HYPERBOLIC REPRESENTATION LEARNING IN MULTI-LAYER TISSUE NETWORKS

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MOTIVATION

Domonkos Pogány¹, Péter Antal¹

Predicting tissue-specific protein functions interactions (PPI) is essential for biology understanding and human diseases. Yet, current solutions overlook the geometry of multi-layer PPI networks.

CONTRIBUTION

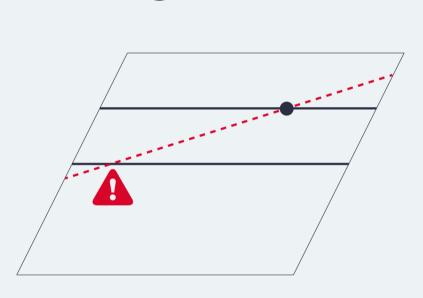
- Proposed a contextualized, tissuespecific representation learning method in non-Euclidean space.
- Compared Euclidean (\mathcal{E}) and hyperbolic (\mathcal{H}) embeddings.

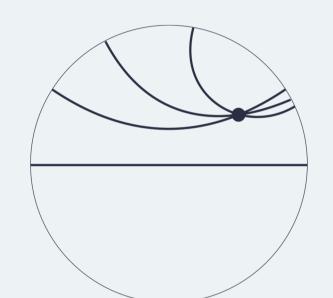
RESULTS

- Hyperbolic geometry captures the structure of multi-layer PPI networks with less distortion.
- Hyperbolic embeddings improve tissuespecific protein function prediction.

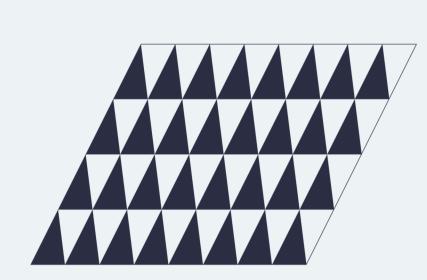
HYPERBOLIC GEOMETRY

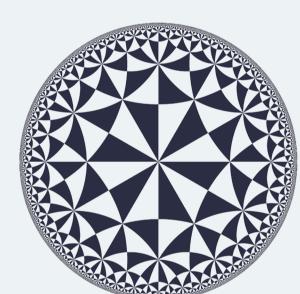
In \mathcal{E} , there is exactly one; in \mathcal{H} , there are at least two parallels through any external point to a given line.



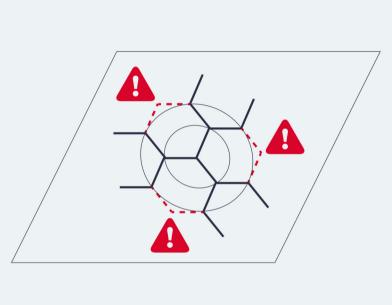


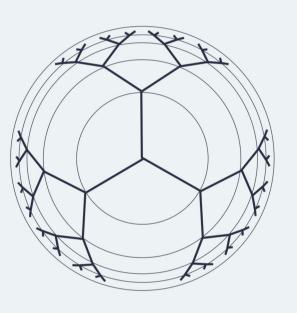
In \mathcal{H} , the area grows exponentially; in \mathcal{E} , it grows only polynomially with respect to the radius.





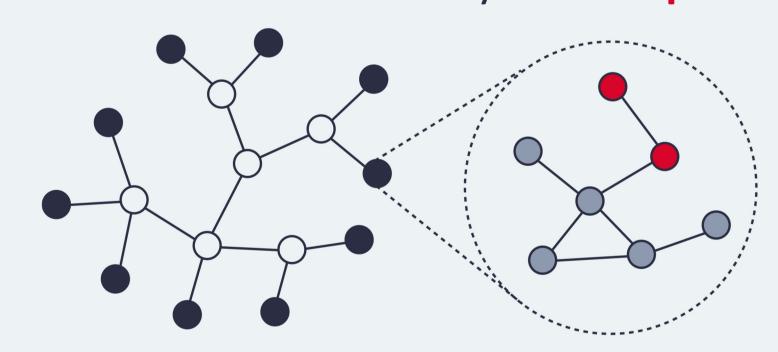
 ${\mathcal H}$ is, therefore, suitable for embedding trees / scale-free networks with many leaves / small degree nodes [1].



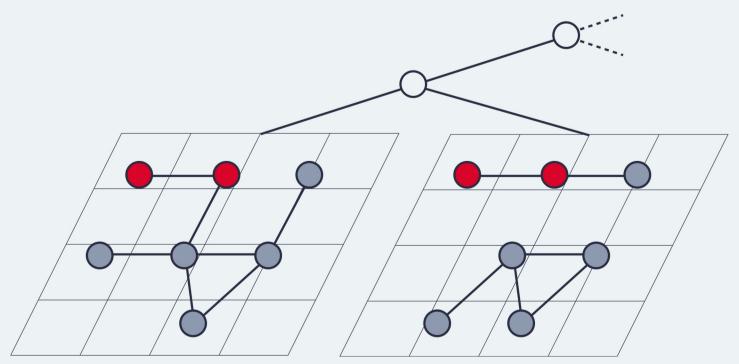


METHODS

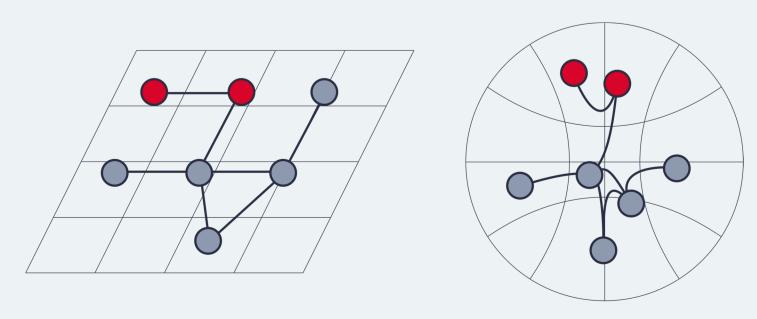
Tissue hierarchy with 112 internal and 107 leaf nodes containing tissue-specific PPI networks and binary-labeled protein functions.



OhmNet model [2]: Leaf nodes: Node2Vec embeddings on PPI networks with hierarchy regularization to align proteins across tissues. Internal nodes: Average of the child and parent embeddings.

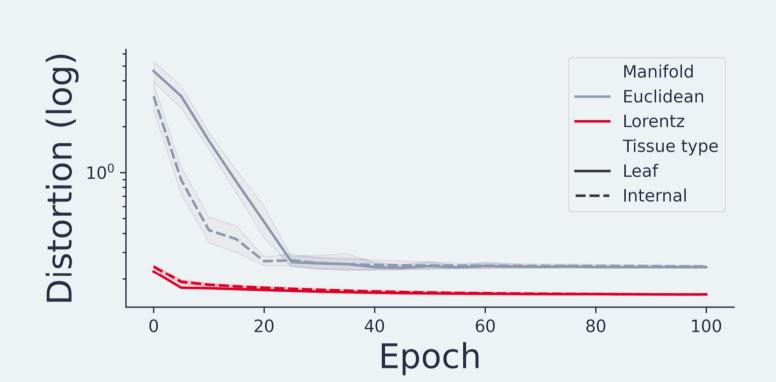


The hyperbolic version utilizes the **Lorentz manifold and distance** for the Node2Vec and hierarchy regularization and it applies the Lorentz centroid for the internal representations.

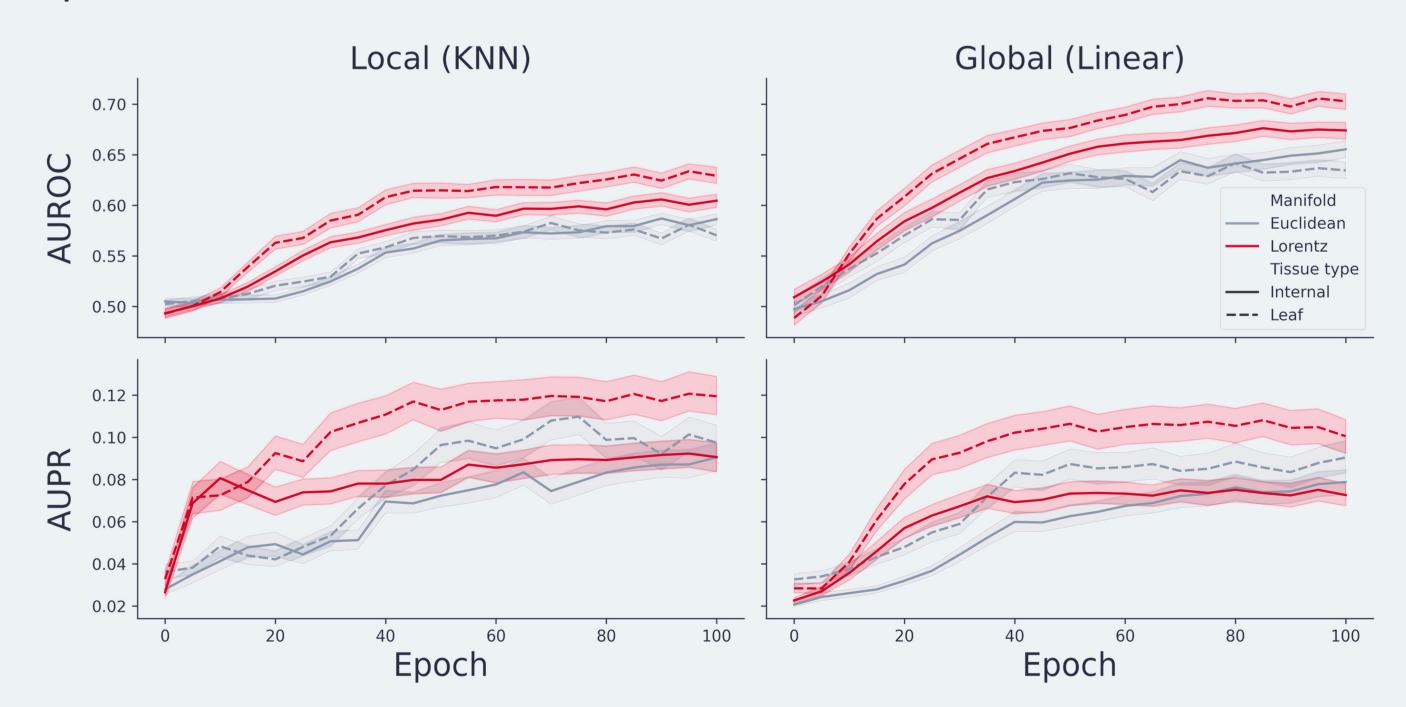


RESULTS

Distortion between manifold distances in the embedding and shortest-path space distances in the PPI networks is lower in \mathcal{H} .



Embeddings in ${\mathcal H}$ achieve superior performance in tissue-specific protein function prediction. Both linear classifiers (relying on a single global separating hyperplane) and K-Nearest Neighbors classifiers (capturing the local structure) perform better in hyperbolic space.



[1] Krioukov, D., Papadopoulos, F., Kitsak, M., Vahdat, A., & Boguná, M. (2010). Hyperbolic geometry of complex networks. Physical Review E—Statistical, Nonlinear, and Soft Matter Physics, 82(3), 036106. [2] Zitnik, M., & Leskovec, J. (2017). Predicting multicellular function through multi-layer tissue networks. Bioinformatics, 33(14), i190-i198.

