A Riemannian Perspective on Graph Foundation Models: Curvature as a Guiding Principle

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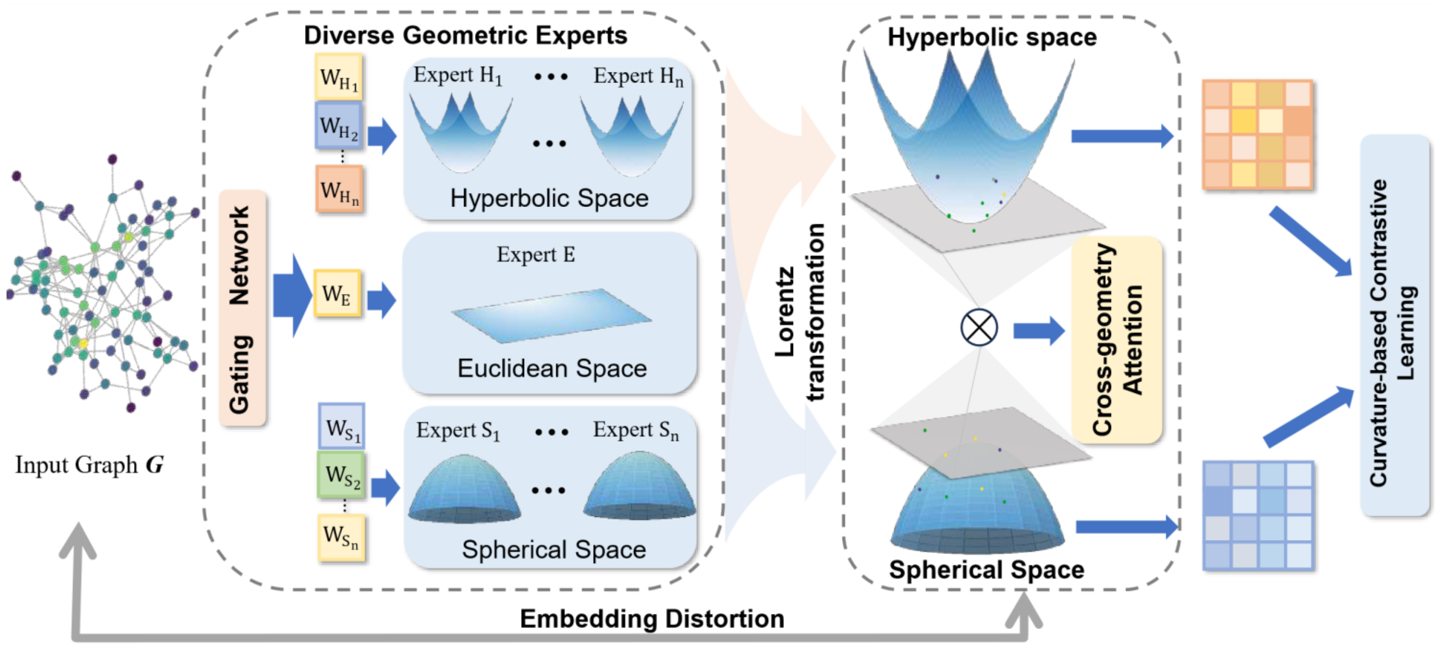
Problems & Ideas

- Problems of Graph Foundation Model:
  - Structural Complexity against Euclidean Backbone Networks.
  - Structural Diversity against the Mission of Model Universality.
- Ideas: Consider the structural complexity and diversity in the graph domain, and propose a novel Curvature-guided Riemannian Graph Foundation Mode



Overall architecture of the pre-training model in CRGFM. Each graph is described by the mixture of geometric experts, standardized in the product bundle, encoded by the Riemannian graph transformer, and pre-trained with contrastive learning between the hyperbolic and hyperspherical geometries.

Main Contributions

- Contributions:
  - We connect GFM to geometric standardization in Riemannian geometry for universal graph structural understanding and modeling.
  - We present a new model, CRGFM. It describes graphs using a combination of "geometric experts," standardizes them with the augmented Lorentz transformation, processes them with a Riemannian graph transformer, and fine-tunes them for specific tasks using prompt learning;
  - Extensive experiments on real-world graphs demonstrate the superior cross-domain transferability of CRGFM in few-shotlearning and zero-shot learning.

	Dataset	vanilla GNNs		Graph SSL		Graph Foundation Models					
		GCN	GraphSAGE	DGI	GraphMAE2	GCOPE	OFA	OpenGraph	LLaGA	RiemannianGFM	CRGFM
Citeseer	ACC	71.39 ±0.35	67.13 ±0.28	72.23 ±0.31	**73.18 ±0.25**	65.57 ±0.29	59.36 ±0.27	58.95 ±0.30	59.71 ±0.26	66.37 ±0.73	67.48 ± 0.63
	F1	70.43 ±0.42	67.20 ±0.35	70.32 ±0.38	**73.54 ±0.32**	65.67 ±0.36	59.36±0.34	58.95 ±0.37	59.79 ±0.33	66.46 ±0.67	68.12 ±0.64
Pubmed	ACC	75.90 ±0.21	77.73 ±0.19	76.13 ±0.20	**82.27 ±0.17**	74.34 ±0.18	75.42 ±0.16	57.49 ±0.17	70.88 ±0.15	76.27 ±0.38	77.86 ±0.74
	F1	74.33 ±0.33	75.69 ±0.31	75.17 ±0.32	**79.81 ±0.29**	73.38 ±0.30	72.64 ±0.28	53.32 ±0.29	63.89 ±0.27	75.83 ±0.39	76.58 ±0.38
Photo	ACC	85.67 ±0.18	87.92 ±0.16	86.40 ±0.17	88.04 ±0.14	87.61 ±0.15	88.87 ±0.13	88.55 ±0.14	84.12 ±0.12	89.95 ±0.89	**90.73 ±0.48**
	F1	85.56 ±0.27	87.81 ±0.25	89.29 ±0.26	88.93 ±0.23	86.50 ±0.24	88.76 ±0.22	85.44 ±0.23	74.01 ±0.21	89.68 ±0.47	**90.42 ±0.69**
Airport	ACC	49.30 ±0.25	49.95 ±0.23	50.63 ±0.24	52.61 ±0.21	39.95 ±0.22	-	41.46 ±0.21	36.56 ±0.19	55.23 ±0.91	**56.78 ±0.38**
	F1	48.26 ±0.31	48.35 ±0.29	48.79 ±0.30	48.97 ±0.27	35.67 ±0.28	-	37.21 ±0.27	38.72 ±0.25	53.17 ±0.50	**55.82 ±0.49**

Cross-domain transfer learning on CiteSeer, Pubmed, Amazon-photo, and Airport datasets. ACC(%) and F1(%) of node classification with standard deviations. The best method in each column is bolded, and the runner-up is underlined.