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Learning Geometry-Aware Recommender Systems with Manifold Regularization

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Introduction

Aim of the research is to explore the benefits of integrating hyperbolic geometry into the architectures of neural recommender systems with manifold regularization.

Our **hypothesis** is that, while we retain the standard architecture, we get an increase in the metric by taking into account hyperbolic geometry in the embedding space for problems with a strong hierarchy.

Contribution:

1) We extend the manifold regularization problem to **handle sequences**;

2) We use manifold regularization for single interaction probability and top-k prediction problem statements for several architectures: **dense NN and SASRec**;

3) The manifold regularization is considered a **soft geometry constraint** in contrast to the direct embedding geometry.

Proposed Approach

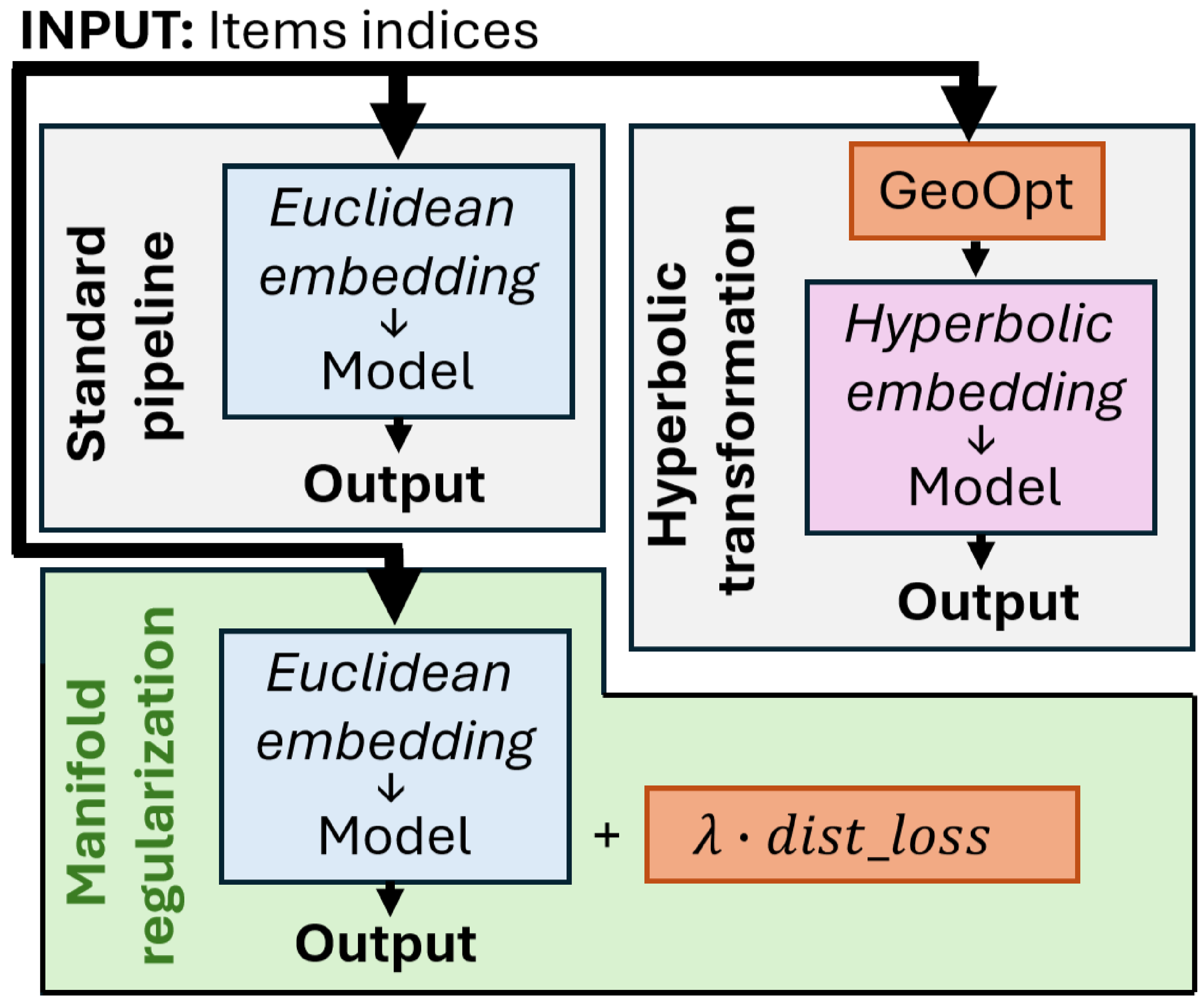
The embedding generator is usually replaced with a pre-defined hyperbolic manifold, thus influences a whole machine learning model architecture. RECMAN impose geometric constraints more softly by introducing a regularizing term in a loss function.

Regularization process with defined input and output distances:

$$f^* = \min_{f \in H_k} \mathcal{L}(f) + \lambda \mathcal{R}$$

Regularizer $\mathcal{R}$ defines the Poincaré ball distance to render the hierarchical structure of the items; λ the dispersion ratio of the combined loss (hyperparameter for Sobol analysis or grid search).

Scheme of the proposed approach of manifold learning in comparison of SASRec case and classical approach



Experiments

Source code

		Explicit		Implicit	
		MSE	Binary accuracy	HR@10	NDCG@10
Movielens	NCF	0.0322	0.6878	0.722	0.547
	NCF+geoopt	0.0324	0.6840	0.563	0.318
	HyperML [21]	n/a	n/a	0.739	0.528
	RECMAN(*ours*)	**0.0320**	**0.6927**	**0.741**	**0.531**
Pinterest	NCF	n/a	n/a	0.834	0.502
	NCF+geoopt	n/a	n/a	0.825	0.478
	RECMAN(*ours*)	n/a	n/a	**0.836**	**0.505**

NCF model variants performance

Explicit and implicit feedback on **MovieLens1M** and **Pinterest** for **NCF** architecture demonstrate the advantage of manifold regularization with hyperbolic geometry.

For **SASRec** manifold regularization improves HR, NDCG, and MRR by reinforcing confident rankings among frequently interacted items clustered in dense regions of the learned geometry. This focus reduces catalog coverage (COV), as less frequent or geometrically isolated items are underrepresented. **HypSASRec** also has the same tendency.

Evaluation results and relative improvements for **SASRec** architecture

		HR@10	MRR@10	NDCG@10	COV@10
Arts	SASRec	0.058	**0.029**	**0.036**	**0.657**
	HypSASRec	0.053	0.027	0.033	0.656
	RECMAN(*ours*)	**0.059**	0.029	0.036	0.374
	best vs SASRec	+2%	+0%	+0%	+0%
Digital	SASRec	0.044	0.020	0.025	**0.602**
	HypSASRec	0.044	**0.021**	0.026	0.601
	RECMAN(*ours*)	**0.048**	0.020	**0.027**	0.383
	best vs SASRec	+9%	+7%	+5%	+0%
Luxury	SASRec	0.123	0.063	0.077	**0.523**
	HypSASRec	0.065	0.028	0.037	0.261
	RECMAN(*ours*)	**0.129**	**0.066**	**0.080**	0.437
	best vs SASRec	+5%	+5%	+5%	+0%
MovieLens	SASRec	0.154	0.056	0.079	0.669
	HypSASRec	0.151	0.055	0.078	**0.675**
	RECMAN(*ours*)	**0.155**	**0.057**	**0.080**	0.658
	best vs SASRec	+1%	+1%	+1%	+1%
Office	SASRec	0.052	0.027	0.033	0.510
	HypSASRec	0.060	0.033	0.039	**0.512**
	RECMAN(*ours*)	**0.064**	**0.035**	**0.043**	0.498
	best vs SASRec	+22%	+28%	+30%	+0%

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