HIVE: A Hyperbolic Interactive Visualization Explorer for Representation Learning

Anonymous ICCV submission

Paper ID *****

Abstract

*We present **HIVE**, an interactive dashboard that supports exploration and interpretation of hyperbolic embeddings in deep learning. Hyperbolic spaces naturally capture hierarchical structure, yet existing visualization tools are either designed for Euclidean geometry or remain static when curvature is taken into account. HIVE closes this gap by offering 2D projections in the Poincaré disk and integrating configurable dimensionality-reduction algorithms, including CO-SNE and HoroPCA. From expert interviews we distilled four analytic needs and realized them in four interaction modes—*comparison, traversal, tree*, and* neighbors*. These modes enable real-time, multimodal analysis through semantic hierarchy tracing, geodesic interpolation, and projection comparison. A hybrid user study demonstrates that HIVE supports practical analysis and uncovers meaningful hyperbolic structure. While currently limited to image and text embeddings, the dashboard shows promise for broader applications, such as reinforcement learning and graph discovery, highlighting HIVE's potential as a useful tool for future hyperbolic learning scenarios. Source code is available at* `https://anonymous.4open.science/r/multimedia-9FF0`.

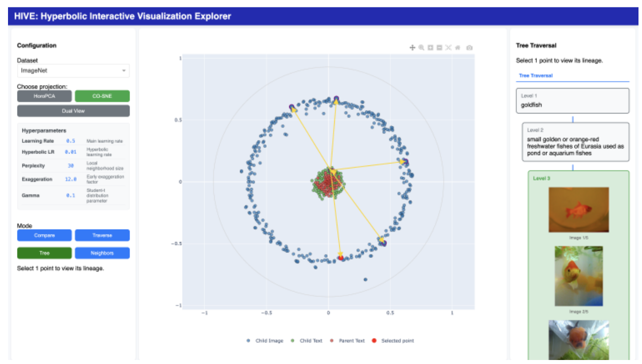


Figure 1. Our system, HIVE, an interactive dashboard for exploring hierarchical structure in high-dimensional data. Users can choose projections (HoroPCA or CO-SNE), and explore different interaction modes (Compare, Traverse, Tree, and Neighbors). The main view visualises embeddings in hyperbolic space in the centre panel, while the right panel shows detailed information for selected points.

1. Introduction

Hyperbolic geometry is increasingly adopted in deep learning for modeling hierarchical, tree-like, and other relational structures that Euclidean embeddings struggle to capture [4, 17]. Because volume in hyperbolic space grows exponentially with radius, it naturally mirrors hierarchical data [12]. Empirical studies further report gains in spatial awareness, ambiguity resolution, and out-of-distribution discrimination [7]. Visualizing these embeddings is not only useful for uncovering the inner workings of hyperbolic models but also lets practitioners verify that semantic hierarchies and distances are preserved in the learned space.

Most existing visualization frameworks, however, are designed for Euclidean spaces and are not well-suited to represent the geometry and hierarchical structure of hyperbolic space. While visualizations compatible with hyperbolic space are mostly static and not interactive, limiting researchers' ability to analyze and interpret hyperbolic embeddings. The following research questions are posed in order to assess whether a dashboard could address this gap, which are answered using an insight-based evaluation and structured survey:

- How well can an interactive dashboard support practical exploration and analysis of high-dimensional hyperbolic embeddings?
- To what extent could an interactive dashboard help users gain meaningful insights into key properties of hyperbolic learning?

To answer these questions, we conducted a requirements analysis with machine-learning researchers working on hyperbolic representations. This process revealed three main needs: (1) interactive exploration of global hierarchical structure; (2) support for multiple projection methods; and (3) inspection of individual embeddings. Based on these requirements, we built HIVE (Hyperbolic Interactive Visualization Explorer), a dashboard that renders 2D projections in the Poincaré disk using two reduction algorithms, CO-SNE [5] and HoroPCA [1], and offers four interaction modes: *comparison*, *traversal*, *tree*, and *neighbors*. These allow users to explore the global and local structure of hyperbolic spaces in a flexible and intuitive manner. Figure 1 shows the interface. Our contributions are:

- An interactive system for visualizing hyperbolic embeddings with multiple projection options and four core features: *comparison*, *traversal*, *tree*, and *neighbors*.
- A hybrid evaluation that combines insight-based analysis and a structured user study.
- A modular open-source framework supporting dataset switching, real-time updates, and rich user interaction.

2. Related work

Our work intersects hyperbolic representation learning and interactive visual analytics, connecting advances in hyperbolic embeddings with the human-centered tools needed to interpret them.

2.1. Hyperbolic representation learning

Nickel and Kiela's Poincaré embeddings first showed that the exponential volume growth of hyperbolic space is ideal for encoding taxonomies and other hierarchies [14]. A follow-up Lorentz formulation retained this curvature-aware bias while improving optimisation efficiency [15]. Since then, hyperbolic embeddings have advanced image classification and uncertainty calibration [9], zero-shot recognition [11], and vision–language retrieval. Examples include MERU [4], HyCoCLIP [17], and HySAC for safe content moderation [18]. These successes increase the demand for tools that expose the latent hierarchical structure of hyperbolic spaces and allow researchers to verify model behaviour.

2.2. Interactive visual analytics for embeddings

Multimedia analytics combines visualisation, human interaction, and analytical routines to explore complex model representations [24]. The MM4AI agenda frames such tools as a means for human–AI teaming [8, 20, 23]. Concrete systems include ReVACNN, which lets users steer CNN training in real time [2], and a dashboard for probing transformer attention [10].

Generic embedding viewers, such as Embedding Projector [21], Embedding Atlas [19], and WizMap [22], support scalable navigation but assume Euclidean geometry. Conversely, browser-based hyperbolic graph viewers render geodesic layouts yet target only graph topology and offer limited interaction [13]. None of these tools provide interactive, multimodal exploration of high-dimensional hyperbolic embeddings.

HIVE fills this gap by combining projection methods for hyperbolic space with four dedicated interaction modes that let users analyze both global hierarchies and local neighborhoods in real time.

3. Background

This section outlines the key concepts that underlie our system. First, we review hyperbolic geometry. Next, we introduce two projection methods that form the basis of our visualization approach.

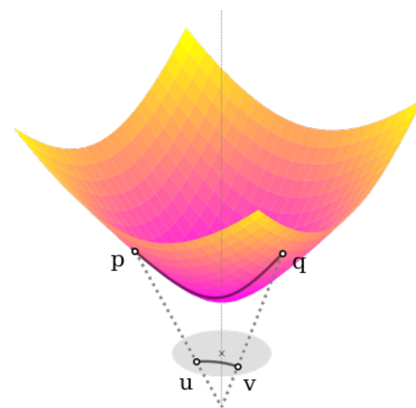


Figure 2. Two common models of hyperbolic space [15]. Top: the Lorentz (hyperboloid) model represents points on the upper sheet of a two-sheeted hyperboloid. Bottom: the Poincaré disk model maps the same geometry inside the unit disk. Both models describe identical hyperbolic structure but use different coordinate systems and reveal different visual properties.

3.1. Hyperbolic space

The Poincaré ball is the most convenient model for visualization. It represents d-dimensional hyperbolic space as the open unit ball in $\mathbb{R}^d$:

$$\mathbb{D}^d = \{\, p \in \mathbb{R}^d : p_1^2 + \cdots + p_d^2 < 1 \,\}.$$

In this model the geodesics (shortest paths) are circular arcs that meet the boundary orthogonally. Although distances, areas, and volumes are distorted relative to Euclidean space, the model is conformal, so angles are preserved. This property makes it well suited to visualizing hierarchical structure.

The hyperboloid, or Lorentz, model embeds d-dimensional hyperbolic space in $\mathbb{R}^{d+1}$ as

$$\mathbb{H}_d = \{\, p \in \mathbb{R}^{d+1} : p_0^2 - (p_1^2 + \cdots + p_d^2) = 1,\ p_0 > 0 \,\},$$

with geometry defined by the Lorentz product

$$p \circ q = p_0 q_0 - (p_1 q_1 + \cdots + p_d q_d).$$

Because isometries can be expressed linearly, distances and geodesics have simple closed forms, giving the model good numerical stability for optimization. The hyperboloid can be projected to the Poincaré ball using stereographic projection, recovering conformality.

3.2. Hyperbolic projection methods

HoroPCA extends principal component analysis from Euclidean to hyperbolic space [1]. Standard PCA relies on linear projections and therefore ignores negative curvature. HoroPCA instead projects data onto horospheres, surfaces orthogonal to a point at infinity within the Poincaré ball, naturally preserving hyperbolic geometry. Many hyperbolic models output embeddings in the Lorentz representation, so we first map them to the Poincaré ball; this conversion preserves geometry while improving interpretability in two dimensions.

CO-SNE adapts the t-SNE algorithm to hyperbolic space [5]. Where t-SNE minimizes the Kullback–Leibler divergence between pairwise similarities in Euclidean space, CO-SNE measures similarity with hyperbolic distance inside the Poincaré ball, thereby maintaining the hierarchical relationships encoded by curvature. As with HoroPCA, embeddings are transferred to the Poincaré ball before optimization.

4. Methodology

This section outlines the methodological components of HIVE, the system architecture, and the interaction modes that enable detailed inspection of the embedding space.

4.1. Requirements Analysis

We first conducted a requirements analysis with researchers in the field to develop a tool supporting meaningful exploration of hyperbolic representations. The identified core requirements led directly to the following key features: (1) interactive exploration of the two-dimensional Poincaré disk, enabling complementary views of hyperbolic geometry; (2) configurable projection methods, such as CO-SNE and HoroPCA, facilitating structural comparisons between embedding techniques; and (3) capabilities for selecting single or multiple embeddings for detailed analysis. Additionally, researchers emphasized the utility of a traversal tool that includes original sample representations for intermediate embeddings, assisting users in comprehending transitions within hyperbolic embedding spaces. These insights significantly guided the design and implementation of HIVE.

4.2. System Architecture

HIVE in its current form visualizes two hierarchical multimodal datasets: GRIT [6] and ImageNet-1K [3]. Each image and text sample is embedded with a configurable encoder; the current implementation uses HyCoCLIP [17].

The encoder produces a high-dimensional representation in the Lorentz model, which is converted to the equivalent Poincaré-ball form. HIVE then applies two curvature-aware reduction techniques, HoroPCA and CO-SNE, mapping the high-dimensional points to two-dimensional coordinates inside the Poincaré disk. These 2D projections form the basis for all interactive views. Figure 3 shows the full HIVE processing pipeline.

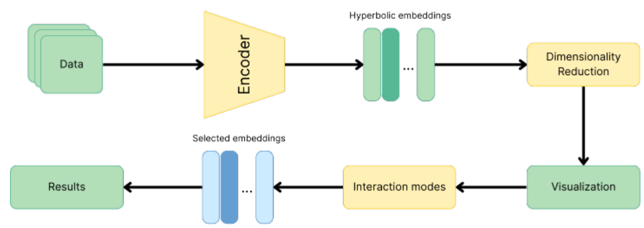


Figure 3. HIVE processing pipeline. Samples are embedded in hyperbolic space, reduced to two dimensions, and rendered for interactive exploration.

4.3. Interaction Modes

The four interaction modes shown in Figure 4 provide distinct ways for users to explore and analyze the embedding space. Each mode reconfigures the dashboard to support a specific analytical intent.

Comparison Users can simultaneously visualize and analyze up to five selected embeddings, each shown with its associated image or textual description. This allows direct comparison of embedding characteristics.

Neighbors Users select a point to inspect its local embedding structure by retrieving its k nearest neighbors. Given a dataset $\mathcal{D} = \{x_1, \ldots, x_N\}$, a query point x, and an arbitrary distance function d, the nearest neighbors are defined as:

$$\mathrm{NN}_k(x) = \arg\mathrm{top}_k \{d(x, x_i) \mid x_i \in \mathcal{D}\},$$

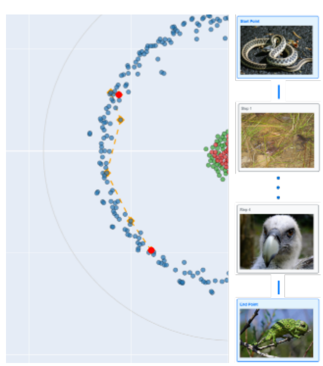
where $\arg\mathrm{top}_k$ selects the k points with the smallest distances to x. The distance function d can be Euclidean, hyperbolic, or another metric. The detail panel highlights the images or texts of these neighbors, enabling users to assess spatial and semantic proximity.

Tree Users visualize hierarchical relationships around a selected embedding, showing parent and child connections in the semantic taxonomy. In this mode, the right panel renders the local hierarchy, displaying both textual and visual context for the selected point, its parent, and its children. The tree visualization makes explicit the relationships between abstract and concrete concepts, with nodes closer to the origin representing higher-level semantics. Figure 5a shows an example hierarchy for a class in ImageNet.

Traversal Users can create paths between two embeddings in Lorentz space, interpolating intermediate points along the shortest geodesic. Given two points $\mathbf{s}, \mathbf{t} \in \mathbb{L}^n$, intermediate points are computed using logarithmic mapping at the origin, following formulas presented in [17]. After exponential mapping back to hyperbolic space, each interpolated point is matched to its nearest neighbor using the same nearest-neighbor retrieval method defined above. Duplicate matches are removed, resulting in a discrete approximation of the geodesic path. The detail panel visualizes the sampled sequence, with each intermediate embedding linked to its original sample and metadata. Figure 5b demonstrates a typical traversal, showing a progression of images along the path.

Figure 4. Interaction modes in the HIVE system. Users can explore the embedding space through four main modes: Compare, Traverse, Tree, and Neighbors.

(a) Fish tree. A visual and textual hierarchy for the class tench, showing the WordNet label, definition, and a set of representative images at different semantic levels.



(b) Traversal. A path through the hyperbolic embedding space is illustrated via selected points and associated images, showing classes (e.g., snake, bird, chameleon) are connected along the embedding manifold.

Figure 5. Overview of tree and traversal. (a) A class-specific hierarchy for the fish category "tench" (b) A traversal through the hyperbolic embedding space with corresponding image previews.

5. Evaluation

Evaluating multimedia analytics systems requires balancing qualitative insight with quantitative assessment. As argued by North [16], insight-based evaluation captures rich, open-ended user interactions, while benchmark-driven assessments provide structured metrics. Building on this principle, we adopt a hybrid evaluation approach consisting of two complementary components: (1) an insight-based evaluation to explore user interaction and reflection, and (2) a structured Likert-scale survey to quantify perceptions of usability.

5.1. Likert-Scale Survey

We conducted a structured Likert-scale survey with four participants to quantify user perceptions of Usefulness, Quality of Visualization, and User Experience. The full survey is provided in the supplementary material. Each dimension was measured using multiple items on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Results are summarized in Table 1.

Table 1. Average Likert-scale scores for each evaluation aspect. Scores range from 1 (strongly disagree) to 5 (strongly agree).

Aspect	Mean Score
Usefulness	4.6
Quality of Visualization	4.8
User Experience	4.7
Overall Average	4.7

The survey indicates that participants evaluated the dashboard very positively across all aspects. Quality of Visualization received the highest score (4.8), highlighting the clarity and expressiveness of the visual components. User Experience (4.7) suggests the interface was intuitive and responsive, while Usefulness (4.6) reflects the perceived value for exploring hyperbolic embeddings.

Participants were also invited to provide open-ended feedback. Visualization of the tree structure was particularly appreciated, and users found the traversal feature valuable for revealing hierarchical relationships.

5.2. Insight-Based Evaluation

An insight-based evaluation was performed with the same participants. After a brief introduction to the dashboard, participants explored the system freely without predefined tasks. They then reflected on what they learned about the embedding space and provided informal feedback, which also inspired ideas for further use cases.

A key shared observation was the difference between projection methods: participants noted that CO-SNE often produced more coherent neighborhoods than HoroPCA.

Another consistent finding was the global spatial arrangement of modalities as text embeddings appeared near the center of the Poincaré disk, while image embeddings were positioned near the boundary. This was interpreted as reflecting the greater generality of text compared to the specificity of images.

Both tree and traversal features were received positively. Tree mode helped validate semantic hierarchies and quickly spot misclassifications, while traversal mode supported exploration of intermediate representations. In some cases, traversals or trees appeared semantically inconsistent, leading participants to see the dashboard as a useful tool for diagnosing incorrect embeddings.

5.3. Suggested Improvements

Evaluation feedback highlighted several directions for future development. Participants consistently recommended additional features and dataset support to enhance the dashboard's utility for research.

Suggestions included visualizing entailment cones to better reveal local structure in hyperbolic space, since this is more relevant than standard neighbor retrieval in non-Euclidean geometry. Another frequently requested improvement was the ability to load and visualize custom or larger datasets, such as scene composition.

6. Conclusion

This work addressed the lack of dedicated tools for exploring and interpreting hyperbolic embeddings. By conducting a requirements analysis with researchers, we identified the need for interactive, multimodal visualization tools that surpass the limitations of static hyperbolic plots and Euclidean-focused dashboards. This motivated the development of HIVE, a modular dashboard that enables the analysis of high-dimensional hyperbolic embeddings through various projection methods and interaction modes. HIVE supports both global and local structure analysis with its comparison, traversal, tree, and neighbors functionalities.

To evaluate HIVE, we formulated two research questions. The first, concerning the effectiveness of an interactive dashboard for practical exploration and analysis of high-dimensional hyperbolic embeddings, was assessed through a structured Likert-scale survey. The results indicated high ratings for usefulness, visualization quality, and user experience, suggesting that the tool is effective and intuitive for practical analysis.

The second research question focused on the extent to which the dashboard facilitates meaningful insights into the properties of hyperbolic learning. An insight-based evaluation showed that participants were able to interpret semantic structures in the embedding space, such as the global arrangement of modalities and the hierarchical relationships between general and specific embeddings. These findings suggest that HIVE enables users to uncover important aspects of hyperbolic learning.

While current insights are closely linked to the dashboard's main use case—visualizing semantic structure in multimodal hyperbolic embeddings—participants also identified several promising directions for future applications. These suggestions highlight HIVE's broader potential for supporting a variety of research scenarios. To realize this potential, further extensions are needed to accommodate new datasets and analytical tasks. In summary, our evaluation suggests that HIVE provides a robust foundation for the exploration of hyperbolic embeddings and offers a valuable starting point for future developments in this area.

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