KDSH: Knowledge-Driven Story Hallucination Detection

A Multi-Dimensional Approach to Narrative Consistency

Ishan Surdi
GitHub: https://github.com/ishansurdi/KDSH

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Abstract

I present KDSH, a system for detecting inconsistencies in narrative claims by combining hierarchical memory structures, multi-hop retrieval, temporal and causal reasoning engines, and ensemble machine learning. My approach achieves 78.7% accuracy and 84.1% F1 score by extracting 20-dimensional features from a custom reasoning pipeline, avoiding end-to-end generation in favor of interpretable, step-by-step refinement. The system handles long narratives (40K+ tokens) through scene-based memory and character state tracking, distinguishes causal signals from noise via explicit causal graph construction, and provides evidence-grounded explanations for predictions.

1 Introduction

Detecting narrative inconsistencies requires understanding complex interactions between events, characters, and causal relationships across long documents. Unlike factual error detection in short contexts, narrative consistency demands:

- **Long-context reasoning**: Novels span 40K+ tokens with events separated by thousands of words
- **Causal understanding**: Distinguishing plausible causal chains from impossible ones
- **Temporal tracking**: Maintaining event timelines and detecting anachronisms
- **Character state evolution**: Tracking character knowledge, location, and relationships over time

I address these challenges through a *knowledge-driven* approach that combines structured memory, symbolic reasoning, and learned classification, avoiding the pitfalls of purely generative or template-based RAG systems.

2 Overall Approach

2.1 System Architecture

KDSH implements a five-stage pipeline:

1. **Document Ingestion & Chunking**: Novels are segmented into paragraph-level chunks and indexed using Pathway AI's document store with sentence-transformer embeddings (all-MiniLM-L6-v2).

2. **Hierarchical Memory Construction**: Build multi-level memory structures tracking scenes, episodes, character states, and timelines (Section 3).

3. **Claim Processing**: Extract atomic claims and constraints (temporal, causal, entity-based) from test statements using rule-based parsing and semantic analysis.

4. **Multi-Hop Evidence Retrieval**: Iteratively gather supporting/contradicting evidence using semantic search, expanding from initial matches to related chunks.

5. **Dual Reasoning Engines**:

   - Temporal Reasoner: Detect event ordering conflicts, timeline violations, anachronisms
   - Causal Reasoner: Identify missing causal links, impossible chains, contradictions (Section 4)

6. **Multi-Dimensional Scoring**: Aggregate temporal, causal, entity, semantic, and evidence scores using weighted combination ($\alpha_{\text{temp}} = 0.35$, $\alpha_{\text{causal}} = 0.30$, $\alpha_{\text{entity}} = 0.15$, $\alpha_{\text{semantic}} = 0.15$, $\alpha_{\text{evidence}} = 0.05$).

7. **ML Ensemble Classification**: Train Random Forest, Gradient Boosting, MLP, and Logistic Regression on 20 extracted features (Section 5).

2.2 Design Philosophy

My approach prioritizes *interpretability* and *modularity* over end-to-end black-box generation:

- **No LLM generation**: I use sentence transformers for embeddings but avoid generative models for reasoning
- **Explicit representations**: Temporal events, causal links, and character states are explicitly modeled as structured objects
- **Step-by-step refinement**: Each stage adds a specific reasoning capability, enabling targeted debugging
- **Evidence grounding**: All conflict detections cite specific text spans from the source novel

This design aligns with the competition's emphasis on "thoughtful use of NLP...beyond basic or template-based pipelines" and "small generative components used selectively" rather than end-to-end generation.

3 Handling Long Context

Novels in the dataset range from 20K to 70K tokens, with critical evidence often separated by entire chapters. I address this through three mechanisms:

3.1 Hierarchical Narrative Memory

Inspired by Zhang & Long (2024) and cognitive memory models, I implement three memory levels:

1. **Scene Memory**: Tracks individual scenes with characters present, locations, and local events. Scenes are detected via paragraph boundaries and character mention co-occurrence.
2. **Episode Memory**: Groups related scenes into episodes (e.g., "escape from prison", "voyage to the island"). Episodes are discovered via event clustering and temporal proximity.
3. **Character State Memory**: Maintains a state vector for each character at different timestamps:

$$\text{CharState}(c, t) = \{\text{location}_t, \text{alive}_t, \text{relationships}_t, \text{knowledge}_t, \text{commitments}_t\} \quad (1)$$

Example: When evaluating the claim "Character X knew about the treasure in Chapter 1", I query Character State Memory to verify X's knowledge set at timestamp t_1, even if the relevant evidence appears in Chapter 15.

3.2 Multi-Hop Retrieval with Memory Indexing

Standard RAG retrieves top-K chunks based on query similarity. This fails for long narratives where:

- Causal chains span multiple chapters (e.g., A causes B, B causes C, but A and C are 10K tokens apart)
- Character state changes accumulate over time

My **MultiHopRetriever** implements:

Algorithm 1 Multi-Hop Evidence Retrieval

Input: Query q, Memory M, max hops h
Output: Evidence set E
$E_0 \leftarrow \text{SemanticSearch}(q, \text{top-k} = 5)$
for $i = 1$ to h **do**
    entities $\leftarrow \text{ExtractEntities}(E_{i-1})$
    scenes $\leftarrow M.\text{FindScenes}(\text{entities})$
    expanded $\leftarrow \text{SemanticSearch}(\text{scenes}, \text{top-k} = 3)$
    $E_i \leftarrow E_{i-1} \cup \text{expanded}$
    if no new evidence **then break**
    end if
end for
return E_h

This enables discovering "Character X was at location L in Chapter 3" $\rightarrow$ "Location L is the treasure site (Chapter 8)" $\rightarrow$ "Therefore X knew about the treasure".

3.3 Chunking Strategy

I use **paragraph-level chunks** rather than fixed-size windows:

- Preserves semantic coherence (sentences within paragraphs are typically related)
- Respects narrative structure (paragraphs often correspond to scene boundaries)
- Enables scene detection via chunk clustering

Average chunk size: 150-200 tokens. Long paragraphs (> 300 tokens) are split at sentence boundaries.

4 Distinguishing Causal Signals from Noise

Identifying genuine causal inconsistencies requires separating:

- True causal violations ("X died before Y was born, but Y's actions caused X's death")
- Narrative gaps (unmentioned but plausible intermediate events)
- Stylistic choices (non-chronological storytelling, flashbacks)

4.1 Causal Reasoning Engine

My `CausalReasoner` implements three detection strategies:

4.1.1 Explicit Causal Markers

I extract causal links from text using linguistic patterns:

- **Explicit markers**: "because", "caused", "led to", "resulted in", "due to"
- **Conditional structures**: "if...then", "when...subsequently"
- **Purpose clauses**: "in order to", "so that"

Each extracted link forms an edge in a causal graph: cause $\xrightarrow{\text{confidence}}$ effect.

4.1.2 Temporal-Causal Consistency

Causality implies temporal precedence: cause must precede effect. I check:

$$\forall (c \to e) \in \text{CausalGraph} : \quad t_c < t_e \tag{2}$$

Violations indicate either:

- Genuine inconsistency (effect precedes cause)
- Flashback/non-linear narration (resolved via narrative structure analysis)

Example: Claim: "The fire destroyed the mansion before John lit the match." Temporal order ($t_{\text{fire}} < t_{\text{match}}$) contradicts causal link (match $\to$ fire).

4.1.3 Causal Chain Validation

For multi-hop causal claims (A causes B causes C), I verify:

1. **Completeness**: All intermediate links are supported by evidence
2. **Coherence**: No contradictory evidence blocks the chain
3. **Plausibility**: Physical/logical constraints are satisfied

Conflict Types:

- `missing_link`: Claim asserts A $\rightarrow$ C but no evidence supports A $\rightarrow$ B $\rightarrow$ C
- `impossible_chain`: Intermediate state B is impossible given A (e.g., "dead character performs action")
- `contradiction`: Evidence explicitly states A $\not\rightarrow$ C

4.2 Signal vs. Noise Filtering

To reduce false positives, I apply:

1. **Evidence Strength Thresholding**: Only flag conflicts with ≥ 2 supporting evidence chunks and semantic similarity > 0.7.
2. **Uncertainty Propagation**: Causal links derived from uncertain evidence (e.g., character speculation, modal verbs) are downweighted:

$$\text{confidence(link)} = \text{similarity(evidence)} \times (1 - \text{uncertainty}) \tag{3}$$

3. **Severity Weighting**: Not all conflicts are equally important. Missing minor details receive lower severity than logical impossibilities:

$$\text{severity(missing\_link)} = 0.5 \tag{4}$$
$$\text{severity(impossible\_chain)} = 0.9 \tag{5}$$
$$\text{severity(contradiction)} = 1.0 \tag{6}$$

4. **Cross-Validation with Temporal Reasoner**: Causal conflicts are validated against temporal constraints. If temporal analysis shows no violation, causal severity is reduced.

4.3 Example: Distinguishing Signal from Noise

Claim: "Character X's decision to leave caused Character Y's downfall."
Noise (False Positive):

- Evidence mentions X leaving and Y's downfall in separate chapters
- No explicit causal link in text
- Multiple other factors contributed to Y's downfall
- $\rightarrow$ Missing link but low confidence, not flagged

Signal (True Positive):

- Evidence: "After X abandoned Y, Y lost all hope and made the fatal mistake"
- Explicit causal marker ("after...led to")
- High semantic similarity (0.92)
- No contradictory evidence
- → Strong causal link, flagged as consistent with narrative

5 Machine Learning Features

Rather than training on raw text, I extract 20 interpretable features from the reasoning pipeline:

5.1 Conflict Features (8 dimensions)

- `temporal_conflict_count`: Number of temporal violations detected
- `temporal_severity_max`: Maximum severity of temporal conflicts
- `temporal_severity_mean`: Average temporal conflict severity
- `causal_conflict_count`: Number of causal violations
- `causal_severity_max`: Maximum causal conflict severity
- `causal_severity_mean`: Average causal conflict severity
- `entity_mismatch_count`: Character state contradictions
- `semantic_contradiction_score`: Semantic similarity of contradicting evidence

5.2 Evidence Features (6 dimensions)

- `evidence_count`: Number of retrieved evidence chunks
- `evidence_avg_similarity`: Mean semantic similarity of evidence to claim
- `evidence_max_similarity`: Best matching evidence score
- `evidence_diversity`: Entropy of evidence source chapters
- `supporting_evidence_ratio`: Fraction of evidence supporting vs. contradicting
- `evidence_coverage`: Proportion of claim covered by evidence

5.3 Interaction Features (4 dimensions)

- `conflict_evidence_interaction`: `conflict_count` × `evidence_strength`
- `temporal_causal_interaction`: `temporal_severity` × `causal_severity`
- `severity_coverage_ratio`: `max_severity` / `evidence_coverage`
- `multimodal_conflict`: Binary flag for conflicts in ≥ 2 dimensions

5.4 Meta Features (2 dimensions)

- `claim_complexity`: Number of sub-claims and constraints
- `novel_length`: Token count (normalized)

5.5 Ensemble Classifier

I train four models and use majority voting:

1. **Random Forest** (100 trees, depth=10): Handles non-linear feature interactions
2. **Gradient Boosting** (100 estimators): Captures sequential dependencies
3. **MLP** (64-32-16 hidden units): Learns complex feature combinations
4. **Logistic Regression** (L2 penalty): Provides linear baseline

Training uses 5-fold cross-validation with class balancing (SMOTE) to address the 60% consistent / 40% inconsistent label distribution.

6 Results

6.1 Performance Metrics

On the 80-example training set (with 10-fold cross-validation):

Model	Accuracy	Precision	Recall	F1
Random Forest	76.3%	78.1%	85.7%	81.7%
Gradient Boosting	77.5%	79.5%	87.5%	83.3%
MLP	75.0%	76.2%	88.9%	82.0%
Logistic Regression	73.8%	75.0%	84.0%	79.2%
Ensemble (Majority Vote)	**78.7%**	**80.4%**	**88.2%**	**84.1%**

Table 1: Cross-validation performance on training set (80 examples)

6.2 Feature Importance

Top 5 most important features (Random Forest feature importance):

1. `temporal_severity_max` (0.18): Strong predictor of inconsistency
2. `causal_conflict_count` (0.15): Direct signal of causal violations
3. `conflict_evidence_interaction` (0.12): High conflicts + weak evidence → inconsistent
4. `evidence_coverage` (0.11): Low coverage suggests unsupported claims
5. `semantic_contradiction_score` (0.09): Direct contradictions in text

6.3 Test Set Predictions

On the 60-example test set, my system predicts:

- 23 inconsistent (38.3%)
- 37 consistent (61.7%)

This aligns with the expected ∼36% inconsistency rate in the test distribution.

7 Limitations and Failure Cases

7.1 Implicit Knowledge Gaps

Limitation: My system struggles with claims requiring world knowledge not stated in the novel.

Example: "The character traveled from Paris to London by train." If the novel mentions the character is in Paris (Chapter 1) and later in London (Chapter 5) without describing the journey, my system may flag this as a missing causal link (travel mechanism unspecified), even though train travel is plausible.

Mitigation: I apply low severity (0.3) to missing links without explicit contradictions, but this trades recall for precision.

7.2 Figurative Language

Limitation: Metaphorical or figurative statements are sometimes treated as literal claims.

Example: "The news killed him" (metaphor for emotional distress) vs. actual death. If a character is mentioned later, my temporal reasoner may incorrectly flag this as a "revived character" inconsistency.

Mitigation: I detect uncertainty markers ("as if", "like", "seemed") and reduce confidence, but sophisticated metaphor detection requires deeper semantic understanding.

7.3 Non-Linear Narratives

Limitation: Flashbacks, dream sequences, and parallel timelines complicate temporal reasoning.

Example: A novel with alternating past/present chapters may have legitimate temporal "violations" (e.g., event in Chapter 4 precedes event in Chapter 2 chronologically).

Mitigation: I implement narrative structure detection (identifying flashback markers like "years earlier", "meanwhile"), but complex nested timelines remain challenging.

7.4 Long Causal Chains

Limitation: Multi-hop causal reasoning degrades with chain length. For chains with > 4 hops, evidence retrieval becomes noisy.

Example: A $\rightarrow$ B $\rightarrow$ C $\rightarrow$ D $\rightarrow$ E, where each link has 0.8 confidence, yields overall confidence $0.8^4 = 0.41$, potentially missing genuine inconsistencies.

Mitigation: I limit multi-hop retrieval to 3 hops and require $\geq$0.7 confidence per link, but this may miss distant causal connections.

7.5 Ambiguous Entity Resolution

Limitation: Characters with similar names or pronouns cause entity tracking errors.

Example: "John" vs. "John Smith" vs. "Mr. Smith" referring to the same character, or "he" with multiple male characters nearby.

Mitigation: I use coreference resolution (NeuralCoref) but achieve only ∼85% accuracy, leading to occasional false conflicts.

7.6 Computational Cost

Limitation: Full pipeline (ingestion + memory + reasoning + ML) takes 8-12 minutes per novel on Google Colab (T4 GPU).

Trade-off: I prioritize thoroughness over speed, but this limits real-time applications. A faster mode (skip hierarchical memory, use top-K retrieval only) achieves 2-3 minutes but loses 5-7% accuracy.

8 Related Work

My approach builds on:

- **Long-document inconsistency detection**: Lattimer et al. (2023) demonstrate that inconsistencies span >10K tokens, motivating my hierarchical memory.
- **Narrative coherence**: Zhang & Long (2024) introduce narrative gap theory and multi-level memory, which I adapt for character state tracking.
- **Causal inference in NLP**: Feder et al. (2022) and Basu et al. (2022) show neural-symbolic methods outperform pure neural approaches for causal reasoning, guiding my explicit causal graph design.
- **Evidence attribution**: Rashkin et al. (2021) emphasize grounding predictions in source text, which I implement via multi-hop retrieval.

9 Conclusion

KDSH demonstrates that narrative inconsistency detection benefits from *structured reasoning* over *end-to-end generation*. By explicitly modeling temporal constraints, causal relationships, and character states, I achieve strong performance (78.7% accuracy, 84.1% F1) while maintaining interpretability. Key innovations include:

1. Hierarchical memory for long-context tracking (scenes, episodes, character states)
2. Multi-hop retrieval with memory indexing
3. Dual reasoning engines (temporal + causal) with severity weighting
4. 20-dimensional feature extraction for ensemble ML

Future work should address:

- Better figurative language understanding

- Nested timeline handling
- World knowledge integration (external knowledge bases)
- Efficiency improvements for real-time deployment

Code and models: `https://github.com/ishansurdi/KDSH`

Appendix

A. Component Score Formulation

The final inconsistency score combines five components:

$$S_{\text{inconsistency}} = \sum_{i \in \{\text{temp, causal, entity, semantic, evidence}\}} \alpha_i \cdot s_i \tag{7}$$

where:

$$s_{\text{temporal}} = \frac{\sum_{c \in C_{\text{temp}}} \text{severity}(c)}{1 + |C_{\text{temp}}|} \tag{8}$$

$$s_{\text{causal}} = \frac{\sum_{c \in C_{\text{causal}}} \text{severity}(c)}{1 + |C_{\text{causal}}|} \tag{9}$$

$$s_{\text{entity}} = \frac{|\text{CharStateMismatches}|}{1 + |\text{EntitiesInClaim}|} \tag{10}$$

$$s_{\text{semantic}} = \max_{e_1, e_2 \in E} (1 - \text{sim}(e_1, e_2)) \quad \text{if contradicting} \tag{11}$$

$$s_{\text{evidence}} = 1 - \frac{|\{e \in E : \text{sim}(e, \text{claim}) > 0.7\}|}{1 + |E|} \tag{12}$$

B. Hyperparameters

C. Example Walkthrough

Claim: "After escaping prison, Edmond immediately traveled to Rome."
Novel: *The Count of Monte Cristo*
Pipeline Execution:

1. **Claim Parsing**: Extract constraints: `temporal(escape → travel, immediately)`, `destination(Rome)`
2. **Evidence Retrieval**:
   - Hop 1: Find escape scene (Chapter 20) → 3 chunks
   - Hop 2: Search for "Edmond travel" → finds shipwreck scene (Chapter 21)
   - Hop 3: Search for "Rome" → finds Rome visit (Chapter 35)
3. **Temporal Reasoning**:
   - Event 1: Escape (Chapter 20, timestamp t_1)
   - Event 2: Shipwreck/island stay (Chapter 21-25, timestamp t_2)
   - Event 3: Rome visit (Chapter 35, timestamp t_3)

Component	Parameter	Value
Document Store	Embedding model	all-MiniLM-L6-v2
	Chunk size	150-300 tokens
	Index type	HNSW (M=16, ef=100)
Multi-Hop Retrieval	Max hops	3
	Top-K per hop	5
	Similarity threshold	0.65
Temporal Reasoner	Uncertainty threshold	0.3
	Anachronism window	50 years
Causal Reasoner	Min evidence for link	2 chunks
	Confidence threshold	0.7
Scorer Weights	α_{temporal}	0.35
	α_{causal}	0.30
	α_{entity}	0.15
	α_{semantic}	0.15
	α_{evidence}	0.05
ML Ensemble	Random Forest trees	100
	RF max depth	10
	GB estimators	100
	MLP hidden layers	(64, 32, 16)
	Cross-validation folds	5

Table 2: System hyperparameters

- Conflict: $t_1 \to t_3$ not immediate (14 chapters, $\sim$3 years narrative time)

4. **Causal Reasoning**:
   - Expected: escape $\xrightarrow{\text{immediately}}$ Rome
   - Evidence: escape $\to$ shipwreck $\to$ island $\to$ Rome
   - Conflict: Missing link (immediate travel), extra intermediate events
5. **Scoring**:

$$
\begin{aligned}
s_{\text{temporal}} &= 0.8 \quad \text{(high severity: timeline violation)} \\
s_{\text{causal}} &= 0.6 \quad \text{(medium: missing immediate link)} \\
s_{\text{entity}} &= 0.0 \quad \text{(no entity mismatches)} \\
s_{\text{semantic}} &= 0.4 \quad \text{(some contradiction)} \\
s_{\text{evidence}} &= 0.2 \quad \text{(good evidence coverage)} \\
S_{\text{inconsistency}} &= 0.35 \cdot 0.8 + 0.30 \cdot 0.6 + \ldots = \mathbf{0.72}
\end{aligned}
$$

6. **ML Features**: Extract 20 features, feed to ensemble
7. **Prediction**: All 4 models vote `inconsistent` $\to$ **Label: 1**