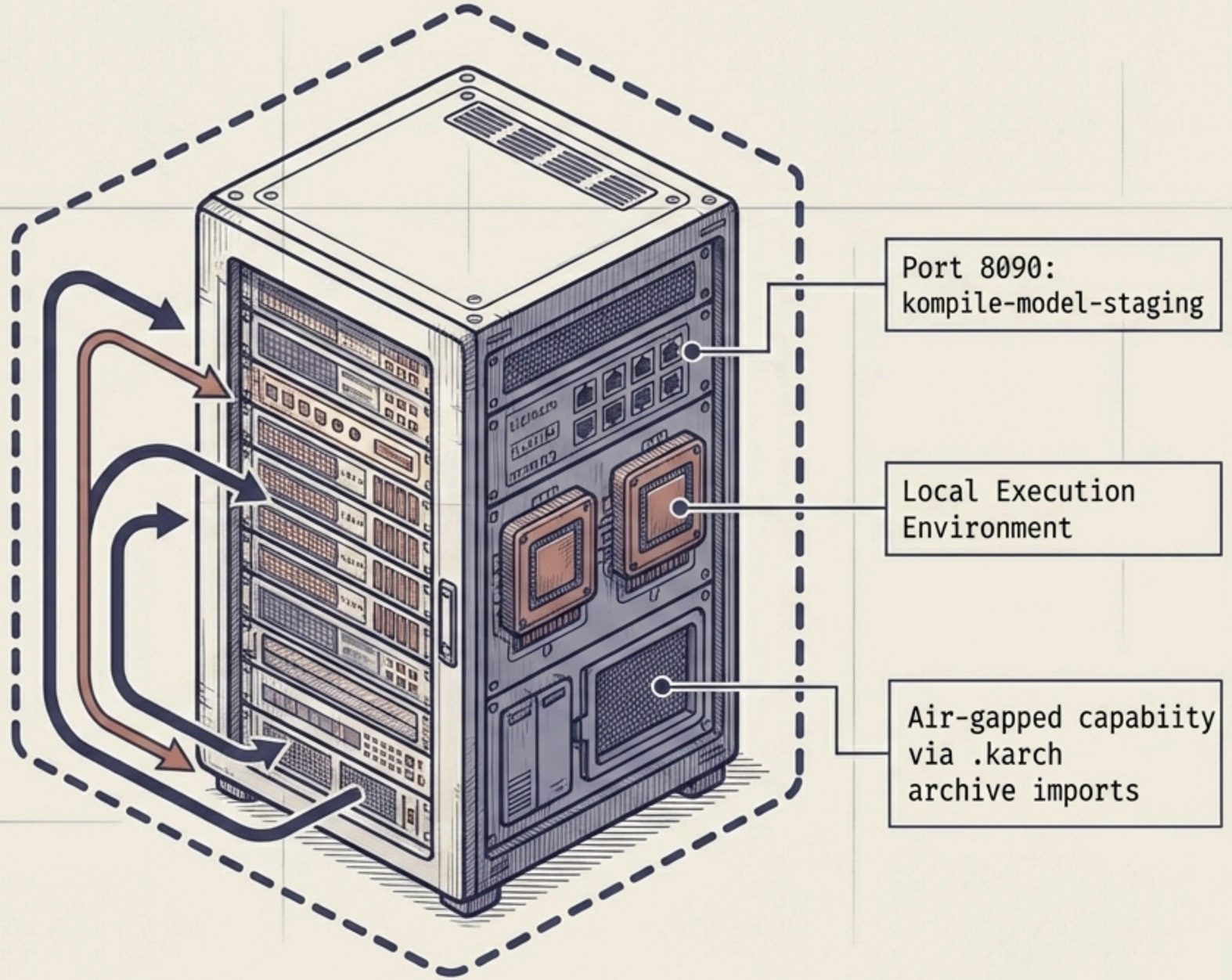
Kompile natively compiles fragmented raw models into optimized computation graphs, fusing operations and pre-casting weights to maximize performance on your specific hardware.



# The Model Control Engine

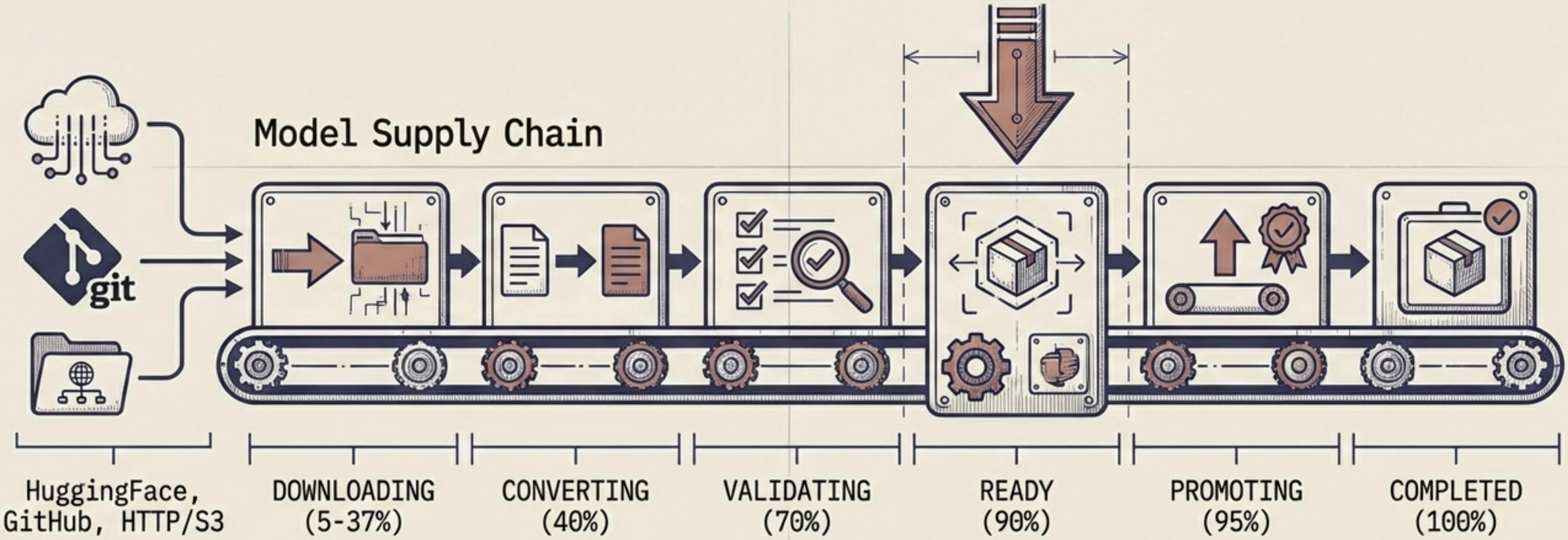
True sovereignty requires pulling models out of third-party clouds and into your own environment.

The Model Staging Server is a standalone Spring Boot service that manages the complete ML lifecycle entirely within your network—even operating fully air-gapped.



# The Automated Model Lifecycle

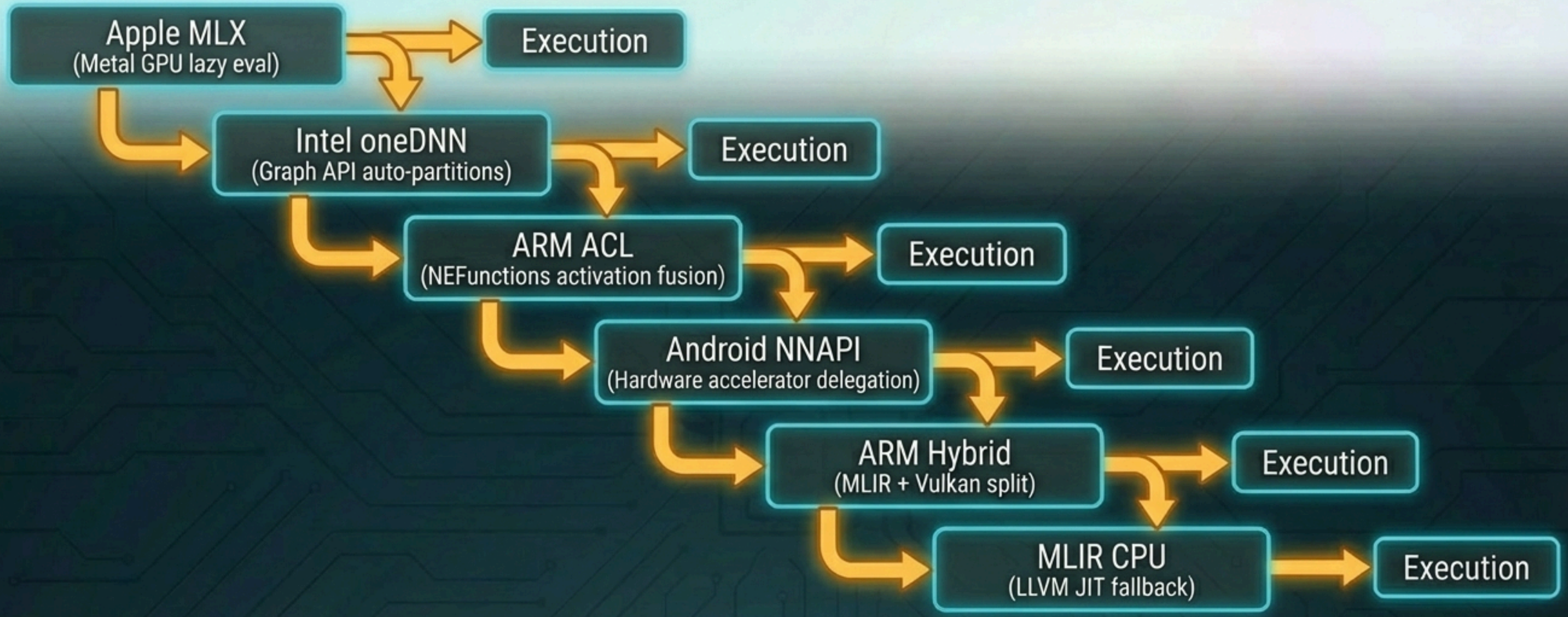
The `StagingController` orchestrates the exact state of proprietary or open-source models, completely abstracting the complexities of model acquisition and deployment.



# Model Execution

# CPU and Mobile Backend Cascade

On non-CUDA platforms, segments are intercepted by a deterministic priority cascade. Each backend applies platform-native fusion (e.g., MLX lazy evaluation on Apple Silicon, oneDNN graph partitioning on x86) using the exact same shape-key caching model as the GPU.



# Structural Matrix: GPU vs. CPU Compilation Models

| Dimension | GPU (Triton) | CPU Backends |
| --- | --- | --- |
| Fusion Granularity | Typed Sections (19 categories) | Whole-segment or backend-library decided |
| Code Generation | MLIR -> TTIR -> PTX | MLIR -> LLVM JIT or Native Library Call |
| Kernel Shape | Parallel Blocks / Grid | Sequential loops with SIMD vectorization |
| Memory Model | tt.ptr (Global memory) / SSA registers | memref (Main memory) / L1 cache |

# Inference Execution Models: The Industry Landscape

DSP occupies the optimal middle ground: fully compiled unlike llama.cpp, but far more deterministic and predictable than torch.compile's recompilation machinery.

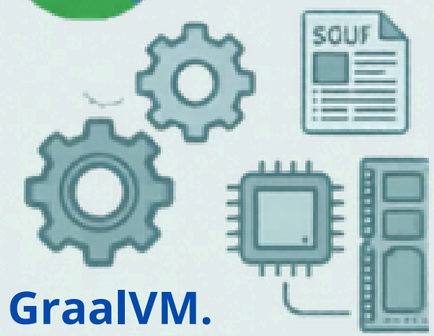
| Dimension | DSP | llama.cpp | torch.compile |
|---|---|---|---|
| Graph Construction | Compiled once, slot-indexed | Rebuilt every token | Captured via bytecode hijacking |
| Dynamic Shapes | Shape key hash recompilation | DAG rebuild per shape | SymInt symbolic ranges |
| Fusion Strategy | Section categories to JIT Triton | Strictly handwritten kernels | Automatic fusion scheduler |
| CUDA Graphs | Per-segment capture | Whole-graph, batch=1 only | Tree structures with shared pools |

# Compile on 2 levels. Your Applications customized. Your models optimized.

## 1. FULL AOT BINARY GENERATION & EXECUTION

**- Native Image & Native Infrastructure**

GraalVM.

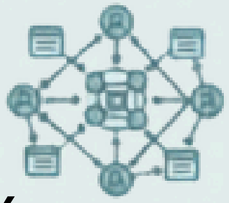



- **AOT Generation:** GraalVM Native Image compiler
- **Applications:** All RAG applications, web servers (Spring Boot), microservices (Quarkus)
- **Model Support:** AOT-comiled models (SameDiff DSP on JVM)
- **Performance:** Instant startup, minimal memory footprint
- **Infra Integration:** AOT-aware databases, vector stores (e.g., Lucene on JVM, Neo4j, pgvector via JVM driver)

## 2. MODEL COMPILATION PIPELINE & INFERENCE

**- SameDiff DSP & OptimizedRuntime**


ONNX



Sol

GGUF/HF

- **Conversion & Optimisation:** ONNX/SensorFlow
- **SameDiff (sdz),** FP16 weight casting, GGF metadata extraction
- **Training & Fine-tuning:** PEFT (LoRA), alignment (RLHF, DPO, KTO), evaluation
- **DSP Execution:** Cuda, Triton GPU compilation, dead code elimination, algebraic simplification
- **Airgap Support:** Model archiving (Karch) and promotion to **PRODUCTION**

**INFRASTRUCTURE SERVICE LAYER & INTEGRATION (SPRING AI)**

## 3. AOT-Aware Data Infrastructure

Lucene

neo4j

- HNSW Dense Vectors (Lucene on JV)
- AOT-aware pgvector SQL
- Neo4j Graph (via Native JVM tools)

neo4j

DGraph

## 4. AOT-Aware Model Tool Stack

GGUF/HF

ND4J

- tokenizers-rust/ libtokenizers
- Sentence-Transformers (Python subprocess)
- ND4J Workspace Cleanup & interruption handling

**KNOWLEDGE BASE & PROVIDER CONNECTOR LAYER**

A comprehensive, performance-aware AI/ML platform combining AOT-based execution and optimized model compilation through plugin architecture and Spring AI connection, all designed for universal integration with leading AI providers.

# Thank you!

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