Intriguing Properties of Hyperbolic Embeddings in Vision-Language Models

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Abstract

Vision-language models have in short time been established as powerful networks, demonstrating strong performance on a wide range of downstream tasks. A key factor behind their success is the learning of a joint embedding space where pairs of images and textual descriptions are contrastively aligned. Recent work has explored the geometry of the joint embedding space, finding that hyperbolic embeddings provide a compelling alternative to the commonly used Euclidean embeddings. Specifically, hyperbolic embeddings yield improved zero-shot generalization, better visual recognition, and more consistent semantic interpretations. In this paper, we conduct a deeper study into the hyperbolic embeddings and find that they open new doors for vision-language models. In particular, we find that hyperbolic vision-language models provide spatial awareness that Euclidean vision-language models lack, are better capable of dealing with ambiguity, and effectively discriminate between distributions. Our findings shed light on the greater potential of hyperbolic embeddings in large-scale settings, reaching beyond conventional down-stream tasks.

1 Introduction

Continued advances in large-scale contrastive learning between visual data and rich semantic descriptions have produced influential vision-language models, such as Flamingo (Alayrac et al., 2022), FLAVA (Singh et al., 2022), and CLIP (Radford et al., 2021). These models not only allow for multimodal retrieval, their original training objective, but also show to be powerful networks for down-stream zero-shot (Ge et al., 2023b; Menon & Vondrick, 2023; Pratt et al., 2023) and fine-tuning tasks (Luo et al., 2022; Goyal et al., 2023; Paiss et al., 2023). Though commonly optimized in Euclidean space, Desai et al. (2023) recently proposed using hyperbolic embeddings instead, yielding further improvements on retrieval and zero-shot generalization. Since hyperbolic geometry differs vastly from Euclidean geometry, embedding image-text pairs in this alternative space leads to inherently different representational properties. The goal of our work is to uncover the new capabilities that emerge from using a hyperbolic geometry for vision-language models.

The potential of hyperbolic geometry has recently been shown for single-modality analysis in computer vision (Atigh et al., 2021; Ermolov et al., 2022; Franco et al., 2023; Ge et al., 2023b; Liu et al., 2020a; Khrulkov et al., 2020) and language understanding (Tifrea et al., 2019; Zhu et al., 2020; Dhingra et al., 2018). A key advantage of the hyperbolic space is its inherent ability to represent hierarchical structures and complex tree structures with minimal distortion (Ganea et al.; Nickel & Kiela, 2017; Sala et al., 2018) which is not directly feasible in the Euclidean space (Nickel & Kiela, 2017). Building on those insights, Desai et al. (2023) integrated vision-language models in the hyperbolic space. Their results demonstrate that the benefits generalize to common tasks in the multimodal domain, with competitive zero-shot image classification and improved zero-shot retrieval over Euclidean models, in particular with lower dimensional embeddings. However, an open question remains: are hyperbolic vision-language models useful beyond the common tasks and do hyperbolic embeddings bring new capabilities to vision-language models?

Hyperbolic embeddings have shown advantages over Euclidean embeddings in unimodal settings for tasks including out-of-distribution generalization, uncertainty quantification, and hierarchical representation learning (Mettes et al., 2023). In multimodal scenarios, hyperbolic embeddings might show similar benefits. In

this work, we systematically compare Euclidean and hyperbolic image-text embeddings and find three properties where hyperbolic embeddings shine. These properties provide insights into why hyperbolic embeddings achieve strong performance and also demonstrate their potential for real-world impact.

- **Spatial Awareness.** Our analysis reveals that hyperbolic vision-language models have superior spatial awareness compared to Euclidean models. While recent benchmarks have been proposed for evaluating spatial reasoning (Zhao et al., 2022; Yüksekgönül et al., 2023; Lewis et al., 2023), large vision-language models still struggle on such tasks, potentially due to contrastive training encouraging shortcut behaviors Yüksekgönül et al. (2023). We demonstrate that the hyperbolic vision-language model strongly outperforms its Euclidean counterpart on three spatial awareness benchmarks. Notably, the Euclidean model performs no better than random chance on two cases, whereas the hyperbolic model succeeds. To our knowledge, spatial awareness remains unexplored for hyperbolic vision-language works and our findings reveal new potential for hyperbolic embeddings in vision-language learning in overcoming its limitation in spatial reasoning.

- **Ambiguity Resolution.** We find that hyperbolic vision-language models are better in handling ambiguity. While many multimodal tasks involve literal appearances, real-world data contains substantial ambiguity; from words with context-dependent meanings to memes with vague image-text relationships. We demonstrate that the hyperbolic vision-language model outperforms the Euclidean model on three tasks involving ambiguity: propaganda classification (Dimitrov et al., 2021), visual word sense disambiguation (Raganato et al., 2023) and text-to-GIF retrieval (Song & Soleymani, 2019). A potential explanation is that the hyperbolic space better preserves semantic hierarchies in text embeddings. Through experiments mapping hierarchical relationships, we confirm significantly lower distortion with the hyperbolic model compared to the Euclidean model. We suggest that the improved performance on ambiguity tasks likely comes from implicit hierarchical representations in the hyperbolic embedding space.

- **Out-of-distribution Discrimination.** We find that hyperbolic vision-language models effectively discriminate between in-distribution and out-of-distribution samples. For deployable real-world systems, simply classifying test samples is insufficient and models must detect when inputs differ semantically from the training distribution Yang et al. (2022). Evaluating across three evaluation metrics, three out-of-distribution detection methods, and five distinct datasets, we consistently observe substantial gains in out-of-distribution detection for the hyperbolic vision-language model compared to the Euclidean model.

With these findings, we shed new light on the importance of the embedding space and the potential of hyperbolic geometry in vision-language models.

2 Related Work

2.1 Image-Text Representation Learning

Large-scale vision-language models have demonstrated strong performance on a wide variety of downstream tasks (Alayrac et al., 2022; Singh et al., 2022; Radford et al., 2021). These models have been applied to classification, retrieval and detection across both unimodal and multimodal contexts in zero-shot (Roth et al., 2023; Pratt et al., 2023; Menon & Vondrick, 2023), few-shot (Zhang et al., 2022; P et al., 2023), and full fine-tuning scenarios Goyal et al. (2023); Ibrahimi et al. (2023); Paiss et al. (2023). Beyond individual tasks, research has also explored robustness to natural distribution shifts (Manli et al., 2022), interpretability (Materzynska et al., 2022) and embedding space properties (Liang et al., 2022). Another emerging area evaluates reasoning about objects, attributes, and relations (Zhao et al., 2022; Yüksekgönül et al., 2023; Lewis et al., 2023). The dominant performance of vision-language models across a plethora of down-stream tasks has made them a staple technique in the field.

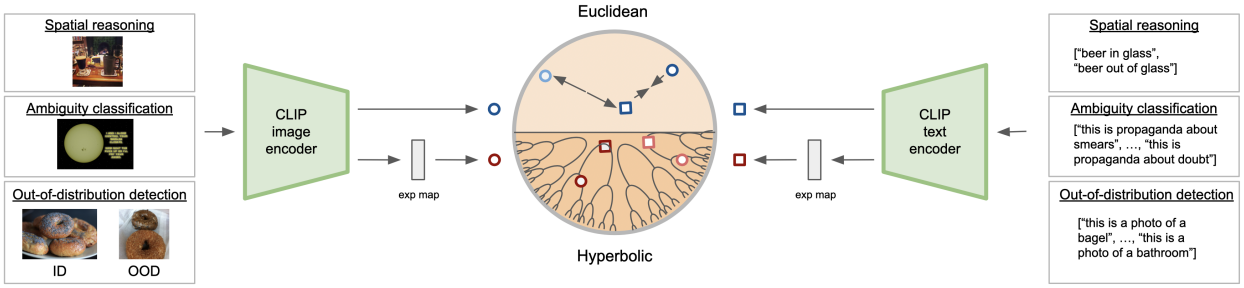


Figure 1: **Hyperbolic and Euclidean Geometry for Vision-Language Representation Learning.** An image and text encoder are used to map images to embeddings in the embedding space. To map the embeddings into the hyperbolic space, an additional exponential mapping function is required, defined by Equation 1. Examples of the visual and textual input for the three properties are presented on the left and right. The color tones indicate whether the embeddings are Euclidean (blue) or hyperbolic (red) and the shapes represent a visual embedding (circle) or a text embedding (square). The Euclidean space brings corresponding image and text embeddings closer together and pushes dissimilar embeddings apart. In the hyperbolic space, the concept of imaginary entailment cones is visualized with a text embedding at the start of the cone and an image embedding within its cone.

2.2 Hyperbolic Learning

Recent years have witnessed rapid progress in hyperbolic learning, as surveyed in Mettes et al. (2023); Peng et al. (2022); Yang et al. (2023). Specifically in the visual domain, hyperbolic learning has shown effectiveness for hierarchical learning (Dhall et al., 2020; Atigh et al., 2021; Long et al., 2020; Liu et al., 2020a), few-shot learning (Gao et al., 2021; Ma et al., 2022; Khrulkov et al., 2020), robust learning (van Spengler et al., 2023; Jie Hong, 2023), and low-dimensional learning (Chami et al., 2020; Nagano et al., 2019; Bose et al., 2020). Beyond these general areas, promising results have been demonstrated for specific vision tasks such as object detection (Lang et al., 2022; Ge et al., 2023a), image segmentation (Atigh et al., 2022), action recognition (Gulshad et al., 2023; Franco et al., 2023), and deep metric learning (Ermolov et al., 2022). For language specific tasks, hyperbolic learning has improved word embeddings (Tifrea et al., 2019; Zhu et al., 2020; Dhingra et al., 2018), graph representations (Chami et al., 2020; Liu et al., 2019) and recommender systems (Mirvakhabova et al., 2020; Wang et al., 2021). The effectiveness of hyperbolic spaces across diverse learning paradigms and tasks emphasizes their potential as a fundamental technique in machine learning.

Desai et al. (2023) introduced the first large-scale hyperbolic vision-language model, demonstrating the emergence of hierarchical structure at text level representations when trained with a loss function enforcing entailment cones (Ganea et al.). In follow-up work, Shen et al. (2023) evaluated the hierarchical properties of this hyperbolic model on superclass-based image classification and subclass clustering of image embeddings. Their experiments showed comparable performance to a Euclidean baseline, indicating limitations in capturing hierarchical semantics. Shen et al. (2023) highlighted that hyperbolic vision-language models are not only effective for standard evaluation tasks, but also for interpretability. In this work, we show that hyperbolic embeddings in vision-language models indeed open new doors, namely for spatial reasoning, ambiguity, and out-of-distribution discrimination, all out-of-the-box.

3 Insights into the Hyperbolic Geometry for Vision Language Models

3.1 Background

Image-Text Representation Learning

Typical large-scale vision-language models consist of an image encoder I and a text encoder T that encode the two modalities separately and use a linear projection layer to retrieve the respective embedding. The resulting embeddings E_I and E_T are then ℓ_2 normalized and aligned through either (1) a loss function operating on the encoder outputs directly or (2) an additional multimodal encoder. Due to their overwhelming popularity, we focus on (1) with two unimodal encoders and a shared embedding space. Given the image embedding

and text embedding, their similarity is measured by the cosine similarity. During training, this similarity is maximized for matching image-text pairs and minimized for dissimilar pairs. The cross-entropy loss is applied over the similarity scores to achieve this. In this paper, we focus on the ubiquitous CLIP model (Radford et al., 2021), which consists of a Vision Transformer (ViT) (Dosovitskiy et al., 2021) as the image encoder and a regular Transformer (Vaswani et al., 2017) as the text encoder following Radford et al. (2019). As CLIP is trained on image-sentence pairs, text prompts are typically formatted into full sentences at inference time to match the training distribution. For the visual recognition task, the common approach is to transform class labels into descriptions akin to "this is a photo of a [class name]" Menon & Vondrick (2023); Pratt et al. (2023); Radford et al. (2021). This space is visualized in the upper half of Figure 1.

Hyperbolic Geometry for Visual and Textual Representation Learning

Hyperbolic geometry possesses constant negative curvature, contrasting the zero curvature of the flat Euclidean space. This enables unique properties relevant for representation learning, including an inherent hierarchical structure and exponential expansion, meaning that the volume of a ball in hyperbolic space grows exponentially as a function of its diameter, rather than polynomially as in Euclidean geometry. Seminal work on hyperbolic learning leverages these traits for hierarchical embeddings with minimal distortion, vastly outperforming Euclidean embeddings (Nickel & Kiela, 2017). This finding has resulted in a rapid uptake in machine learning, with the development of hyperbolic network layers Ganea et al. (2018); Shimizu et al. (2021); van Spengler et al. (2023) and corresponding optimization methods Lou et al. (2020); Weber et al. (2020).

More generally, hyperbolic space can be represented by multiple models (Cannon et al., 1997), with the Poincaré ball and the Lorentzian hyperboloid as common choices in vision (Mettes et al., 2023) and language (Peng et al., 2022) representation learning. Each formulation uses a specific distance metric as well as exponential maps, which project points from the tangent (Euclidean) space to hyperbolic space.

Following Desai et al. (2023), we adopt the Lorentzian hyperboloid to avoid numerical instabilities associated with the Poincaré distance metric (Nickel & Kiela, 2018). For completeness, we provide the key equations for projecting Euclidean embeddings and measuring similarity in this space, leveraged subsequently in our analysis. The model represents an n-dimensional hyperbolic space on the upper half of a two-sheeted hyperboloid in $\mathbb{R}^{n+1}$. Aligning with special relativity theory, Desai et al. (2023) delineate the axis of symmetry as the *time dimension*, with the remaining axes termed *space dimensions*. A vector $\boldsymbol{x} \in \mathbb{R}^{n+1}$, written as $[\boldsymbol{x}_{space}, x_{time}]$, comprises space dimensions $\boldsymbol{x}_{space} \in \mathbb{R}^n$ and a time dimension $x_{time} \in \mathbb{R}$. We project Euclidean embeddings $\mathbf{E_I}$ and $\mathbf{E_T}$ into the Lorentzian manifold via the exponential mapping:

$$\mathbf{E}^*_{space} = \frac{sinh(\sqrt{c}\,\|\mathbf{E}_{space}\|)}{\sqrt{c}\,\|\mathbf{E}_{space}\|}\mathbf{E}_{space} \tag{1}$$

Only the space dimensions are needed in this projection. See Desai et al. (2023) for the full theoretical grounding.

We measure the similarity between $\mathbf{E}^*_\mathbf{I}$ and $\mathbf{E}^*_\mathbf{T}$ using the Lorentzian inner product $\langle\cdot,\cdot\rangle_\mathcal{L}$ which is induced from the Riemannian metric of the Lorentz model. $\langle\cdot,\cdot\rangle$ represents the Euclidean inner product.

For two vectors $\mathbf{E}^*_\mathbf{I}, \mathbf{E}^*_\mathbf{T} \in \mathbb{R}^{n+1}$, it is computed as follows:

$$\langle \mathbf{E}^*_\mathbf{I}, \mathbf{E}^*_\mathbf{T}\rangle_\mathcal{L} = \langle \mathbf{E}^*_{\mathbf{I_{space}}}, \mathbf{E}^*_{\mathbf{T_{space}}}\rangle - E_{I_{time}}\, E_{T_{time}}, \tag{2}$$

where the vectors for the time dimension can be computed by

$$E_{time} = \sqrt{\frac{1}{c} + \|\mathbf{E}^*_{\mathbf{space}}\|^2} \tag{3}$$

Desai et al. (2023) train a hyperbolic CLIP model using a combination of contrastive and entailment losses. The constrastive component mirrors the loss from Radford et al. (2021), substituting the Euclidean similarity

function with the negative Lorentzian distance function. The entailment loss is based on work by Ganea et al.; Le et al. (2019) and aims to enforce hierarchical structure. Specifically, image embeddings $\mathbf{E}_\mathbf{I}^*$ are pushed into imaginary cones projected by the corresponding text embeddings $\mathbf{E}_\mathbf{T}^*$, positioning visual concepts towards the edges of the hyperbolic space. This space is visualized in the lower half of Figure 1. Since fine-tuning and implementation details for these losses are out of scope of this work, we refer readers to Desai et al. (2023) for specifics.

Next, we discuss three hypotheses on the potential benefits of hyperbolic geometry for vision-language modeling.

3.2 Hypothesis 1: Hyperbolic vision-language models exhibit improved spatial awareness

Recent work has analyzed the spatial reasoning capacities of pre-trained Euclidean vision-language models by studying compositional relationships, regarding objects, attributes and relations (Yüksekgönül et al., 2023; Zhao et al., 2022; Lewis et al., 2023). Results show poor zero-shot performance, with models failing to capture semantic relationships between objects, attributes, and relations (Yüksekgönül et al., 2023; Zhao et al., 2022; Lewis et al., 2023). The models exhibit "bag-of-words" behavior, with performance unrelated to scale or training data size (Zhao et al., 2022; Yüksekgönül et al., 2023). Yüksekgönül et al. (2023) hypothesize contrastive pre-training enables shortcuts that inhibit learning true compositionality. Unlike Euclidean alternatives, hyperbolic CLIP uses an additional entailment loss that may prevent shortcuts and enforce latent hierarchies during training. We hypothesize this geometric structure and optimization offers improved spatial awareness lacking in conventional vision-language models.

3.3 Hypothesis 2: Hyperbolic vision-language models are better in dealing with ambiguity

Ambiguity is pervasive in language (Piantadosi et al., 2012). More important, ambiguity is omnipresent in real-world multimodal data, making it an important aspect to consider for deployment. As Chen et al. (2022) observed, ambiguity adds representational granularity by presenting multiple perspectives on identical concepts. We hypothesize that hyperbolic vision-language models are better equipped to tackle ambiguity given their latent hierarchical organization. We investigate this hypothesis by first quantitatively comparing Euclidean and hyperbolic models on tasks with ambiguity, after which we dive deeper into the hierarchical nature of both models.

3.4 Hypothesis 3: Hyperbolic vision-language models are good out-of-distribution discriminators

Hyperbolic learning has demonstrated potential for robustness tasks and uncertainty quantification in unimodal scenarios (Mettes et al., 2023). A critical challenge in this domain is out-of-distribution (OOD) detection, aiming to identify inputs that deviate from the distribution of training or fine-tuning data. OOD detection links to several active research areas like open-set recognition, anomaly detection, novelty detection, and selective prediction (Yang et al., 2022). We hypothesize that the geometric properties of hyperbolic embeddings can enhance distributional awareness in vision-language models. Specifically, the concentration of semantic concepts combined with expansion towards the borders could sharpen discrimination of in- versus out-of-distribution data. We test this via OOD detection tasks comparing hyperbolic and Euclidean CLIP.

3.5 Setup

Throughout this paper, we compare two models, namely the Euclidean CLIP model and the hyperbolic CLIP model presented by Desai et al. (2023). Both models share the same ViT-L/16 encoder architecture and were trained on 12M image-text pairs from RedCaps (Desai et al., 2021). For fair assessment, we focus on zero-shot evaluation, directly comparing models as provided without further tuning and use their 512-dim embedding sizes. Tasks use the original similarity score from CLIP Radford et al. (2021) and the Lorentzian inner product for hyperbolic CLIP, unless otherwise specified. An overview of the pipeline is presented in Figure 1.

Table 1: **Hyperbolic vision-language models exhibit spatial awareness.** The Euclidean CLIP exhibits little to no spatial awareness, even leading to results worse than random guessing for some spatial tasks. Hyperbolic CLIP performs clearly better across all three challenging spatial tasks, highlighting that these models do not shortcut spatial relations between objects and attributes and provide a richer embedding space, even though they are trained on the exact same data.

Model	VL-Checklist	VG-Relations	CLIPbind-r
Random guess	50.0	50.0	20.0
Eucidean CLIP	52.4	56.1	12.8
Hyperbolic CLIP	**59.9** (↑ 7.5)	**59.1** (↑ 3.0)	**25.2** (↑ 12.4)

4 Results

4.1 Hyperbolic vision-language models exhibit spatial awareness

Setup. To study the first property, we take three benchmarks that have been recently formulated to study spatial awareness: *VL-Checklist* (Zhao et al., 2022), *VG-Relations* (Yüksekgönül et al., 2023) and *CLIPbind-r* (Lewis et al., 2023).

- **VL-Checklist**: their spatial reasoning task uses 30k Visual Genome (Krishna et al., 2017) images with two different descriptions, a correct description d_+ of a relation R between two nouns a and b (aRb) and a hard-negative description d_- with a different relation S between the same two nouns (aSb). The model is given an image with two sentences as input and returns similarity scores between the image and both sentences, the Lorentzian inner products $\langle \mathbf{E}^*_{\mathbf{I}}, \mathbf{E}^*_{\mathbf{T}d_+} \rangle_{\mathcal{L}}$ and $\langle \mathbf{E}^*_{\mathbf{I}}, \mathbf{E}^*_{\mathbf{T}d_-} \rangle_{\mathcal{L}}$ for the hyperbolic model and cosine-similarity$(\mathbf{E}_{\mathbf{I}}, \mathbf{E}_{\mathbf{T}d_+})$ and cosine-similarity$(\mathbf{E}_{\mathbf{I}}, \mathbf{E}_{\mathbf{T}d_-})$ for the Euclidean model. When $\langle \mathbf{E}^*_{\mathbf{I}}, \mathbf{E}^*_{\mathbf{T}d_+} \rangle_{\mathcal{L}} > \langle \mathbf{E}^*_{\mathbf{I}}, \mathbf{E}^*_{\mathbf{T}d_-} \rangle_{\mathcal{L}}$, the prediction is considered as correct for the hyperbolic model. The same holds for the cosine similarity scores. Accuracy is the percentage of images correctly scored higher for the true relation. As this is a binary task, random chance is 50%.
- **VG-Relations**: their spatial reasoning benchmark dataset consists of 48 relations with nearly 24k test cases, with images from Visual Genome (Krishna et al., 2017), containing both spatial relations such as 'in front of' and 'below' as well as actions such as 'eating' and 'standing on'. Each image is paired with two descriptions, one being correct and one incorrect, similar to *VL-Checklist*. However, the main difference is that instead of a change in relation, the order of the two nouns is reversed, which results in aRb and bRa. The score calculations are the same as for *VL-Checklist*.
- **CLIPbind-r**: this is a synthetic CLEVR-inspired benchmark dataset (Johnson et al., 2017) created by a tool for 3D modelling and rendering (Lewis et al., 2023) with 10k images for validation. Each image has two objects, chosen out of a set of three, and one relation, out of four possibilities, which results in 24 combinations of spatial relations. Therefore a label has a combination of aRb, where a and b are objects and R is the relation. Next to this pair, four hard negatives are created with a different relation S, a different object c and reverse ordering, namely $d_- = \{bRa, aSb, aRc, cRb\}$. Similar to the other tasks, this task looks at the highest similarity scores between the image and the spatial relation compositions, except that there are four distractors. With five candidates per image, random performance is 20%.

Results. Quantitative results in Table 1 show clear advantages for the hyperbolic model on the three benchmarks. On *VL-Checklist*, Euclidean CLIP scores near random chance (50%), while the hyperbolic architecture achieves 59.9% accuracy which is significantly higher. For *CLIPbind-r* the euclidean model scores lower than random, which is similar to the behavior of some models evaluated in Lewis et al. (2023), but we notice that the hyperbolic model performs better than random. In fact, the CLIP trained by OpenAI (Radford et al., 2021), which has been pre-trained on 400M image-text pairs, has an accuracy of 26.8%, which is only slightly higher than the hyperbolic CLIP trained on 12M image-text pairs. The gap reduces on *VG-Relations* but remains substantial at over 3% absolute improvement.

lemon on / under food
(a)

road in between / nearby cone
(b)

grass near / far from runway
(c)

Figure 2: **Success and failure cases of hyperbolic spatial reasoning.** We show three examples from the *VL-Checklist* spatial split, each with an image and two relational descriptions: one correct (green) and one incorrect (red), e.g. lemon on food (correct) and lemon under food (incorrect) in example (a). For samples (a) and (b) the hyperbolic model assigns higher similarity to the correct relations, while the Euclidean embeddings score the incorrect relation higher. However, in (c) both models fail because of incorrectly preferring "grass far from runway" over the true "grass near runway" description, likely due to the high contextual nature of the relation as it requires explicit knowledge about the size of the object and understanding about the distance between the photographer and the objects in the scene.

Analysis. To gain further insights into which spatial properties are better preserved in hyperbolic vision-language models, we have performed additional qualitative and quantitative analyses. In Figure 2, we show a few samples from the *VL-Checklist* dataset, indicating the correct/incorrect relation by color. Euclidean CLIP struggles with more complex relations such as on/under and in between/nearby compared to the hyperbolic alternative. For spatial relations that are contextual, such as near/far from, both models still struggle, as such cases require explicit knowledge about the real world size of the corresponding objects.

Since the *VG-Relations* benchmark uses spatial prepositions and action verbs, we analyze performance per relation in Figure 3, focusing on frequently occurring spatial terms. To this set we use the relations and actions with spatial relations with at least 20 occurrences in the dataset. For a few relations such as "at", "above", "sitting at", and "lying on", Euclidean CLIP is able to compete with hyperbolic CLIP. For many other relations however, large differences occur, especially for "standing on", "sitting on", and "looking at". Overall, hyperbolic CLIP is more robust to the different spatial relations and provides a better option across all settings.

4.2 Hyperbolic vision-language models are better in dealing with ambiguity

Setup. Where deep networks excel when given clearly defined semantic labels, they struggle to deal with ambiguity Kim et al. (2023). Ambiguity can take many forms, from disambiguating words to dealing with data that is ambiguous and playful by design, such as memes. Here we investigate which embedding space is more suited for dealing with ambiguity. We study three benchmarks:

- **Propaganda Memes**: This benchmark dataset contains 950 ambiguous image-text memes spanning 22 propaganda techniques, including whataboutism, obfuscation, and glittering generalities (Dimitrov et al., 2021). Each meme comes with an extracted textual description and one or more category labels. The task is multi-label classification with models ranking similarity between prompted label embeddings of the form "this is propaganda about [class label]" and the meme embedding. For the hyperbolic model, we compute the similarity score by Equation 2 between the meme embedding and the text embedding of the prompted class names $\langle \mathbf{E}^*_{\mathbf{meme}}, \mathbf{E}^*_{\mathbf{T}} \rangle_{\mathcal{L}}$, with four variants for the meme embedding:
  1. text-only $\mathbf{E}^*_{\mathbf{meme}} = \mathbf{E}^*_{\mathbf{meme}_{\text{text}}}$
  2. image-only $\mathbf{E}^*_{\mathbf{meme}} = \mathbf{E}^*_{\mathbf{meme}_{\text{image}}}$
  3. averaged embeddings $\mathbf{E}^*_{\mathbf{meme}} = (\mathbf{E}^*_{\mathbf{meme}_{\text{text}}} + \mathbf{E}^*_{\mathbf{meme}_{\text{image}}})/2$
  4. averaged similarity scores $(\langle \mathbf{E}^*_{\mathbf{meme}_{\text{image}}}, \mathbf{E}^*_{\mathbf{T}} \rangle_{\mathcal{L}} + \langle \mathbf{E}^*_{\mathbf{meme}_{\text{text}}}, \mathbf{E}^*_{\mathbf{T}} \rangle_{\mathcal{L}})/2$.

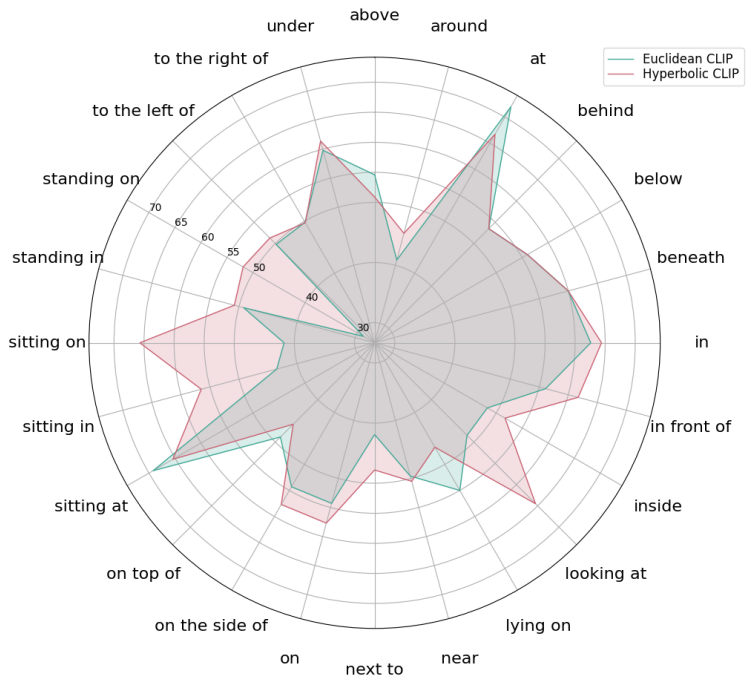


Figure 3: **Hyperbolic CLIP covers more spatial relations.** In this plot, the difference in performance is shown for spatial relations with more than 20 samples. Hyperbolic and Euclidean CLIP are competitive for a number of spatial relations, but hyperbolic CLIP performs much better for others, highlighting a more robust and diverse spatial awareness in hyperbolic CLIP.

The Euclidean model uses the cosine similarity on the same variations. We evaluate with the weighted mean Average Precision described in Wang et al. (2023).

- **My Reaction When**: This benchmark dataset has 50K video-sentence pairs from social media depicting physical/emotional reactions to textual captions including a high ambiguity (Song & Soleymani, 2019). Videos are GIFs representing responses to the paired sentences. We evaluate on video-text and text-video retrieval using common mean pooling to aggregate per-frame CLIP embeddings into a single video representation (Luo et al., 2022). For hyperbolic CLIP, video-text similarity is the Lorentzian inner product between mean pooled video and sentence embeddings. Euclidean CLIP uses cosine similarity. Evaluation is via recall@k (top-k accuracy), checking if ground truth pairs are retrieved in closest neighborhoods. This tests semantic matching between ambiguous pairs of reactions and descriptive captions.

- **Visual Word Sense Disambiguation**: This benchmark evaluates associating ambiguous words like "mouse", with intended meanings from contextual images (Raganato et al., 2023). Each case has a target word and 10 candidate images, one of which matches its sense. Words are provided alone or with 1-2 word phrases for minimal context, e.g. "andromeda" alone vs "andromeda tree". Models rank image similarity to the word/phrase to identify the intended visual depiction among distractors. We compute hyperbolic CLIP's Lorentzian inner product and Euclidean CLIP's cosine similarity, following the setup in (Raganato et al., 2023). The test set has 463 cases. Evaluation uses Mean Reciprocal Rank at 5 and 10 (MRR@5, MRR@10) plus Hit Rate at 1 (HIT@1) to measure disambiguation capabilities given varying levels of contextual grounding.

The *Propaganda Memes* and *My Reaction When* benchmark datasets involve ambiguity in aligning textual captions with corresponding visuals. Memes combine images and text for rhetorical effect, with complex connotations that obscure intended meanings. Likewise, associating social media posts to emotive animated GIFs relies on interpreting nuanced contextual implications. On the contrary, the *Visual Word Sense Dis-*

Table 2: **Hyperbolic vision-language models can deal with ambiguity (I)**, as demonstrated on the *Propaganda memes* benchmark. Regardless of whether we investigate text only, image only, or averaging image-text features or predictions, hyperbolic embeddings provide vastly better results.

Model	Text only	Image only	Avg image-text feats	Avg image-text preds
Eucidean CLIP	36.08	33.29	33.65	33.65
Hyperbolic CLIP	**37.47**	**34.01**	**35.72**	**35.76**

(a) (b)

Figure 4: **Propaganda Memes samples.** We show two examples from the Propaganda Memes benchmark dataset with their ground truth labels and the predictions of both models where the meme embedding is the average of the image and text embedding. In example (a) the hyperbolic CLIP model is able to predict two out of four ground truth labels correctly whereas the Euclidean model does not predict any of those. In example (b), the hyperbolic is able to predict two out of three categories correctly, including smears, where its Euclidean counterpart has only one correct prediction.

ambiguation benchmark directly evaluates resolution of ambiguous words through selection among depictive image candidates. Rather than complex compositional understanding between modalities, the core challenge is isolating the intended sense of polysemous concepts given limited grounding context.

While ambiguity types vary, all tasks require models to handle uncertainty in cross-modal correlations: sociopolitical, affective, or lexical. They measure how well vision-language models leverage context to illuminate intended meanings amidst ambiguity spanning text, static visuals, and video.

Results. In Table 2, we show the results on the *Propaganda Memes* benchmark. We see that the hyperbolic embeddings perform significantly better than their Euclidean counterpart. Dimitrov et al. (2021) have indicated that smears, loaded language and name calling/labeling are the most common meme types in propaganda memes, with smears covering more than half of the dataset, where they argue that this dataset is a good representation of memes that can be found on social media. They define smears as an effort to damage or call into question someone's reputation, by propounding negative propaganda. Examples of memes are given in Figure 4.

Table 3 shows text-video retrieval results on the *My Reaction When* validation (1K) and test (5K) sets. Scaling up the dataset increases the retrieval difficult, as observed from the decreased performance on the test set. Still, hyperbolic CLIP consistently surpasses its Euclidean variant, particularly for top few (small k) retrieved results.

Table 4 shows *Visual Word Sense Disambiguation* results, with hyperbolic CLIP outperforming Euclidean on both phrase and word inputs. Notably, gains persist even when only the ambiguous word is provided without any disambiguating context. This suggests inherent benefits in reasoning about polysemous lexical ambiguity. However, strong overall performance remains elusive - vision-language models struggle to resolve fine-grained distinctions absent in pre-training data like RedCaps. In summary, while hyperbolic space better handles ambiguity, truly contending with granular real-world ambiguity requires acquiring specialist visual knowledge of distinctions like mouse-animal versus mouse-computer. Nevertheless, the consistent improvements validate geometric advantages in multimodal ambiguity.

Table 3: **Hyperbolic vision-language models can deal with ambiguity (II)**, as demonstrated on the *My Reaction When* benchmark. Also when dealing with video inputs and emotional ambiguity, hyperbolic embeddings are preferred.

	Val-set(1k)								Test-set(5k)							
Model	Text-Video Retrieval				Video-Text Retrieval				Text-Video Retrieval				Video-Text Retrieval			
	r@1	r@5	r@10	r@20	r@1	r@5	r@10	r@20	r@1	r@5	r@10	r@20	r@1	r@5	r@10	r@20
Euclidean CLIP	0.20	0.80	1.70	3.31	0.20	0.60	1.60	2.91	0.10	0.30	0.48	0.90	0.14	0.54	0.74	1.20
Hyperbolic CLIP	**0.20**	**1.30**	**2.40**	**4.21**	**0.50**	**1.20**	**2.40**	**4.21**	**0.12**	**0.52**	**0.94**	**1.38**	**0.14**	**0.54**	**0.90**	**1.46**

Table 4: **Hyperbolic vision-language models can deal with ambiguity (III)**, as demonstrated on the *Visual Word Disambiguation* benchmark. The hyperbolic CLIP outperforms its Euclidean variant in ranking images similar to the ambiguous word or phrase.

Model	Target	HIT	MRR@5	MRR@10
Euclicean CLIP	phrase	47.5	61.7	63.7
Hyperbolic CLIP	phrase	**48.4**	**62.4**	**64.3**
Euclidean CLIP	word	28.5	43.4	47.3
Hyperbolic CLIP	word	**29.2**	**44.1**	**48.0**

Analysis. One potential explanation for the superior performance of hyperbolic CLIP on ambiguity tasks is its inherent hierarchical embedding space. Ambiguity introduces additional granularity in recognition tasks by adding an instance-level layer (Chen et al., 2022). However, hyperbolic vision-language models are trained on the same image-text pairs as Euclidean models rather than explicit hierarchies. Recent work showed limitations in visual hierarchy encoding (Shen et al., 2023), but the textual encoder capturing task semantics is more relevant here. Before relating ambiguity and hierarchy, we first verify if hyperbolic text embeddings exhibit stronger latent hierarchical properties.

To quantify textual hierarchy encoding, we leverage label trees from six vision datasets: CIFAR-100, Animals with Attributes 2 (AWA2) (Xian et al., 2019), PASCAL-VOC (Everingham et al., 2010), UCF (Soomro et al., 2012), Kinetics (Kay et al., 2017), and ActivityNet (Heilbron et al., 2015). The first three are provided by the creators of the datasets, while the latter three are taken from Long et al. (2020) and Gulshad et al. (2023). Leaf nodes are encoded as "this is a photo of a [class name]" sentences using Euclidean and hyperbolic CLIP text encoders. We evaluate whether hierarchy distance corresponds with embedding distance, where hierarchy distance between classes is defined by tree levels to the common ancestor. We use the Pearson correlation coefficient to measure whether a linearity between the embedding distances and hierarchy distances is present.

Table 5 shows Pearson correlation between embedding and hierarchy distances. Hyperbolic CLIP exhibits significantly higher correlation than Euclidean variants on five of six datasets, demonstrating improved latent encoding of hierarchical relationships. To validate that these gains span beyond the lowest hierarchy level, we filter leaf nodes from the ActivityNet taxonomy and remeasure correlations. Even within higher layers, hyperbolic embeddings show greater alignment with tree distances (Euclidean: 0.2434, Hyperbolic: 0.2823).

In summary, hyperbolic text encoders intrinsically structure semantic concepts more hierarchically, which is an advantage originating from the underlying geometry. Augmenting contrastive pre-training with an entailment loss amplification further enables hyperbolic models to capture hierarchies lacking in Euclidean counterparts. We hypothesize these latent textual hierarchies aid in resolving ambiguity by providing a framework to structurally represent uncertain, fine-grained distinctions. However, directly confirming the connection between hierarchy and improved ambiguity handling remains an open question for future work and would require extensive further analysis into geometric mechanisms granting these advantages.

4.3 Hyperbolic vision-language models are powerful out-of-distribution discriminators

Setup. Lastly, we evaluate the out-of-distribution discrimination potential of hyperbolic image-text embeddings. The ability to discriminate between in- and out-of-distribution samples is a requirement for real

Table 5: **Hyperbolic vision-language models are more hierarchically structured.** We embed six hierarchies in Euclidean and hyperbolic embeddings through prompting and find that hyperbolic embeddings better correlate with the underlying structure of the hierarchies. While trained on exactly the same data, the hierarchical nature of hyperbolic geometry allows for a better latent hierarchical structuring of semantics.

Model	PASCAL-VOC	AWA2	UCF101	CIFAR-100	Kinetics	ActivityNet
Hierarchy levels	4	6	3	3	3	3
Number of concepts	55	77	125	127	239	244
Euclidean CLIP	0.3689	0.2313	**0.1200**	0.2683	0.1675	0.1450
Hyperbolic CLIP	**0.4562**	**0.2861**	0.1179	**0.3646**	**0.2190**	**0.1830**

world deployment. Here, we leverage the comprehensive out-of-distribution detection benchmark of Yang et al. (2022). We evaluate three common out-of-distribution detection methods that can be directly applied as a post-processing technique on pre-trained models:

- **MLS**: The Maximum Logit Score (MLS) (Hendrycks et al., 2022) uses the negative of the maximum unnormalized logit. Operating on logits provides compatibility across manifolds and robustness to overconfidence in extreme multi-class scenarios. For hyperbolic CLIP, logits are computed via the Lorentzian inner product (Equation 2) between image embeddings and embeddings of prompted class names: "this is a photo of a [class name]". The Eucliean CLIP uses the cosine similarity.
- **EBO**: Energy-Based OOD scoring applies an energy function to the logit outputs (Liu et al., 2020b). Energy scores are theoretically aligned with the probability density of the inputs and mitigate overconfidence. Like MLS, this score is manifold agnostic and the logits are calculated in the same manner as for MLS.
- **MDS**: The Mahalanobis Distance Score (MDS) fits the class-conditional Gaussian distribution on the penultimate layer features of the classifier and computes OOD scores using the Mahalanobis distance metric, which is only defined for Euclidean spaces (Lee et al., 2018). For valid comparison, hyperbolic embeddings are first projected back into the Euclidean geometry via the logarithmic map (the inverse of Eqn 1) before applying MDS. This projection is done for both image and text embeddings in the hyperbolic case. Cosine similarity between the resulting Euclidean embeddings provides the logits for MDS across both models.

For these three out-of-distribution techniques, we use the following settings for evaluation:

- **Out-of-distribution type**: we consider two out-of-distribution detection scenarios. 1) Standard out-of-distribution detection considers distribution shifts in semantic content. 2) Full Spectrum out-of-distribution detection additionally takes the covariate shift into account, which in this setup specifically addresses image corruptions, style change, and resampling bias.
- **Metrics**: We use four metrics: 1) false positive rate at 95% true negative rate (FPR@95), 2) the area under the receiver operating characteristic (AUROC) which indicates the probability that the detector correctly separates in- and out-of-distribution samples, and 3) area under the Precision-Recall curve (AUPR) where either ID images are specified as positive (AUPR-in) or 4) out-of-distribution images are seen as positive (AUPR-out) (Yu & Aizawa, 2019).
- **Datasets**: As In-Distribution (ID) datasets, we use ImageNet200 and ImagNet-1k. The out-of-distribution datasets are divided in two categories: near-OOD (hard-OOD) and far-OOD (easy-OOD), based on image semantics and empirical difficulty. For near-OOD, we use SSB-hard (Vaze et al., 2022), a dataset composed of images from ImageNet-21K and NINCO by Bitterwolf et al. (2023). For far-OOD, we use iNaturalist (Horn et al., 2018), Textures (Cimpoi et al., 2014), and OpenImage-O (Wang et al., 2022).

For more details regarding the evaluation setup, we refer to Zhang et al. (2023).

Table 6: **Out-of-distribution detection** with the post-processing techniques MLS, EBO, and MDS, on ImageNet200 and ImageNet-1k by using the AUROC score.

Method	Model	ImageNet-200		ImageNet-1K		ImageNet-200 -fsood		ImageNet-1K - fsood	
		Near-OOD	Far-OOD	Near-OOD	Far-OOD	Near-OOD	Far-OOD	Near-OOD	Far-OOD
EBO	Euclidean CLIP	59.71	48.77	61.02	48.33	73.67	63.05	68.63	56.35
	Hyperbolic CLIP	**60.35**	**51.28**	**61.17**	**50.02**	**75.65**	**66.77**	**69.41**	**58.54**
MLS	Euclidean CLIP	79.32	87.69	63.73	74.45	68.64	79.34	60.23	71.60
	Hyperbolic CLIP	**80.27**	**88.75**	**66.03**	**75.60**	**69.70**	**80.69**	**63.01**	**73.23**
MDS	Euclidean CLIP	78.29	88.14	66.81	81.41	43.42	59.21	50.40	66.87
	Hyperbolic CLIP	**82.23**	**93.39**	**72.05**	**89.57**	**45.69**	**66.96**	**53.52**	**74.90**

Table 7: **Out-of-distribution detection** with the MDS method on Imagenet-1k with SSB-Hard and NINCO as near out-of-distribution datasets and iNaturalist, Textures and Openimage-O as far out-of-distribution datasets. Across different near and far and out-of-distribution datasets, hyperbolic CLIP is more robust than its Euclidean counterpart.

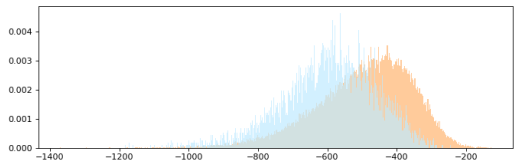
	Model	ImageNet-1k			
		FPR95 ↓	AUROC ↑	AUPR-in ↑	AUPR-out ↑
SSB-hard	Euclidean CLIP	85.44	62.58	61.39	61.38
	Hyperbolic CLIP	**80.73**	**66.79**	**66.02**	**66.09**
NINCO	Euclidean CLIP	75.56	71.04	94.83	21.27
	Hyperbolic CLIP	**70.10**	**77.32**	**95.96**	**30.38**
iNaturalist	Euclidean CLIP	62.79	71.55	92.75	27.64
	Hyperbolic CLIP	**45.50**	**84.42**	**96.23**	**46.20**
Textures	Euclidean CLIP	41.71	90.32	98.67	60.05
	Hyperbolic CLIP	**26.82**	**94.38**	**99.25**	**73.70**
Openimage-O	Euclidean CLIP	52.70	82.36	93.20	58.11
	Hyperbolic CLIP	**38.57**	**89.91**	**96.15**	**74.52**

Results. Table 6 shows AUROC scores for the three OOD methods on near- and far-OOD data. Across all techniques, hyperbolic embeddings consistently improve OOD detection over Euclidean counterparts in both standard and full spectrum settings. The Mahalanobis Distance Score (MDS) performs best overall, achieving 70.69% and 88.30% AUROC for near- and far-OOD with hyperbolic embeddings. These gains are significant compared to 66.81% and 81.41% for Euclidean MDS. Interestingly, this improvement comes despite projecting hyperbolic embeddings back into the Euclidean space required for computing Mahalanobis distance. The robustness to this transformation indicates the hyperbolic geometry provides intrinsic distribution-discriminating properties beyond the distance metric alone.

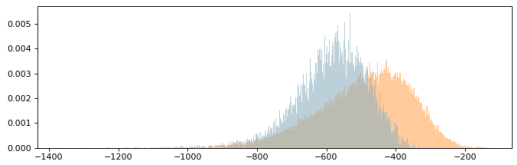
Table 7 breaks down ImageNet1k results by dataset for Mahalanobis scoring, providing per-distribution FPR95, AUROC AUPR-in, and AUPR-out. Significant OOD detection improvements from hyperbolic over Euclidean are observed consistently. These granular outcomes support the aggregate near/far-OOD conclusions from Table 6: hyperbolic geometry is better in out-of-distribution discrimination. The substantial gains demonstrate real-world viability for deploying hyperbolic vision-language models in open-domain applications.

Analysis. To investigate the OOD gains, Figure 5 plots distribution shifts for Mahalanobis scoring on near-OOD NINCO (left) and far-OOD iNaturalist (right). ID scores (orange) separate further from OOD (blue) with hyperbolic embeddings. The peaks flatten and variance increases, reducing overlap.

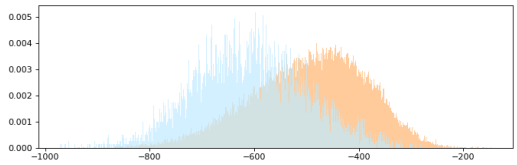
Figure 6 shows per-class FPR95 difference between hyperbolic and Euclidean CLIP embeddings on the NINCO near-OOD dataset. Images in NINCo's 64 fine-grained categories are visually similar to some ImageNet classes but belong to different distributions. According to Bitterwolf et al. (2023), images from the NINCO dataset from for instance the categories chicken quesadilla, spaghetti bolognese, and donut are most confusing to ImageNet classes burrito, carbonara, and bagel respectively. Remarkably, hyperbolic embeddings improve OOD detection over Euclidean on 54 out of 64 NINCO categories. Over half exhibit



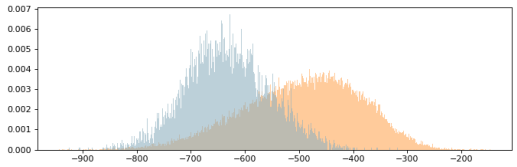
(a) Near-OOD: Ninco(Blue) vs ID(orange) for Euclidean CLIP



(b) Far-OOD: iNaturalist(Blue) vs ID(orange) for Euclidean CLIP



(c) Near-OOD: Ninco(Blue) vs ID(orange) for hyperbolic CLIP



(d) Far-OOD: iNaturalist(Blue) vs ID(orange) for hyperbolic CLIP

Figure 5: **Out-of-distribution detection**. This distribution plot presents the Mahalanobis score (x-axis) and frequency (y-axis) for Euclidean CLIP (top) and hyperbolic CLIP (bottom). The ID and OOD samples show less overlap in the plots for hyperbolic CLIP, which indicates better OOD detection performance.

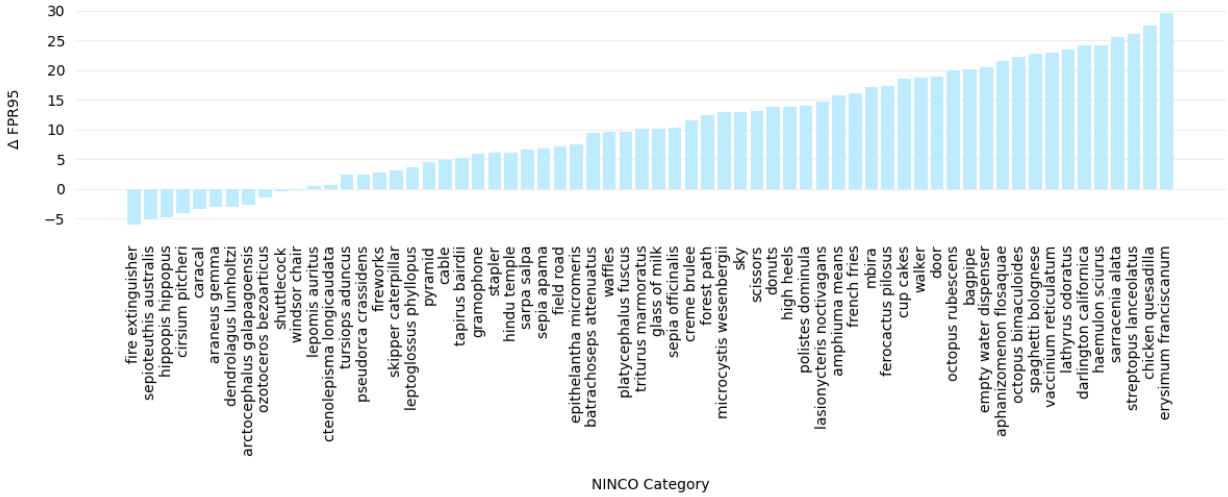


Figure 6: **Out-of-distribution detection** results for NINCO per-class: FPR95 difference between hyperbolic and Euclidean CLIP embeddings. A positive score means that hyperbolic embeddings are better for the considered category.

substantial gains above 10% FPR95. This granular analysis confirms and provides insight into the aggregated near-OOD conclusion.

5 Conclusion

Vision-language models have gained a lot of traction due to their broad applicability and strong performance on established down-stream tasks. In vision-language models, the de facto shared embedding space is Euclidean. Recent work shows that this default choice is not the only option and hyperbolic geometry provides a viable alternative with strong performance on often studied benchmarks such as retrieval and zero-shot recognition. In this work, we broaden the scope of the potential of hyperbolic vision-language models and demonstrate their power on their important but under-studied goals.

We find that hyperbolic vision-language models obtain strong spatial reasoning results compared to their Euclidean counterpart, confirming higher intrinsic awareness of visual compositionality. The consistent im-

provements over the Euclidean baseline indicates room for further advances, for instance, by developing specialized fine-tuning strategies targeting compositional tasks. Beyond explicit spatial relationships, analogous ideas may generalize to other latent forms of visual and linguistic compositionality. An investigation of the inductive biases introduced the hyperbolic geometry remains an intriguing direction for future work. Additionally, hyperbolic models exhibit enhanced reasoning amid ambiguity in text, images, and video. We argued a possible connection between improved ambiguity handling and the hierarchical structure of the embedding space, but further in-depth analysis is required to confirm this. Lastly, hyperbolic vision-language models outperform Euclidean vision-language models in out-of-distribution detection, which complements existing evidence of this advantage in unimodal settings. However majority of the OOD detection techniques require specific fine-tuning and this remains an open challenge for future work.

Overall, to make more progress in this field, fine-tuning hyperbolic vision-language models on more tasks and exposing such models to more data for pre-training are promising next steps. This could be done by exploring new constraints for the fine-tuning process, for example through new loss functions to complement the contrastive and entailment losses, or even different architectural modifications such as the use of hyperbolic layers. Due to its potential, we hope that this work can serve as a starting point for more hyperbolic vision-language related research in both the hyperbolic learning and vision-language communities.

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