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Proceedings of the Annual Meeting of the Cognitive Science Society

Title

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Journal

Proceedings of the Annual Meeting of the Cognitive Science Society, 48(0)

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Publication Date

2026

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Peer reviewed

Topology-Preserving Incremental Cognitive Diagnosis for Emerging Skills

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Abstract

In real-world educational platforms, the knowledge space for cognitive diagnosis is dynamic, continually introducing new skills and items. For embedding-based neural cognitive diagnosis models (CDMs), naïvely updating on new skills degrades performance on previously learned items. Beyond prediction drift, we identify a structural cause of this forgetting: incremental updates distort the relational geometry among old skill embeddings, which we formalize as topology drift. To address this, we propose **TopoCD**, a topology-preserving continual learning framework for skill-incremental cognitive diagnosis. We maintain a session-wise topology snapshot of previously learned skills—defined by their embedding similarity matrix—and regularizes subsequent updates by penalizing deviations from it. Additionally, to ensure old skills remain optimized despite limited coverage in later sessions, supervised replay is incorporated via a bounded interaction memory. Experiments on three real-world datasets show TopoCD improves the stability-plasticity trade-off, mitigating forgetting while remaining competitive on new skills.