

# Detecting Citation Anomalies in Hyperbolic Space with the Poincaré Ball Model

**Project CODE**  
25-1-R-3

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## Abstract

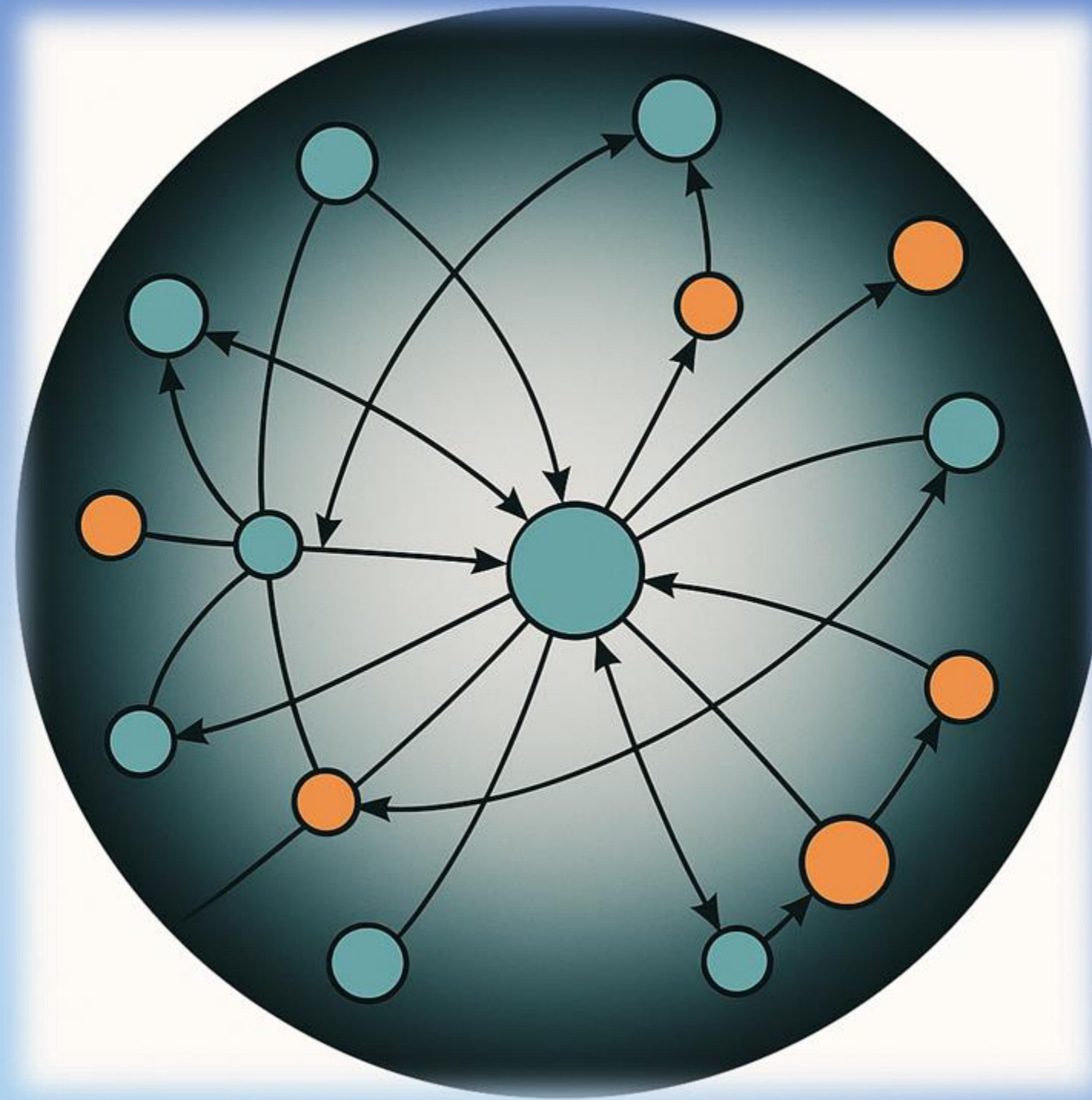
**Goal:** Improve the trustworthiness of scientific communication by detecting **citation anomalies** using **hyperbolic geometry**.

**Challenge:** Traditional citation analysis is **manual** and **biased**.

**Proposed Solution:** We introduce a model inspired by **DynHAT**, combining:

- Hyperbolic Structural Attention (HSA)
  - Position Embedding
  - Isolation Forest for Anomaly Detection
- This approach captures the hierarchical, temporal, and semantic structure of citation networks.

**Outcome:** 91.8% of synthetic anomalies successfully detected, validating the model's accuracy and scalability.



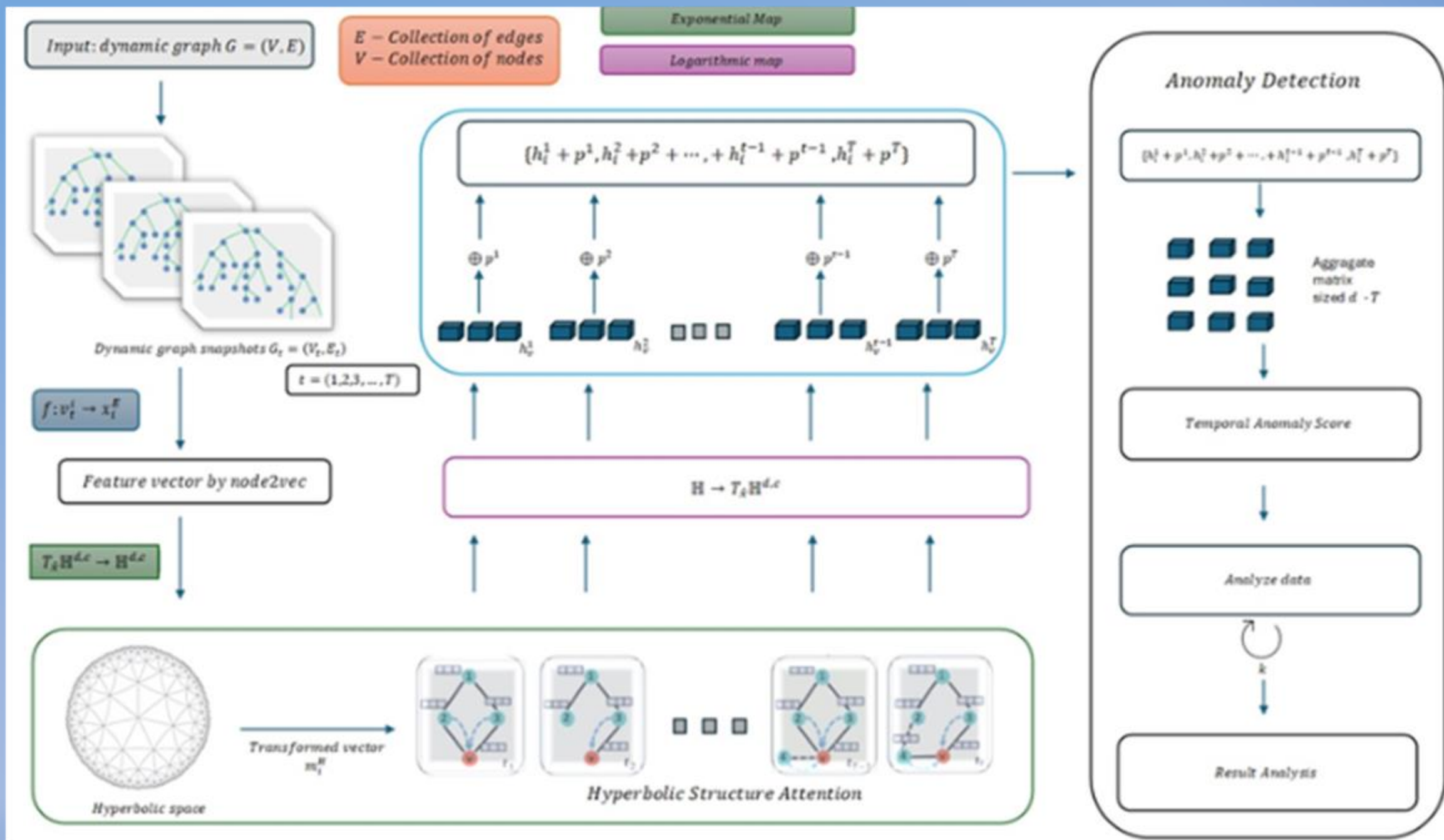
## Proposed Model

- Embed citation graph in hyperbolic space via Exponential map.
- Apply Möbius transformations and self-attention to model semantic and structural importance.
- Incorporate position embeddings for time-awareness.
- Use Isolation Forest to detect abnormal citation trajectories.

**Why hyperbolic?** Captures hierarchy and exponential node growth typical in academic networks.

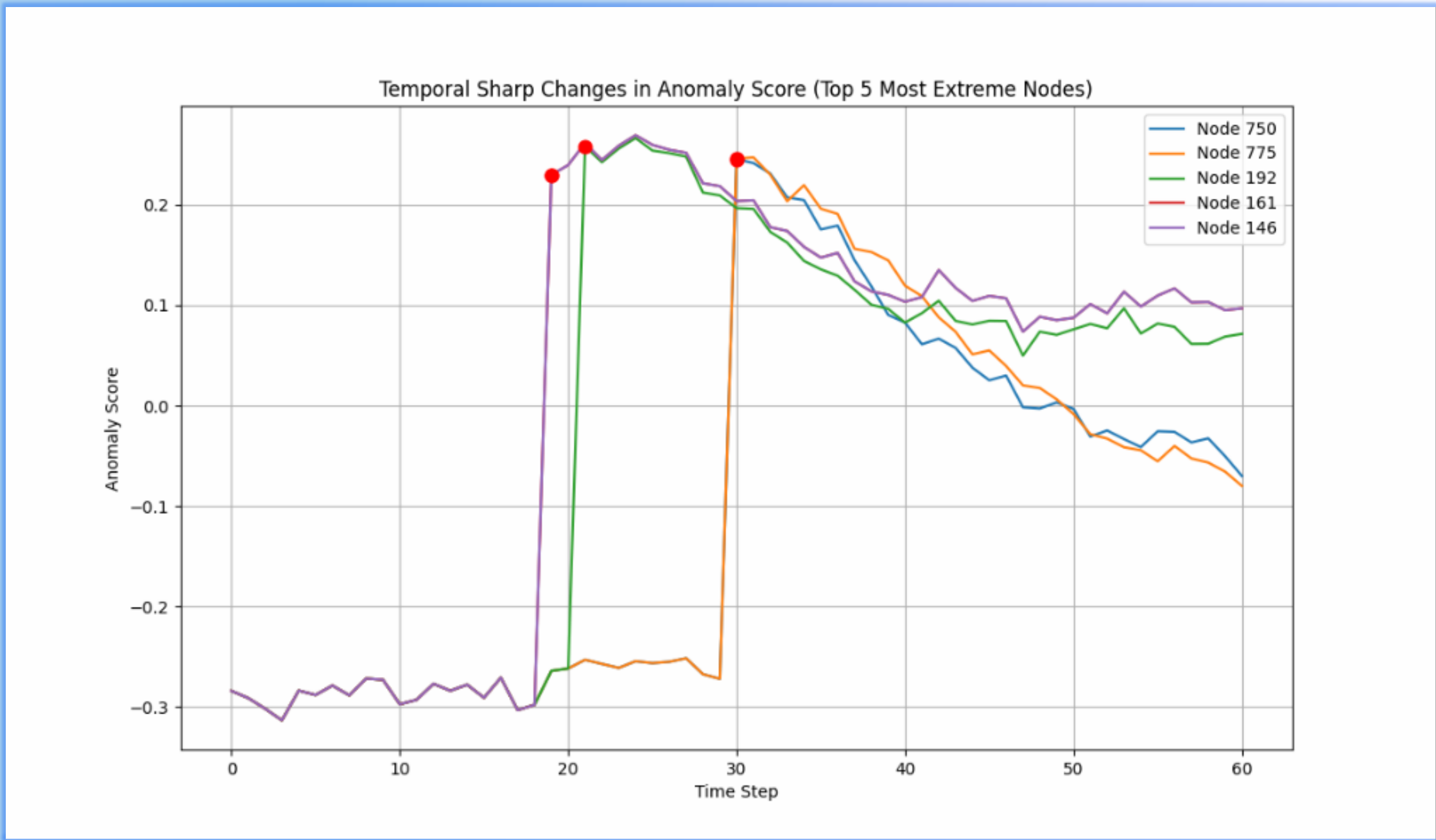
## Model Validation

- Injected synthetic nodes to simulate anomalies
- Measured anomaly scores **before and after injection**
- Model detected **significant deviations**, even for previously stable nodes
- Robust across time windows and structural noise



## Results: Key Patterns in Citation Anomalies

### A. Temporal Anomaly Score–Sleeping Beauty Pattern

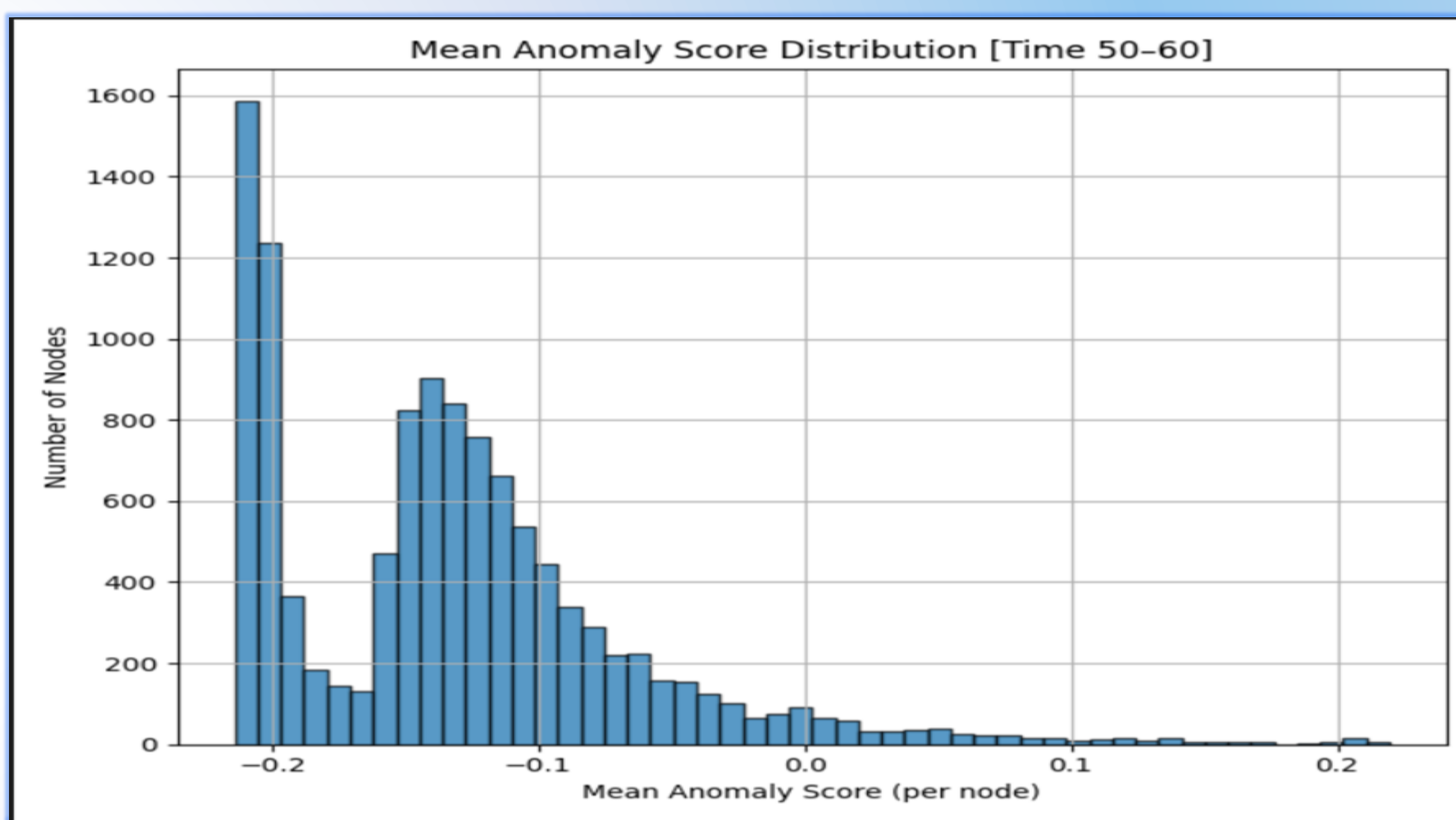


This graph shows anomaly scores over time for five nodes with extreme fluctuations.

- **Low scores** → prolonged dormancy (“**sleeping phase**”)
- **Sudden spike** → surge in citations (“**awakening**”)
- **Gradual decline** → return to baseline (“**post-awakening**”)

This trajectory illustrates the Sleeping Beauty effect: papers that remain unnoticed for a long time, then receive sudden, intense attention.

### C. Mean Anomaly Score Distribution – Beyond Zipf

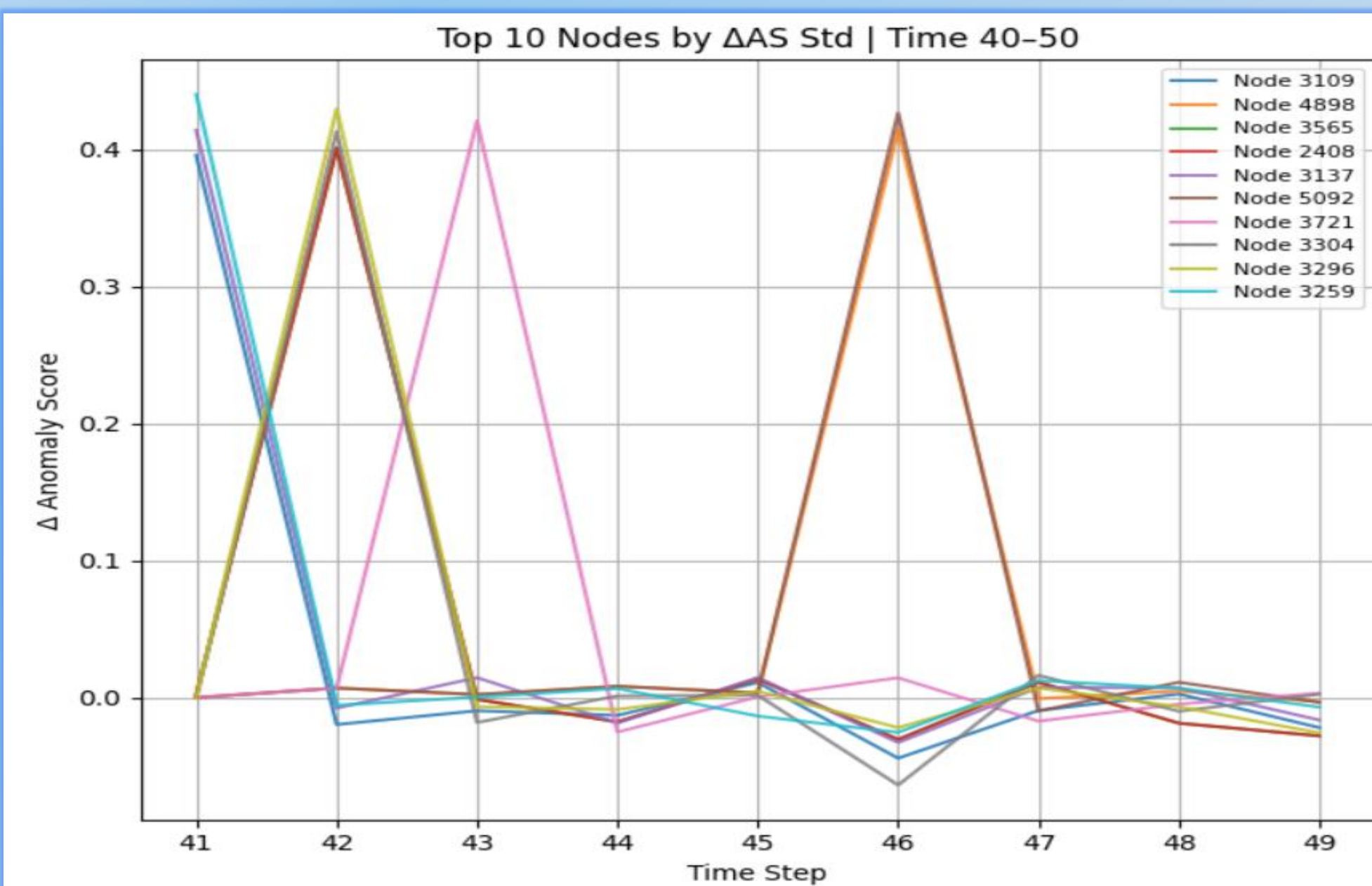
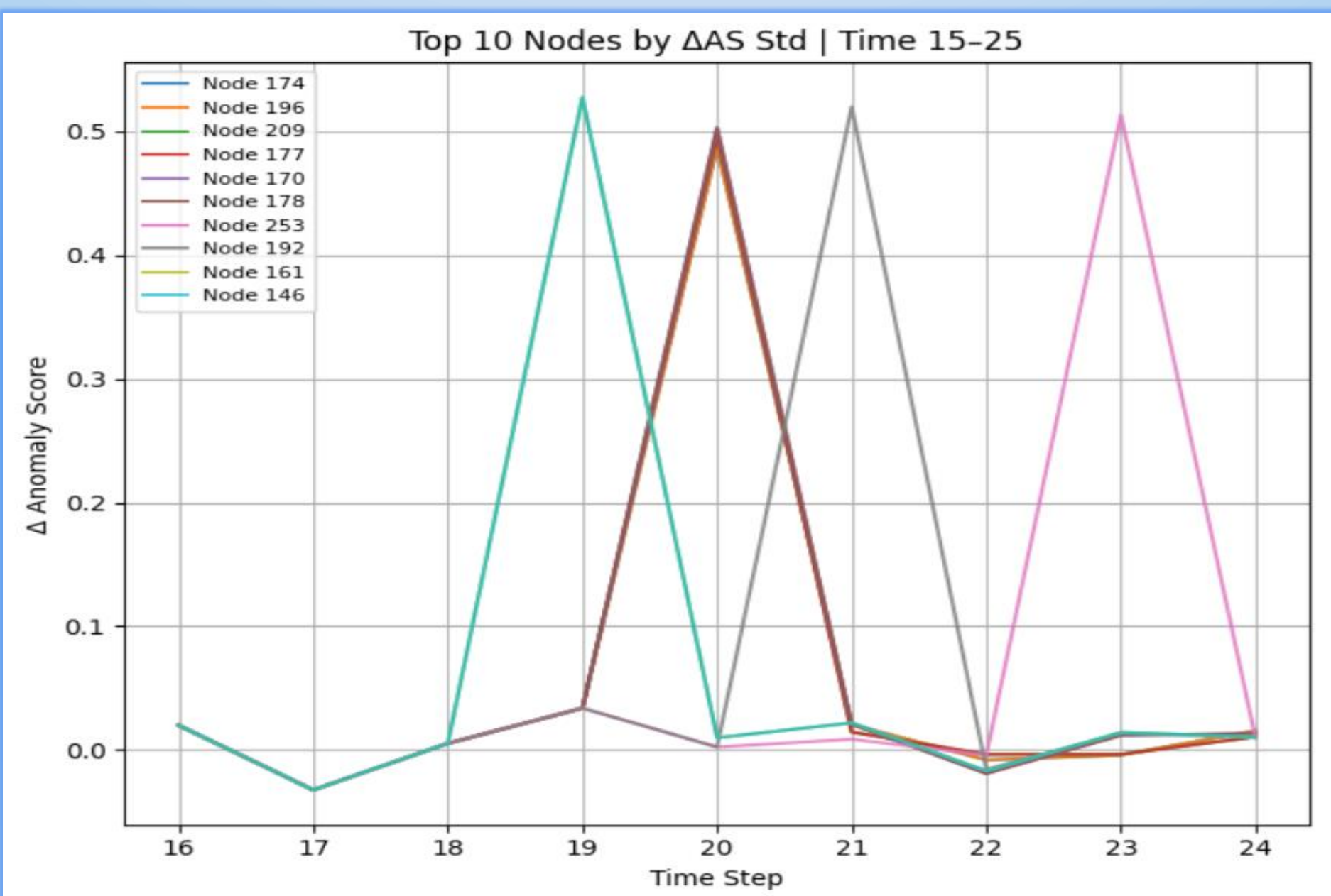
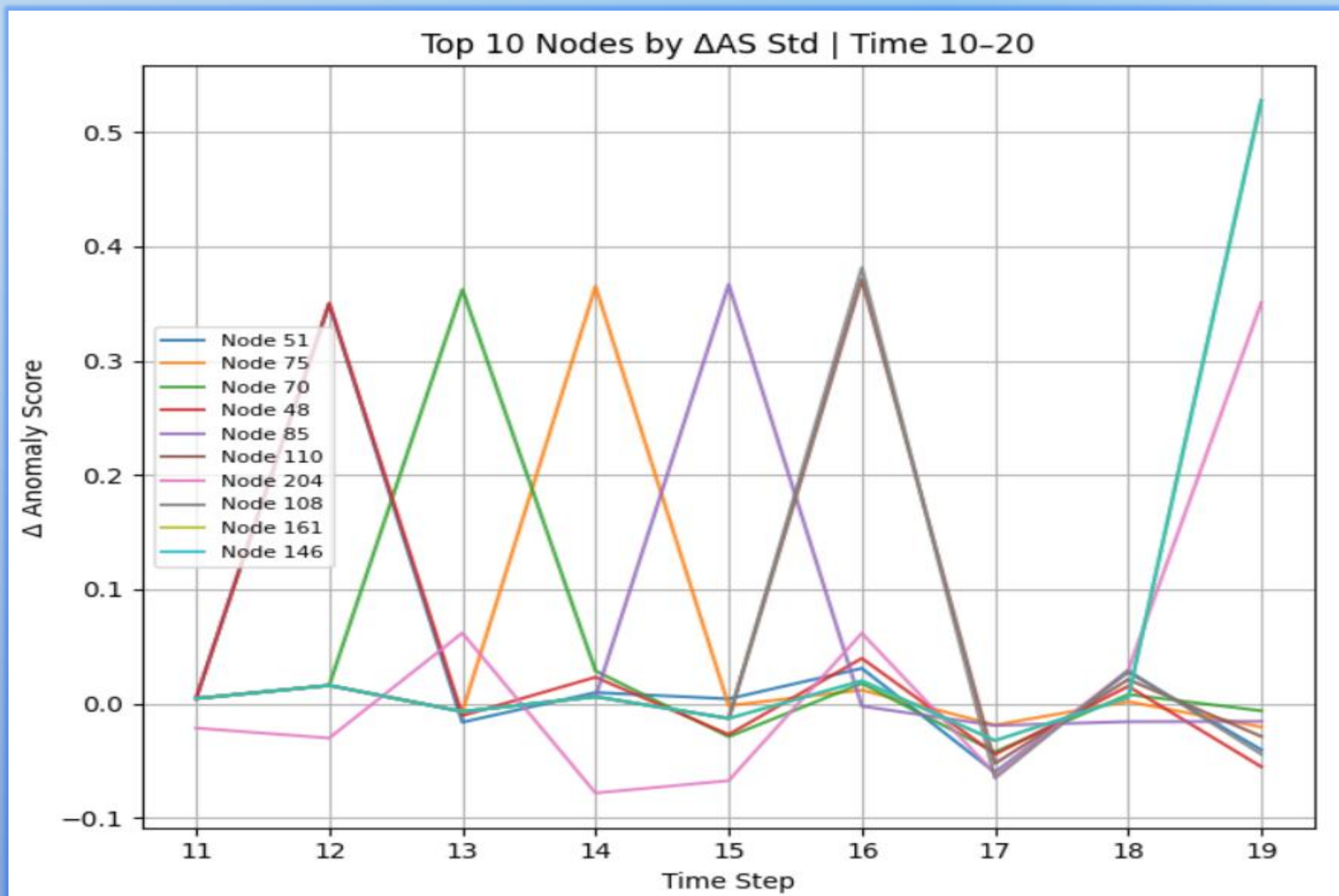


This histogram (time steps 50–60) reveals a **bimodal distribution**, deviating from typical Zipfian (power-law) expectations.

- **Peak at -0.2:** Dormant or low-activity nodes
- **Secondary peak at -0.1:** Nodes with mild, consistent anomalies
- **Right tail:** Rare, high-impact events like Sleeping Beauties and Falling Stars

The non-Zipfian shape highlights the model's ability to detect emerging patterns and hidden subpopulations beyond what classic citation models capture.

### B. ΔAnomaly Score – Falling Star Patterns



We analyzed the change in Anomaly Score (ΔAS) over time by measuring its standard deviation across sliding time windows. The poster illustrates this analysis through three representatives of such windows: [10–20], [15–25], and [40–50].

- Sharp spikes + rapid decline → indicate Falling Star patterns
- These nodes gain brief attention, then fade
- Found consistently across time → model detects ephemeral citation events.

This confirms the value of **ΔAS-based metrics** for identifying short-lived, time-sensitive anomalies in citation behavior.

## Conclusions

The project achieved its goals detecting anomalies in dynamic citation networks using hyperbolic geometry and temporal attention.

### Key Results:

- **Anomaly Detection Accuracy:** ~91.8% in controlled tests
- **Scalability & Temporal Sensitivity:** Effectively tracks evolving citation behavior
- **Robustness to Noise:** Maintains high performance under structural perturbations
- **Computational Feasibility:** Runs efficiently on real datasets using available GPU resources



Minor challenges (e.g., dataset customization, parameter tuning) were addressed. This approach offers new insights into citation dynamics and promotes greater trust in scholarly evaluation.