LLM-Enhanced Random Forests in Orthogonal Hyperbolic Subspaces for Tabular Learning

HOT

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IMAGIC ACT BIG DATA

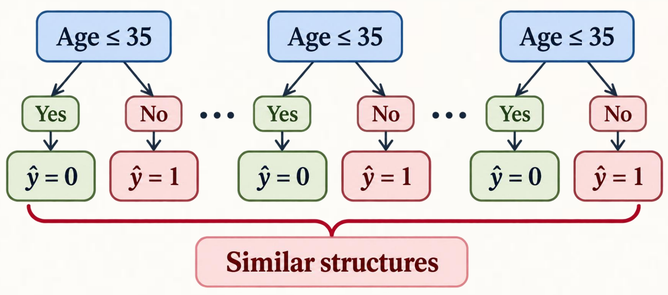
NEURAL INFORMATION PROCESSING SYSTEMS

MOtivation

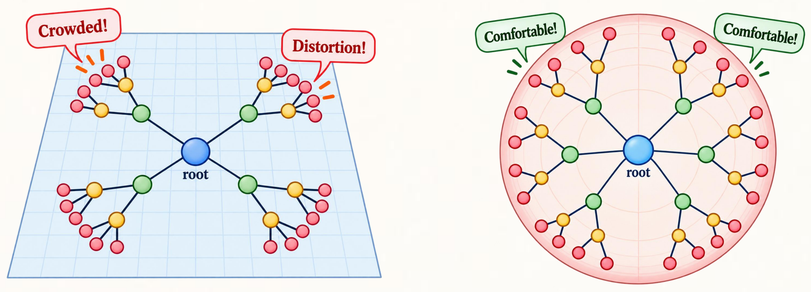
Why use Hyperbolic Forests?

Tabular Learning & Tree Ensembles

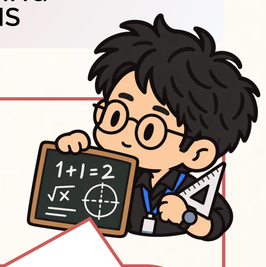
Feature Overlap



Why Hyperbolic Geometry?



Euclidean Space($\mathbb{E}^D$) Hyperbolic Space($\mathbb{H}^D$)



Exponential Growth And **Negative Curvature** reduce crowding and preserve tree structures.

How can we construct efficient, diverse hyperbolic forests using geometric priors and LLM-guided semantic reasoning?

Key Mechanisms



Hyperbolic Is Great, But ...

Hard to Build Trees!

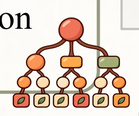
- Difficult in curved spaces.

Trees Think Too Alike!

- Costly optimization and limited diversity.

Orthogonal Subspaces Construction

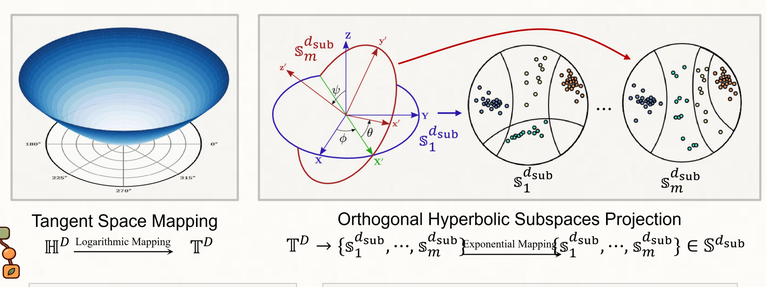
- Building trees in curved spaces is challenging. Orthogonal projections in tangent space make the construction simpler and more efficient.

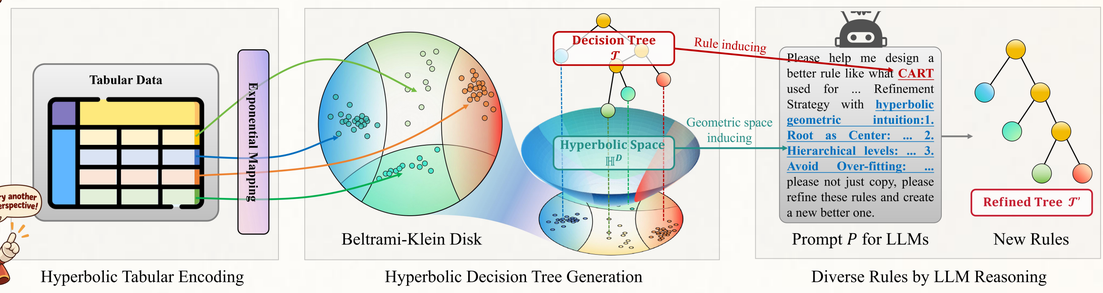


Geometric Views + LLM Guidance

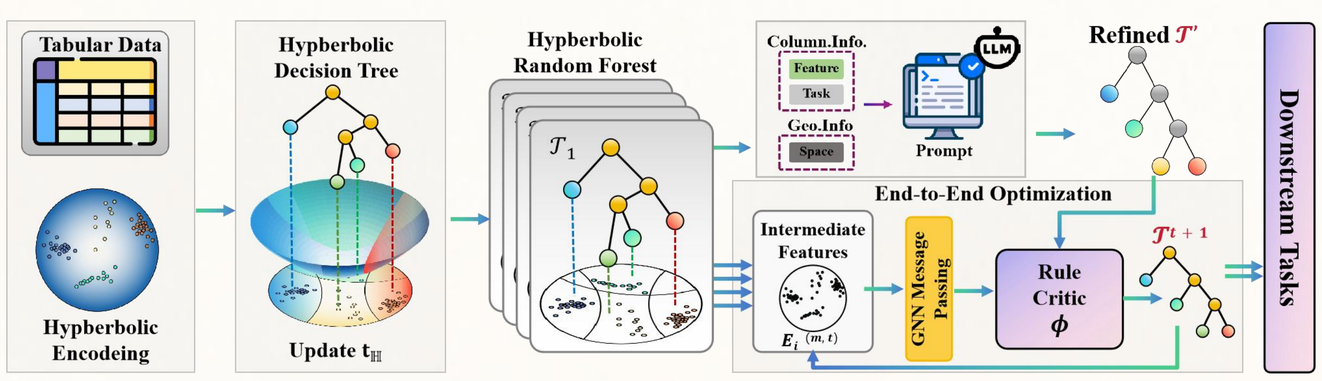
- Diversity is not merely about looking at decision trees. We also need the guidance of knowledgeable experts.







Framework



HOT integrates hyperbolic geometry, diverse tree representations, and LLM-guided semantic reasoning into a unified framework. By combining complementary geometric perspectives with semantic guidance, HOT enables efficient and diverse forest construction for effective tabular learning.

Experimental

Num	model	Blood	Credit	Car	Bank	Adult	Jannis	Heart
All	TabLLM	0.700	0.723	0.991	0.921	0.920	**0.853**	0.872
	LIFT	0.675	0.680	0.880	0.816	0.805	0.730	0.835
	TP-BERT	0.710	0.715	0.940	0.912	0.835	0.781	0.822
	FeatLLM	0.715	0.779	0.942	0.930	0.885	0.802	0.895
	DeLTa	0.781	0.782	0.982	0.924	0.916	0.845	0.860
	Ours	**0.791**	**0.801**	**0.992**	**0.931**	**0.921**	0.846	**0.910**
64	TabLLM	0.680	0.612	0.971	0.690	0.842	0.732	0.771
	LIFT	0.643	0.635	0.786	0.754	0.764	0.581	0.708
	TP-BERT	0.655	0.608	0.853	0.804	0.785	0.623	0.725
	GTL	0.624	0.593	0.845	0.784	0.763	0.594	0.745
	P2T	0.458	0.58	0.799	0.686	0.711	0.523	0.681
	FeatLLM	0.711	0.604	0.868	0.774	0.838	0.581	0.693
	DeLTa	0.729	0.614	0.969	0.811	0.869	0.721	0.701
	Ours	**0.772**	**0.660**	**0.988**	**0.818**	**0.870**	**0.773**	**0.795**

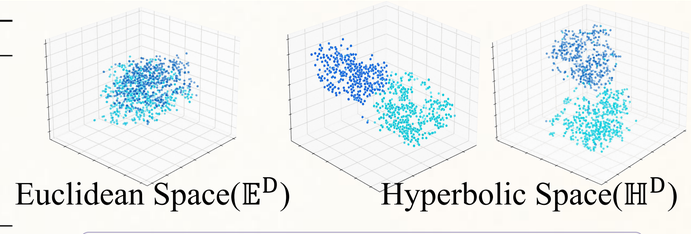
Methods	BL ↑	CR ↑	Car ↑	BA ↑	AD ↑	JA ↑	Heart ↑
KNN	0.7251	0.6684	0.9912	0.7721	0.8345	0.592	0.78
CART	0.7212	0.7015	0.9833	0.8998	0.851	0.5891	0.795
MLP	0.7056	0.7388	0.955	0.9125	0.8688	0.7256	0.825
RandomForest	0.7145	0.7582	0.9322	0.9056	0.8754	0.6812	0.84
XGBoost	0.702	0.741	0.991	0.9188	0.889	0.7365	0.901
Catboost	**0.8015**	0.7765	0.9288	0.9205	0.8901	0.845	0.865
ResNet	0.6689	0.742	0.9554	0.915	0.8675	0.7389	0.815
FT-Transformer	0.7056	0.7455	0.9045	0.916	0.8755	0.8412	0.824
SAINT	0.7288	0.769	0.9765	0.918	0.872	0.7288	0.848
TabPFN (Version 2)	0.719	0.751	**0.995**	0.922	0.8585	0.7245	0.892
ModernNCA	0.7315	0.751	0.9754	0.9175	0.8865	0.748	0.851
our	0.791	**0.801**	0.992	**0.931**	**0.921**	**0.846**	**0.91**

Main Experiment

We evaluate HOT on 13 benchmark datasets against LLM-based and traditional baselines across multiple dimensions.



Dataset	HOT	Random Forest
Blood	0.827	0.124
Credit	0.762	0.316
Car	0.845	0.230
Adult	0.795	0.092
Jannis	0.641	0.282
Heart	0.896	0.202
Bank	0.099	0.060
Avg.	0.695	0.187



Diversity verification

# Num	Stage	TabLLM	LIFT	TP-BERTa	FeatLLM	HOT
All	Train	169974.84	149847.46	1347.46	1147.34	**38.15**
	Inference	164.75	89456.68	2.74	0.17	**0.08**
64	Train	274.35	184.48	374.20	1147.34	**27.45**
	Inference	174.64	88471.77	7.45	0.79	**0.06**



We achieved the best and second-best results.

Open to collaboration and communication - feel free to contact us!

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