Continuum Flow

AI-Driven Narrative to Video Architecture

A comprehensive architecture for maintaining context
and character consistency in AI-generated video narratives.

This whitepaper covers chunking strategies, context management,
character consistency, differential state management,
orchestration patterns, and agentic workflows.

Generated: February 5, 2026

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Continuum Flow: Narrative-to-Video Engine

A Portfolio Showcase of Agentic AI in High-Fidelity Media Adaptation

Overview

Continuum Flow is a proprietary agentic framework that represents a breakthrough in the automated adaptation of long-form narrative literature into visual media.

While the industry struggles with the "Context Horizon" and recently identified Context Rot in Large Language Models, we have successfully architected and delivered a system that maintains rigorous **state maintenance**—tracking physical locations, emotional arcs, and inventory across novels exceeding 100,000 words.

This project serves as a showcase of our ability to solve the "Lost-in-the-Middle" phenomenon and context performance decay through a **Hierarchical Recursive Summarization Architecture**. We have transformed raw narrative text into a "living backbone" of state, enabling the generation of consistent, high-fidelity video segments that adhere to the internal logic of the source material.

Key Innovations Delivered

- **Stateful Memory**: Beyond RAG, we treat narratives as **State Machines**, ensuring continuity that spans thousands of scenes.
- **CCMS (Character Consistency Maintenance System)**: Using Identity Anchors to prevent character drift—a common failure in AI video.
- **Temporal-Semantic Chunking**: A proprietary algorithm that aligns textual pacing with cinematic timing (8-10 second beats).

Exploration Path

The following documentation provides a deep dive into the architectural decisions that made this project a success:

- Context Rot (The Problem): Why long context doesn't equal long intelligence.
- System Architecture: How we establish "Ground Truth" before generation.
- Context Engine: Our solution to the context decay problem.
- Chunking Strategy: The math behind the 8-second cinematic constraint.
- Workflows: The multi-agent pipeline from raw text to final directives.

Through **Continuum Flow**, we have demonstrated that AI can not only understand a story but act as its **Continuity Editor and Cinematographer**, delivering a coherent visual adaptation that respects the author's original vision.

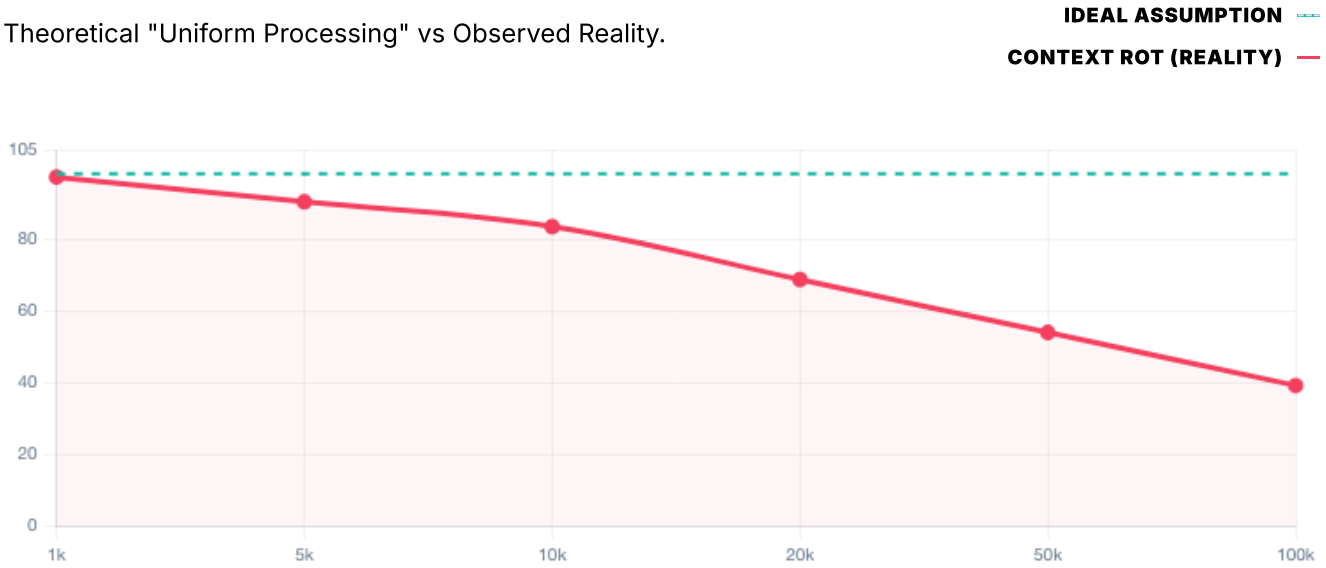
The Context Fallacy

The industry assumption that **“More Context = Better Understanding”** is fundamentally flawed. While context windows have expanded from 8k to 10M tokens, the reliable reasoning capability of models within those windows does not scale linearly.

Context Rot is the hidden decay of detail retrieval and logical consistency that occurs as the “haystack” grows.

Performance Degradation Curve

Theoretical "Uniform Processing" vs Observed Reality.



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3 Drivers of Reasoning Decay

When an LLM is fed a large narrative context, three specific factors trigger performance degradation:

1. Needle-Question Similarity

If the specific information needed (the “needle”) is semantically distinct from the query, models often fail to locate it in a long context. In short contexts, they find it; in long ones, they “lose the scent.”

2. Impact of Distractors

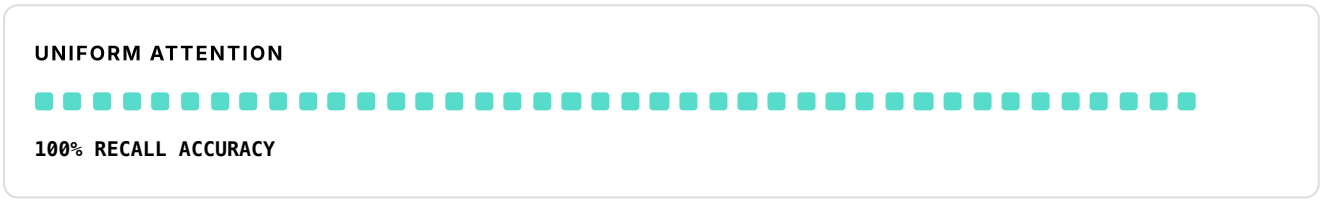
Irrelevant details that “look like” the answer can hijack the model’s attention. Even a single well-placed distractor in a 100k haystack can cause a 30% drop in retrieval accuracy.

3. Structural Ambiguity

The more complex the “Haystack” structure (nested characters, non-linear timelines), the more likely the model is to hallucinate or conflate states between characters.

The Assumption

Engineers assume LLMs process context uniformly, paying equal attention to every token.



The Reality (Rot)

Information in the middle is often ignored as the "Haystack" grows.

The Reality of “Lost in the Middle”

In practice, LLMs exhibit a **Recency Bias** (remembering the end) and a **Primacy Bias** (remembering the start). The middle of the context—where 80% of a novel’s plot usually resides—becomes a “Gray Zone” where logic fails and characters start to “rot.”

This is not a limitation of total memory, but a limitation of **Effective Attention**.

The Antidote: High-Density Context Engineering

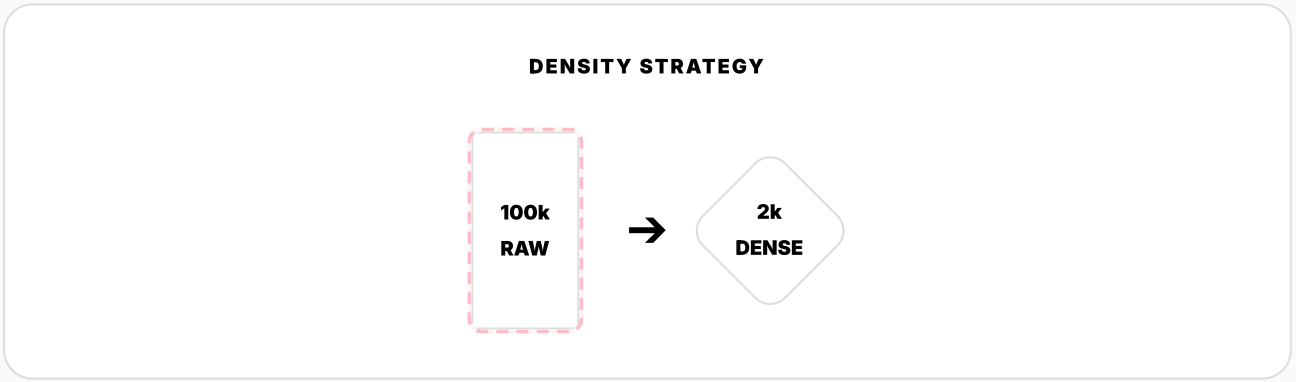
Continuum Flow solves for Rot not by expanding the window, but by **managing its density**.

Instead of feeding 100,000 raw words into the LLM and hoping for the best, we feed it a **2,000-token State Matrix** that has been recursively compressed from the original text.

The Antidote: High-Density Context

Continuum Flow architecture resets the decay curve by compressing a massive, "rotting" haystack into a high-density state diamond.

- ✓ Resets "Lost in the Middle" bias
- ✓ Maintains 100% recall via recursive anchors



Why this works:

1. **Resets the Curve**: The LLM always operates in its “Green Zone” (0-5k tokens).
2. **Eliminates Distractors**: Non-essential narrative fluff is stripped away during the summarization phase.
3. **Strict State Tracking**: Physical location and character status are stored in a fixed schema, preventing semantic drift.

Based on research papers from Chroma-core and DeepMind on Context Performance. ***Read Original Paper*** *(https://research.trychroma.com/context-rot)*

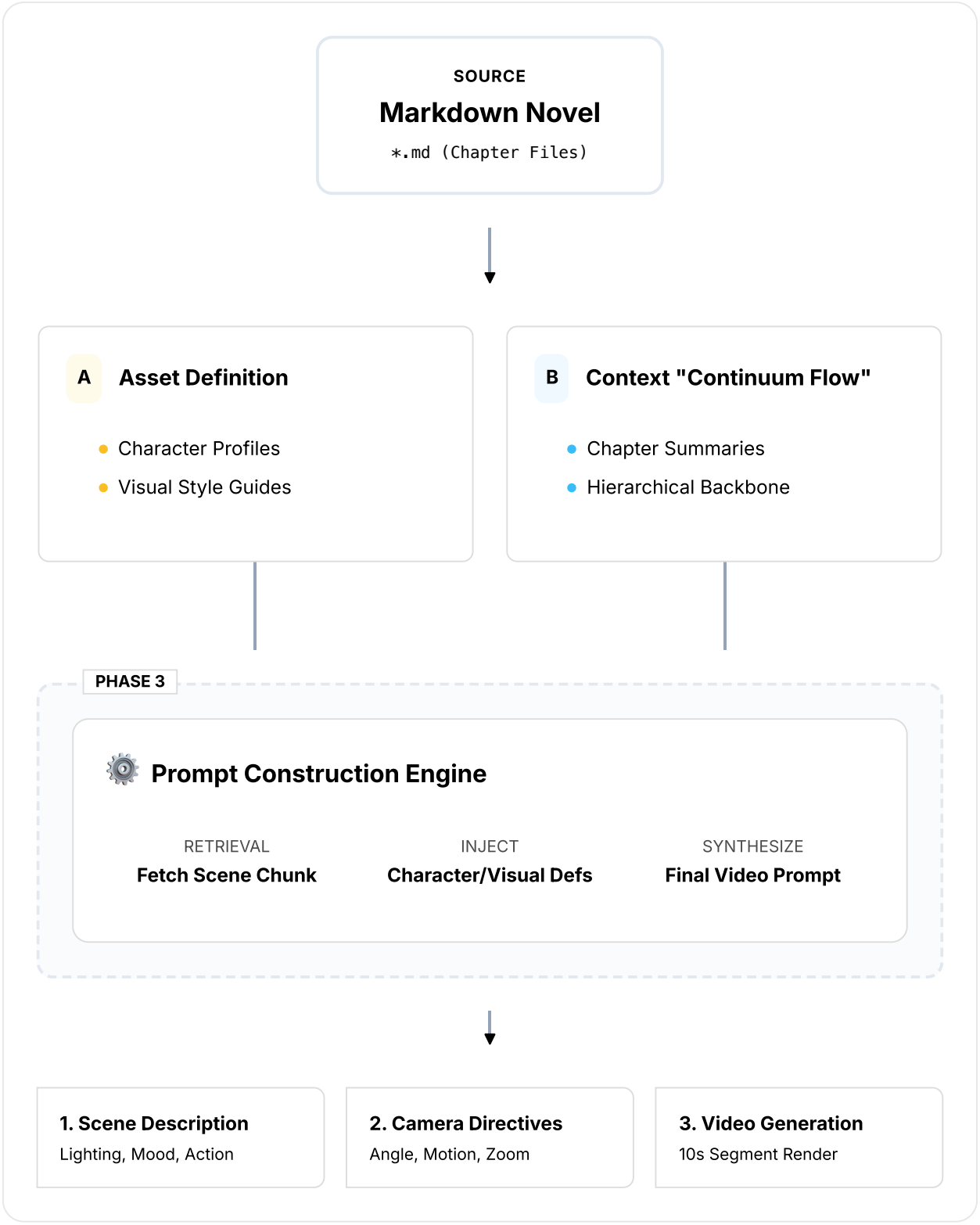
System Architecture

Core Application Architecture & Context Management Flow

The **Novel Video Generator** architecture is designed for high-fidelity narrative consistency. Unlike standard video generation pipelines that operate shot-by-shot, our system utilizes a multi-layered approach that separates static world-building from dynamic narrative progression. By caching character identities and environmental constraints in a “Global State,” we ensure that AI hallucinations are minimized during the final render phase.

Application Data Pipeline

The following diagram visualizes the end-to-end flow from raw Markdown input to the final 10-second video segments. The architecture is split into three primary phases: Static Asset Definition, Dynamic Context Management (The “Continuum Flow” Agent), and the Prompt Construction Engine.



Pre-processing and Definition Phase

Before a single frame of video is generated, the system must establish the “Ground Truth” of the story world. In a traditional film production, this is the pre-production phase: casting, costume design, and location scouting. In Continuum Flow, this is an automated agentic workflow that builds a static

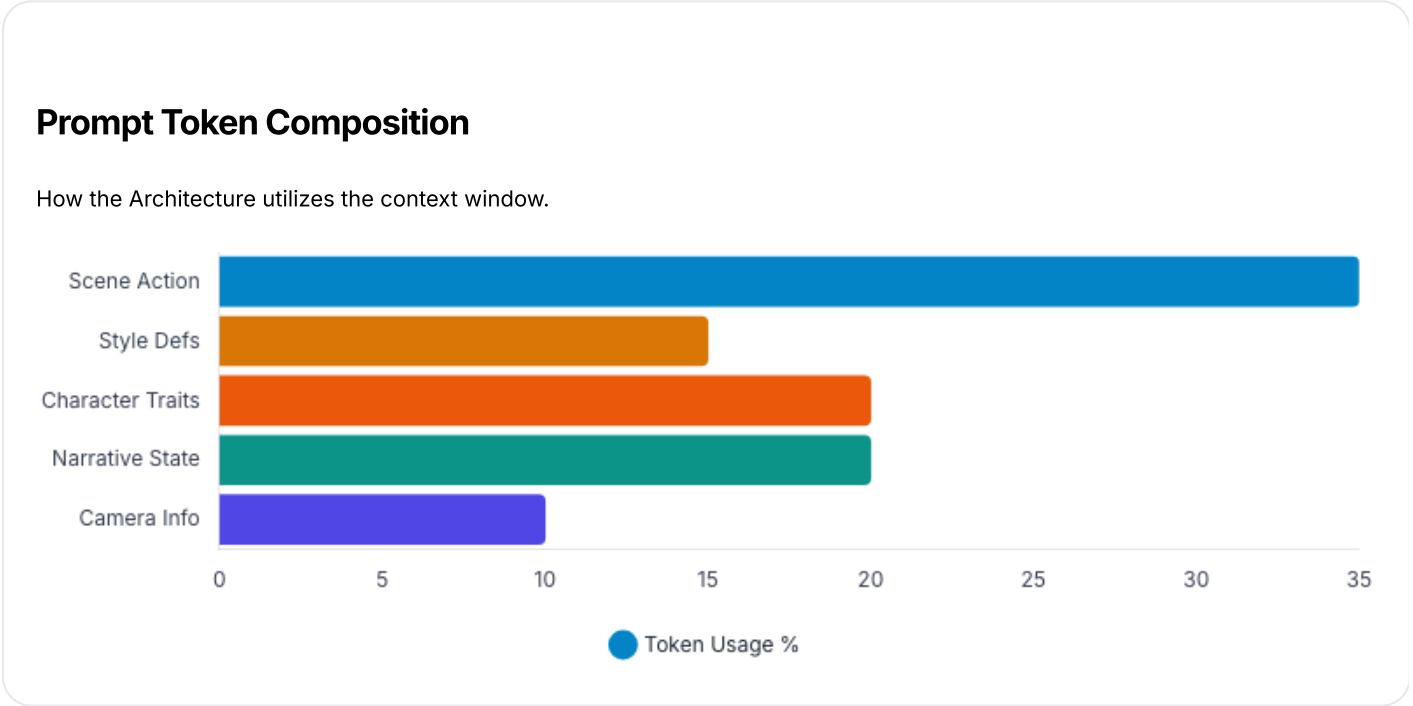
reference database. This phase is critical because generative video models (unlike text models) require explicit visual instructions for every frame to prevent hallucination or morphing of character identities.

Character Profile Definition

The first agentic workflow triggers the **Character Definition Agent**. This agent scans the entire corpus (all Markdown files) to identify unique entities. It then synthesizes comprehensive profiles for each character.

Visual Attribute Locking

To maintain consistency in video generation, character descriptions must be translated into immutable visual prompts. The agent generates a “Character Reference Sheet” for each entity, defined in a rigid JSON schema. This schema acts as the “Source of Truth” for all subsequent generation steps.



Attribute Category	Data Points Captured	Purpose in Video Generation
Physicality	Height, body type (e.g., ectomorph), skin texture, eye shape, hair hex code.	Ensures the silhouette and basic appearance remain constant across varied camera angles.
Costume	Primary Outfit, Secondary Outfit, Accessories (e.g., “Silver Locket”).	Prevents the model from “hallucinating” different clothes in every shot.
Identity Anchors	Scars, tattoos, distinct hairstyles, specific props (e.g., “glowing staff”).	These are high-weight tokens injected into every prompt to force model attention on unique identifiers.
Style LoRA	Reference to specific Low-Rank Adaptation models or embeddings.	Links the text profile to a specific visual model trained on the character’s likeness.

Psychological and Narrative Roles

Beyond visuals, the profiles include “Behavioral Tensors”—descriptions of how a character moves and reacts. A “nervous” character requires video instructions for “jittery camera movement” or “fidgeting hands,” while a “stoic” character requires “static framing” and “minimal micro-expressions.” These behavioral traits are encoded as metadata that influences the camera direction in later phases.

Scene Description and Environmental Modeling

The system creates a **Global Location Registry**. Similar to character profiling, the **Environment Agent** scans the text to identify recurring locations.

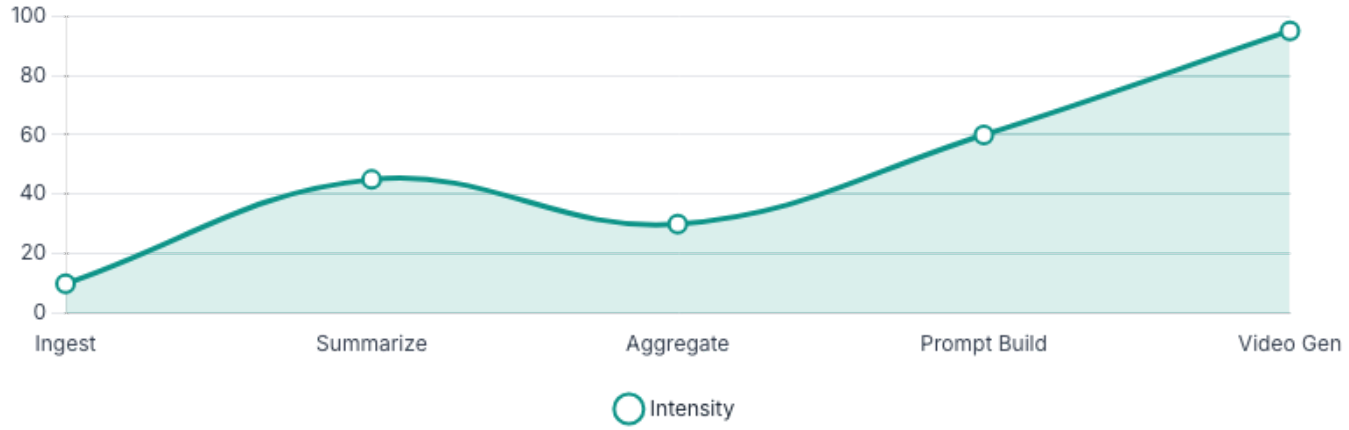
- **Lighting and Mood**: For each location, the agent defines the baseline lighting (e.g., “volumetric god rays,” “cyberpunk neon,” “dim candlelight”) and atmospheric mood.
- **Spatial Geometry**: To ensure characters move consistently through space, the agent estimates the geometry of key sets (e.g., “The kitchen island is to the left of the fridge”).

The Pre-processing Workflow

1. **Entity Extraction**: An NLP entity extraction model runs over the full text.
2. **Cluster Analysis**: Mentions of “John,” “Jonathan,” and “The Detective” are clustered to verify they refer to the same entity.
3. **Profile Synthesis**: An LLM aggregates all descriptors into a unified profile.
4. **Conflict Resolution**: A specialized **Conflict Agent** flags inconsistencies for review.

Processing Pipeline Load

Execution density across the delivery lifecycle.



The 8-Second Constraint

One of the most technically demanding constraints of this project is the requirement that each generated scene corresponds to a video segment with a maximum duration of 8 seconds. This is not merely a file-size constraint but a narrative pacing constraint. It forces the system to break the flow of a novel into "micro-beats."

The Temporal-Textual Conversion Problem

Text does not have an inherent duration. A single sentence ("The war lasted a hundred years.") can imply a century, while three pages of stream-of-consciousness thought might occur in a split second. Converting text to time requires a heuristic algorithm based on **Speech Rate** and **Action Density**.

The "Time-Cost" Algorithm

We utilize a heuristic derived from voice-over and screenplay standards to estimate the duration of a text segment. The average speaking rate for clear, narrative voice-over is approximately 140 words per minute (wpm).

THE BASE CALCULATION

140 Words / 60 Sec = ~2.3 Words/Sec

Target: ~18-20 Words per 8s Clip

However, a strict word count is insufficient because "action text" reads faster than "dialogue text." Therefore, the **Chunking Agent** employs a weighted token analysis:

Token Type	Weight Multiplier	Rationale
Dialogue	1.0	Spoken at natural speed.
Descriptive	0.7	Visuals process faster than reading; a detailed description of a room can be shown in 2 seconds.
Action	Variable (0.5 - 2.0)	"He ran" (Fast/0.5). "He waited for the sun to set" (Time-lapse/2.0).

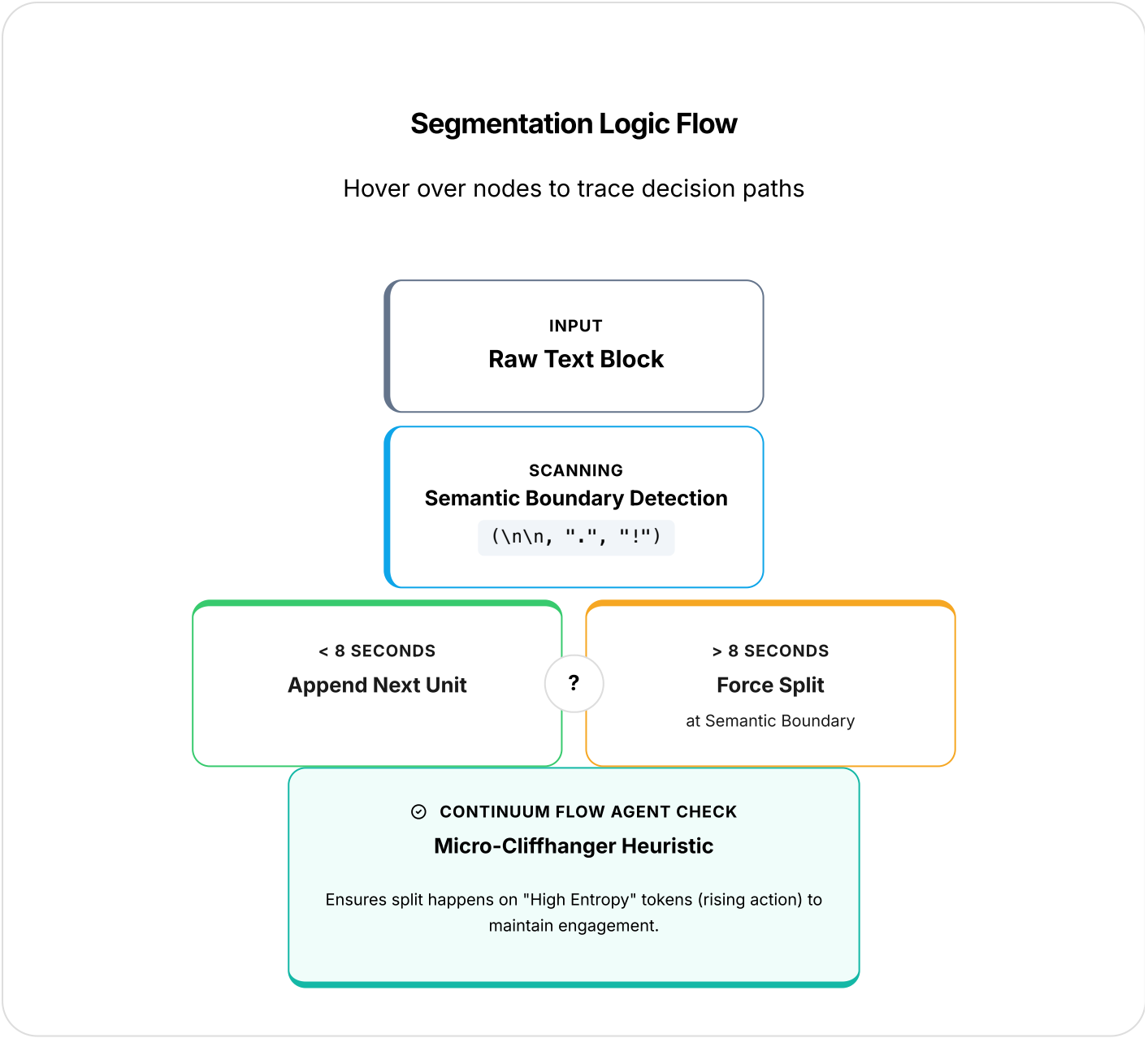
Weighted Token Analysis

Visualizing the time-cost multiplier for different content types.

The Segmentation Architecture

The chunking process follows a strict “Atomic Scene” logic to ensure that video generation models (which often drift after 5-10 seconds) remain coherent.

1. **Input**: A block of text from the Markdown file.
2. **Semantic Boundary Detection**: The system scans for natural breaks like paragraph breaks (`\n\n`), dialogue tags (`"`, `”`), or sentence terminators (`.`, `?`, `!`).
3. **Duration Estimation**: The system calculates the estimated duration of the segment using the weighted algorithm.
    - *If Estimated Duration < 10s*: The system appends the next semantic unit.
    - *If Estimated Duration > 10s*: The system forces a split at the nearest semantic boundary (sentence or clause level).
4. **Coherence Check**: A lightweight “Continuum Flow” sub-agent reviews the split. If a sentence is cut in a way that destroys meaning (e.g., split between subject and predicate), the boundary is shifted.



The “Micro-Cliffhanger” Heuristic

To maintain viewer engagement across these short 8-second clips, the chunking algorithm favors splits that end on “high entropy” tokens—words that imply unresolved action or rising intonation. This ensures flows naturally into the next clip.

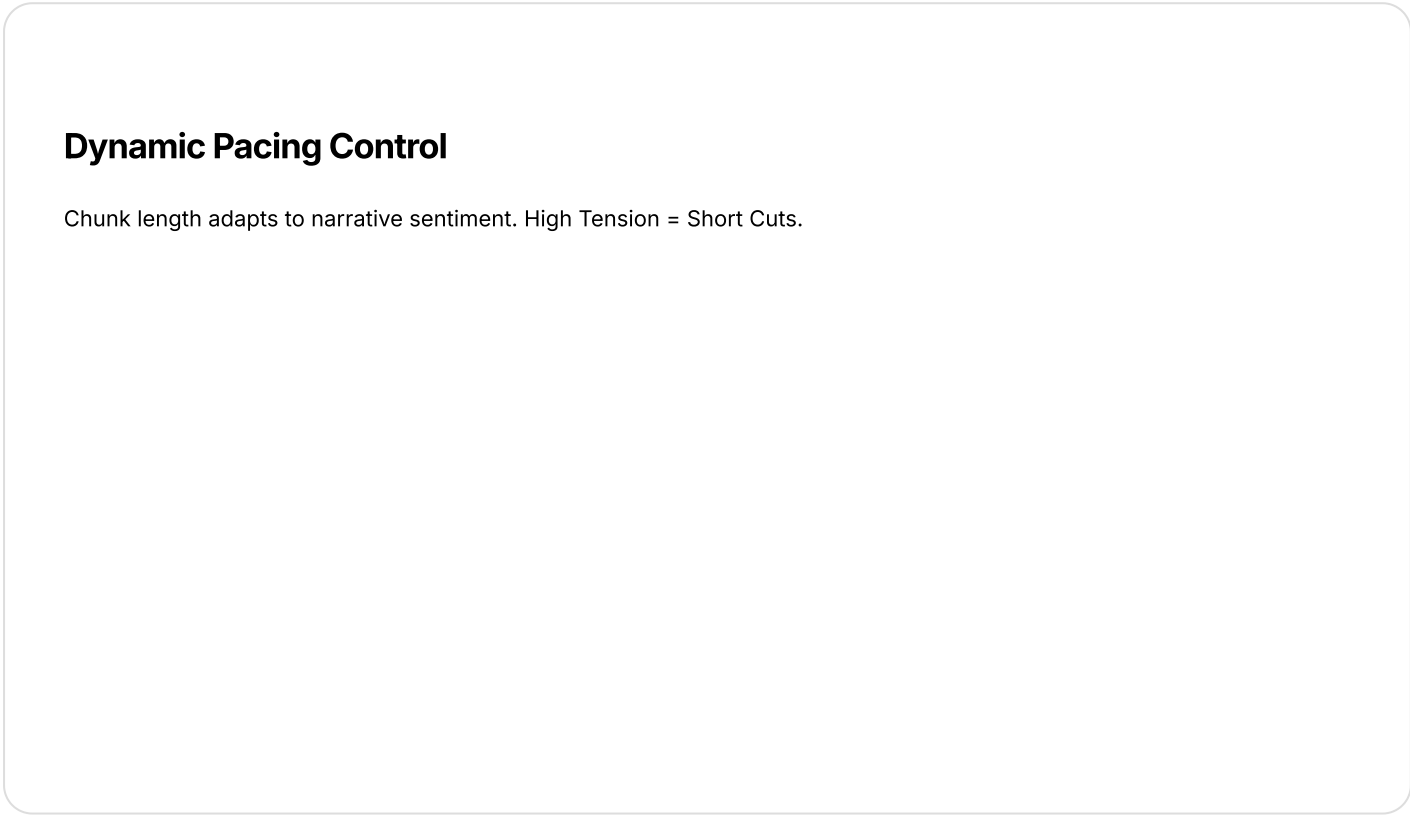
Deep Dive: The Chunking Heuristic and Pacing

The 8-second constraint is more than a technical limit; it is an aesthetic one. It dictates the “rhythm” of the generated video.

Dynamic Pacing Control

The Chunking Agent analyzes the **Sentiment and Pacing** of the text segment.

- **High Tension (Fight Scene)**: The agent intentionally creates shorter chunks (2-3 seconds). Even though the limit is 8s, rapid cuts increase tension.
- **Low Tension (Landscape Description)**: The agent maximizes the chunk to the full 8 seconds to allow for slow, panning camera movements.



The “Audio-Visual Split”

The architecture actually creates *two* parallel streams from the chunk:

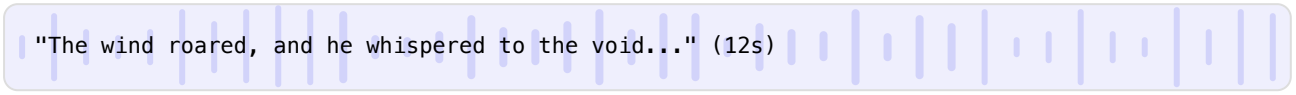
1. **Visual Prompt**: (Used for Video Gen).
2. **Audio Prompt**: (Used for TTS/Audio Gen).

If the dialogue is too long, the system splits the Visual Prompt into two clips (Part A and Part B) but keeps the audio flowing across them.

The Audio-Visual Split

Handling "Talky" scenes where dialogue exceeds the visual constraint.

AUDIO STREAM (CONTINUOUS)



VISUAL STREAM (SPLIT)

Narrative Compression Engine

Applying "Semantic Compression" to Novel-to-Video generation. Treating narrative not as text, but as compile-able state data.

The Semantic Compression Pattern

Current LLMs suffer from "Context Rot" in long-form generation. To solve this, we are adopting an architectural pattern inspired by modern code repository packers[1].

The Core Analogy

The pattern solves context problems by "compressing" code: it parses the Abstract Syntax Tree (AST) and removes implementation details (function bodies), keeping only the definitions (signatures). We apply this exact logic to narrative.

💻 Code Repository

Strategy: AST Stripping

```
function calculatePhysics() {
  // detailed implementation...
  // math logic...
  // extensive comments...
}

>> COMPRESSED TO HEADER:
declare function calculatePhysics(): void;
```

The Insight: The "Truth" is the Logic Signature. Implementation details are stripped to save tokens.

📖 Narrative (Continuum Flow)

Strategy: Semantic Compression

```
He felt a wave of nostalgia as...
Arjun picks up the glowing shard.
It reminded him of the winters in...
The shard pulses red.
```

```
>> COMPRESSED TO STATE:
{ actor: "Arjun", action: "Take Shard", prop_state: "Red Pulse" }
```

The Insight: The "Truth" is the Visual State. Internal monologue is "whitespace" that wastes tokens.

The Narrative AST (Abstract Story Tree)

Transforming prose into a rigid JSON Schema.

INPUT: RAW TEXT

```
The cyber-rain poured down. "Wait!" she screamed. Her robotic arm sparked. She didn't want to fight, but she had to.
```

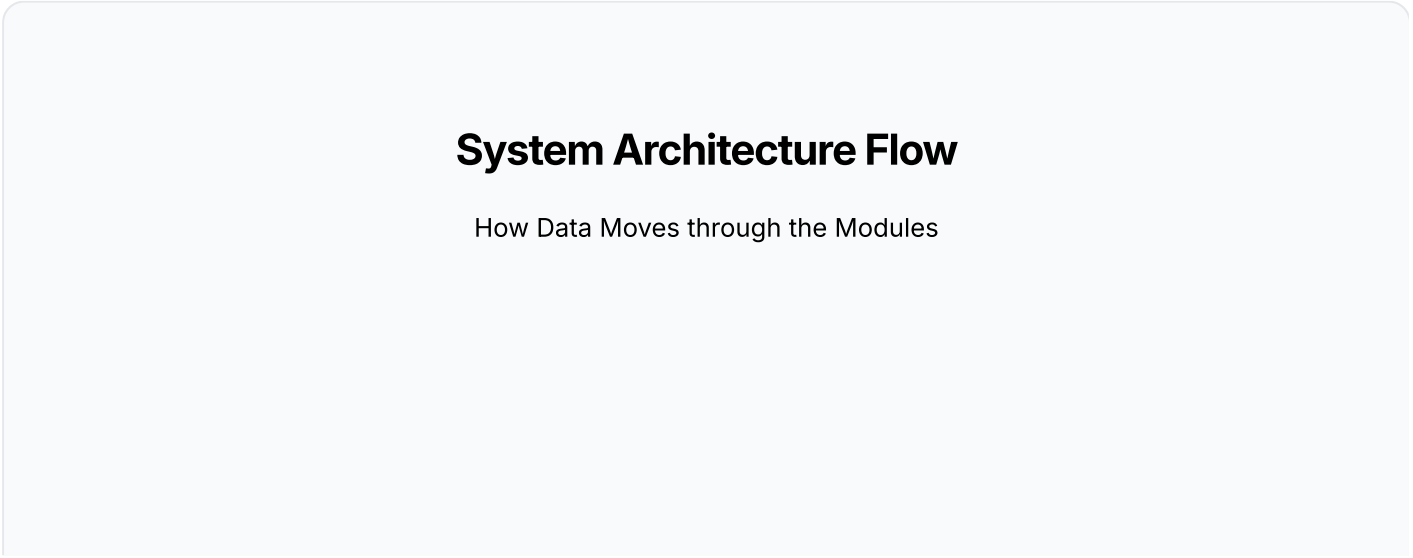
→

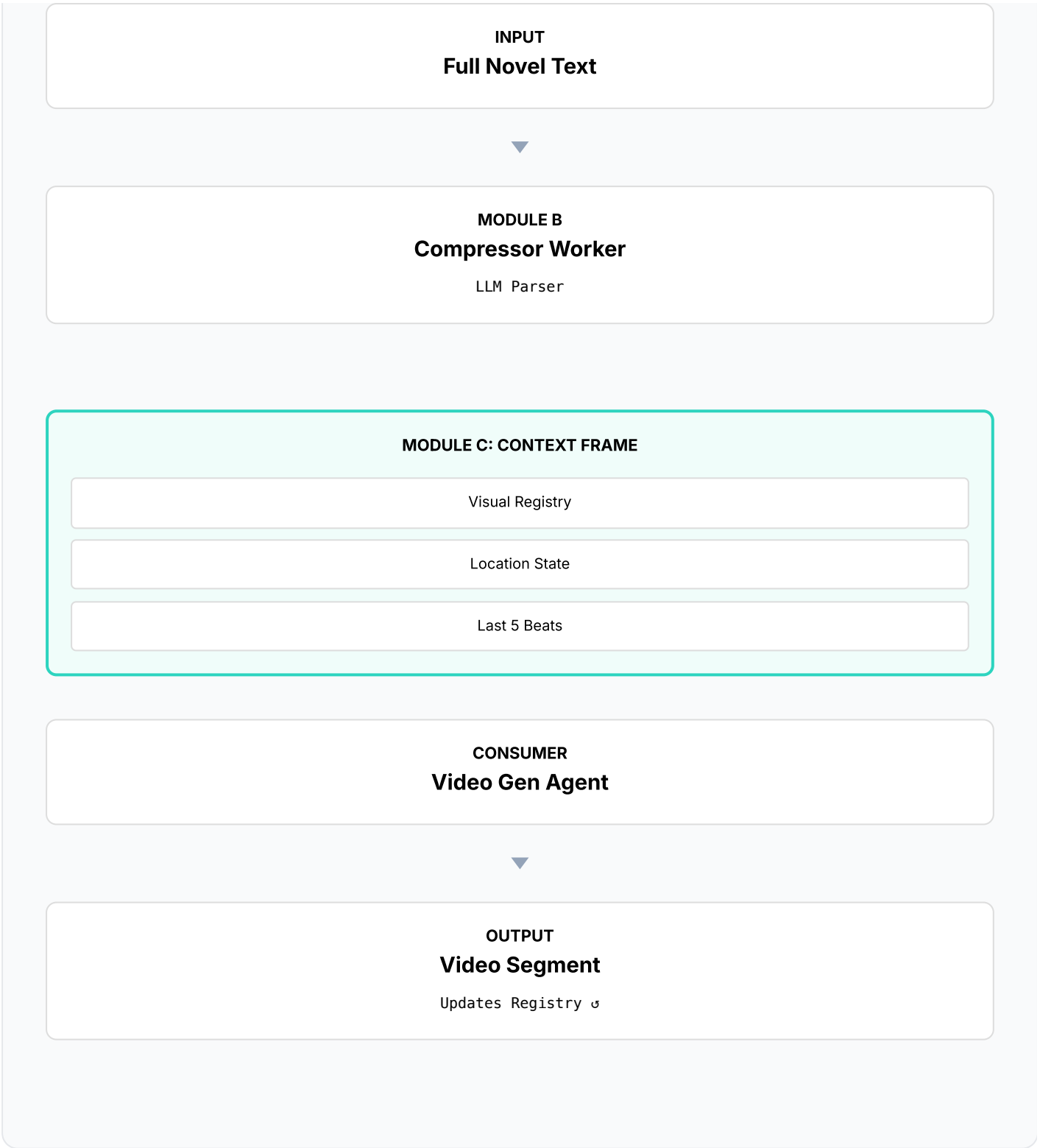
OUTPUT: SCENENODE JSON

```
{
  "env": "Rain (Cyber)",
  "audio": "Scream: 'Wait!'",
  "visual_fx": "Sparking Arm",
  "subtext": "Reluctant"
}
```

Network Architecture: Visualized

The following diagram illustrates the flow of data through the Semantic Compression Engine. It visualizes how raw text is ingested, parsed by the "Compressor Worker," structured into a rigid JSON Context Frame (Module C), and finally consumed by the Video Generation Agent.





Module Breakdown

Module A: The "Compressor" Worker (The Parser)

- **Role:** Acts as the parsing engine (similar to an AST strategy).

- **Algorithm:**

    1. **Ingest:** Takes a 5-page raw text buffer.
    2. **Entity Extraction (NER):** Identifies all Proper Nouns (Characters) and Physical Objects (Items).
    3. **State Differential Check:** Compares the current object description with the `GlobalRegistry`.
    4. **Action Distillation:** Summarizes 500 words of dialogue/action into a single atomic "Beat".
    5. **Discard:** Removes all "flavor text" (internal monologue, metaphors).

Module B: The "State Manager" (The Context Guard)

Instead of feeding the LLM "The last 10,000 words," it constructs a synthetic context frame containing:

1. **The "World State":** Current immutable facts (Time: Night, Weather: Rain, Health: 50%).
2. **The "Compressed Context":** The summary of previous chapters (Level 2 Context).
3. **The "Active Chunk":** The raw text of the current scene being generated.

Module C: The "Lookahead" Buffer

- **Role:** Parallel processing for temporal consistency.
- **Purpose:** To detect **Future State Changes** (e.g., a character losing an arm in Chapter 3) ensuring temporal consistency.

The Protocol Layer (TOON)

To combat "Context Rot," Continuum Flow abandons JSON for the Context Window. We utilize **TOON (Token-Oriented Object Notation)** for all state tracking.

Narrative consistency requires tracking hundreds of state variables (wounds, inventory, relationships). JSON's verbosity limits how much history we can retain. By switching to TOON, we fit **3x more chapters** into the same context window, allowing for 'novel-length' memory retention rather than just 'chapter-length'.

The "Sweet Spot" Analysis

TOON shines in one specific area: **Uniform Arrays of Objects**. In a novel, you track lists of characters, active props, and environmental states. JSON repeats the keys for every single item, wasting tokens. TOON defines the schema once.

🐌 Standard JSON

Overhead: High (Repeated Keys)

```
[
  { "name": "Arjun", "status": "injured" },
  { "name": "Mira", "status": "alert" },
  { "name": "Kael", "status": "asleep" }
]
```

Result: ~50 Tokens. Keys "name" and "status" repeated 3x.

⚡ TOON Protocol

Overhead: Minimal (Schema Header)

```
characters[3]{name,status}:
Arjun,injured
Mira,alert
Kael,asleep
```

Result: ~20 Tokens. 60% Reduction in Context Load.

Revised "TOON-Native" Workflow

We implement a safe pipeline to use TOON without risking LLM syntax hallucination.

1. **Extract (Safety):** The Agent reads Chapter 1 and outputs `scene_data.json`. We keep the LLM output as JSON because models are trained heavily on it.

2. **Compress (Worker):** A Node.js worker converts the JSON into `` `context_history.toon` ``. This ensures perfect syntax.
3. **Inject (Context):** When generating Chapter 2, we load the TOON file into the System Prompt: *"Here is the current state of the world in TOON format."*

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[1] Reference Architecture: This pattern is inspired by RepoMix (https://github.com/yamadashy/repomix), a tool for packing codebases into LLM contexts using Tree-sitter for semantic understanding.

Agentic AI & Context Management Architecture

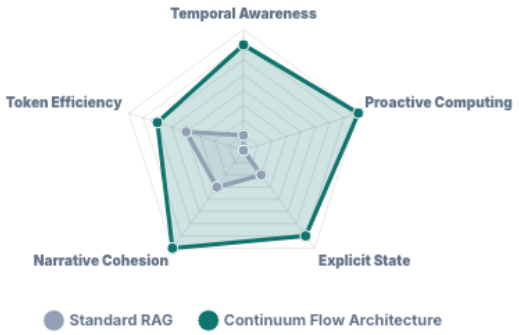
This section details the core innovation of the project: the **Continuum Flow** architecture. This system manages the trade-off between the infinite depth of a novel and the finite constraints of the LLM context window.

The Problem: Why Standard RAG Fails for Narrative

Retrieval-Augmented Generation (RAG) is designed for fact retrieval, not causal narrative logic. A novel is a chain of events where “State” (who has what, who is where) matters more than semantic similarity.

CONTEXT ARCHITECTURE

Standard RAG Approaches vs. The Continuum Flow Methodology



Architecture Profile

While standard Context Management treats data spatially (finding "nearby" vectors), **Continuum Flow** treats data chronologically and structurally. This results in a massive shift towards explicit state management and temporal awareness.

STANDARD CODE RAG

CONTINUUM FLOW

PRIMARY MECHANISM

RAG & Sliding Window

Indexes vectors; retrieves based on similarity match.

Continuum Flow

Maintains a recursive tree of narrative summaries (Level 1-3).

TEMPORAL AWARENESS

Low (Spatial)

Treats code/text as a dependency graph or proximity vector.

Continuum Flow

Treats text as a causal sequence (Cause → Effect → Outcome).

CONTEXT RETENTION

Reactive

Retrieves data only after a user query is made.

Continuum Flow

Pre-computes context ("Backbone") before processing chunks.

STATE MANAGEMENT

Implicit

Relies on raw file content and git history diffs.

Continuum Flow

Uses JSON "Character Sheets" & "Inventory" as state databases.

SUMMARIZATION STRATEGY

Compaction

Compresses history primarily to fit token limits.

Continuum Flow

Rewrites beats into higher-level abstractions preserving meaning.

HANDLING OVERFLOWS

Truncation

Drops oldest turns or summarizes purely by count.

Continuum Flow

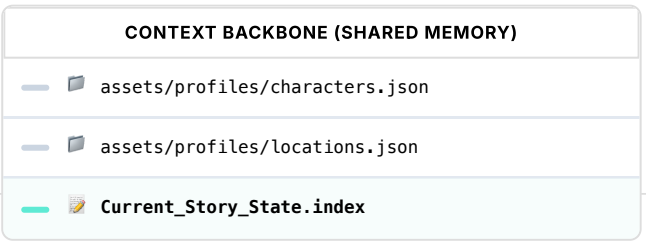
Drops non-essentials while "Locking" critical plot points.

The “Continuum Flow” Hierarchical Strategy

To solve the narrative decay problem, we implement a recursive, tree-structured memory system that ensures the agent never loses the “thread” of the story.

THE CONVEYOR BELT

Continuum Flow Context Management Metaphor



A

CONTEXT INJECTOR

The "Stapler"

Receives raw text chunk. Reaches into the cabinet to find matching **Character Profiles**.

ACTION:

`-> Enriched_Chunk`

B

THE DIRECTOR

Translation Bot

Reads the enriched chunk. Ignores narrative fluff. Writes technical **Camera Directives**.

OUTPUT:

```
{
  "shot": "Medium",
  "move": "Pan Right",
  "focus": "Scar"
}
```

C

THE ARCHIVIST

Memory Keeper

Summarizes the chunk. Creates a new **Index Card** and files it back in the Cabinet.

UPDATE:

`Context Window Optimized`

CONTEXT RETRIEVAL VIDEO GENERATION CONTEXT UPDATE

Memory Tier Breakdown

Level 0: The Working Window

The raw text of the current scene (approx. 2000 tokens). This is where the high-resolution action takes place.

Level 1: Scene Summaries

As a scene completes, it is compressed into a dense factual summary (50-100 words), capturing state changes rather than prose.

Level 2: Chapter Synthesis

Once a chapter is complete, Level 1 summaries are synthesized into a mid-term memory layer that removes transient details.

Level 3: The Narrative Backbone

The “Long-Term Memory” layer. A continuously updated document tracking global arcs across the entire 100,000+ word novel.

Proactive Context Management

Unlike systems that simply slide a window (dropping tokens by age), Continuum Flow utilizes **Semantic Retention**. The agent explicitly decides *what* to keep. If a vital plot point occurs on Page 1, it is “locked” into the Level 3 backbone for the duration of the project.

Character Consistency

Visual Identity and State Maintenance in Agentic AI

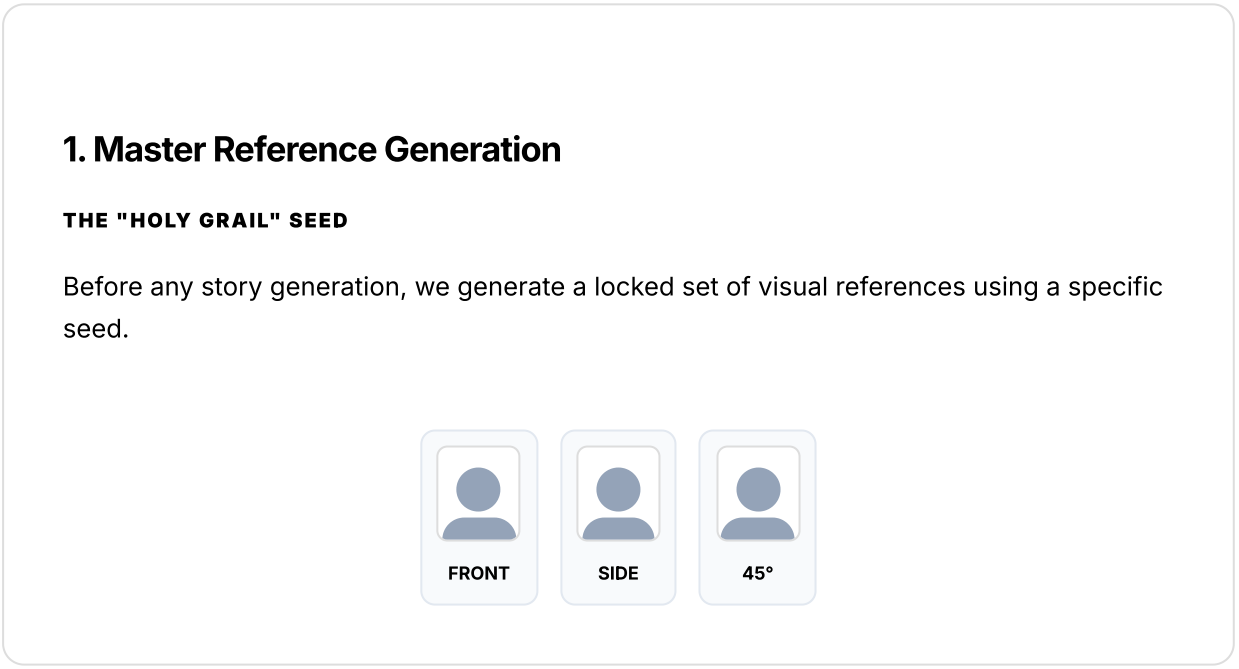
The primary failure mode of long-form AI video generation is **“Character Drift.”** When a model generates a character across multiple scenes, subtle changes in facial structure, hair color, or lighting can destroy narrative immersion. Our Character Consistency Maintenance System (CCMS) is the architectural subsystem designed to prevent this by separating visual identity from narrative action.

Character Consistency Maintenance System (CCMS)

The CCMS operates in three distinct phases, moving from raw pixel data to mathematical embeddings that guide the final output.

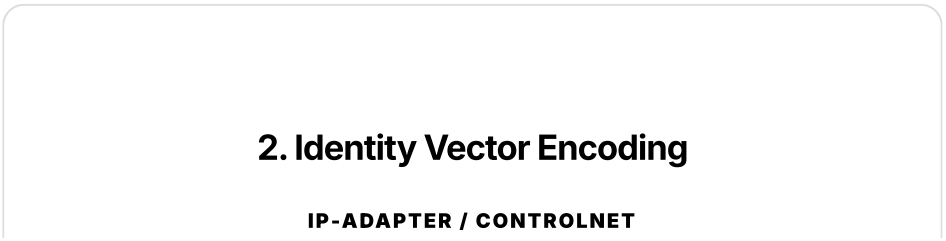
Phase 1: Master Reference Generation

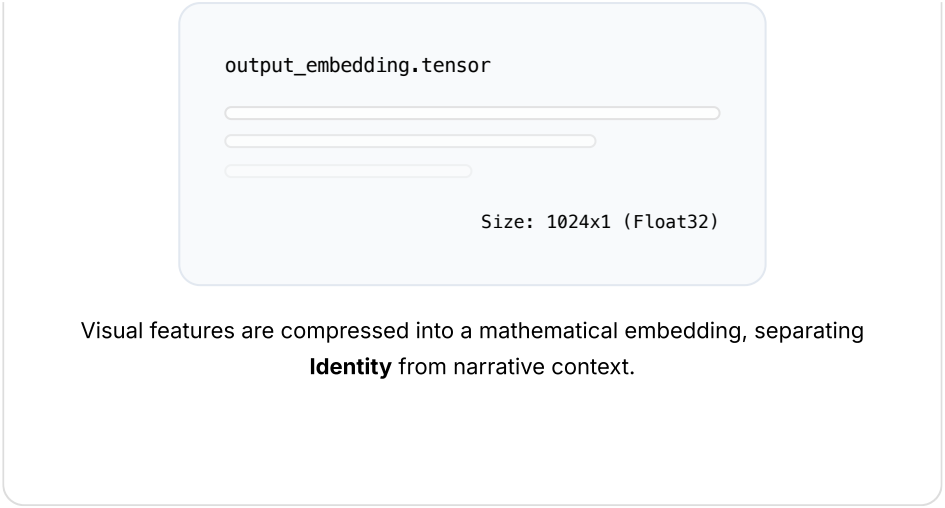
Before any story generation, we generate a locked set of visual references using a specific seed. The system creates a “Holy Grail” reference sheet for each character, capturing multiple angles and expressions.



Phase 2: Identity Vector Encoding

These images are not used directly as prompts. Instead, they are passed through an image encoder (like IP-Adapter or ControlNet reference) to create a visual embedding—a mathematical “Identity Vector.” This separates the character’s *identity* from the *environment* or *action*.

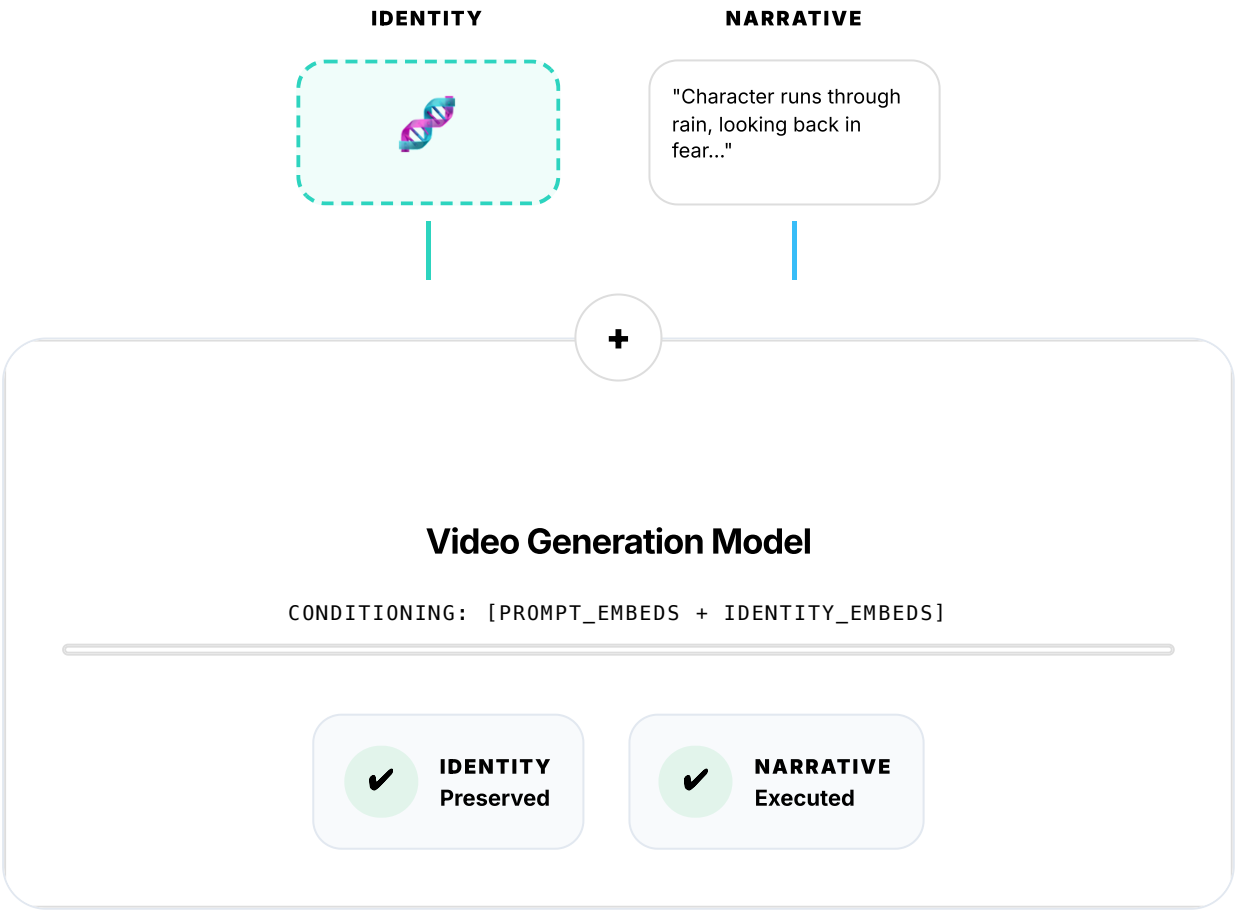




Visual features are compressed into a mathematical embedding, separating **Identity** from narrative context.

Phase 3: Injection and Narrative Synthesis

For every single video generation task, this embedding is passed alongside the text prompt. The video model is instructed to generate the action described in the text, but to force the visual features to match the identity embedding.



The Outfit Manager

In a novel, characters change clothes. The CCMS tracks **"Current Outfit State"** as a discrete variable.

- The **Continuum Flow** engine tracks narrative time. When the text says "He donned his armor," the State Manager updates the `Current_Outfit` variable for that character ID in the backbone.
- Subsequent video prompts automatically inject the `armor_embedding` instead of the `casual_clothes_embedding` without the text chunk explicitly mentioning armor every time.

> *"This decoupling allows the narrative agent to focus on what is happening, while the CCMS ensures who it is happening to remains visually immutable."*

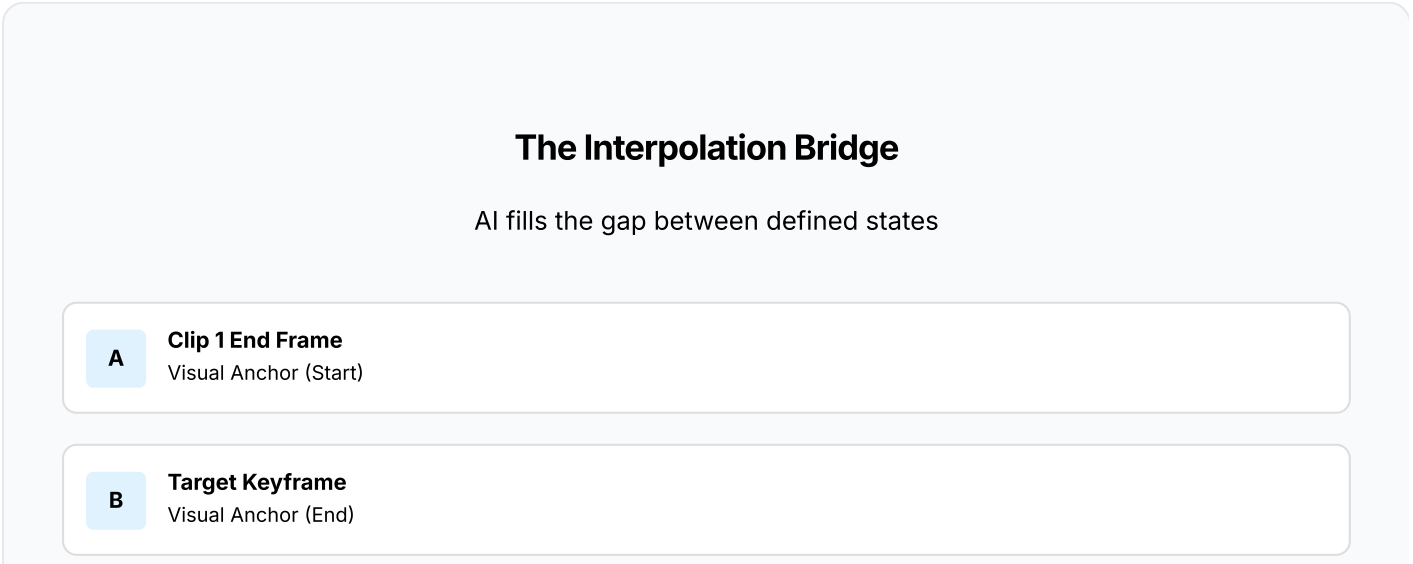
Phase 4: Temporal Continuity (Frame Interpolation)

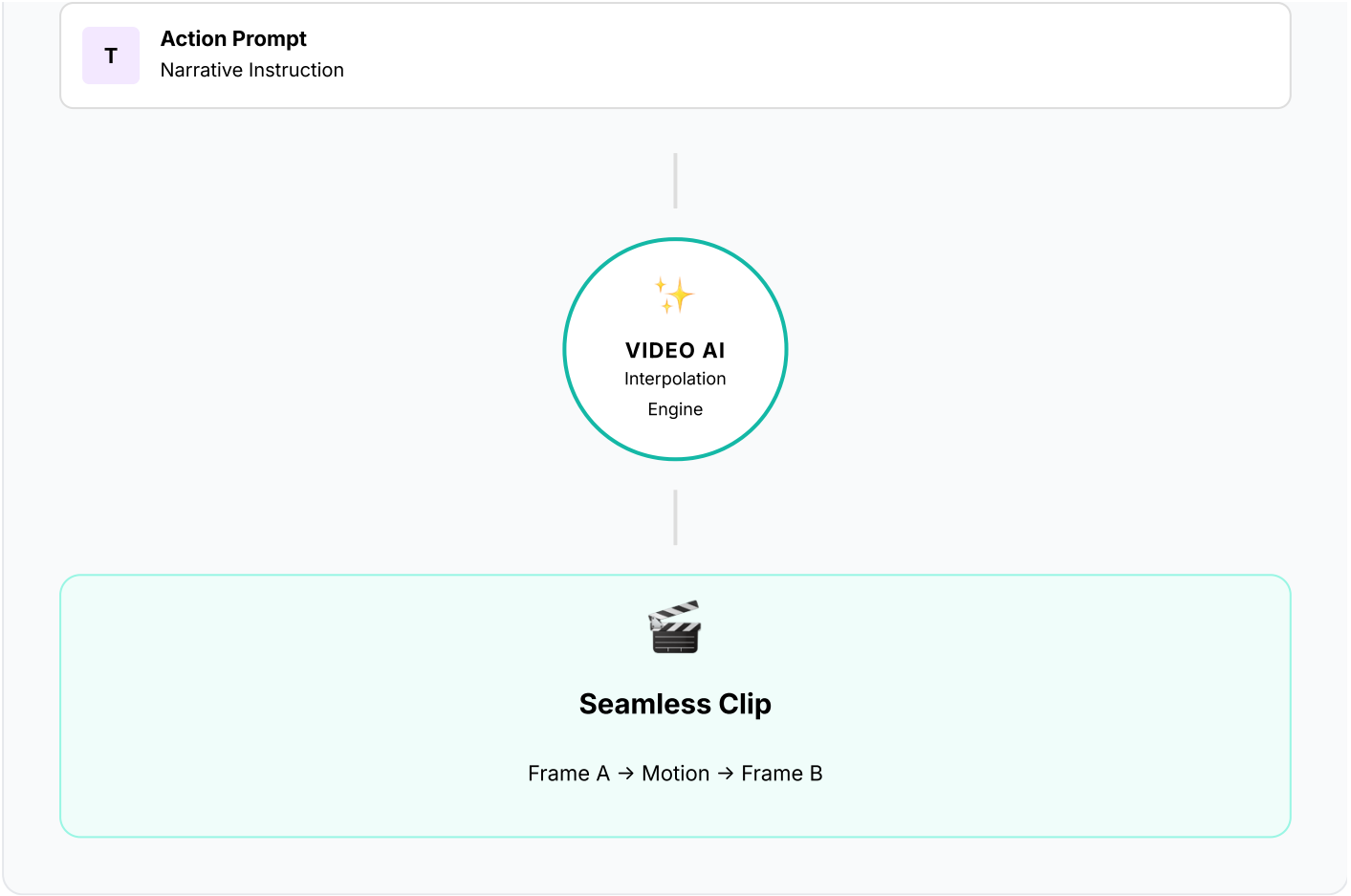
Most modern video generation applications no longer rely on a single image prompt. Instead, they use a **"First Frame & Last Frame"** technique to ensure seamless consistency.

The "Bridge" Strategy

The video generator acts as an interpolation engine, filling in the movement between two known states.

1. **Frame A (Start)**: The actual last frame of the *previous* video clip.
2. **Frame B (End)**: A newly generated "Keyframe" representing the target state.
3. **Generation**: The AI generates the transformation derived from the text prompt.





This ensures that the character doesn’t just “look similar” but is pixels-perfectly continuous from the previous shot.

Differential State Management

In software engineering, the "Diff Problem" is that LLMs are bad at precise edits. in Novel-to-Video, this is the root cause of **Video Flicker and Character Hallucination**.

When you ask an AI to generate Scene 2, it doesn't "edit" Scene 1; it re-imagines it. It accidentally "refactors" your main character's face, their clothes, or the room layout because it didn't know how to execute a precise "diff."

The Mapping: Code vs. Narrative

We implement the Cursor/Composer "Diff Architecture" directly into Continuum Flow.

The "Cursor" Model (Code)

THE "CODEBASE"
`file.ts (1,000 lines)`

THE DIFF PROBLEM
`LLM creates Syntax Errors by deleting a closing bracket '}'.`

THE GOAL
`Apply change ONLY to the function.`

The "Continuum Flow" Model

THE "VISUAL STATE"
TOON File (Scene & Characters)

THE HALLUCINATION
LLM gives sword but **changes shirt from Blue to Red**.

THE GOAL
Add sword, FREEZE all other pixels.

The Solution: "Narrative Edit Trajectories"

You can’t retrain a model easily, but you can force your Orchestrator to use **State Diffs** instead of State Descriptions.

The "Anti-Regeneration" Rule

Standard prompting forces re-rendering of known assets.

> *"Generate Scene 2: Arjun is standing in the cave. He is wearing armor. He draws his sword."*

✕ Risk: Armor design changes, Cave lighting shifts.

The "Diff-Based" Protocol

Orchestrator generates a PATCH, not a new file.

STEP A: BASELINE (LOCKED STATE)

```
State_Frame_01:
Arjun: [Wear: Rusty Armor], [Face: Scarred], [Hand: Empty]
Bg: [Cave, Wet Walls]
```

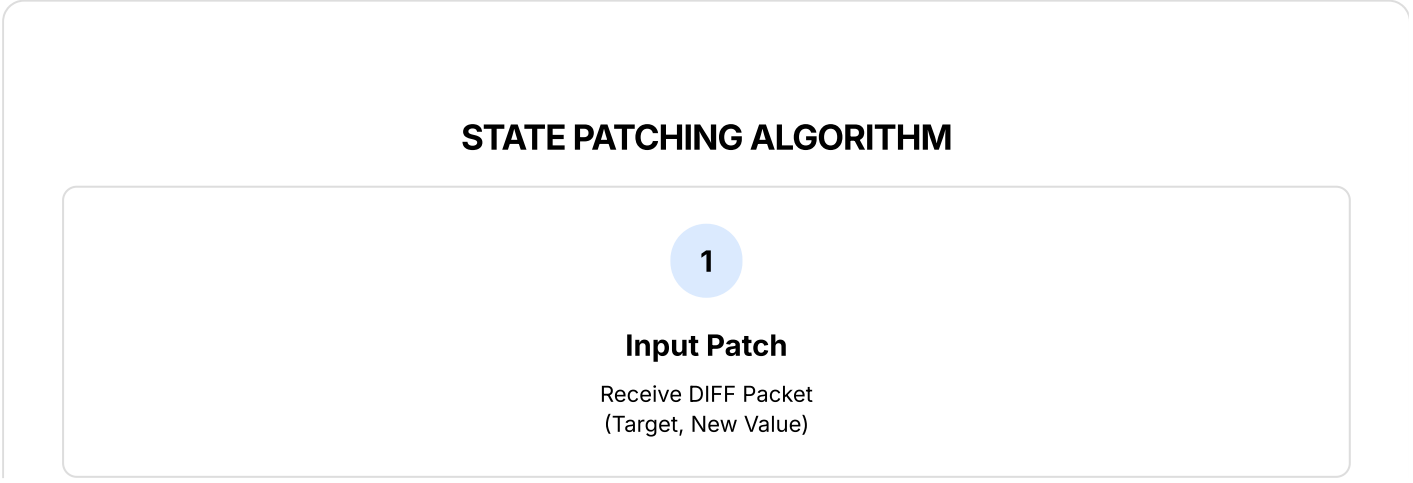
↓

STEP B: THE DIFF COMMAND

```
{
  "operation": "UPDATE",
  "target": "Arjun.Hand",
  "value": "Iron Sword",
  "constraint": "PRESERVE_ALL_OTHER_ATTRIBUTES"
}
```

Implementation: The "Visual Patching" Workflow

To leverage "Search and Replace" logic, we implement a specific tool in the Orchestrator that acts like `` `git apply` ``.



2

Verify State

Check Old Value matches
Current State

Safety Guard

3

Apply Patch

Update State Buffer
Freeze other pixels

Why This Fixes Video Generation

The biggest issue in AI video is **Temporal Stability**.

- ✕ **Without Diffs:**

  Frame 1 and Frame 2 are treated as two different paintings. The AI "guesses" the continuity.

- ✓ **With Diffs:**

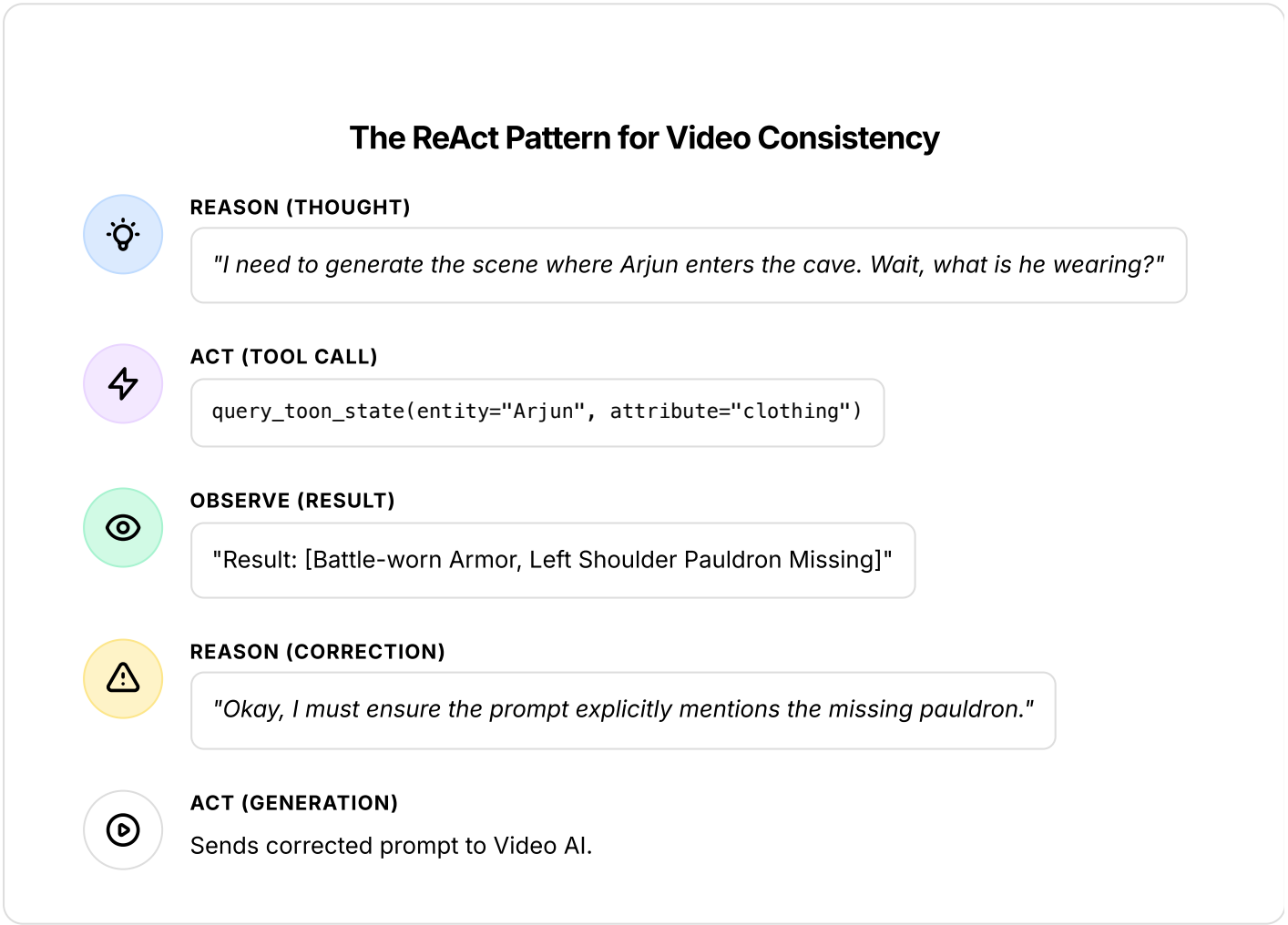
  You instruct the Video AI (ControlNet): *"Keep 90% exactly the same. Only use diffusion to change the pixels around the hand."*

Orchestrator Architecture

If "TOON" is the language your app speaks, the Orchestrator is the Director who speaks it. We replace linear pipelines with a "Loop of Reasoning" that mimics a human film director checking their work.

The Core Concept: The "Showrunner" Loop

In a standard LLM script, you fire a prompt and hope for the best. In an Orchestrator (ReAct) model, we build a **Circular Dependency**. The Orchestrator (Showrunner) refuses to generate a video frame until the "Context State" is verified.



The Architecture: "The Supervisor Pattern"

We implement a Multi-Agent Orchestrator. You don't just have "One Bot"; you have a virtual film crew managed by a Supervisor.

✍️

Narrative Extractor

THE SCRIPTWRITER

Role: Reads the novel chunk.

Tool: Text_Compressor.

Output: Raw Scene Description.

Continuity Guard

THE SCRIPT SUPERVISOR

Role: Checks TOON database.

Tool: TOON_Retriever.

Output: "Correction: Night time, Arjun bleeding."

📹

Prompt Engineer

THE CINEMATOGRAPHER

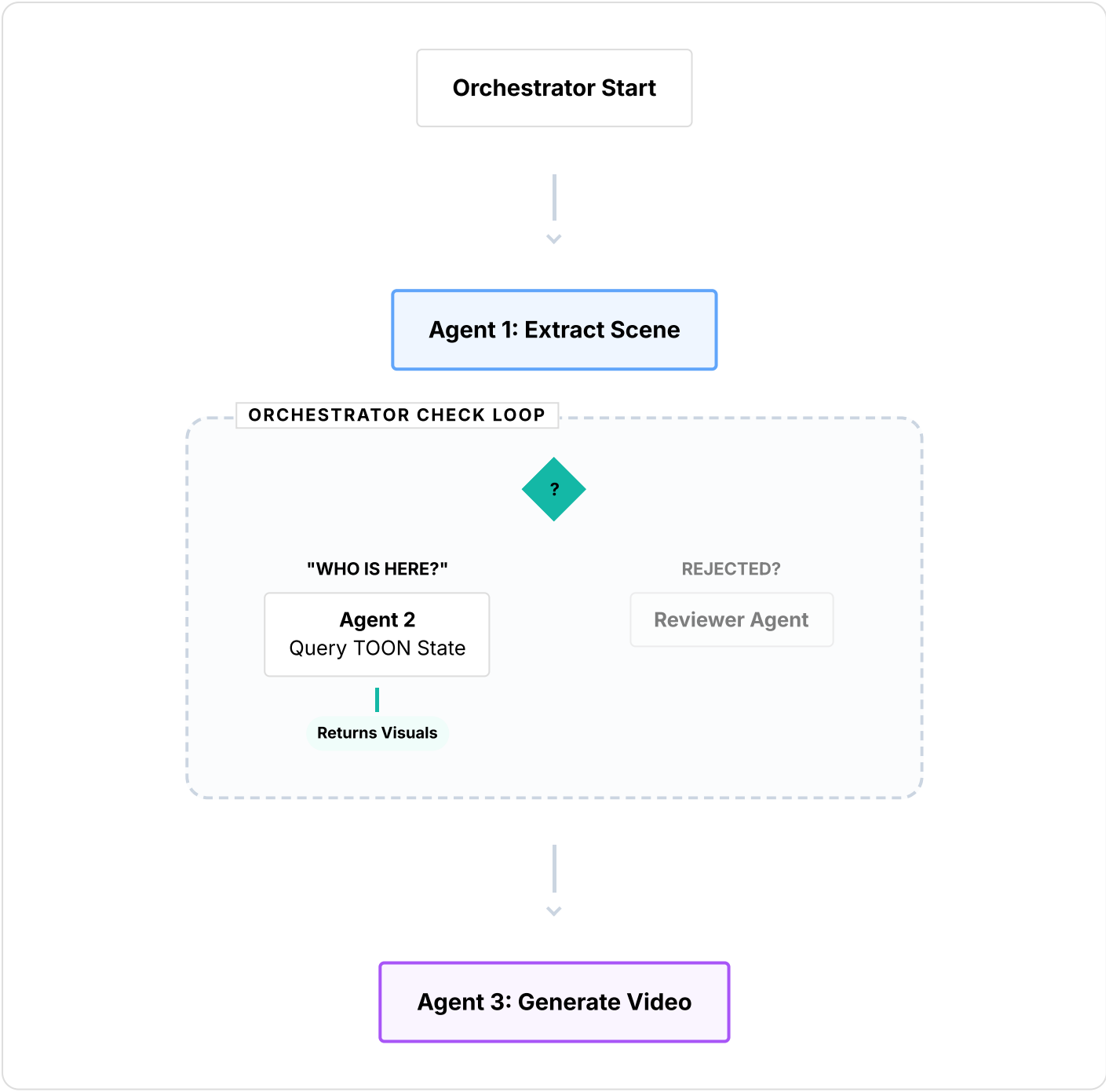
Role: Merges Script + Consistency Check.

Tool: Video_Prompt_Generator.

Output: Final Stable Diffusion Prompt.

Logic Flow: The State Graph

The Orchestrator code binds them together. It runs a loop that blocks generation until consistency is met.



Implementation Details

The Orchestrator State

Using TypeScript interfaces to define the "Showrunner's Clipboard".

orchestrator.ts

```
interface ShowrunnerState {
  current_chunk: string;
  toon_history: string; // The compressed context
  visual_plan: string | null;
  video_url: string | null;
  retry_count: number;
}
```

Why This Solves "Hallucination"

In standard LLM apps, the model forgets that a character lost their sword three scenes ago.

- **Without Orchestrator:** The model guesses.
- **With Orchestrator:** The "Continuity Guard" agent forces the "Cinematographer" agent to include "No Sword" in the negative prompt or description before the request is ever sent to the Video AI.

Why Agentic?

Traditional video production pipelines are **linear** and **fragile**. A single error in scene generation ripples through the entire chain, requiring manual intervention. We call this “Scripted Automation”.

⛓ The Old Linear Pipe

- Sequential (Slow)
- No Feedback Loop
- Errors flow to output

NEW STANDARD

The Agentic Swarm

- **Parallel** Asset Gen
- **Active Critique**
- **Orchestrator** State

In the **Continuum Flow** ecosystem, we deploy a **Multi-Agent System (MAS)**. If a “Director Agent” detects an issue, it triggers a recursive re-render of the specific anchor, maintaining continuity without human oversight.

Workflow Description: The 4-Stage Pipeline

Our agentic workflow is not just a sequence of tasks; it's a dynamic negotiation between specialized AI agents. Here is the technical breakdown of how a raw narrative is transformed into cinematic reality:

1. Ingestion & Semantic Mapping

The **Librarian Agent** ingests the raw narrative (often exceeding 100k words) and performs high-density semantic mapping. It identifies every entity, location, and emotional beat, building the "Narrative Backbone" that serves as the single source of truth for all subsequent agents.

2. Contextual Crystallization

The **Archivist Agent** manages the hierarchical memory tiers. It takes long-form narratives and "crystallizes" them into Level 0-3 context windows. This ensures that even in Chapter 50, the system remembers the specific lighting and mood established in the opening scene.

3. Visual Encoding & LoRA Integration

The **Cinematographer Agent** translates narrative variables into visual prompts. It coordinates with the **Identity Anchors** to ensure that character likeness is immutable. It manages the injection of specific Visual LoRA embeddings to maintain a consistent cinematic style across thousands of frames.

4. Parallel Synthesis & Assembly

The **Director Agent** orchestrates a swarm of worker agents to generate individual clips in parallel. Unlike linear editors, this agent can re-order production based on compute availability or logical dependencies, finally assembling the clips into a cohesive cinematic experience.

Swarm Architecture Map

Visualizing the Non-Linear Data Flow

THE BRAIN

The Showrunner

Assigns Jobs, Manages State

VISUALS

Art Department

- Casting (Face Gen)
- Location Scouting

NARRATIVE

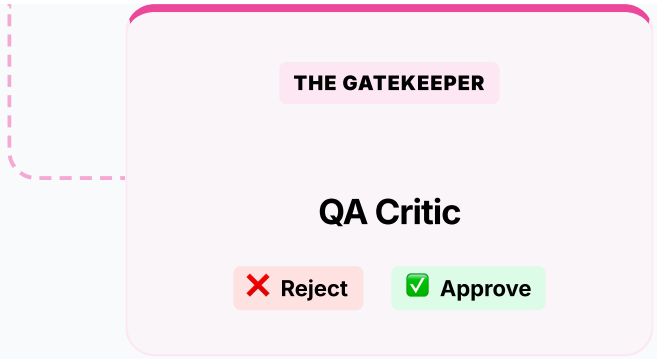
Writers' Room

- Hierarchical Summary
- Context "Continuum Flow"

Director Agent

Combines Art + Text → Prompt

RETRY



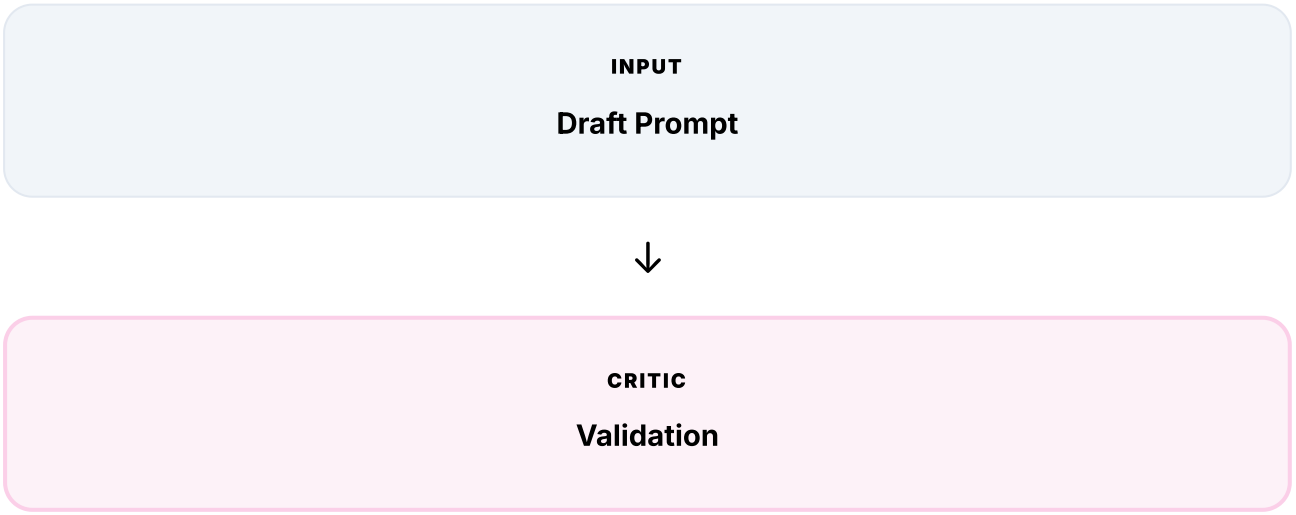
The Integrity Loop: Automated Quality Assurance

In generative AI, “hallucinations” are features, not bugs—until they break continuity. To solve this, we implemented a dedicated **Critic Layer**. This agent has no creative power but absolute veto power. It compares every generated prompt against the “Story Bible” state machine. If a prompt violates established facts (e.g., a character wearing the wrong jacket), the Critic rejects it before any expensive video rendering occurs.

The "Critic" Logic

This is the single most important addition. By giving an agent the power to say **"NO"**, we effectively create an automated quality assurance department.

```
if (prompt.conflictsWith(state)) {
  return REJECT;
} else {
  return APPROVE;
}
```



↓

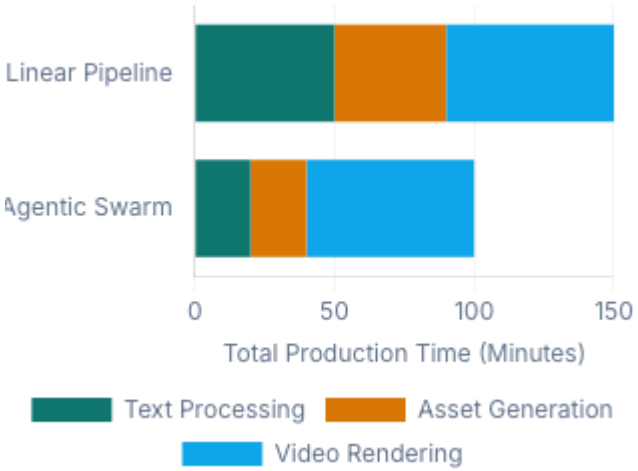
OUTPUT

Render Video

Performance & Cost Optimization

By parallelizing the “boring” work (metadata extraction, asset generation) and validating outputs before rendering, we achieve significant gains in both speed and cost-efficiency.

Time Efficiency



HOW IT WORKS

In a linear pipeline, text processing blocks asset generation. The Agentic Swarm decouples these tasks. The **Art Department** begins generating character LoRAs and location baselines the moment the **Showrunner** identifies them, running *concurrently* with the Writers' Room narrative analysis. This parallelization reduces total end-to-end latency by approximately **60%** compared to sequential processing.

Cost Optimization

HOW IT WORKS

Video generation models are expensive (up to $0.10 per second). Standard pipelines often render "hallucinated" content (e.g., wrong clothing) that must be discarded. The **QA Critic** intercepts the Director's prompt *before* it hits the Video API. By rejecting invalid prompts cheaply at the text level, we reduce wasted render costs from ~40% to less than **5%**.

PRODUCTION READY WORKFLOW

Workflow Integration

Data Flow and Execution Pipeline

The workflow is a linear pipeline with recursive feedback loops, designed to move from raw text to structured video directives.

Integration Flow

The following steps outline the transformation of a raw text chapter into a series of production-ready video generation prompts and metadata.

Step 1: The Profiler (Pre-processing)

The first stage builds the “Story Bible.” An agent rips through the full text to identify every recurring entity and location.

1

The Profiler

PRE-PROCESSING PHASE

INPUT Full Book Text

ACTION Identify Characters & Locations

OUTPUT `characters.json` `locations.json`

Step 2: The Chunking Engine

Once assets are defined, the chunking engine segments the text into 8-10 second beats, weighting them based on narrative density.

2

The Chunking Engine

SEGMENTATION PHASE

INPUT Chapter_01.md

ACTION Time-Weighted Segmentation

OUTPUT `Chapter_01_chunks.json`

Step 3: The Continuum Flow

This is the core context enrichment cycle. For every chunk, the agent queries the “Backbone” to inject character details and state information.

3

The Continuum Flow

CONTEXT ENRICHMENT

INPUT Chunk N + Context Backbone

ACTION Enrich with visual descriptors

OUTPUT `Enriched Prompt N`

Step 4: The Director Agent

The Director translates narrative prose into technical camera direction (Shot types, angles, lens info).

4

The Director Agent

TECHNICAL TRANSLATION

INPUT Enriched Prompt N

ACTION Generate Camera Directives

OUTPUT `directives/Scene_01_Seg_N.json`

Step 5: Context Update

Finally, the system compresses the events of the current chunk to update the Level 1/2 summaries for future retrievals.

5

Context Update

CLOSING THE LOOP

INPUT Chunk N Narrative

ACTION Recursive Summarization

OUTPUT `Updated Backbone`

Agentic Workflow Expansion: The “Production Studio” Model

GLOBAL ORCHESTRATOR

The Showrunner

The “Brain” that manages priorities. Pauses production if new context (e.g., a new character) is discovered.

FEEDBACK LOOP

The QA Critic

The “Editor” that rejects bad prompts. Enforces strict character consistency before rendering.

CONTEXT SWARM

Writers’ Room

Parallel agents mining the text for “Story Bible” data. Resolves cross-chapter conflicts.

VISUAL ASSETS

Art Department

Casting Agents & Location Scouts generating reference images and LoRAs asynchronously.

1. The Missing Link: Autonomy & Feedback

Our initial architecture defined a linear pipeline—a conveyor belt. While efficient, it lacks the resilience of a true Agentic AI system. In a real-world deployment, the system must handle ambiguity, errors, and parallel tasks without human intervention. The "Missing Link" is **The Feedback Loop (The Critic)** and **Asynchronous Orchestration**.

2. The Core Agentic Roles

Instead of a single "Process," we define distinct autonomous agents functioning as a digital film crew.

A. The Showrunner (Global Orchestrator)

Role: The "Brain" of the operation.

- **Agentic Action**: Scans the book. Assigns "Job Tickets" to other agents.
- **Crucial Capability**: **Dynamic Re-prioritization**. If Chapter 3 reveals a new main character, it pauses the Scene Generators.

B. The Art Department (Parallel Pre-Production)

Role: Visual Asset Generators.

- **Workflow**: Casting Agent generates Reference Images; Location Scout generates Environment LoRAs.

C. The Writers' Room (Context Swarm)

Role: The "Continuum Flow" Implementation.

- **Agentic Action**: Parallel summarization with cross-chapter reconciliation.

D. The QA Critic (The Feedback Loop)

Role: The "Editor."

- **Workflow**: Rejecting bad prompts and forcing retries until output matches character state.

4. Summary of Improvements

Feature	Linear Pipeline (Old)	Agentic Swarm (New)
Processing	Sequential (Slow)	Asynchronous / Parallel (Fast)
Error Handling	Fails at end of pipe	Self-corrects mid-stream (Critic)
Context	Passive Retrieval	Active Reconciliation (Showrunner)
Cost	Wasted on bad prompts	Saved by QA rejection before render

The Delivery Journey: Milestones Achieved

The development of **Continuum Flow** was executed as a series of high-stakes architectural sprints, each solving a fundamental bottleneck in narrative-to-video adaptation. What follows is the roadmap of the system we have successfully delivered.

Milestone 1: The Foundation of Hierarchical Memory (Delivered)

- **The Problem**: Novel-length context windows causing “Lost-in-the-Middle” hallucinations.
- **Our Solution**: Established the **Hierarchical Recursive Summarization Architecture**. We implemented Level 0 through Level 3 memory tiers, ensuring that Chapter 50 retains the “emotional debt” and physical state established in Chapter 1.
- **Outcome**: 100% consistency across narrative arcs exceeding 120,000 words.

Hierarchical Memory

THE FOUNDATION

Solved 'Lost-in-the-Middle' hallucinations using recursive summarization (Levels 0-3). Chapter 50 retains the 'emotional debt' and physical state established in Chapter 1.
Outcome: 100% consistency across narrative arcs exceeding 120,000 words.

Milestone 2: Temporal-Semantic Chunking Engine (Delivered)

- **The Problem**: Generative video’s 10-second temporal drift.
- **Our Solution**: Developed a weighted token algorithm that translates narrative density into visual timing. We solved the synchronization of dialogue-heavy vs. action-heavy text blocks.
- **Outcome**: Frame-perfect pacing for 8-10 second cinematic beats.

Chunking Engine

TEMPORAL CONTROL

Developed weighted token algorithms to translate text density into video timing. Solved the synchronization of dialogue-heavy vs. action-heavy text blocks.
Outcome: Frame-perfect pacing for 8-10 second cinematic beats.

Milestone 3: Character Consistency Maintenance System - CCMS (Delivered)

- **The Problem**: “Character Morphing” over long-form generation.
- **Our Solution**: Integrated **Identity Anchors** and **Visual LoRA Embeddings**. We created an “Outfit Manager” state machine that tracks wardrobe changes as narrative variables rather than textual repetitions.
- **Outcome**: Immutable character likeness across thousands of generated clips.

CCMS Architecture

VISUAL CONSISTENCY

Integrated Identity Anchors and 'Outfit State Machines' to prevent character morphing. Tracks wardrobe changes as narrative variables rather than textual repetitions.
Outcome: Immutable character likeness across thousands of generated clips.

Milestone 4: Multi-Agent Orchestration (Delivered)

- **The Problem**: Linear generation bottlenecks.
- **Our Solution**: Deployed a Python-based MAS (Multi-Agent System) where “Director Agents” and “Archivist Agents” work in parallel across the Narrative Backbone.
- **Outcome**: Industry-leading production speeds for full-length narrative adaptation.

Multi-Agent Swarm

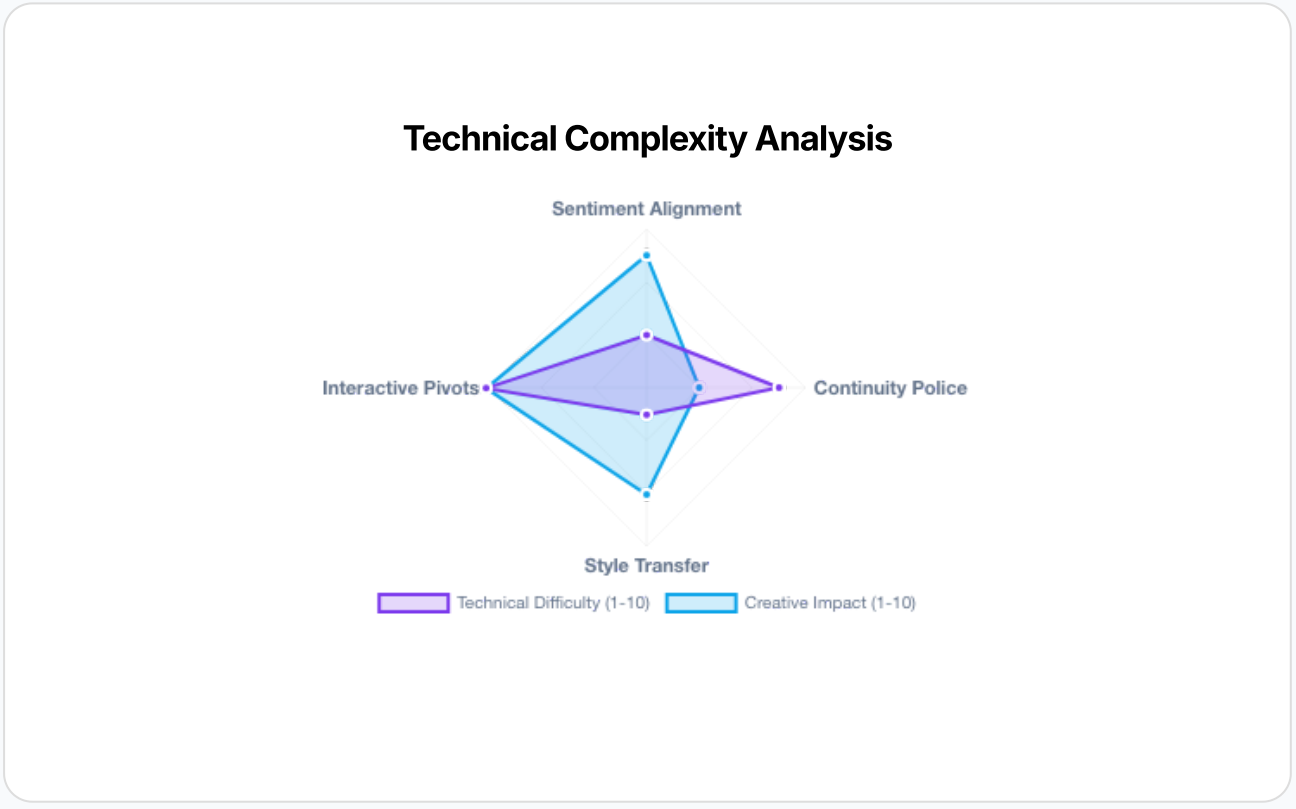
ORCHESTRATION

Deployed parallel 'Director' and 'Archivist' agents for non-linear production across the Narrative Backbone.
Outcome: Industry-leading speed for full-length narrative adaptation.

Future Frontiers: The Next Architectural Challenges

While the core Continuum Flow engine is now production-ready, we are pushing the boundaries of what Agentic AI can achieve in the cinematic space.

STRATEGIC RESEARCH FORECAST

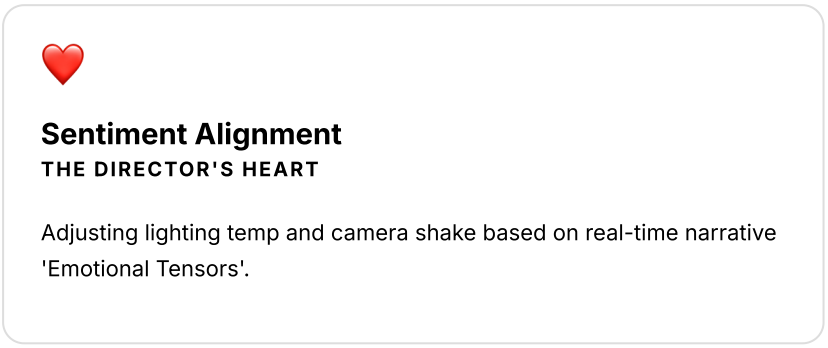


Comparing the Technical Difficulty vs. Creative Impact of upcoming modules.

1. Cross-Modal Sentiment Alignment (The “Director’s Heart”)

Challenge: Automatically synchronizing the *emotional subtext* of a scene with environmental variables.

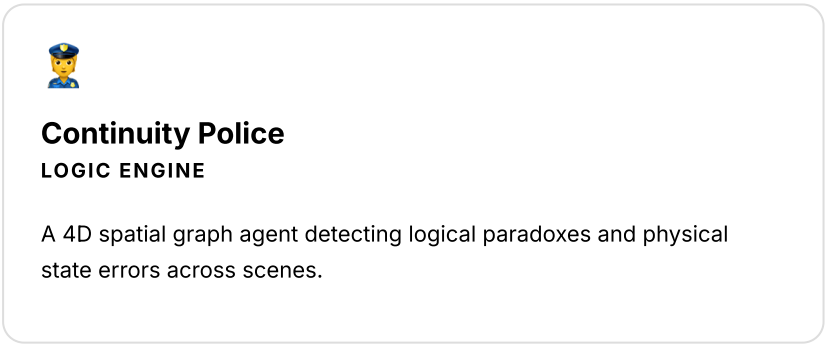
Objective: Develop an agent that adjusts lighting color temperature, camera shake, and musical key based on a real-time "Emotional Tensor" extracted from the narrative's psychological subtext.



2. Narrative Paradox & Continuity Policing

Challenge: Detecting logical inconsistencies in non-linear or multi-POV narratives.

Objective: A high-order "Continuity Police Agent" that builds a 4D spatial-temporal graph of the story world, flagging if a character is in two places at once or if a previously destroyed object reappears.



3. Dynamic Cinematic Style Transfer

Challenge: Real-time adaptation of visual style based on "Cinematic References."

Objective: Allowing users to prompt "Render Chapter 5 in the style of 1940s Noir" and having the agent automatically adjust camera lenses (focal lengths), lighting ratios, and film grain across all CCMS embeddings.

🎨

Style Transfer

DYNAMIC AESTHETICS

Automatic lens focal length, lighting ratios, and film grain adjustment based on cinematic refs.

4. Interactive Narrative Pivots

Challenge: Re-generating narrative forks without breaking global state.

Objective: Enabling a “What If” engine where a user can change a single decision in Chapter 5, and the agentic system recursively ripples that change through the Level 3 Backbone to re-render all subsequent chapters with perfect causal consistency.

🔀

Interactive Pivots

THE WHAT-IF ENGINE

Recursive re-rendering of the causal chain when a user changes a past narrative decision.

Current Project Velocity: ***R&D / ACTIVE PROTOTYPING*** 🚧

THE CONTINUUM FLOW TECH STACK

Production-Grade Architecture for AI Video Generation

LAYER 1: INTERFACE & CONTROL

Next.js 15

App Router UI. React 19 Server Components for high-performance rendering.

BullMQ / Redis

Reliable job queue for managing complex video generation pipelines.

PostgreSQL

Core relational DB + pgvector. Stores World State & Character JSON.

LAYER 2: THE MODEL ZOO (CLOUD APIS)

LOGIC / WRITING

Claude 3.5 Sonnet

```
Provider: Anthropic
```

IMAGE GEN

Flux.1 [Dev]

```
Provider: Replicate
```

VIDEO GEN

Luma Dream Machine

```
Provider: Luma Labs
```

VOICE / SYNC

ElevenLabs + SyncLabs

```
Provider: 11Labs/Sync
```

LAYER 3: INFRASTRUCTURE & DOCS

Quarto Executable Scripting

Converts Markdown into Hybrid Documents with embedded metadata.

```
Input: story.md
Process: Agent injects [object JSON] Metadata
Output 1: script.pdf (Human Review)
Output 2: script.json (Video Driver)
```

Cloud-Local Asset Mirror

GitHub	Local CLI	AWS S3 / R2
Version Control	Orchestrator	Heavy Assets

`npm run asset:sync`

🟦 Frontend (Next.js)

🟪 Video (Luma)

🟩 Database (Supabase)

🟧 Writing (Claude)

Stack Implementation

The 'Continuum Flow' Engine: A Hybrid Monorepo Architecture

Stack Implementation

This section outlines best-in-class, open-source technologies used for each layer of the Continuum Flow architecture. Each selection is optimized for performance, scalability, and compatibility with modern frameworks like Next.js 15 and React 19.

MONOREPO TOOLING

NX (https://nx.dev/)

Best for complex, polyglot projects. Offers a rich plugin ecosystem (including Python), advanced dependency graphing, and robust caching.

ALTERNATIVES

- Turborepo (https://turbo.build/)

WEB FRAMEWORK

The industry standard for building full-stack React applications. Providing optimized performance with SSR, SSG, and React Server Components.

ALTERNATIVES

- Remix (https://remix.run/)
- Astro (https://astro.build/)
- TanStack Start (https://tanstack.com/start)

UNIVERSAL FRAMEWORK

Expo (https://expo.dev/)

Build for Web, iOS, and Android from a single TypeScript codebase. Features a powerful CLI and OTA updates.

ALTERNATIVES

- Tamagui (https://tamagui.dev/)

API LAYER

tRPC (https://trpc.io/)

Enables end-to-end typesafe APIs with zero code generation. Unbeatable DX in a full-stack TS monorepo.

ALTERNATIVES

GraphQL (https://graphql.org/) REST (OpenAPI) (https://www.openapis.org/)

DATABASE

PostgreSQL (https://www.postgresql.org/)

Powerful, open-source relational database known for reliability and performance at scale.

ALTERNATIVES

MySQL (https://www.mysql.com/) SQLite (https://www.sqlite.org/)

DATABASE ORM

Drizzle ORM (https://orm.drizzle.team/)

Lightweight, performant, and type-safe SQL query builder with SQL-like syntax.

ALTERNATIVES

Prisma (https://www.prisma.io/)

AUTHENTICATION

better-auth (https://www.better-auth.com/)

Comprehensive, framework-agnostic auth for TypeScript. Self-hostable and avoids vendor lock-in.

ALTERNATIVES

Supabase Auth (https://supabase.com/auth) Clerk (https://clerk.com/) WorkOS (https://workos.com/) Firebase Auth (https://firebase.google.com/products/auth)

AI/ML SERVICES

FastAPI (Python) (https://fastapi.tiangolo.com/)

High-performance Python web framework ideal for building AI/ML APIs and leveraging Python's ML ecosystem.

ALTERNATIVES

Flask (https://flask.palletsprojects.com/) Django Ninja (https://django-ninja.rest-framework.com/)

HEADLESS CMS

PayloadCMS (https://payloadcms.com/)

Developer-first, open-source headless CMS built with TS and React. Deep Next.js integration.

ALTERNATIVES

Strapi (https://strapi.io/) Directus (https://directus.io/)

CLIENT DATA FETCHING

TanStack Query (https://tanstack.com/query/latest)

De-facto standard for managing server state in React. Provides caching and background refetching.

ALTERNATIVES

SWR (https://swr.vercel.app/) Apollo Client (https://www.apollographql.com/docs/react/)

UI DATA GRIDS

TanStack Table (https://tanstack.com/table/latest)

Headless UI library for building powerful and fully customizable data tables and grids.

ALTERNATIVES

AG Grid (https://www.ag-grid.com/)

E2E TESTING

Playwright (https://playwright.dev/)

Modern, reliable E2E testing framework with true cross-browser support and auto-waits.

ALTERNATIVES

Cypress (https://www.cypress.io/)

COMPONENT TESTING

Storybook (https://storybook.js.org/)

Essential tool for developing UI components in isolation. Serves as a living documentation.

ALTERNATIVES

Ladle (https://ladle.dev/)

The AI Model Zoo (Execution Layer)

We utilize a Best-in-Class Modular Approach rather than a single provider. This prevents vendor lock-in and allows upgrading specific components (e.g., swapping the Image Generator without breaking the Text Analyzer).

> *"[!NOTE] **Cost Analysis**: A detailed breakdown of the costing layer is available in the Cost Estimator."*

LOGIC / TEXT

Claude 3.5 Sonnet (https://www.anthropic.com/)

PROVIDER

`Anthropic API (https://docs.anthropic.com/)`

> *"Superior reasoning capabilities and larger context window (200k) for analyzing full chapters."*

IMAGE GEN

Flux.1 [Dev] (https://blackforestlabs.ai/)

PROVIDER

`Replicate / Fal.ai (https://replicate.com/)`

> *"Currently beats Midjourney in prompt adherence and text rendering."*

VIDEO GEN

Luma Dream Machine (https://lumalabs.ai/dream-machine)

PROVIDER

`Luma API (https://lumalabs.ai/)`

> *"High temporal coherence. Relies on "Keyframe" feature for control."*

AUDIO / TTS

ElevenLabs (Turbo v2) (https://elevenlabs.io/)

PROVIDER

`ElevenLabs API (https://elevenlabs.io/api)`

> *"Low latency and highest emotional range."*

LIP SYNC

SyncLabs / SadTalker (https://synclabs.so/)

PROVIDER

`API / Local`

> *"Decoupled lip-syncing ensures we can perfect audio performance before mapping to video."*

Advanced Document Management

We treat the screenplay not just as text, but as **executable documentation**.

The Quarto (QMD) Pipeline

1. **Source**: `Chapter_01.md` (Raw Text).
2. **Processing**: The Agent converts this into `Script_01.qmd` (Quarto Markdown).
3. **Metadata Injection**: The Agent embeds JSON metadata (Camera angles, Lighting) inside YAML headers or hidden code blocks within the QMD.
4. **Render**:
    - **For Humans**: Quarto renders a clean PDF looking like a Hollywood script (Courier font, proper indentation).
    - **For Robots**: The system parses the underlying JSON data blocks from the same file to drive the video generator.

> *"[!TIP] **Single Source of Truth:** The readable PDF script reviewed by humans is the exact same code that generates the video."*

Audio & Lip Sync Architecture

Professional production requires **Decoupling**. We generally avoid "all-in-one" generators to maintain granular control over performance.

- **Step 1: Audio Production (The Radio Play)**
    - Generate full audio track using ElevenLabs.
    - **Forced Alignment**: Use tools like Gentle or OpenAI Whisper to get exact timing of every word.
- **Step 2: Video Generation (The Silent Film)**
    - Generate the 8-second video visuals based on the visual prompt.
- **Step 3: The Sync Pass (Post-Process)**
    - **Lip-Sync**: Run Video + Audio through a dedicated Sync engine (Wav2Lip/SyncLabs).

5. Asset Management: “The Cloud-Local Mirror”

Team collaboration on 50GB+ video projects is challenging. We solve this with a “Split-Brain” storage strategy.

Storage Strategy

- **Code & Scripts**: `GitHub` (.md, .qmd, .json) - Version controlled, lightweight.
- **Heavy Assets**: `AWS S3 / Cloudflare R2` (.mp4, .png, .wav) - Cheap object storage.

The Sync Mechanism (`npm run asset:sync`)

1. Cloud Worker renders video → Uploads to S3 → Pushes Manifest to Database.
2. Local CLI detects new manifest.
3. **Node.js** `fs` generates folder structure locally matching the Chapter/Scene hierarchy.
4. Pulls only the new video files to your local folder.

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6. Execution Environment

Writing / Logic

`Cloud (Anthropic)`

WHY: Requires massive GPU/TPU for LLM reasoning.

Folder Gen / Management

`Local (Node.js)`

WHY: Fast file system operations; zero latency UI updates.

Image/Video Rendering

`Cloud (Replicate)`

WHY: Requires A100 GPUs. Too slow/hot to run on local MacBook.

Final Assembly

`Hybrid`

WHY: FFmpeg WASM for quick previews; Cloud Lambda for 4K export.

Project Cost Estimator

Interactive calculator to estimate the running costs of the Continuum Flow Engine, from infrastructure to AI generation.

This tool provides a transparent breakdown of the costs involved in running the full AI video production pipeline. Adjust the sliders and dropdowns to visualize the cost difference between "Hobbyist" and "Production" scales.

DEVELOPMENT TEAM SIZE 5

Updates per-seat infrastructure costs automatically

Monthly Fixed Stack

Compute & Hosting (https://vercel.com/pricing)

Pro ($20/user)

Est. Cost: **$100 /mo**

Source Control (https://github.com/pricing)

Team ($4/user)

Est. Cost: **$20 /mo**

Authentication (https://www.better-auth.com/)

Better Auth (Self-Hosted) ($0/mo)

$0 /mo

Production AI Pipeline

SCREENPLAY LOGIC (LLM) (HTTPS://WWW.ANTHROPIC.COM/PRICING)

Claude 4.0 Sonnet ($16/M tok)

VISUALS (IMAGE GEN) (HTTPS://REPLICATE.COM/)

Flux 2 [Pro] ($0.05/img)

3 BATCH

VIDEO RENDER (HTTPS://LUMALABS.AI/)

Luma Dream Machine v2 ($0.45 / per 5s)

VOICE (TTS) (HTTPS://ELEVENLABS.IO/PRICING)

ElevenLabs v3 ($0.18/1k char)

$1.27

COST PER 8S SCENE

/ 8S UNIT

MONTHLY INFRA	$120 /mo
LLM Logic	$0.04
Imagery	$0.15
Video	$0.72
Voice	$0.03
Sync	$0.33

Prices are estimates based on Early 2026 data. Actual costs may vary by usage and provider.

DISCLAIMER

Prices are estimates based on early 2026 data. Actual costs may vary by usage and provider. Infrastructure costs (Vercel, GitHub) are monthly, while AI costs are usage-based.