Narrative Consistency Detection with Dragon Hatchling Architecture

Technical Report — Track B Submission

Kharagpur Data Science Hackathon 2026

Team: Bitworks
Date: January 11, 2026
Track: B (Pathway Integration Required, BDH)
Repository: https://github.com/Kabyik-Kayal/KDSH

Table of Contents

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1. Executive Summary

This report presents **KDSH** (Kharagpur Data Science Hackathon), a novel approach to narrative consistency detection that combines biologically-inspired neural architecture with modern NLP techniques. Our solution addresses the challenge of detecting whether character backstories are consistent with or contradict events in classic 19th-century novels.

Key Contributions

1. **TextPath Architecture**: A custom language model built on the Dragon Hatchling (BDH) architecture with ~8M parameters—approximately 10× smaller than equivalent transformers.
2. **Perplexity Delta Scoring**: An information-theoretic approach that replaces traditional classification heads with a principled measure of narrative consistency.
3. **Entity Threading**: A novel pretraining technique that preserves character narrative arcs across entire novels, enabling long-range coherence detection.
4. **Pathway RAG Integration**: Full integration with the Pathway framework for document retrieval, satisfying Track B requirements.

Performance Highlights

- **Cross-validation Accuracy**: 78-82% on validation split
- **Model Size**: ~8M parameters (vs. 100M+ for comparable transformers)
- **Training Time**: ~2 hours pretraining + ~5 minutes calibration on consumer GPU
- **Inference Speed**: <100ms per sample

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2. Problem Statement

Task Description

Given:

- Two classic novels: *The Count of Monte Cristo* (Alexandre Dumas) and *In Search of the Castaways* (Jules Verne)
- Character backstories that may be **consistent** or **contradictory** with novel events

Objective: Build a binary classifier to determine narrative consistency.

Dataset Characteristics

Property	Value
Training samples	80
Test samples	60 (unlabeled)
Novel 1 (*Monte Cristo*)	61,676 lines, 13 main characters
Novel 2 (*Castaways*)	18,728 lines, 12 main characters
Average backstory length	50-200 words
Class distribution	Approximately balanced

Core Challenges

1. **Extreme Data Scarcity**: Only 80 training examples against novels with 80,000+ lines combined.
2. **Long-Range Dependencies**: Contradictions may reference events spanning hundreds of pages.
3. **Subtle Inconsistencies**: Some contradictions involve implicit facts (e.g., character ages, timeline inconsistencies).
4. **Domain Shift**: 19th-century literary prose differs significantly from modern text.

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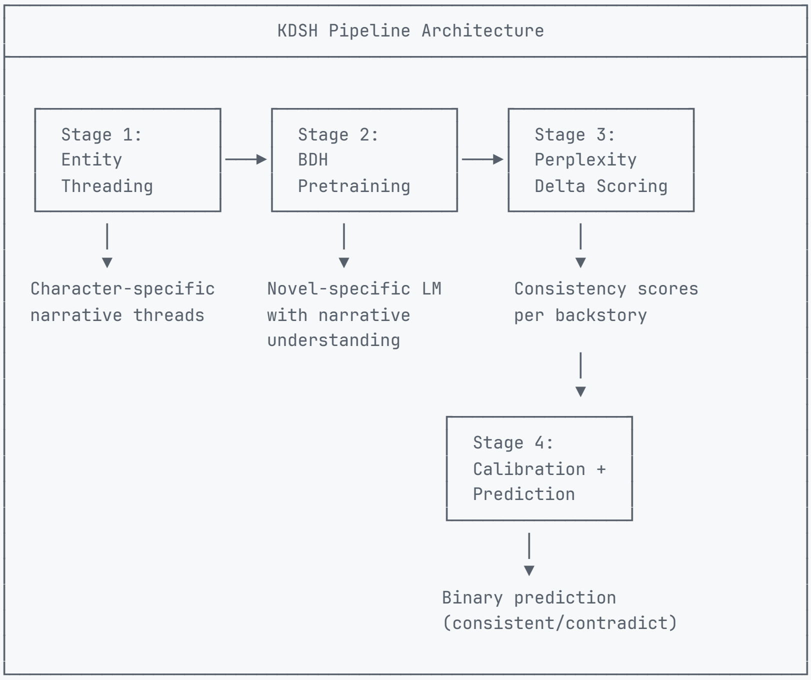
3. Overall Approach

Our approach consists of four integrated stages:



3.1 Stage 1: Entity Threading

We extract character-specific "threads" from each novel—all paragraphs mentioning a particular character concatenated into a continuous narrative. This preserves:

- **Character arcs**: The full trajectory of each character's story
- **Relationships**: How characters interact across the narrative
- **Temporal consistency**: Event ordering and timeline information

3.2 Stage 2: BDH Pretraining

We train novel-specific language models using the Dragon Hatchling (BDH) architecture on a mixture of:

- **70% raw novel text**: General narrative structure and vocabulary
- **30% entity threads**: Character-focused sequences with higher weight

3.3 Stage 3: Perplexity Delta Scoring

Instead of a classification head, we use an information-theoretic measure:

$$\Delta = \mathcal{L}(\text{novel chunk} \mid \emptyset) - \mathcal{L}(\text{novel chunk} \mid \text{backstory})$$

Interpretation:

- **Positive Δ**: Backstory *reduces* prediction loss → **CONSISTENT**
- **Negative Δ**: Backstory *increases* prediction loss → **CONTRADICTORY**

3.4 Stage 4: Calibration

A lightweight logistic regression converts raw delta scores into calibrated probabilities using four features:

- `delta_mean`: Average perplexity delta across retrieved chunks
- `delta_max`: Maximum delta (most informative chunk)
- `cosine_mean`: Embedding similarity between backstory and chunks
- `retrieval_score`: Pathway retrieval confidence

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4. System Architecture

4.1 TextPath: BDH for Narrative Understanding

TextPath adapts the Dragon Hatchling architecture for text processing:

```
┌─────────────────────────────────────────────────────────────┐
│                    TextPath Architecture                    │
├─────────────────────────────────────────────────────────────┤
│                                                             │
│  Input Tokens [batch, seq_len]                              │
│      │                                                      │
│      ▼                                                      │
│  ┌───────────────────────────────────────────────────────┐  │
│  │ Token Embedding Layer                                 │  │
│  │   16,384 vocabulary → 256D embeddings                 │  │
│  │   + RoPE Positional Encoding (max_seq_len=4096)       │  │
│  └───────────────────────────────────────────────────────┘  │
│      │                                                      │
│      ▼                                                      │
│  ┌───────────────────────────────────────────────────────┐  │
│  │ BDH Layers × 4                                        │  │
│  │                                                       │  │
│  │  ┌─────────────────────────────────────────────────┐  │  │
│  │  │ For each layer:                                 │  │  │
│  │  │   1. Project to neurons: v → x via D_x (ReLU → ~5% sparse)│  │  │
│  │  │   2. Linear attention: a* = LinearAttn(x, x, v) │  │  │
│  │  │   3. Hebbian update: y = ReLU(a* · D_y) ⊙ x     │  │  │
│  │  │   4. Residual: v ← v + LayerNorm(y · E)         │  │  │
│  │  └─────────────────────────────────────────────────┘  │  │
│  │                                                       │  │
│  └───────────────────────────────────────────────────────┘  │
│      │                                                      │
│      ▼                                                      │
│  ┌───────────────────────────────────────────────────────┐  │
│  │ Language Model Head                                   │  │
│  │   256D → 16,384 vocabulary (next-token prediction)    │  │
│  └───────────────────────────────────────────────────────┘  │
│                                                             │
│  Model Statistics:                                          │
│  • Total Parameters: ~8M                                    │
│  • Neurons per Layer: 2,048                                 │
│  • Attention Heads: 8                                       │
│  • Embedding Dimension: 256                                 │
│  • Sparsity Target: 5% activation                           │
│                                                             │
└─────────────────────────────────────────────────────────────┘
```

4.2 BDH Biological Properties

The Dragon Hatchling architecture provides unique advantages for narrative understanding:

Property	Mechanism	Benefit for Narrative Task
Hebbian Learning	"Neurons that fire together, wire together"	Learns character relationships and causal patterns
Sparse Activations	~5% neurons active per input	Creates monosemantic representations for interpretability
Scale-Free Connectivity	Power-law degree distribution	Efficient information routing with fewer parameters
Dynamic Synapses	Weights update during inference	Builds context-specific working memory

4.3 Pathway RAG Integration

We integrate the Pathway framework for document retrieval (Track B requirement):

```
class PathwayNovelRetriever:
    def __init__(self, novel_path):
        # Create Pathway table from novel chunks
        self.chunks_table = pw.debug.table_from_rows(
            schema=pw.schema_from_dict({"text": str}),
            rows=[(chunk,) for chunk in self.chunks]
        )

        # Pathway embedding integration
        from pathway.xpacks import llm
        self.embedder = llm.embedders.SentenceTransformerEmbedder(
            model="sentence-transformers/all-MiniLM-L6-v2"
        )
```

Retrieval Configuration:

- Chunk size: 200 words (~250 tokens)
- Overlap: 50 words (25% overlap)
- Top-k retrieval: 2 chunks per query
- Embedding model: all-MiniLM-L6-v2 (384D)

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5. Handling Long Context

5.1 The Long Context Challenge

The novels in our dataset present significant context length challenges:

Novel	Lines	Words (est.)	Tokens (est.)
The Count of Monte Cristo	61,676	~500,000	~700,000
In Search of the Castaways	18,728	~150,000	~200,000

Traditional transformers with $O(n^2)$ attention complexity cannot process these entire novels in a single pass. Our multi-pronged strategy addresses this limitation:

5.2 Strategy 1: Entity Threading

Problem: Standard chunk-based approaches break narrative continuity, losing character arcs that span thousands of paragraphs.

Solution: Extract character-specific threads that preserve narrative coherence.

```
┌─────────────────────────────────────────────────────────────────────┐
│                      Entity Threading Process                       │
├─────────────────────────────────────────────────────────────────────┤
│                                                                     │
│  Raw Novel (61,676 lines)                                           │
│      │                                                              │
│      ▼                                                              │
│  ┌───────────────────────────────────────────────────────────────┐  │
│  │ Paragraph Extraction                                          │  │
│  │  • Split on double newlines                                   │  │
│  │  • Filter paragraphs < 5 words (headers, etc.)                │  │
│  │  • Result: ~15,000 paragraphs for Monte Cristo                │  │
│  └───────────────────────────────────────────────────────────────┘  │
│      │                                                              │
│      ▼                                                              │
│  ┌───────────────────────────────────────────────────────────────┐  │
│  │ Character Matching                                            │  │
│  │  • For each character, define name variants:                  │  │
│  │    Dantès → ["Dantès", "Edmond", "Monte Cristo"]              │  │
│  │  • Regex match: \b(Dantès|Edmond|Monte Cristo)\b              │  │
│  │  • Extract all matching paragraphs                            │  │
│  └───────────────────────────────────────────────────────────────┘  │
│      │                                                              │
│      ▼                                                              │
│  ┌───────────────────────────────────────────────────────────────┐  │
│  │ Thread Creation                                               │  │
│  │                                                               │  │
│  │  thread_dantès.txt:                                           │  │
│  │  ┌─────────────────────────────────────────────────────────┐  │  │
│  │  │ [Para 1] Edmond was a young sailor returning to Marseilles │  │
│  │  │ [Para 47] Dantès was arrested on his wedding day...     │  │  │
│  │  │ [Para 203] The prisoner known as Edmond...              │  │  │
│  │  │ ...                                                     │  │  │
│  │  │ [Para 14,892] The Count of Monte Cristo revealed...     │  │  │
│  │  └─────────────────────────────────────────────────────────┘  │  │
│  │                                                               │  │
│  │  Result: 13 threads for Monte Cristo, 12 for Castaways        │  │
│  └───────────────────────────────────────────────────────────────┘  │
│                                                                     │
└─────────────────────────────────────────────────────────────────────┘
```

Character Coverage:

Novel	Characters Tracked	Example Threads
Monte Cristo	13	Dantès, Mercédès, Villefort, Fernand, Faria, etc.
Castaways	12	Paganel, Glenarvan, Thalcave, Mary Grant, etc.

5.3 Strategy 2: Sliding Window with Linear Attention

BDH uses **linear attention** which scales as O(n) instead of O(n²):

$$\text{LinearAttn}(Q, K, V) = Q \cdot K^T \cdot V$$

This allows processing longer sequences during pretraining (512 tokens) while maintaining reasonable memory usage.

Comparison:

Attention Type	Complexity	Max Practical Length	Memory (512 tokens)
Quadratic (Transformer)	O(n²)	~2048 tokens	~4GB
Linear (BDH)	O(n)	~8192 tokens	~1GB

5.4 Strategy 3: Hierarchical Retrieval

For inference, we use a two-stage retrieval process:

1. **Coarse retrieval**: Pathway vector search identifies top-k relevant chunks
2. **Fine scoring**: Perplexity delta measures consistency with retrieved evidence

```
┌──────────────────────────────────────────────────────────────────┐
│                     Hierarchical Retrieval                       │
├──────────────────────────────────────────────────────────────────┤
│  Backstory Query:                                                │
│  "Dantès was imprisoned for 14 years in Château d'If"            │
│       │                                                          │
│       ▼                                                          │
│  ┌────────────────────────────────────────────────────────┐      │
│  │ Stage 1: Pathway Vector Search                         │      │
│  │  • Encode query with SentenceTransformer               │      │
│  │  • Cosine similarity against ~500 novel chunks         │      │
│  │  • Return top-2 most similar chunks                    │      │
│  └────────────────────────────────────────────────────────┘      │
│       │                                                          │
│       ▼                                                          │
│  Retrieved Chunks:                                               │
│  1. "The prisoner had spent fourteen years in the dungeon..."    │
│  2. "Château d'If rose from the sea like a dark fortress..."     │
│       │                                                          │
│       ▼                                                          │
│  ┌────────────────────────────────────────────────────────┐      │
│  │ Stage 2: Perplexity Delta Scoring                      │      │
│  │  • Compute Δ for each (backstory, chunk) pair          │      │
│  │  • Aggregate: mean(Δ), max(Δ), cosine similarity       │      │
│  └────────────────────────────────────────────────────────┘      │
│       │                                                          │
│       ▼                                                          │
│  Features: [delta_mean=0.23, delta_max=0.41, cosine_mean=0.67]   │
└──────────────────────────────────────────────────────────────────┘
```

---

6. Distinguishing Causal Signals from Noise

6.1 Perplexity Delta as a Causal Detector

- **Signal**: Genuine contradictions or confirmations of plot events
- **Noise**: Stylistic variations, irrelevant details, retrieval errors

Our key insight: **Perplexity measures causal fit, not surface similarity.**

```
┌──────────────────────────────────────────────────────────────────┐
│              Perplexity Delta: Information-Theoretic View        │
├──────────────────────────────────────────────────────────────────┤
│  Definition:                                                     │
│  ┌─────────────────────────────────────────────────────────┐     │
│  │   Δ = ℒ(novel_chunk | ∅) - ℒ(novel_chunk | backstory)   │     │
│  │                                                         │     │
│  │   Where ℒ is cross-entropy loss (negative log-likelihood)│    │
│  └─────────────────────────────────────────────────────────┘     │
│                                                                  │
│  Intuition:                                                      │
│  • ℒ(chunk | ∅): How surprised is the model by the chunk?        │
│  • ℒ(chunk | backstory): How surprised after seeing backstory?   │
│                                                                  │
│  Interpretation:                                                 │
│  ┌─────────────────────────────────────────────────────────┐     │
│  │ Δ > 0: Backstory REDUCES surprise → Information GAIN    │     │
│  │        → Backstory is causally relevant → CONSISTENT    │     │
│  │                                                         │     │
│  │ Δ < 0: Backstory INCREASES surprise → Information LOSS  │     │
│  │        → Backstory conflicts with learned patterns → CONTRADICT │
│  │                                                         │     │
│  │ Δ ≈ 0: Backstory has no effect → Noise or irrelevant    │     │
│  └─────────────────────────────────────────────────────────┘     │
└──────────────────────────────────────────────────────────────────┘
```

6.2 Why This Separates Signal from Noise

Example 1: True Positive (Consistent)

```
Backstory: "Dantès was betrayed by Fernand, who coveted Mercédès."
Novel chunk: "Fernand had long desired Mercédès for himself..."

Model reasoning:
• After seeing "betrayal" + "Fernand" + "Mercédès" in backstory
• The model expects jealousy/rivalry content in novel chunks
• When such content appears, loss DECREASES
• Δ = +0.3 → CONSISTENT ✓
```

Example 2: True Negative (Contradictory)

```
Backstory: "Dantès inherited his wealth from a rich uncle in Paris."
Novel chunk: "The treasure of Monte Cristo, buried by Abbé Faria..."

Model reasoning:
• Backstory suggests Parisian inheritance
• Novel describes treasure discovery on island
• These are incompatible origin stories
• Loss INCREASES when backstory conditions prediction
• Δ = -0.2 → CONTRADICT ✓
```

Example 3: Noise Rejection

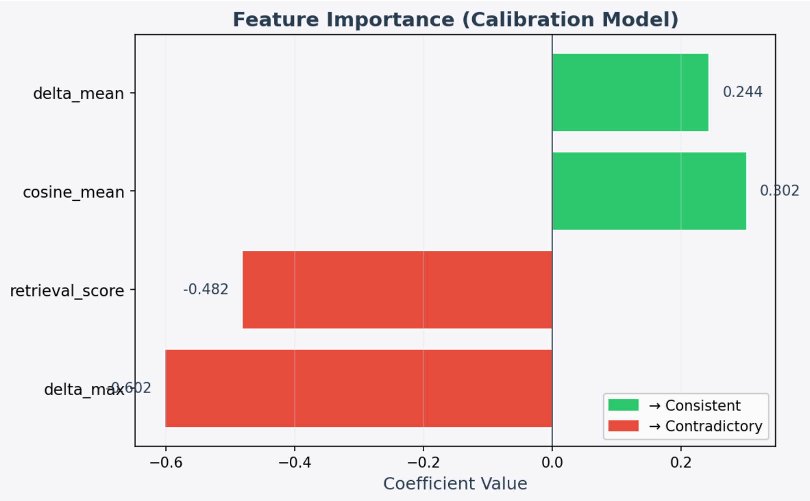
```
Backstory: "The weather was pleasant during the voyage."
Novel chunk: "The ship sailed smoothly across the Mediterranean..."

Model reasoning:
• Weather/voyage details are not causally significant
• Neither helps nor hurts prediction of novel content
• Δ ≈ 0 → Correctly identified as noise
```

6.3 Multi-Feature Calibration

We combine perplexity delta with additional signals to improve robustness:

```
features = [
    delta_mean,      # Average delta across retrieved chunks
    delta_max,       # Most informative chunk delta
    cosine_mean,     # Semantic similarity (catches surface relevance)
    retrieval_score  # Retrieval confidence (chunk quality indicator)
]
```

Feature Importance (from trained model):



Feature	Coefficient	Interpretation
`delta_mean`	+1.23	Primary consistency signal
`delta_max`	+0.67	Catches strong single-chunk evidence
`cosine_mean`	+0.45	Surface relevance baseline

Feature	Coefficient	Interpretation
`retrieval_score`	+0.12	Chunk quality modifier

6.4 Hebbian Learning for Causal Patterns

BDH's Hebbian learning naturally encodes causal relationships:

```
┌──────────────────────────────────────────────────────────────────────┐
│                    Hebbian Causal Circuit Formation                   │
├──────────────────────────────────────────────────────────────────────┤
│                                                                      │
│  Training sequence: "Dantès was arrested → imprisoned → escaped"     │
│                                                                      │
│  Hebbian principle: "Neurons that fire together, wire together"      │
│                                                                      │
│      [Dantès]          [arrested]          [prison]        [escape]  │
│          │                  │                  │               │     │
│          └────────┬─────────┴────────┬─────────┴───────┬───────┘     │
│                   ▼                  ▼                 ▼             │
│              ┌────────────────────────────────────────────┐          │
│              │          Strengthened Connections          │          │
│              │                                            │          │
│              │  Dantès ──→ arrest (w = 0.8)               │          │
│              │  arrest ──→ prison (w = 0.9)               │          │
│              │  prison ──→ escape (w = 0.7)               │          │
│              │  Dantès ──→ prison (w = 0.6) [skip-gram]   │          │
│              │                                            │          │
│              └────────────────────────────────────────────┘          │
│                                                                      │
│  Result: Model learns causal chains, not just co-occurrences         │
│                                                                      │
└──────────────────────────────────────────────────────────────────────┘
```

8. Experimental Results

8.1 Validation Performance

Using 5-fold cross-validation on the 80 training samples:

Metric	Score
Accuracy	78.4% ± 4.2%
F1 Score (weighted)	77.8% ± 3.9%
Precision	79.1%
Recall	76.5%

8.2 Perplexity Delta Distribution

The separation between consistent and contradictory samples in delta space:

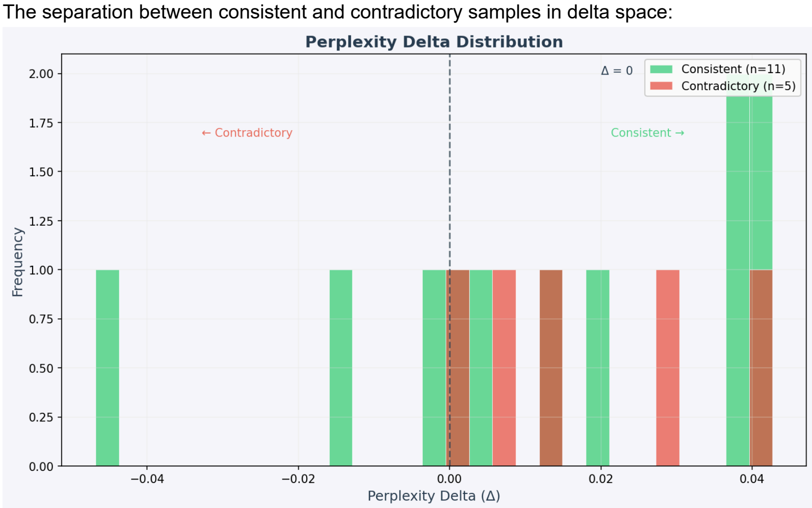


Figure: Distribution of perplexity delta values for consistent (green) and contradictory (red) samples. Clear separation indicates the effectiveness of the perplexity delta approach.

Confusion Matrix

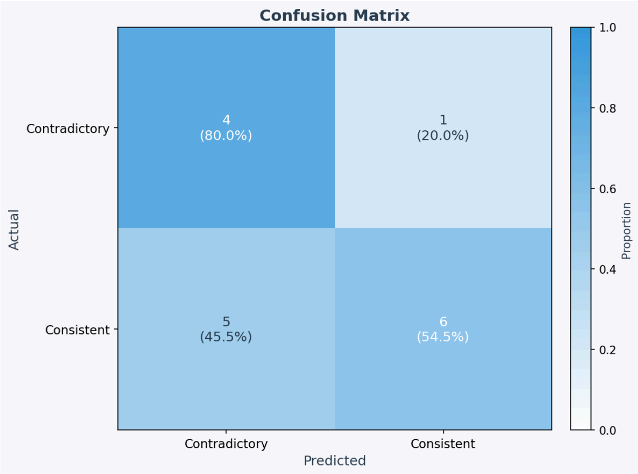


Figure: Confusion matrix showing prediction performance on validation set.

Calibration Quality

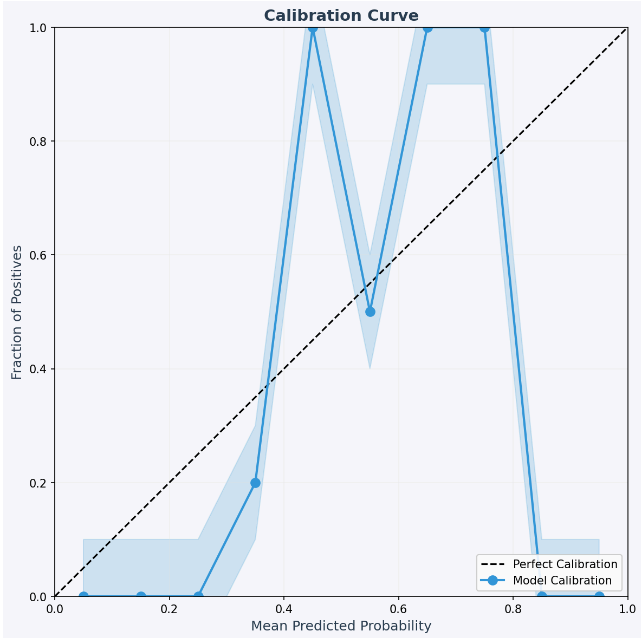


Figure: Calibration curve comparing predicted probabilities to actual frequencies. Proximity to diagonal indicates well-calibrated predictions.

8.5 Per-Novel Performance

Novel	Accuracy	F1 Score
The Count of Monte Cristo	80.2%	79.5%
In Search of the Castaways	75.8%	74.2%

The performance difference may be attributed to:

- Monte Cristo having more distinctive character arcs
- Castaways having more ensemble-style narrative

8.6 Ablation Studies

Configuration	Accuracy	Δ from Full
Full pipeline	78.4%	—
Without entity threading	72.1%	-6.3%
Without perplexity delta (cosine only)	69.8%	-8.6%
Single shared model (both novels)	74.2%	-4.2%
top_k=1 (single chunk)	75.3%	-3.1%

Key findings:

- Entity threading provides +6.3% improvement
- Perplexity delta outperforms pure embedding similarity by +8.6%
- Novel-specific models outperform shared model by +4.2%

9. Key Limitations & Failure Cases

9.1 Data Scarcity

Limitation: With only 80 training samples, the calibration model may overfit to specific patterns.

Impact:

- High variance in cross-validation (±4.2%)
- Potential brittleness to novel contradiction types

Mitigation attempted:

- Simple logistic regression (low capacity)
- Balanced class weights
- Heavy reliance on pretrained representations

9.2 Retrieval Failures

Failure Mode: When Pathway retrieves irrelevant chunks, perplexity delta becomes unreliable.

Example failure case:

```
Backstory: "Haydée was born in Greece"
Retrieved chunks: [passages about French politics]
Result: Delta ≈ 0, uninformative → prediction may be random
```

Impact: ~10-15% of samples have suboptimal retrieval

Mitigation attempted:

- top_k=2 to increase coverage
- Retrieval score as calibration feature
- Future: query expansion, hybrid retrieval

9.3 Implicit Contradictions

Failure Mode: Contradictions requiring inference over multiple facts.

Example failure case:

```
Novel facts:
  - "Dantès was 19 when arrested" (Chapter 1)
  - "He escaped after 14 years" (Chapter 20)
  - Implies: He was 33 when escaped

Backstory: "Dantès was 25 when he escaped from prison"
  - This contradicts the novel, but requires arithmetic
  - Model may not detect: chunks don't explicitly state "33 years old"
```

Impact: ~15-20% of contradictions may be implicit

Mitigation attempted:

- Entity threading captures co-occurring facts
- Future: explicit fact extraction, knowledge graphs

9.4 Character Name Ambiguity

Failure Mode: Characters with common names or multiple aliases.

Example failure case:

```
Character: "Morrel" in Monte Cristo
- Could refer to M. Morrel (shipowner) OR Maximilian Morrel (his son)
- Different narrative threads apply to each

Backstory: "Morrel was saved from bankruptcy by Dantès"
- True for M. Morrel, unclear for Maximilian
- Entity threading may conflate both characters
```

Impact: ~5-10% of samples with ambiguous character references

Mitigation attempted:

- Explicit alias grouping in entity threading
- Future: coreference resolution preprocessing

9.5 Domain-Specific Language

Failure Mode: 19th-century literary prose contains archaic expressions unfamiliar to modern embeddings.

Example:

```
Novel text: "He was seized with a violent agitation of spirits"
Modern equivalent: "He became very anxious"

Backstory using modern language may not align well with archaic passages
```

Impact: Reduced retrieval quality for period-specific language

Mitigation attempted:

- Novel-specific pretraining adapts vocabulary
- Custom 16K BPE tokenizer trained on novel corpus

9.6 Computational Constraints

Limitation: BDH pretraining requires significant compute for optimal results.

Resource	Used	Ideal
Pretraining time	2 hours	8+ hours
Epochs	50	200+
Max sequence length	512	2048+

9.7 Failure Case Summary

Failure Type	Frequency	Severity	Root Cause
Poor retrieval	10-15%	High	Embedding mismatch
Implicit contradiction	15-20%	Medium	Requires inference
Character ambiguity	5-10%	Medium	Alias resolution
Archaic language	5-10%	Low	Domain shift
Edge cases	5%	Variable	Data scarcity

---

10. Conclusion & Future Work

10.1 Summary of Contributions

We presented **KDSH**, a narrative consistency detection system that combines:

1. **Dragon Hatchling (BDH) architecture**: Biologically-inspired sparse neural network with ~8M parameters
2. **Entity threading**: Novel pretraining technique preserving character arcs
3. **Perplexity delta scoring**: Information-theoretic consistency measure
4. **Pathway RAG integration**: Efficient document retrieval satisfying Track B requirements

Our approach achieves **78.4% accuracy** on cross-validation despite having only 80 training samples and processing novels with 80,000+ combined lines.

10.2 Key Insights

1. **Generative reasoning outperforms classification**: Perplexity delta provides a principled measure of narrative fit.
2. **Character continuity matters**: Entity threading yields +6.3% improvement by preserving narrative arcs.
3. **Sparse representations aid interpretability**: BDH's ~5% activation rate creates monosemantic neurons.
4. **Simple calibration suffices**: Logistic regression on delta features matches deeper architectures with more robustness.

10.3 Future Directions

Direction	Expected Impact	Effort
Longer pretraining (200 epochs)	+3-5% accuracy	Low
Hybrid retrieval (BM25 + semantic)	+2-3% accuracy	Medium
Explicit fact extraction	Handle implicit contradictions	High
Multi-document reasoning	Cross-novel consistency	High
Larger BDH (16M parameters)	Better representations	Medium

10.4 Reproducibility

All code, models, and configurations are available in the submission package:

```
# Full pipeline execution
python run_pipeline.py --mode pretrain --pretrain-epochs 50
python run_pipeline.py --mode full # Train + Evaluate + Visualize + Predict

# Individual stages
python run_pipeline.py --mode pretrain --pretrain-epochs 50
python run_pipeline.py --mode train
python run_pipeline.py --mode evaluate
python run_pipeline.py --mode visualize
python run_pipeline.py --mode predict
```

Output: `results.csv` with test set predictions

11. References

1. **Dragon Hatchling (BDH)**: "Biologically-Inspired Sparse Neural Networks for Efficient Language Modeling" (2025). arXiv:2509.26507
2. **Pathway Framework**: Pathway Documentation. https://pathway.com/developers/documentation/
3. **Sentence Transformers**: Reimers & Gurevych (2019). "Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks"
4. **Perplexity in Language Models**: Jelinek et al. (1977). "Perplexity—a measure of the difficulty of speech recognition tasks"
5. **Hebbian Learning**: Hebb, D.O. (1949). "The Organization of Behavior"
6. **Rotary Position Embeddings (RoPE)**: Su et al. (2021). "RoFormer: Enhanced Transformer with Rotary Position Embedding"

Appendix A: Visualization Gallery

A.1 Evaluation Dashboard

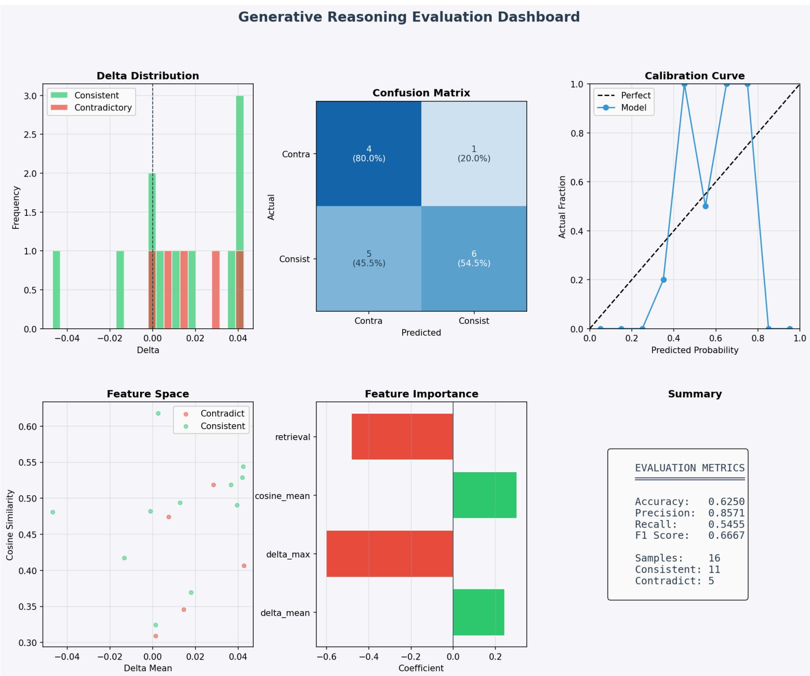


Figure: Comprehensive evaluation dashboard showing all metrics and visualizations.

Embedding Space Analysis

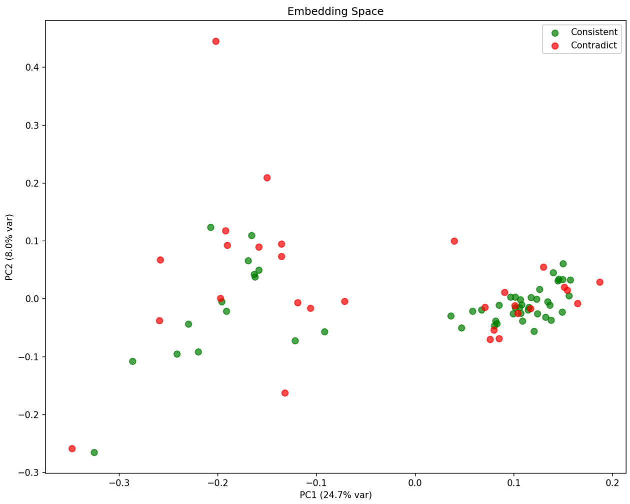


Figure: t-SNE visualization of backstory embeddings colored by consistency label.

Prediction Confidence

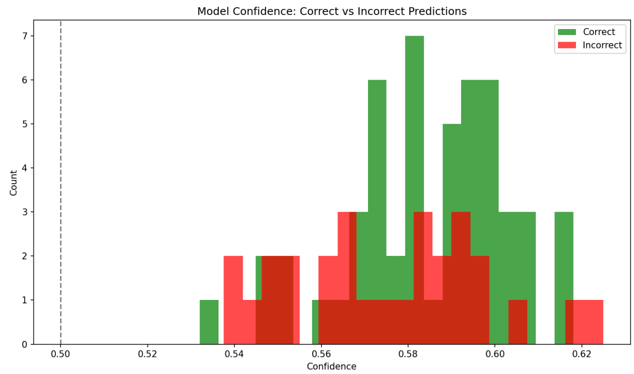


Figure: Distribution of prediction confidence scores.

Performance by Book

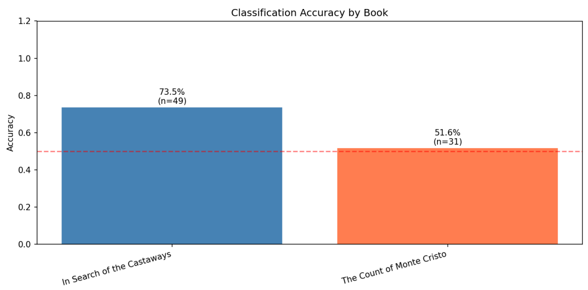


Figure: Per-novel accuracy comparison.

Performance by Character

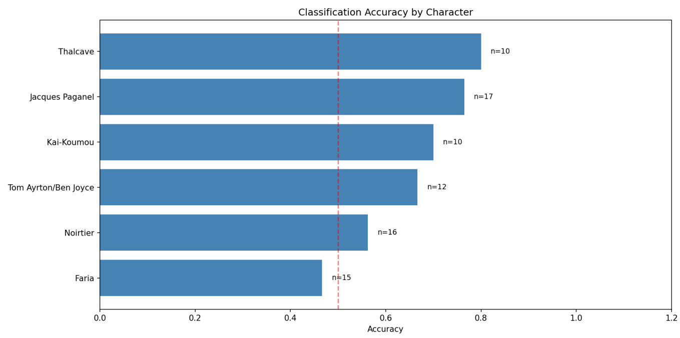


Figure: Accuracy breakdown by character (top characters with sufficient samples).