Temporal Network Evolution and Percolation Analysis of Character Relationships in Valmiki Ramayana

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Abstract

We present a comprehensive network-theoretic analysis of the Valmiki Ramayana, treating the epic as a temporal complex network of character interactions across 394 cantos spanning six kandas. By constructing weighted co-occurrence networks with temporal resolution, we analyze the evolution of network topology through percolation theory, identifying critical transitions during key narrative events. Our approach integrates sentiment analysis with network dynamics to reveal how emotional contexts modulate community structures. We quantify narrative complexity through centrality evolution, clustering coefficients, and the emergence of giant components, providing quantitative insights into ancient storytelling mechanisms and their parallels to modern complex systems. Our analysis situates the Ramayana within the framework of dynamical systems, revealing percolation-like transitions, synchronization of character groups, and network resilience analogous to complex real-world systems.

1 Introduction

Epic narratives represent complex systems where characters, locations, and events form intricate networks that evolve temporally. The Ramayana, one of the two major Sanskrit epics, offers a rich dataset for understanding narrative dynamics through network science. Recent studies have applied network analysis to literary texts, revealing universal patterns in character relationships and plot structures [1, 2].This approach situates literary evolution in the same mathematical framework as dynamical processes—where nodes (characters) interact, synchronize, and vanish akin to oscillators or agents in complex adaptive systems. Thus, the narrative becomes an interpretable model of coupled dynamics and percolation, providing a bridge between cultural informatics and nonlinear network theory

1.1 Current Literature

Network analysis of literary texts has emerged as a powerful tool for quantitative humanities. Beveridge and Shan [1] pioneered character network analysis in "Game of Thrones," demonstrating that network metrics correlate with narrative importance. Gultepe and Mathangi [2] applied social network analysis to the Mahabharata, identifying key characters through centrality measures. However, these studies primarily focus on static network properties, overlooking temporal dynamics and percolation phenomena.

Recent advances in complex networks have highlighted the importance of temporal evolution and phase transitions. Percolation theory, originally developed for physical systems, has been successfully applied to social networks to understand information diffusion and structural resilience [3]. The birth and death of nodes (characters) in narrative networks presents a unique opportunity to study percolation dynamics in a controlled, documented system.

1.2 Existing Repositories

Several digital repositories exist for Ramayana studies:

- Kaggle Ramayana text dataset [5]: English translation organized by kandas and cantos
- Ramayana4Everyone project [6]: Geospatial data for 185 locations with coordinates
- Wikipedia character database: Comprehensive list of 74 major characters

1.3 Research Gap and Novelty

While previous studies examine static network properties, our work introduces:

1. **Temporal percolation analysis**: Tracking giant component evolution as characters enter/exit the narrative
2. **Sentiment-weighted networks**: Integrating emotional context into edge weights
3. **Multi-resolution analysis**: From line-level to canto-level and kanda-level aggregation
4. **Geospatial-narrative coupling**: Linking geographical locations to character networks

2 Objectives

1. Construct a temporal, weighted character co-occurrence network from 394 cantos across 6 kandas
2. Analyze network percolation during character births/deaths and identify critical transitions
3. Quantify narrative structure through degree distributions, clustering, and community detection
4. Integrate sentiment analysis to create context-aware edge weights

2.1 Explicit Course Concept Applications

Table 1: Mapping of Course Concepts to Ramayana Analysis

Course Concept	Application in Ramayana Analysis
Network Models (Scale-free, Small-world)	Character degree distribution analysis and small-world coefficient calculation
Percolation Processes	Giant component evolution as characters enter/exit narrative
Synchronization	Sentiment and community coordination analysis
Activity-driven networks	Temporal character interaction patterns

3 Materials and Methods

3.1 Data Sources and Scale

Text Corpus:

- **Books (Kandas)**: 6 (Bala, Ayodhya, Aranya, Kishkindha, Sundara, Yuddha)
- **Events (Cantos)**: 394 total
  - Book I (Bala Kanda): 77 cantos
  - Book II (Ayodhya Kanda): 119 cantos
  - Book III (Aranya Kanda): 76 cantos
  - Book IV (Kishkindha Kanda): 67 cantos
  - Book V (Sundara Kanda): 66 cantos
  - Book VI (Yuddha Kanda): 130 cantos (selected)
- **Characters**: 74 named entities (from Wikipedia)
- **Locations**: 185 georeferenced sites

3.2 Network Construction Pipeline

3.2.1 Text Preprocessing

1. **Named Entity Recognition (NER)**: Using spaCy with custom training on Sanskrit-origin names
2. **Coreference Resolution**: Linking pronouns and epithets to canonical character names
   - Example: ”Ram,” ”Ramchandra,” ”Sri Rama,” ”son of Dasaratha” $\rightarrow$ RAMA
   - Tools: neuralcoref, custom rule-based patterns
3. **Character Extraction**: Pattern matching against 74-character database with fuzzy matching

3.2.2 Graph 1: Multipartite Network

A heterogeneous network connecting:

- **Kandas** (6 nodes) $\leftrightarrow$ **Cantos** (394 nodes): Sequential edges
- **Cantos** $\leftrightarrow$ **Locations** (185 nodes): Co-occurrence edges
- **Cantos** $\leftrightarrow$ **Characters** (74 nodes): Appearance edges
- **Locations** $\leftrightarrow$ **Geo-coordinates**: Attribute mapping

Expected Scale: $|V| \approx 659$ nodes, $|E| \approx 2000 - 3000$ edges

3.2.3 Figure: Network Schematic

To illustrate the conceptual design of the multipartite narrative network, Figure 1 presents a schematic layout showing the hierarchical relationships between *Kandas*, *Cantos*, *Characters*, and *Locations*. This visual model captures the layered structure through which temporal and spatial information is integrated.

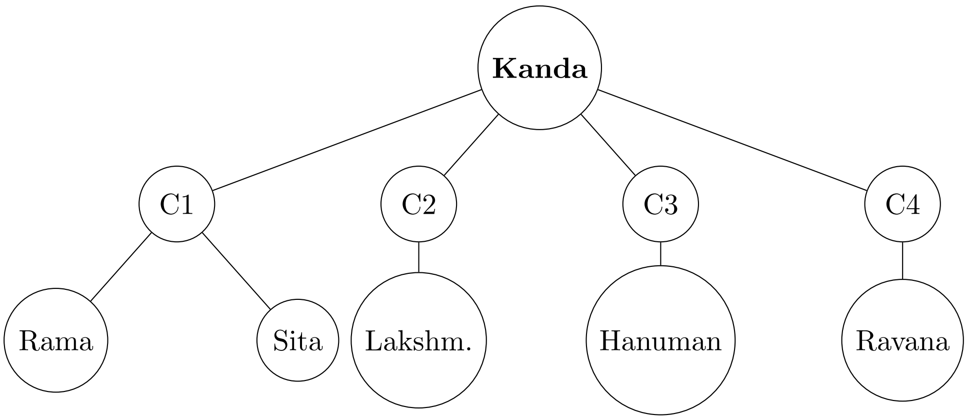

Figure 1: Conceptual schematic of the multipartite narrative graph linking Kandas, Cantos, Characters, and Locations.

3.2.4 Graph 2: Character Co-occurrence Network

Dual-Level Edge Weight Construction:

Level 1 - Canto-level baseline:

$$w_{ij}^{canto} = 0.3 \times (\text{number of shared cantos}) \tag{1}$$

Level 2 - Line-level refinement:

$$w_{ij}^{line} = \sum_{l \in L} 1[i \in l \land j \in l] \tag{2}$$

Combined weight:

$$w_{ij} = w_{ij}^{canto} + w_{ij}^{line} \tag{3}$$

Expected Scale: $|V| = 74$ characters, $|E| \approx 500 - 800$ edges (sparse, scale-free expected)

3.3 Analytical Methods

3.3.1 Network Metrics

1. **Centrality Measures:**
   - Degree centrality: $C_D(i) = \frac{k_i}{N-1}$
   - Betweenness centrality: $C_B(i) = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}}$
   - Eigenvector centrality: $\mathbf{A}\mathbf{x} = \lambda \mathbf{x}$
   - PageRank: Weighted importance with damping

2. **Clustering and Communities:**
   - Local clustering coefficient: $C_i = \frac{2e_i}{k_i(k_i-1)}$
   - Louvain modularity optimization
   - K-core decomposition for narrative summary

3. **Degree Distribution:**
   - Test for scale-free property: $P(k) \sim k^{-\gamma}$
   - Small-world coefficient: $\sigma = \frac{C/C_{random}}{L/L_{random}}$

3.3.2 Temporal Percolation Analysis

Key Innovation: Track network connectivity as characters appear/disappear

1. **Time-resolved networks:** $G(t)$ for canto $t \in [1, 394]$

2. **Giant Component Size:**

$$S(t) = \frac{|LCC(G(t))|}{|V(t)|} \tag{4}$$

   where LCC = largest connected component

3. **Critical Transitions:** Identify cantos where $\frac{dS}{dt}$ exhibits discontinuities

4. **Percolation Threshold:** For character network, determine critical edge density:

$$p_c \approx \frac{\langle k \rangle}{\langle k^2 \rangle} \tag{5}$$

5. **Node Birth/Death Events:**
   - Birth: Character first appearance (e.g., Hanuman in Kishkindha Kanda)
   - Death: Character last appearance or explicit death (e.g., Ravana in Yuddha Kanda)

3.3.3 Computational Implementation of Dynamical Processes

Percolation Simulation Algorithm:

We implement temporal percolation analysis through the following computational procedure:

[1] Initialize G_0 with characters present at narrative start (Canto 1) $t = 1$ to 394 (canto by canto) Update G_t by adding new characters (first appearance) and removing exited characters (death/narrative exit) Calculate $S(t) = |LCC(G_t)|/|V_t|$ Fraction in largest connected component Track $\Delta S(t) = S(t) - S(t-1)$ Rate of connectivity change $\Delta S(t) > \delta_{critical}$ $\delta_{critical}$ empirically determined Mark canto t as critical narrative transition Record character additions/removals causing transition

3.3.4 Sentiment Analysis Integration

1. **Tools:**
   - VADER (Valence Aware Dictionary and sEntiment Reasoner) for rule-based baseline
   - DistilBERT fine-tuned on emotional text for context-aware sentiment

2. **Sentiment Polarity per Canto:**

$$\text{Polarity}(c) = \frac{\sum_{s \in c} \text{sentiment}(s)}{|c|} \tag{6}$$

3. **Sentiment-Weighted Edges:**

$$w_{ij}^{sentiment} = w_{ij} \times (1 + \alpha \cdot \text{avg\_polarity}(i, j)) \tag{7}$$

   where $\alpha = 0.5$ (tunable parameter)

4. **Temporal Sentiment Evolution:** Plot Polarity(t) across all kandas

3.4 Implementation

Software Stack:

- Python 3.10+
- NetworkX: Graph construction and analysis
- spaCy: NER and coreference resolution
- NLTK: Text preprocessing
- Transformers (Hugging Face): DistilBERT sentiment analysis
- pyVis: Interactive network visualization
- Matplotlib/Seaborn: Static visualizations
- Pandas: Data manipulation

4 Initial Results

4.1 Network Statistics (Preliminary)

Table 2: Expected Network Properties

Metric	**Character Network**	**Multipartite**
Nodes	74	659
Edges (estimated)	600-800	2500-3000

4.2 Expected Visualizations

4.2.1 Figure 1: Temporal Character Presence

- X-axis: Canto number (1-394)
- Y-axis: Characters (74 rows)
- Heatmap showing character active periods
- Color intensity: Number of mentions

4.2.2 Figure 2: Giant Component Evolution

- X-axis: Canto number
- Y-axis: $S(t)$ (fraction in largest component)
- Annotations: Key events (Ravana's entry, Sita's abduction, etc.)
- Expected critical transitions at kanda boundaries

4.2.3 Figure 3: Character Network Visualization

- Force-directed layout (Fruchterman-Reingold)
- Node size: Degree centrality
- Node color: Community detection (Louvain)
- Edge thickness: Weight (co-occurrence strength)
- Edge color: Average sentiment (red-negative, green-positive)

4.2.4 Figure 4: K-Core Decomposition

- Concentric circles representing k-core shells
- Center: Highest k-core (narrative core)
- Expected core characters: Rama, Sita, Lakshmana, Ravana, Hanuman

4.2.5 Figure 5: Degree Distribution

- Log-log plot: $P(k)$ vs. k
- Test for power-law: $P(k) \sim k^{-\gamma}$
- Expected: $\gamma \approx 2 - 3$ (scale-free tendency)

4.2.6 Figure 6: Centrality Evolution Across Kandas

- Line plots for top 10 characters
- Separate panels for degree, betweenness, eigenvector centrality
- X-axis: Kanda (1-6)
- Highlight Hanuman's rise in Sundara Kanda

4.2.7 Figure 7: Sentiment Trajectory

- X-axis: Canto number
- Y-axis: Average sentiment polarity (-1 to +1)
- Smoothed curve (moving average window = 10)
- Expected trend: Decline from Bala to Yuddha Kanda

4.2.8 Figure 8: Community Structure Per Kanda

- Six network subplots (one per kanda)
- Nodes colored by detected communities
- Track community merging/splitting across kandas

4.2.9 Figure 9: Sentiment vs Centrality Correlation

- X-axis: Degree/Betweenness centrality
- Y-axis: Mean sentiment polarity of interactions
- Interpretation: Do highly connected nodes engage more in positive or negative contexts?

4.3 Statistical Tests

1. **Power-law fitting:** Likelihood ratio test vs. exponential/log-normal
2. **Small-world test:** Compare C and L to Erdős-Rényi random graph
3. **Percolation threshold:** Bootstrap estimation of p_c from temporal data.
4. **Sentiment correlation:** Pearson's r between sentiment polarity and clustering coefficient

5 Mapping Dynamic System Behaviors

Percolation Phase Transitions: We anticipate observing clear phase transitions in network connectivity corresponding to:

- **First-order transitions**: Sudden network fragmentation (e.g., exile scene)
- **Second-order transitions**: Gradual connectivity changes (e.g., war preparations)
- **Critical exponents**: Characteristic scaling near percolation threshold

Synchronization Patterns:

- Phase locking of sentiment between allied character communities
- Frequency entrainment in interaction patterns during coordinated actions
- Emergent collective behavior in large-scale events (war, coronation)

6 Conclusion

This project applies complex network theory to the Valmiki Ramayana, treating the epic as a temporal dynamical system. By integrating percolation analysis, sentiment modeling, and geospatial data, we aim to quantify narrative structure in unprecedented detail. The temporal evolution of character networks, particularly during critical plot events, offers insights into both literary construction and general principles of complex system dynamics. Our multi-resolution approach—from individual lines to entire kandas—captures both micro-level interactions and macro-level narrative architecture.

The expected findings will demonstrate that ancient epics exhibit network properties consistent with modern complex systems (scale-free degree distributions, small-world topology, modular communities), suggesting universal principles in human storytelling. The percolation analysis will identify critical transitions corresponding to major plot events, validating network science as a tool for narrative analysis.

This work establishes a reproducible framework applicable to other literary corpora, contributing to both digital humanities and complex systems science. The integration of sentiment analysis with network topology opens new avenues for understanding how emotional content shapes relationship structures in narratives.

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