C4-Narrative Framework:

A Layered Architecture for Narrative Structure Analysis and
Structured Stylistic Deviation Detection in Studio Ghibli Films

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Abstract
Traditional Natural Language Processing excels at statistical pattern recognition yet fundamentally lacks the capability to model narratives as engineering systems with explicit architectural properties. This paper proposes C4-NLP, a novel layered framework that adapts the software engineering C4 Model to computational narratology. Unlike conventional approaches that treat texts as flat structures, C4-NLP introduces hierarchical decomposition that preserves both micro-level lexical details and macro-level discourse structures. Our core innovation employs the Isolation Forest algorithm across multi-layer features (L1–L4) to identify aesthetic anomalies—moments where masters deliberately violate conventions to create impact. Through empirical validation on eight Studio Ghibli film scripts compared with Hollywood baselines, we demonstrate: (1) successful four-layer architectural mapping with 97% feature extraction completeness; (2) identification of Hayao Miyazaki's non-linear Motif Injection(e.g., the positive second-order difference) pattern, which maintains 33% higher audience engagement in mid-sections; and (3) Agent-Based Modeling validation of structural patterns. This integrated methodology establishes C4-NLP as the first architecture-driven framework for narrative computing with complete reproducibility through PlantUML notation.
Keywords: C4 Model, Narrative Architecture, Computational Narratology, Isolation Forest, Structured Stylistic Deviation Detection, Studio Ghibli, PlantUML.

1. Introduction

1.1 The Architecture Gap in Narrative Computing

Contemporary Natural Language Processing (NLP) is characterized by two dominant yet fundamentally limited paradigms. Large Language Models treat narratives as probabilistic token sequences $P(w_t \mid w_{<t})$, achieving impressive generative capabilities but providing no explicit representation of hierarchical narrative structure [1]. Character network analysis [2] and narrative arc extraction [3] model texts as graphs $G = (V, E)$ but remain at a single-level abstraction.

Critical Gap: Neither paradigm provides a multi-scale architectural framework analogous to established software engineering methodologies. In software development, the C4 Model [4] enables systematic visualization across four abstraction levels (Context, Containers, Components, Code), facilitating stakeholder communication and progressive refinement from high-level design to implementation details.

1.2 Research Motivation

We argue that narratives—whether short poems or feature film screenplays—are structured systems with well-defined architectural properties. By adapting software architecture methodologies to literary texts, we enable: (1) systematic decomposition across explicit layers; (2) objective measurement through quantitative features; (3) anomaly detection identifying architectural rule-breaking; (4) dynamic validation via simulation; and (5) reproducible analysis using standardized PlantUML notation.

Differentiation from Prior Work: Unlike Propp's Morphology [5], which operates at a single abstraction level, or computational narratology [6], which extracts isolated features, our contribution integrates software engineering (C4 layered architecture), machine learning (Isolation Forest), narratology (structural analysis), and dynamic modeling (Agent-Based simulation).

1.3 Research Questions

RQ1 (Architecture Mapping): Can narratives be systematically decomposed into C4-equivalent layers where vertical dependencies are explicitly traceable?

RQ2 (Structured Stylistic Deviation Detection): Do quantifiable structural deviations correlate with critical evaluation in contemporary cinema?

RQ3 (Dynamic Validation): Can agent-based modeling validate that identified architectural patterns optimize engagement compared to conventional structures?

2. Related Work

2.1 Structural Narratology

Classical structuralism—Propp's narrative functions [5], Genette's three narrative levels [7], Barthes' five codes [8]—provides theoretical vocabulary but lacks: (1) multi-layer computational decomposition; (2) quantitative feature extraction; and (3) statistical validation. C4-NLP operationalizes Genette's intuition about narrative "levels" by mapping them to explicit layers with defined interfaces.

2.2 Computational Narratology

Character network analysis [2, 9] captures relational structure but operates at a single level, ignoring temporal dynamics and discourse context. Narrative arc extraction [3] reduces narrative to one-dimensional emotion trajectories. Transformer-based models [10] are powerful for generation but offer no explicit architectural representation—attention weights ≠ narrative structure.

2.3 The C4 Model

Simon Brown [4] developed C4 to address software architecture documentation challenges through hierarchical decomposition: Context (system boundaries), Containers (deployment units), Components (modules), and Code (implementation). Recent research has explored C4 beyond software—healthcare systems [11], IoT architecture [12]—but narrative application remains unexplored.

2.4 Anomaly Detection

Traditional NLP anomaly detection targets undesirable deviations [13, 14]. We introduce aesthetic anomalies—structural deviations that create value, grounded in Russian Formalism's "defamiliarization" [15] and Japanese *hakyoku* ("broken form") [16]. We repurpose Isolation Forest [17], hypothesizing that literary masterworks require fewer partitions to isolate in multi-dimensional feature space.

3. C4-NLP Framework Methodology

3.1 Foundational Principles

C4-NLP rests on five engineering principles:

1. **Separation of Concerns**—each layer addresses distinct analytical concerns
2. **Progressive Refinement**—analysis proceeds top-down with increasing granularity
3. **Interface Definition**—clear boundaries enable independent analysis
4. **Objective Verifiability**—all features are quantitatively measurable
5. **Standardized Notation**—PlantUML provides visual consistency

3.2 Layer 1: Discourse Context (L1)

Definition: Maps narrative system interactions with external actors and environment, establishing boundaries by identifying: human actors (author, readers, critics), cultural systems (traditions, genres), temporal factors, and intertextual networks.

Formal Specification: Let narrative N have L1 context tuple:

$$C_1(N) = (A, R, T, I, E)$$

where A = authors, R = readers, T = traditions, I = intertextual references, E = environmental context.

Feature Extraction (8 features):

1. **Genre Deviation Score:** $\text{GDS} = \frac{1}{|T|}\sum_{t\in T} d_{\text{KL}}\,(P_N \parallel P_t)$
2. **Intertextual Density:** $\text{ID} = \frac{|I|}{\text{words}(N)/1000}$
3. **Author Network Centrality** (betweenness)
4. **Temporal Novelty:** $\text{TN} = 1 - \max_{t'<t_N} \text{sim}(N, N_{t'})$
5. Historical period encoding
6. Target audience demographics
7. Publication venue prestige
8. Contemporary reception score

3.3 Layer 2: Narrative Containers (L2)

Definition: Structural boundaries partitioning narratives into organizational units with well-defined encapsulation. In film, containers are scenes with properties: size (duration), transition function, type (action/dialogue/exposition), and boundary strength (semantic discontinuity).

Container Architecture Patterns:

- Linear Sequential: $C_1 \to C_2 \to \cdots \to C_n$
- Circular Recursive: $C_1 \to C_2 \to \cdots \to C_n \to C_1$
- Nested Hierarchical: $C_{\text{outer}} \supset C_{\text{middle}} \supset C_{\text{inner}}$
- Parallel Interleaved: $\{C_{1a}, C_{1b}\} \to \{C_{2a}, C_{2b}\} \to \cdots$

Feature Extraction (6 features):

1. Container Count: $n = | \{\text{containers}\} |$
2. Size Variance: σ^2_{size}
3. Transition Abruptness: $\text{TA}(C_i \to C_{i+1}) = 1 - \text{cos-sim}(v^{\text{end}}_{C_i}, v^{\text{start}}_{C_{i+1}})$
4. Boundary Entropy: $H_{\text{boundary}} = -\sum_i P(\text{Type}(C_i)) \log P(\text{Type}(C_i))$
5. Nesting Depth: $d_{\max}$
6. Architecture Pattern (one-hot encoding)

3.4 Layer 3: Linguistic Components (L3)

Definition: Functional building blocks within containers performing specific narrative operations: plot devices (foreshadowing), character arcs, thematic motifs (recurring symbols), and linguistic techniques (metaphor, parallelism).

Formal Specification: Container C_i decomposes into:

$$C_i = \{c_{i,1}, c_{i,2}, \ldots, c_{i,m_i}\}$$

Each component c has: Function (operation performed), Interface (input/output), and Dependencies (component coupling).

Feature Extraction (15 features):

Component Count, Average Coupling, Dependency Entropy, Semantic Gap Width, Motif Position Deviation, Motif recurrence frequency, Character network density, Arc completion rate, Metaphor density, Parallelism count, Thematic cohesion, Component interface clarity, Circular dependency count, Cohesion score, Cross-container component reuse.

3.5 Layer 4: Lexical Code (L4)

Definition: Implementation details—morphemes, syntactic structures, semantic vectors realizing high-level components. Component c implemented by token sequence: $c = \langle t_1, t_2, \ldots, t_k \rangle$. Each token t_i has: Surface form, Lemma, POS tag, Phonetic transcription, Morpheme decomposition, Dependency structure, and Embedding vector $v(t_i) \in \mathbb{R}^d$.

Feature Extraction (18 features):

Lexical Diversity (Type-Token Ratio), Hapax Legomena Rate, Average Dependency Tree Depth, Phonetic Density (alliteration, assonance), Semantic Cohesion, POS tag entropy, Rare word density, Sentence length variance, Modifier depth, Pronoun frequency, Temporal marker count, Sensory verb ratio, Abstract-concrete noun ratio, Syntactic complexity index, Embedding space dispersion, Polysemy rate, Homophone density, Dialogue-to-narration ratio.

Figure 1: L1 Context Diagram – Studio Ghibli Film Ecosystem (C4 Model)

[Diagram Description: C4 Context Diagram]

System: Ghibli Film System

External Entities:

1. Hayao Miyazaki (Director/Screenwriter)
2. Toshio Suzuki (Producer)
3. Japanese Audience (Family viewers)
4. International Audience (Global fans)
5. Japanese Anime Tradition
6. Disney Influence
7. Environmentalist Thought
8. Edo Period Arts
9. Postwar Japan Society

Relationships:

- Hayao Miyazaki → Ghibli Film System: Directs & writes
- Toshio Suzuki → Ghibli Film System: Produces
- Japanese Audience → Ghibli Film System: Views domestically
- International Audience → Ghibli Film System: Views internationally
- Ghibli Film System → Japanese Anime Tradition: Emerges from
- Ghibli Film System → Disney Influence: Contrasts with
- Ghibli Film System → Environmentalist Thought: Thematizes
- Ghibli Film System → Edo Period Arts: Draws aesthetics from
- Ghibli Film System → Postwar Japan Society: Reflects era

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5. 日本アニメ伝統 (Japanese Anime Tradition)

6. ディズニー影響 (Disney Influence)
7. 環境主義思想 (Environmentalist Thought)
8. 江戸時代芸術 (Edo Period Arts)
9. 戦後日本社会 (Postwar Japan Society)

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Figure 2: L2 Container Diagram – Princess Mononoke Scene Architecture (C4 Model)
[Diagram Description: C4 Container Diagram]
Container: Princess Mononoke Film (134 minutes)

Internal Containers:
1. Act 1: Introduction (Scenes 1-21)
   - Scene 1: Demon attack (TA=0.71)
   - Scene 21: Journey begins (TA=0.68)

2. Act 2: Development (Scenes 22-47)
   - Scene 22: Irontown arrival (TA=0.82)
   - Scene 47: Forest spirit night (TA=0.75)

3. Act 3: Climax (Scenes 48-63)
   - Scene 48: Final battle start (TA=0.89)
   - Scene 63: Ambiguous ending (TA=0.92)

Motif Injection(e.g., the positive second-order difference) Points (Non-linear pattern):
- M1: Nature vs. Machine (t_1 = 12 min)
- M2: Spiritual corruption (t_2 = 27 min)

- M3: Cyclical renewal ($t_3 = 45$ min)
- M4: Ambiguous hope ($t_4 = 66$ min)

Architectural Properties:
- Container Count: n = 63 scenes
- Size Variance: $\sigma^2 = 145\ sec^2$ (high intentional pacing)
- Architecture Pattern: Parallel Interleaved [Diagram Description: C4 Container Diagram]

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Figure 3: L3 Component Diagram – Spirited Away Motif Components (C4 Model)

[Diagram Description: C4 Component Diagram]

Container: Spirited Away Narrative System

Components:
1. Name Loss Motif Component
   - Function: Identity erasure (Chihiro → Sen transformation)
   - Dependencies: Spiritual Growth Arc

2. Spiritual Growth Arc Component
   - Function: Character development (helpless → resilient)
   - Dependencies: Labor Ethic Theme

3. Labor Ethic Theme Component
   - Function: Work & purification (bathhouse labor as redemption)
   - Dependencies: Environmental Critique

4. Environmental Critique Component
   - Function: Pollution & greed critique (Stink spirit, No-Face metaphors)
   - Dependencies: Family Bond Component

5. Family Bond Component
   - Function: Parent-child separation & reunion
   - Dependencies: External Reader Cognition

Semantic Gap Components:
- SG1: Human/spirit world contrast (SGW=0.78)
- SG2: Labor vs. freedom tension (SGW=0.82)
- SG3: Identity loss vs. recovery (SGW=0.85)

External Components:
- Reader Cognition System (audience interpretation)
- Shinto Tradition System (spirit world cosmology)

Quantitative Metrics:
- Component Count: m = 387
- Average Coupling: $\bar{k} = 4.2$
- Semantic Gap Width Average: 0.82 (top 15% in corpus)
- Arc Completion Rate: 67% (intentionally unresolved) [Diagram Description: C4 Component

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4. Structured Stylistic Deviation Detection Pipeline

4.1 Theoretical Motivation

We propose the **Structured Stylistic Deviation Hypothesis:** Literary masterworks create aesthetic value by intentionally deviating from genre conventions. These deviations are detectable as quantifiable structural anomalies in multi-layer feature space. This grounds in Russian Formalism's "defamiliarization" [15]—art makes the familiar strange—and Japanese *hakyoku* [16]—intentional form-breaking signals refinement.

4.2 Isolation Forest Adaptation

Standard Algorithm [17]: Operates on the principle that anomalous points require fewer splits for isolation. Anomaly score:

$$s(x,n) = 2^{-\frac{E(h(x))}{c(n)}}$$

where $E(h(x))$ = average path length, $c(n) = 2H(n-1) - \frac{2(n-1)}{n}$ = normalization.

Our Adaptations:

1. **Multi-Layer Integration:** $\mathbf{f}_{\text{unified}} = [\mathbf{f}_{L1}, \mathbf{f}_{L2}, \mathbf{f}_{L3}, \mathbf{f}_{L4}] \in \mathbb{R}^{47}$
2. **Layer-Specific Scores:** Compute independent $s_{L1}(x), s_{L2}(x), s_{L3}(x), s_{L4}(x)$. Final score: $s_{\text{aesthetic}}(x) = \sum_{i=1}^{4} w_i \cdot s_{Li}(x)$ with optimized weights $(w_1 = 0.15, w_2 = 0.25, w_3 = 0.35, w_4 = 0.25)$
3. **Critical Validation Filter:** Retain only works with $s_{\text{aesthetic}}(x) > 0.65$ and expert rating $> 7.0/10$

4.3 Pipeline Architecture

Stage 1: Corpus Preparation – Text normalization, morphological analysis (MeCab), dependency parsing (GiNZA)

Stage 2: Multi-Layer Feature Extraction – Parallel extraction at L1–L4 producing feature matrix $\mathbf{F} \in \mathbb{R}^{n \times 47}$

Stage 3: Isolation Forest Training – 100 trees, sample size 256, contamination 0.1, scikit-learn implementation

Stage 4: Anomaly Ranking – Compute scores, rank descending

Stage 5: Critical Validation – Blind evaluation by 3 independent experts, 10-point scale, inter-rater agreement via Cohen's κ

5. Empirical Evaluation: Studio Ghibli Case Study

5.1 Research Design

Dataset: 8 Studio Ghibli feature film scripts (1984–2004):

1. *Nausicaä of the Valley of the Wind* (1984) – 11,234 words
2. *Castle in the Sky* (1986) – 9,876 words
3. *My Neighbor Totoro* (1988) – 8,432 words
4. *Kiki's Delivery Service* (1989) – 10,123 words
5. *Porco Rosso* (1992) – 12,567 words
6. *Princess Mononoke* (1997) – 14,890 words
7. *Spirited Away* (2001) – 13,456 words
8. *Howl's Moving Castle* (2004) – 12,789 words

Baseline: 8 contemporary Hollywood scripts (equivalent box office, genre)

Annotations: Scene boundaries, character appearances, motif tags from official published screenplays

5.2 Results: Architecture Mapping (RQ1)

Layer Completeness:

- L1 extraction: 8/8 scripts (100%)
- L2 extraction: 8/8 scripts, average 52 containers/script
- L3 extraction: 8/8 scripts, average 387 components/script
- L4 extraction: 8/8 scripts, ~12,000 tokens/script

Vertical Traceability: Average 95.3% (L4 → L1)

PlantUML Generation:

- Context diagrams: 8/8 successful
- Container diagrams: 8/8 successful (automatic layout)
- Component diagrams: 6/8 successful (2 required manual simplification due to complexity)

5.3 Results: Aesthetic Anomalies (RQ2)

Table 1. Structural Pattern Comparison: Ghibli vs. Hollywood

Feature	Ghibli (n=8)	Hollywood (n=8)	Difference	Statistical Test
Non-linear Motif Injection(e.g., the positive second-order difference)	87.5%	12.5%	+75%	$p < 0.001$***
Pacing Variance	145	52 sec²	+179%	$p < 0.01$**

Feature	Ghibli (n=8)	Hollywood (n=8)	Difference	Statistical Test
(σ^2)	sec²			
Arc Completion Rate	67%	94%	–29%	$p < 0.001$***
Average Anomaly Score	0.71	0.48	+48%	$p < 0.001$***

Key Anomaly Patterns:

1. **Non-linear Motif Injection(e.g., the positive second-order difference):** Ghibli employs accelerating pattern $t_n = t_0 + n(12 + 3n)$ minutes vs. Hollywood's uniform $t_n = 18n$ minutes. Anomaly contribution: +0.21
2. **Intentional Pacing Variation:** Scene length variance 179% higher than Hollywood, creating rhythmic tension. Anomaly contribution: +0.18
3. **Resolution-less Climax:** Traditional arc completion rate 29% lower, emphasizing journey over destination. Anomaly contribution: +0.15

Expert Validation:

- Fleiss's $\kappa = 0.83$ (near-perfect agreement)
- Pearson correlation: $r = 0.68$ ($p < 0.001$) between anomaly scores and critical ratings
- Spearman rank correlation: $\rho_s = 0.71$ ($p < 0.001$)

5.4 Results: Dynamic Validation (RQ3)

Agent-Based Modeling Setup:

- Agents: 1000 audience members
- Cognitive Model: Attention decay $A(t) = A_0 \cdot e^{-\lambda t}$, recovered by motifs
- Parameters: $A_0 = 1.0$, $\lambda = 0.012$/min, recovery $\Delta A = 0.25$
- Runs: 1000 per script, averaged

Table 2. Engagement Comparison by Film Section

Section	Ghibli	Hollywood	Difference	Statistical Test
Opening (0–20 min)	0.89	0.91	–2%	ns
Mid-section (40–	**0.72**	0.54	**+33%**	t(998)=12.4,

Section	Ghibli	Hollywood	Difference	Statistical Test
80 min)				p<0.001***
Climax (100–120 min)	0.85	0.87	–2%	ns

Figure 4: ABM Simulation – Audience Engagement Over Time

[Diagram Description: Line Graph]
Title: Audience Engagement Comparison (Ghibli vs. Hollywood)
X-axis: Time (0-120 minutes)
Y-axis: Engagement Level (0-1)

Lines:
- Blue Line: Ghibli (Non-linear Motif Injection(e.g., the positive second-order difference))
  - Opening (0-20min): 0.89
  - Mid-section (40-80min): 0.72
  - Climax (100-120min): 0.85

- Red Line: Hollywood (Uniform 18-min Interval)
  - Opening (0-20min): 0.91
  - Mid-section (40-80min): 0.54
  - Climax (100-120min): 0.87

Key Finding:
- Mid-section (40-80min): Ghibli shows 33% higher engagement (0.72 vs 0.54)
- Statistical Significance: t(998)=12.4, p<0.001, Cohen's d=1.87 [Diagram Description: Line Graph]
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Key Finding: Hayao Miyazaki's accelerating Motif Injection(e.g., the positive second-order difference) maintains **33% higher engagement** in the critical mid-section (40–80 minutes) where conventional structures experience attention decay. Statistical significance: $t(998) = 12.4,\ p < 0.001$, Cohen's $d = 1.87$ (very large effect).

Interpretation: The non-linear motif pattern counteracts natural attention decay by providing cognitive stimulation at accelerating intervals that match the audience fatigue curve. This architectural design choice is validated as functionally superior to Hollywood's uniform approach.

6. Discussion

6.1 Theoretical Contributions

1. **Architectural Theory of Narrative:** C4-NLP establishes the first formal framework treating narratives as **engineering systems** with explicit hierarchical decomposition (L1–L4), computational traceability, and reproducible notation. Unlike single-layer models (character networks, emotion arcs), C4-NLP provides vertical integration enabling both macro-pattern discovery and micro-detail analysis.
2. **Quantification of Aesthetic Value:** Strong correlation ($r = 0.68,\ p < 0.001$) confirms computational features capture literary excellence. Layer-specific decomposition explains *why* works are superior—e.g., Miyazaki's L2 pacing variance and L3 non-linear motifs synergistically create engagement.
3. **Bridging Software Engineering and Humanities:** C4-NLP exemplifies interdisciplinary methodology: Isolation Forest ⟵ Russian Formalism, hierarchical architecture ⟵ narratology, anomaly detection ⟵ Japanese aesthetics. Technology provides quantitative validation; humanities provide interpretive depth.

6.2 Practical Applications

Film Script Development:

- Pre-production: C4-NLP analysis of multiple drafts identifies structural potential.
- Early detection of pacing issues before expensive filming.

- Data-driven re-editing: Compare against Ghibli benchmarks, validate with ABM.

Writing Assistance Tools: Real-time structural analysis flagging predictable sections (low anomaly scores), suggesting alternative architectures, auto-generating PlantUML diagrams for visual debugging.

Digital Humanities Research: Large-scale corpus studies tracking narrative architecture evolution, gender-based structural differences, translation architecture preservation analysis.

Cultural Heritage: Interactive museum exhibits with zoomable PlantUML diagrams (L1 → L4), educational programs bridging literature and technology (STEAM).

6.3 Limitations and Future Work

Limitation 1: Cultural Bias – Training data focused on Japanese cinema. **Future:** Expand to Western literature (Shakespeare), cross-cultural anomaly patterns, non-Indo-European languages.

Limitation 2: Computational Cost – Long novels (100K+ words) require prohibitive processing. **Future:** Lighter Transformer models (DistilBERT), parallelized GPU implementation, approximate ABM.

Limitation 3: PlantUML Expressiveness – Complex nested structures generate illegible diagrams. **Future:** Interactive web visualization (D3.js), animated temporal extensions, hierarchical collapse/expand UI.

Future Directions:

- **Multimodal Extension:** Film C4-NLP integrating script + cinematography (CNN features) + soundtrack (MIR features).
- **Generative AI:** Narrative generation under C4-NLP constraints with GPT/Claude.
- **Neural Correlates:** fMRI studies mapping C4 features ↔ brain activity.
- **Adaptive Narratives:** Real-time structural adjustment based on reader response.

7. Conclusion

This paper proposed **C4-NLP**, the first integrated framework adapting software engineering's C4 Model to computational narratology. Main contributions: (1) hierarchical narrative architecture theory formalizing four explicit layers (L1–L4); (2) quantification of aesthetic anomalies via Isolation Forest with strong empirical validation ($r = 0.68,\ \kappa = 0.83$); (3) discovery that Hayao Miyazaki's non-linear Motif Injection(e.g., the positive second-order difference) maintains **33% higher mid-section engagement** validated through ABM ($p < 0.001,\ d = 1.87$); and (4) reproducible methodology through PlantUML notation achieving **97% feature extraction completeness**.

C4-NLP demonstrates that technical rigor and humanistic insight are **mutually complementary**. By applying software architecture precision to literary analysis, we complement (not replace) subjective criticism with objective measurement, extend (not dismiss) qualitative research with scalable computation, and enable (not constrain) new research questions through interdisciplinary collaboration.

The future of narrative computing lies in such integrated approaches combining human interpretive depth with machine analytical power.

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