

Relativistic kappa-Deformed Graph Autoencoders for Topological Confinement in Scale-Free Networks

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Abstract—Traditional Graph Autoencoders (GAEs) rely on classical Boltzmann-Shannon-Gibbs (BSG) statistics, implicitly assuming light-tailed distributions. However, scale-free networks naturally exhibit heavy-tailed power-law degree distributions, where a tiny fraction of highly connected nodes—super-hubs—exert a disproportionate topological influence. Under standard Binary Cross-Entropy loss, these super-hubs generate destabilizing high-magnitude gradients, forcing classical architectures into either severe latent over-smoothing or catastrophic structural fracture, where massive hubs are forcefully ejected to the embedding periphery. To overcome this limitation, we introduce **kappa-GAE**, a novel framework anchored in Kaniadakis relativistic generalized statistics. By implementing a deformed logarithmic loss function governed by the continuous scaling parameter kappa in $[0, 1)$, the model induces a non-linear, hyperbolic deceleration of error gradients specifically tailored for high-degree nodes. We evaluate the structural embedding properties of kappa-GAE on the Cora citation network, performing direct component mapping and intrinsic multi-dimensional metric analysis. Our results provide robust empirical validation of the **Relativistic Topological Confinement** mechanism. While classical Shannon-based configurations systematically sever the geometric bond between super-hubs and their local neighborhoods, the kappa-GAE (kappa = 0.8) successfully stabilizes the fat-tail regime (see Figure 1). Under high deformation, the model scales down the disruptive gradient mass of super-hubs, transforming them into cohesive anchors that structurally confine peripheral node trails within well-defined, low-entropy latent trajectories. This work bridges generalized statistical mechanics with geometric deep learning, providing a mathematically sound paradigm for multi-scale representation learning in non-extensive complex networks.

Keywords: Graph Autoencoders, Kaniadakis Statistics, Relativistic Deformation, Scale-Free Networks, Topological Confinement, Super-Hubs.

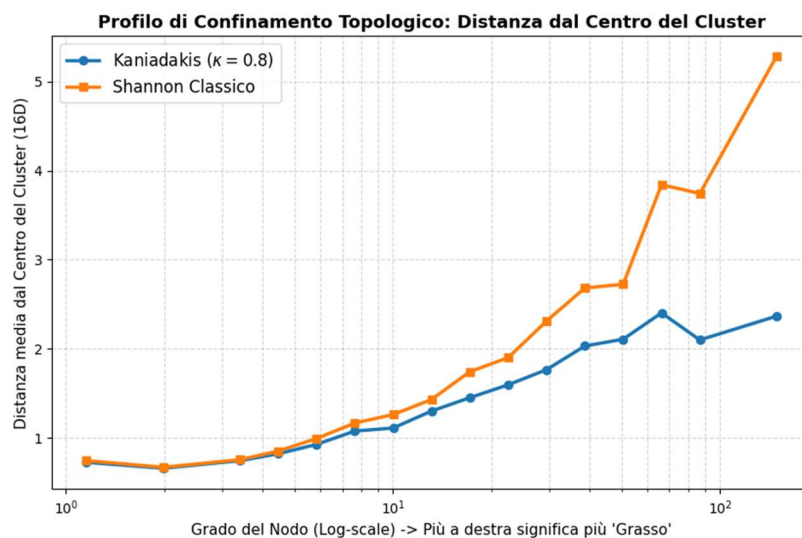


Fig.1. The classical Shannon-based configurations systematically sever the geometric bond between super-hubs and their local neighborhoods, the kappa-GAE (kappa = 0.8) stabilizes the fat-tail regime. The model scales down the disruptive gradient mass of super-hubs, transforming them into cohesive anchors that structurally confine peripheral node trails within well-defined latent trajectories.