ausal Graph Convolution for Bond Recommendation

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Motivation

- Traditional recommendation models (e.g., LightGCN) use static embeddings.
- Financial domains like bond trading are highly dynamic — preferences and offerings shift rapidly.
- Goal: Learn **time-sensitive bond recommendations** that adapt to changing market conditions.

Core Idea

- Construct a temporal bipartite graph: users $\leftrightarrow$ bonds over time snapshots.
- Learn embeddings using **causal graph convolution**: only past interactions influence the present.
- Use a **sliding window** (size w) to focus on recent snapshots and avoid overfitting to outdated behavior.

Model Architecture

- For time t, use graphs $G_t, G_{t-1}, \ldots, G_{t-w+1}$ to update embeddings.
- Causal embedding for user u:

$$h_u^t = \text{GraphConvolution}(G_{t:t-w+1})$$

- Recommendation score:

$$\hat{a}_{u,i}^t = e_u^t \cdot e_i^t$$

- Forward-looking only; no information leakage.

Why Not Just LightGCN?

Feature	LightGCN	LightGCN-W (This Paper)
Embeddings	Static	Time-windowed
Temporal Modeling	None	Causal updates
Dynamics Sensitivity	Low	High

- Static models are prone to stale predictions.
- This approach tracks trends as they evolve.

Empirical Results

- Dataset: Real bond trading logs from BNP Paribas.
- LightGCN-W outperforms standard LightGCN by up to **4x** in precision.
- Best performance with window size $w = 2$.
- Improvement consistent across depths and parameter settings.

Application to Bond Trading

- **Timely recommendations**: Align with short-term trade signals and mandates.
- **Causal design**: Suitable for backtesting and avoids lookahead bias.
- **Simplicity**: Scalable; easy to integrate in ranking pipelines.
- Use case: Enhance sell-side or e-platform bond suggestion tools.

Key Takeaways

- **Time-awareness is critical** in financial recommendation systems.
- **Causal graph convolutions** ensure valid temporal modeling.
- **Sliding windows** balance responsiveness with stability.
- Strong gains observed on real-world credit bond data.