UNIFIED LOSS OPTIMIZATION FOR MULTI-RELATIONAL RECOMMENDATION

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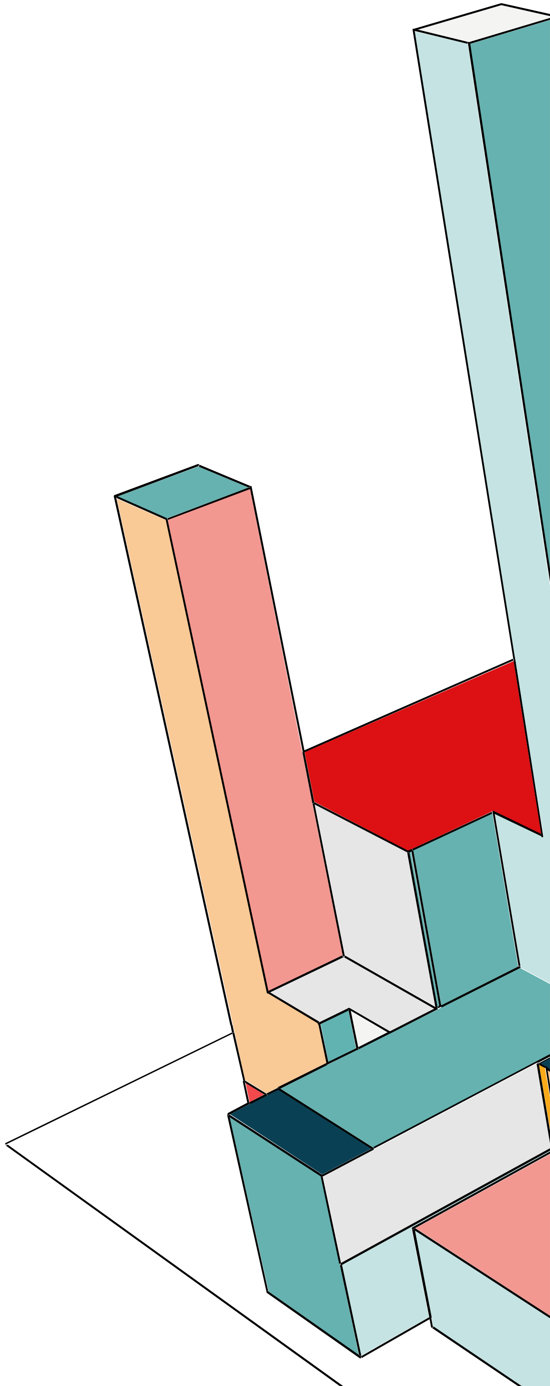
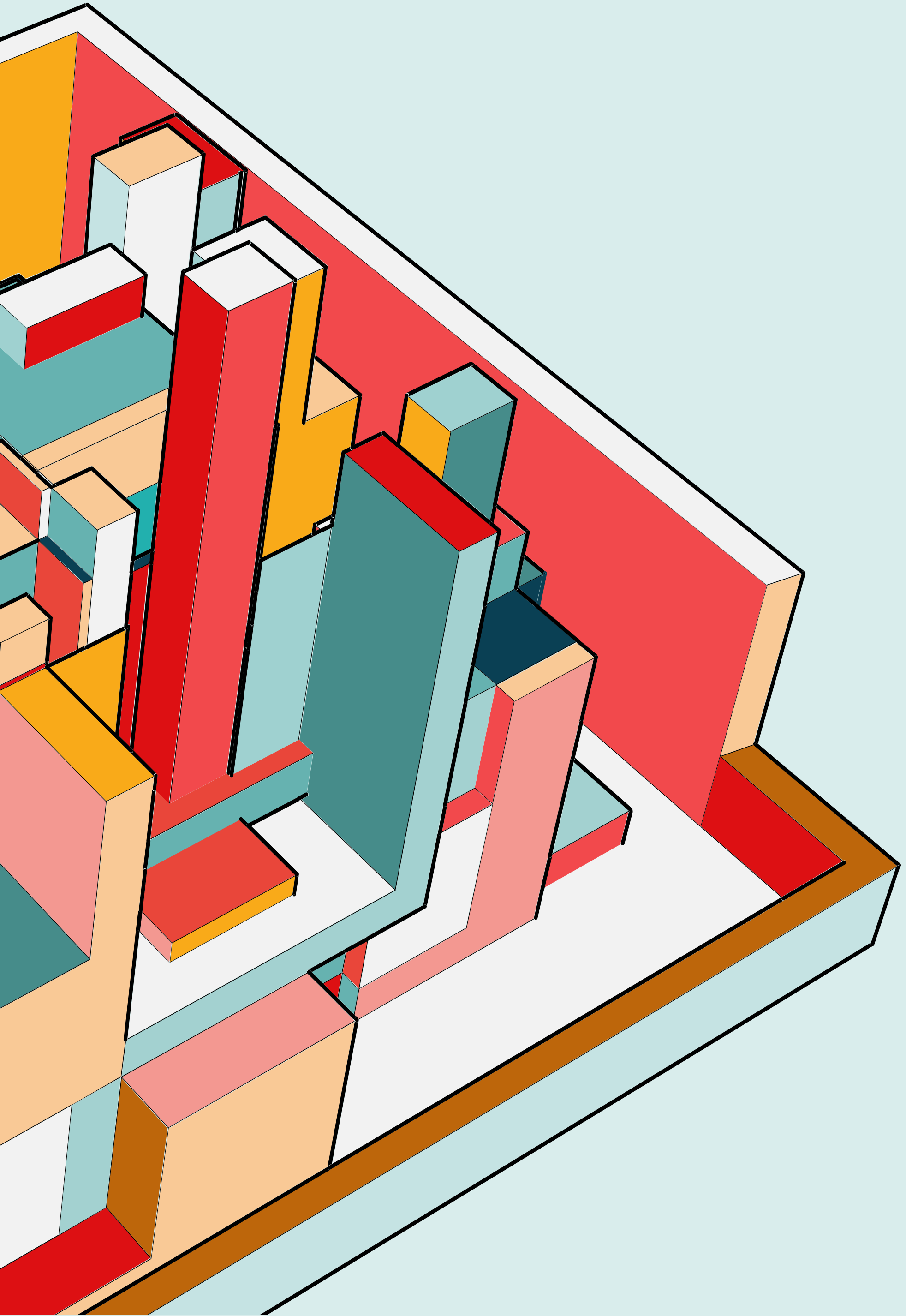
MOTIVATION

- Modern recommenders operate over multi-relational graphs with rich semantics.
- Many pipelines optimize separate objectives for knowledge-graph completion and user–item ranking.
- Fragmented training can dilute specialization and complicate model comparison and attribution.





CONTRIBUTIONS

Q: What happens when KG embedding quality, recommendation accuracy, and regularization are trained under a single objective?

Built a unified framework in RecBole coupling CompGCN and TransE under one loss.

Provided a rigorous theoretical walk-through and reproducible PyTorch blueprint.

Released a harmonized evaluation protocol and ablations on composition operators.

BACKGROUND: TRANSE

Translational scoring: minimize $\|E(h) + R(r) - E(t)\|_2$ for true triples; maximize for negatives.

Simple, efficient baseline with competitive performance.

Used here as a KG component inside a unified recommendation pipeline.

BACKGROUND: COMPGCN

Relation-aware message passing with composition of entity and relation embeddings.

Composition operators: subtraction, element-wise product, addition, and circular correlation (ccorr).

Directional transforms (out/in/loop) and degree-normalized aggregation.

BACKGROUND: COMPGCN LAYER

- Compose ϕ(e_s, r) via chosen operator (e.g., ccorr with FFT/IFFT).
- Apply direction-specific linear maps W_out, W_in, W_loop.
- Aggregate normalized messages; apply BN, dropout, and nonlinearity.
- Relation update via W_rel with basis decomposition to reduce parameters.

$$h_v = f\left(\sum_{(u,r)\in\mathcal{N}(v)} W_{\lambda(r)} \phi(x_u, z_r) \right)$$

UNIFIED OBJECTIVE

- *Single scalar loss*: margin-based KG term + BPR ranking term + ℓ_2 regularization.
- Single backprop step.
- Fixed mixing coefficient **α**; margin **γ** for KG hinge; dot-product user–item score.

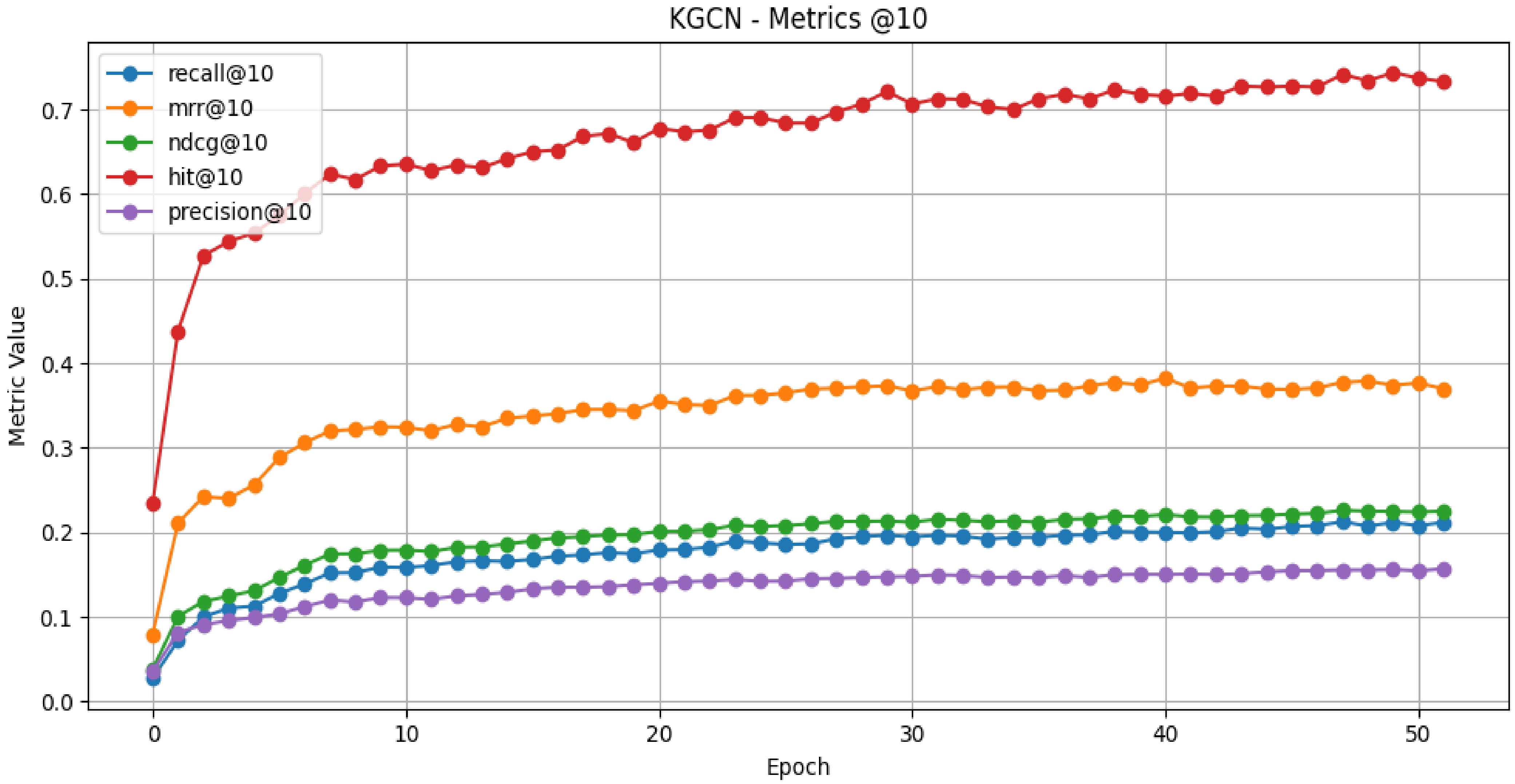
$$\mathcal{L} = \frac{1}{|\mathcal{B}_{\mathrm{KG}}|} \sum_{(h,r,t)\in\mathcal{B}_{\mathrm{KG}}} \max\!\big(0,\ f(h,r,t) - f(h,r,t^{-}) + \gamma\big) + \ \alpha \frac{1}{|\mathcal{B}_{\mathrm{Rec}}|} \sum_{(u,i^{+},i^{-})\in\mathcal{B}_{\mathrm{Rec}}} -\ln\sigma\big(s_{ui^{+}} - s_{ui^{-}}\big) \ + \ \lambda\|\Theta\|_2^2$$

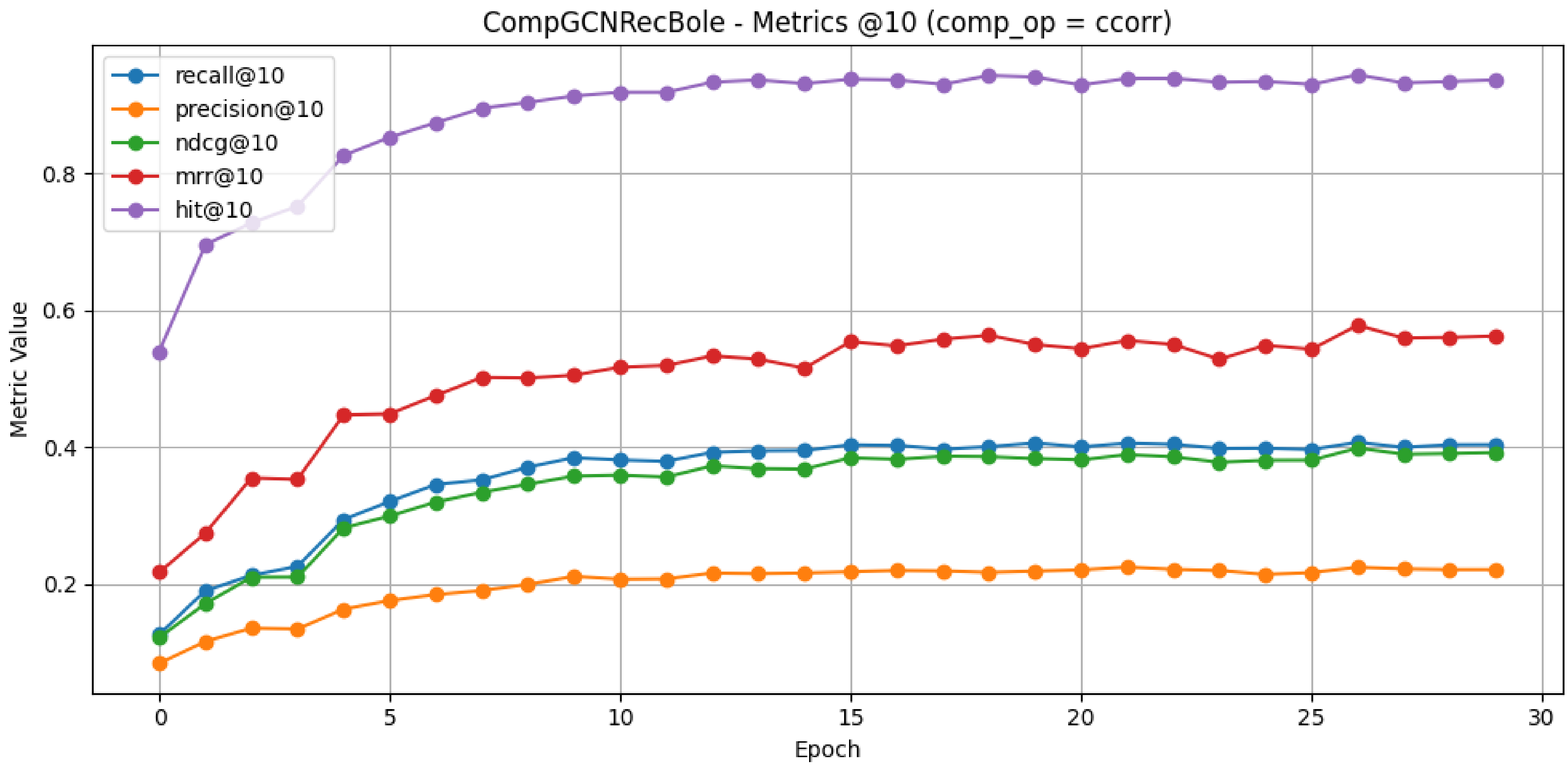
DATA & GRAPH CONSTRUCTION

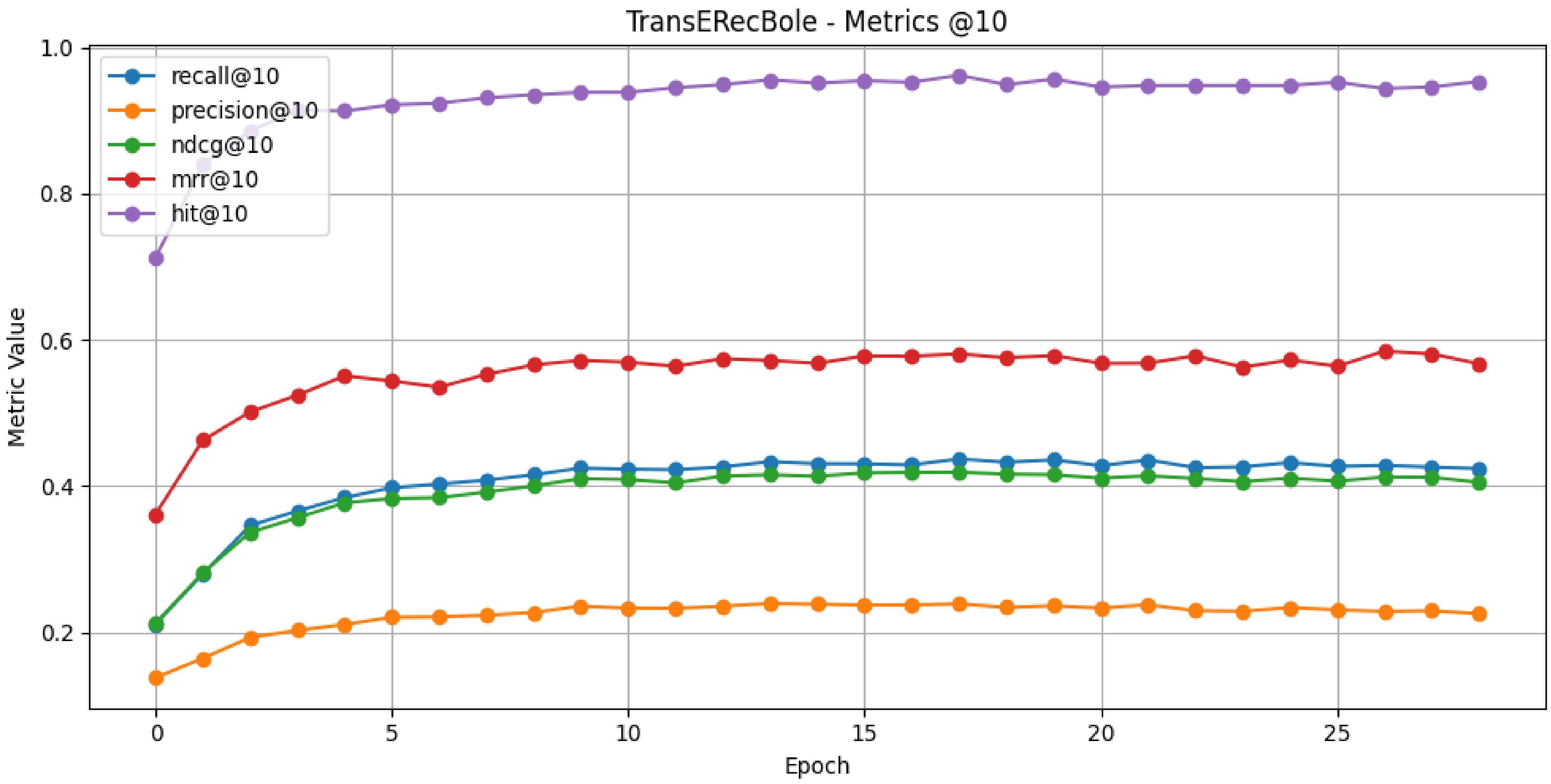
- *MovieLens-100K* with users, items, and enriched side information (genres, directors, actors).
- Deterministic alignment to a KG entity space; inverse edges and self-loops added.
- Restrict edges to the interaction universe; standardized parsing via RecBole.

EXPERIMENTAL SETUP

- Models: BPR, CFKG, CKE, KGCN, ItemKNN, TransE, CompGCN.
- Optimization: Adam (lr=1e-3), early stopping (patience 10).
- Dims: 128 for TransE/CompGCN, 64 for others.
- CompGCN uses 2 layers and 8 relation bases.
- Temporal split; full-ranking metrics (@10): Recall, Precision, NDCG, MRR.


KGCN - Metrics @10
recall@10
mrr@10
ndcg@10
hit@10
precision@10
Metric Value
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
Epoch
0
10
20
30
40
50


CompGCNRecBole - Metrics @10 (comp_op = ccorr)
recall@10
precision@10
ndcg@10
mrr@10
hit@10
Metric Value
0.2
0.4
0.6
0.8
0
5
10
15
20
25
30
Epoch



TransERecBole - Metrics @10
recall@10
precision@10
ndcg@10
mrr@10
hit@10
Metric Value
Epoch
1.0
0.8
0.6
0.4
0.2
0
5
10
15
20
25

RESULTS

- TransE achieves the highest mean score (0.419 at best epoch), leading Recall@10 and NDCG@10.
- CompGCN with ccorr is competitive (mean 0.402), outperforming mult and sub variants.
- Collaborative baselines (BPR, ItemKNN) and classical knowledge-aware models (CKE, KGCN) trail in this regime.

RESULTS

Model	Best epoch	Avg. score	Recall	Precision	NDCG	MRR
BPR	61	0.25005	0.2168	0.1609	0.2340	0.3885
CFKG	3	0.146375	0.1169	0.0947	0.1283	0.2456
CKE	46	0.252275	0.2187	0.1603	0.2349	0.3952
CompGCNRecBole (ccorr)	26	0.402175	0.4072	0.2246	0.3988	0.5781
CompGCNRecBole (mult)	29	0.369100	0.3848	0.2058	0.3611	0.5247
CompGCNRecBole (sub)	21	0.373900	0.3991	0.2087	0.3698	0.5180
ItemKNN	0	0.240100	0.2058	0.1554	0.2213	0.3779
KGCN	47	0.242875	0.2126	0.1556	0.2260	0.3773
TransERecBole	17	0.419125	0.4373	0.2391	0.4192	0.5809

Table 3: Performance at the best epoch for each model.

FUTURE WORKS

Future work should

- explore dynamic or curriculum-based control of alpha,
- investigate hybrid composition mechanisms and attention within multi-relational layers,
- assess scalability on larger, heterogeneous knowledge graphs with richer relation vocabularies.

CONCLUSIONS

- A single objective coupling KG and Rec is compatible with competitive top-k ranking.
- TransE leads in this experimental regime; CompGCN (ccorr) remains close and flexible.
- Unified optimization clarifies trade-offs and simplifies cross-model comparison.

THANKS FOR YOUR ATTENTION!

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