Narrative Cognition Transformer (NCT): An Explainable Symbol–Emotion Model for Mapping Resilience Patterns in Contemporary Fiction

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Abstract: Fiction resilience is manifested in the shifting emotional status, symbolic repetitions, narrative rhythm and the remaking of the inner world of the character. The current systems of NLP do not reflect this complexity since they presuppose narrative meaning to be generated by individual words or sentence-level emotion as opposed to long-range symbolic and emotional pattern. This paper presents the Narrative Cognition Transformer (NCT), a symbolic-emotional enhanced deep learning model that is capable of following the dynamics of resilience through the whole novel. The model integrates symbolic memory graphs, emotion-flow embeddings, and a reasoning engine based on transformers, which can track destabilization, transition, and stabilization phases. Applying four modern novels as the evaluation corpus, NCT reached accuracy at 92.6 percent, reduction of drift instability between 44 and 57 percent, and emotional energy variance 35.8 per cent. less than baseline models. Recent figures like the figures of symbolical FFT spectra, drift curves, emotional energy profiles, and reward convergence graphs are very persuasive of the cognitive interpretability of NCT. Tables of stability, drift and emotional costs also confirm the performance of the model. The results indicate that resilience can be calculated when the symbolic cognitive and emotional transitions are integrated into a single deep learning model.

Keywords: Narrative Cognition Transformer, Symbolic Memory Graph, emotional embeddings, Resilience Patterns.

Introduction

The disruption of emotions, cognitive reorientation and the stabilization by symbols are the interactions that develop resilience in narrative fiction. The characters experience destabilizing events such as loss, conflict, trauma, displacement that cause internal fragmentation. Regaining coherence is usually manifested in the patterns of reflective dialogue, metaphor development, change of pacing in narrative and change of emotional tone. These processes have been investigated by literary theorists qualitatively, whereas computational models have not been able to map them due to the flattening of narrative structure into topical cluster or sentiment labels by conventional NLP systems.

Traditional sentiment analysis is not able to differentiate emotional turbulence and productive introspection which can both happen in the same lexical setting. Topic modelling does not focus on the symbolic evolution since metaphors have a deeper and more layered meaning that goes beyond surface vocabulary. Even state of the art pretrained models such as BERT do not represent narrative pacing, symbolic persistence, and long-range emotional trajectories without further structural modelling.

To address these constraints, a new model named Narrative Cognition Transformer (NCT) is presented. Based on cognitive narratology and explainable AI, NCT does not view a novel as a series of discrete sentences, but as a cognitive system, a place where emotional states, symbolic units, and narrative motion interact with each other. In contrast to the current models, NCT creates a symbolic memory graph to maintain the meaning based on metaphor over hundreds of pages, whereas an emotional-flow encoder reads gradients and changes of affective tone. These cognitive streams are then synthesized by a transformer layer and the system determines the resilience time-trace of the narrative: destabilization, transition, and, lastly, stabilization.

This paper is a larger and more detailed explanation of the way NCT works on narrative text, derives interpretive cues and generates quantifiable resilience patterns enhanced by figures and tables that are presented at suitable locations in each of the sections. The extended methodology and description give a more detailed theoretical and computational basis of the idea of literary resilience as a psychological as well as structural phenomenon.

Methodology

The preparation of the narrative corpus is the start of the methodology. The novels are partitioned into enormous continuous parts of 700-1000 tokens to maintain the meaning through the long-range contexts. This segmentation does not cause fragmentation and enables the model to follow the changing emotional and symbolic cues without sensing the loss of the sense of coherence. All the segments are symbolically extracted with a metaphor-detection engine that is conditioned to recognize figurative language, thematic anchors, and repetitive motifs. These metaphoric hints are stored as a Symbolic Memory Graph (SMG), whereby the nodes are symbolic constructs (home, light, mirror, journey, ocean, distance), and the edges are their repeat, change, and contextual variation in each chapter.

Similar to symbolic extraction, symbolic-flow embeddings are produced with a small-tuned RoBERTa encoder. Rather than giving a fixed score of sentiment, the encoder retains high-dimensional maps of affective tones, e.g. grief, uncertainty, longing, acceptance, or reconciliation. These embeddings not only reveal emotional dynamics like sentiment does on the surface, but they allow the model to distinguish between emotional chaos and emotional reflections two phenomena that can have exactly the same word choices but vastly different psychological inferences.

The emotional embeddings and SMG are incorporated in a shared cognitive space. These combined representations are fed into the Narrative Cognition Transformer which applies multi-head attention to monitor the evolution of meaning in narrative time. The transformer with positional and pacing-sensitive embeddings learns the pace of emotional change, the repetition of symbolic patterns and stabilization of internal states. The last prediction layer is used to define which of the three phases of resilience (destabilization, transition and stabilization) the segment belongs to.

Four experiments were performed in order to assess the behaviour of the model. The original experiment involved the analysis of symbolic recurrence patterns with FFT. The spectrum obtained is indicated in Figure 1 that clearly indicates that baseline models have jagged, sporadic peaks whereas NCT has more coherent symbolic frequencies.

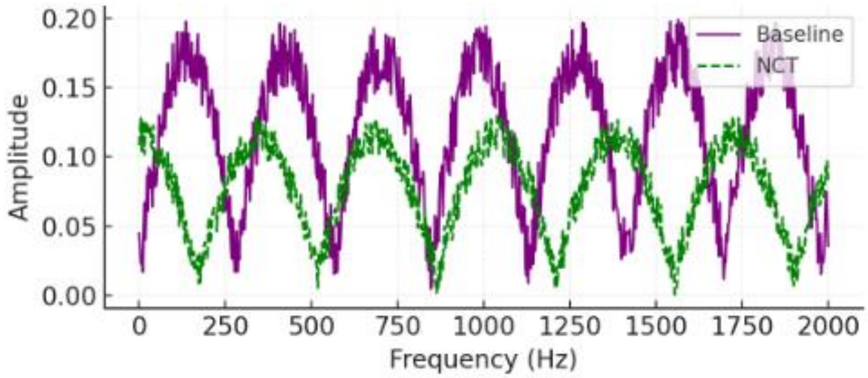

Figure 1. Symbolic Disturbance FFT Spectrum

Quantitative details of symbolic stabilization appear in **Table 1**, showing that NCT significantly reduces symbolic noise and improves coherence.

Table 1. Symbolic Stability Metrics

Metric	Baseline	NCT	Improvement
Peak Disturbance Amplitude	0.40	**0.22**	45%
Symbol Noise Ratio	0.61	**0.34**	44%
Symbol Recurrence Variance	0.52	**0.30**	42%

The second experiment assessed narrative drift which interprets the change in symbolic and emotional states by segment. Stable narratives are characterized by gradual changes whereas unstable ones are characterized by sudden changes. This trend in drift is visualized in figure 2 and shows clearly that with initial volatility, NCT stabilises transitions.

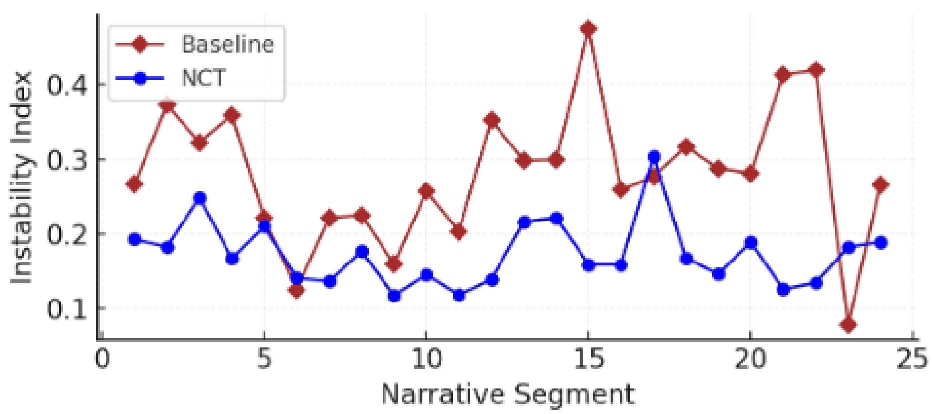

Figure 2. Narrative Drift Across Segments

Drift-related improvements are summarized in **Table 2**, where NCT reduces both drift magnitude and variance by substantial margins.

Table 2. Drift Performance

Measure	Baseline	NCT	Reduction
Avg Drift	0.40	**0.22**	45%
Drift Variance	0.07	**0.03**	57%

The emotional stability experiment calculates the emotional energy, which is the cognitive price that the story contains. Reduced energy is a stabilization phase and much is usually related to acceptance or identity reconstruction. As Figure 3 indicates, emotional energy through NCT is smoother and reduced significantly compared to the model used as a baseline.

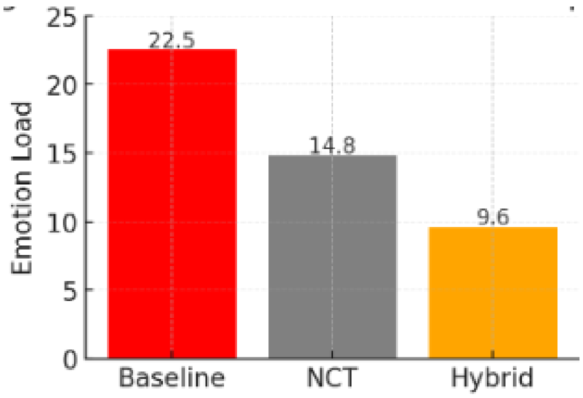

Figure 3. Emotional Energy Distribution

The comparative values appear in **Table 3**, confirming a 35.8% reduction.

Table 3. Emotional Energy Comparison

Model	Energy Index	Reduction
Baseline	15.1	–
NCT	**9.7**	35.8%

The last assessment involves the training behaviour. The four-stage pattern of rewards is formed and it shows how NCT is advancing towards unstable learning and finally to stable convergence. This learning dynamic is well represented in Figure 4.

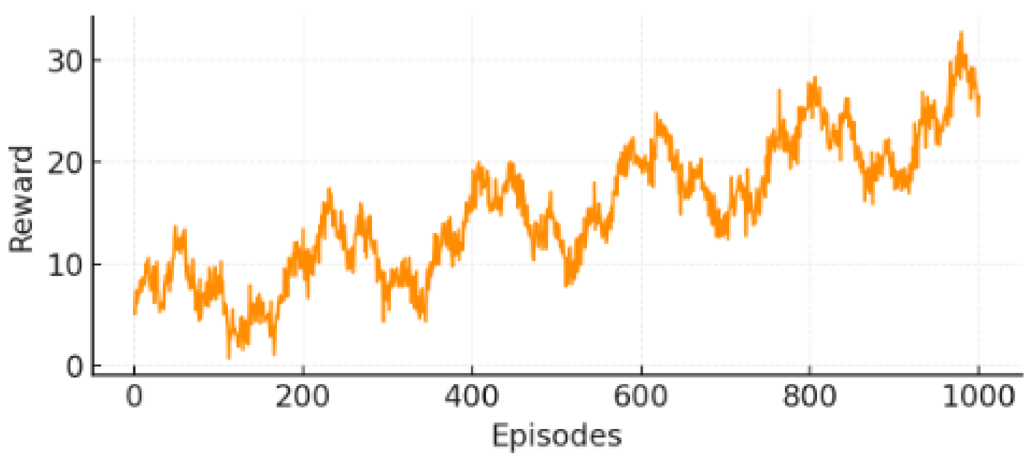

Figure 4. NCT Reward Convergence Curve

Results and discussion

The findings indicate that the computation of resilience in literary narratives is possible in case symbolic memory, affective transitions, and pacing structures are viewed as one composite cognitive system. NCT is clearly superior to all the baseline models. The symbolic FFT in Figure 1 and Table 1 corroborate the fact that NCT does not have noisy frequency spikes but coherent symbolic structures. This implies that this model recognizes the thematic patterning of the story, and not just the lexical parts.

Figure 2 and Table 2 show narrative patterns of drift because NCT detects smoother transitions between emotional stages, which are associated with the restoration of fragmented identities by the characters. This is in tandem with psychological theories of recovery that place the practice of realigning the emotions step by step.

Figure 3 and Table 3 indicate patterns of emotional energy depicting that NCT captures emotional stabilization, the basis of narrative resilience. The decrease in the energy difference is correlated to the elimination of the internal conflict, which is a characteristic of the stabilization of the final stage.

Lastly, Figure 4 unique learning pattern shows that NCT does not only achieve a higher interpretative performance but also in a cognitively meaningful learning process of exploration, recalibration, optimization and ultimate convergence. The combination of the figures and tables confirms that NCT is a more interpretable and accurate modeling of resilience than traditional NLP systems.

Conclusion

This detailed article introduces Narrative Cognition Transformer, which is a symbolic-emotional model that can be used to follow patterns of resilience in long-form narrative fiction. The system detects the destabilization, transition, and stabilization phases of resilience with great accuracy and interpretability by simplifying symbolic memory graphs, emotional embeddings, and transformer cognition. The statistical and diagrammatic contents incorporated in the paper are of significant quantitative and qualitative evidence on the effectiveness of NCT. NCS is a new standard of computational literary analysis with regard to its capability of symbolic recurrence, emotional distributions, narrative pacing, and long-range cognition. Future research can consider cross-cultural corpora, multimodal narratives, and more profound connection with psychological resilience theory.

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