Beyond Euclidean - Hyperbolic Representation Learning

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SDU

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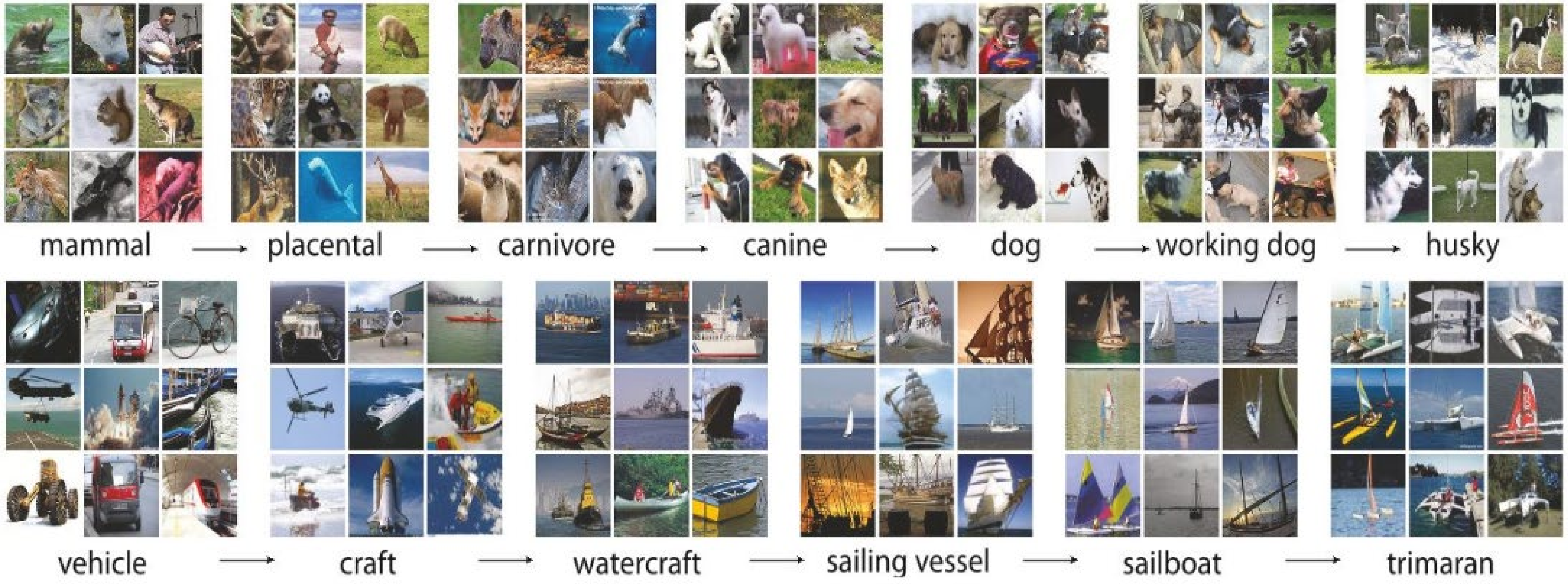

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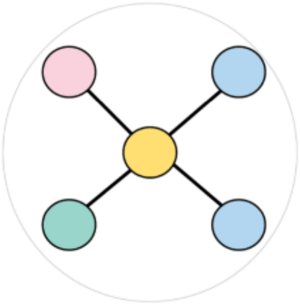

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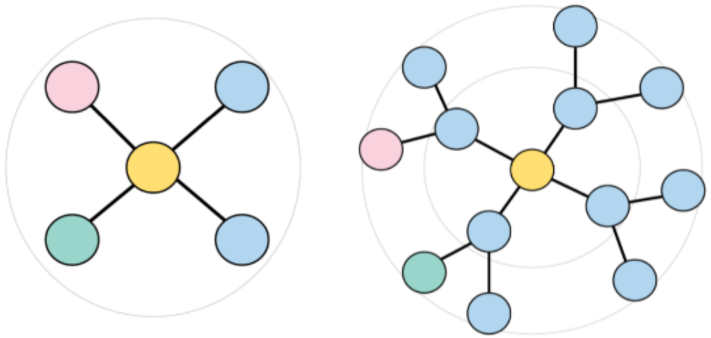

Constant Curvature Graph Convolutional Networks, Bachmann et al. 2020

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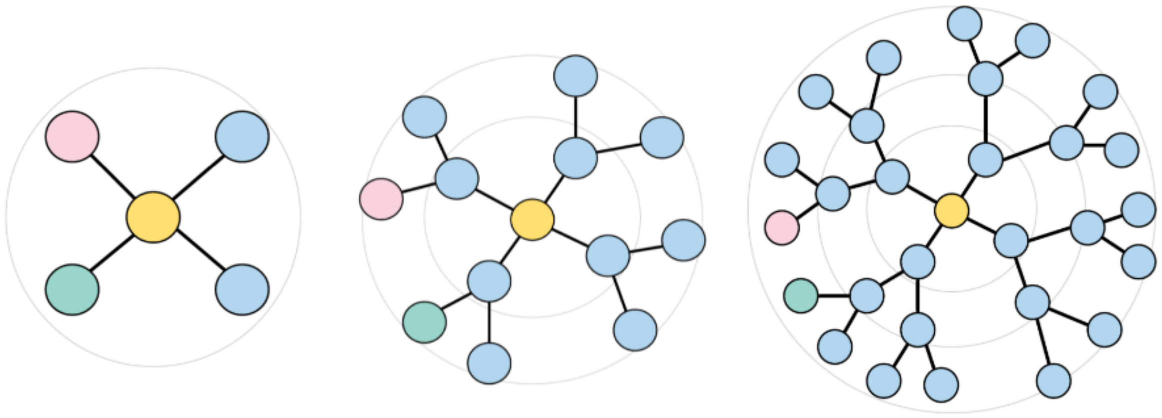

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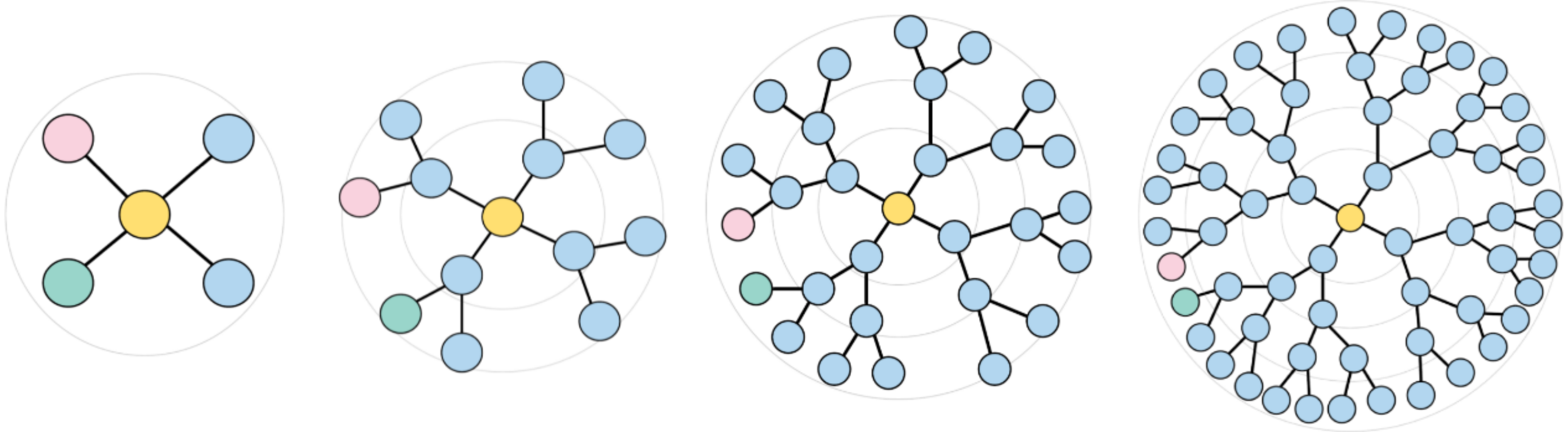

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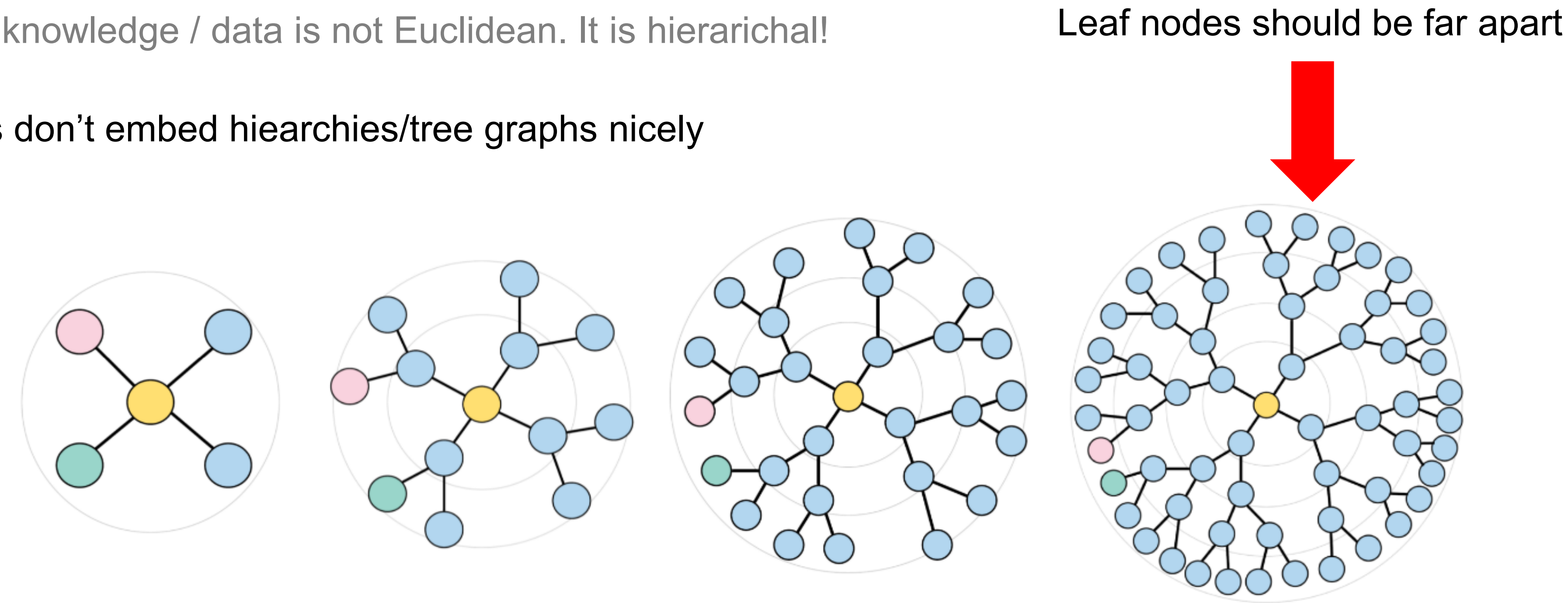

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Hyperbolic Geometry

Euclid’s postulates

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1. To draw a straight line from any point to any point.
2. To produce (extend) a finite straight line continuously in a straight line.
3. To describe a circle with any centre and distance (radius).
4. That all right angles are equal to one another.

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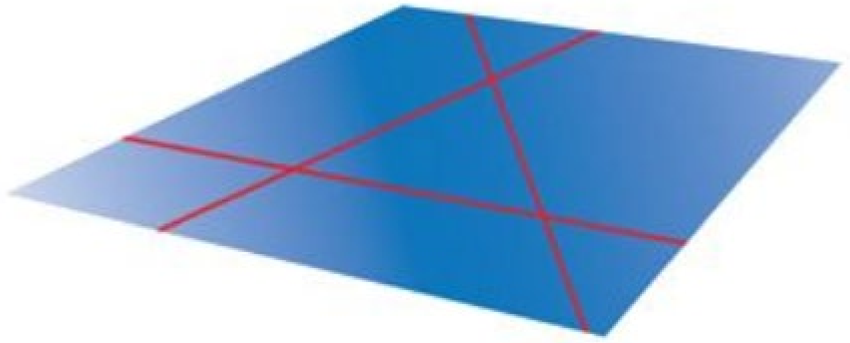
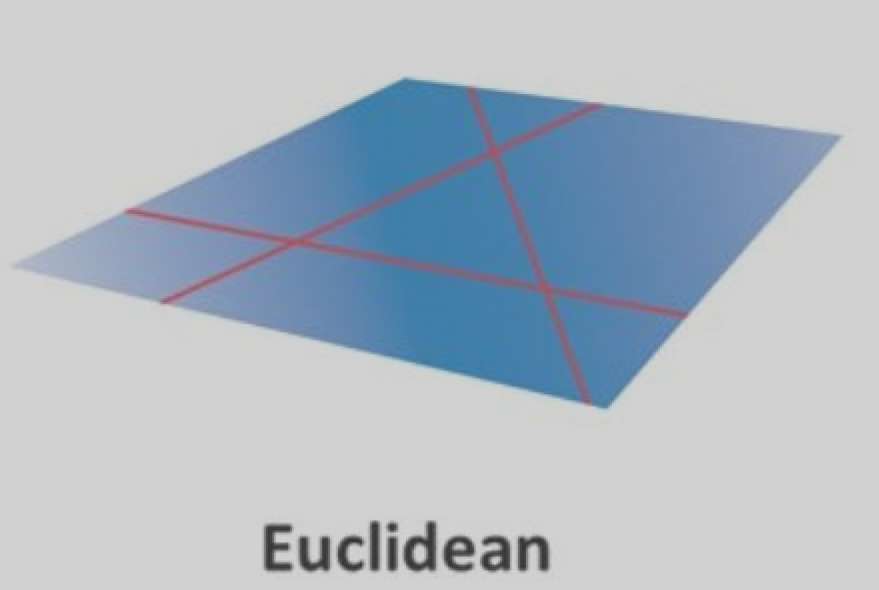
What if this is not true?

What does Non-Euclidean Geometry look like?



Euclidean

Constant 0 curvature
Exactly one set of parallel lines



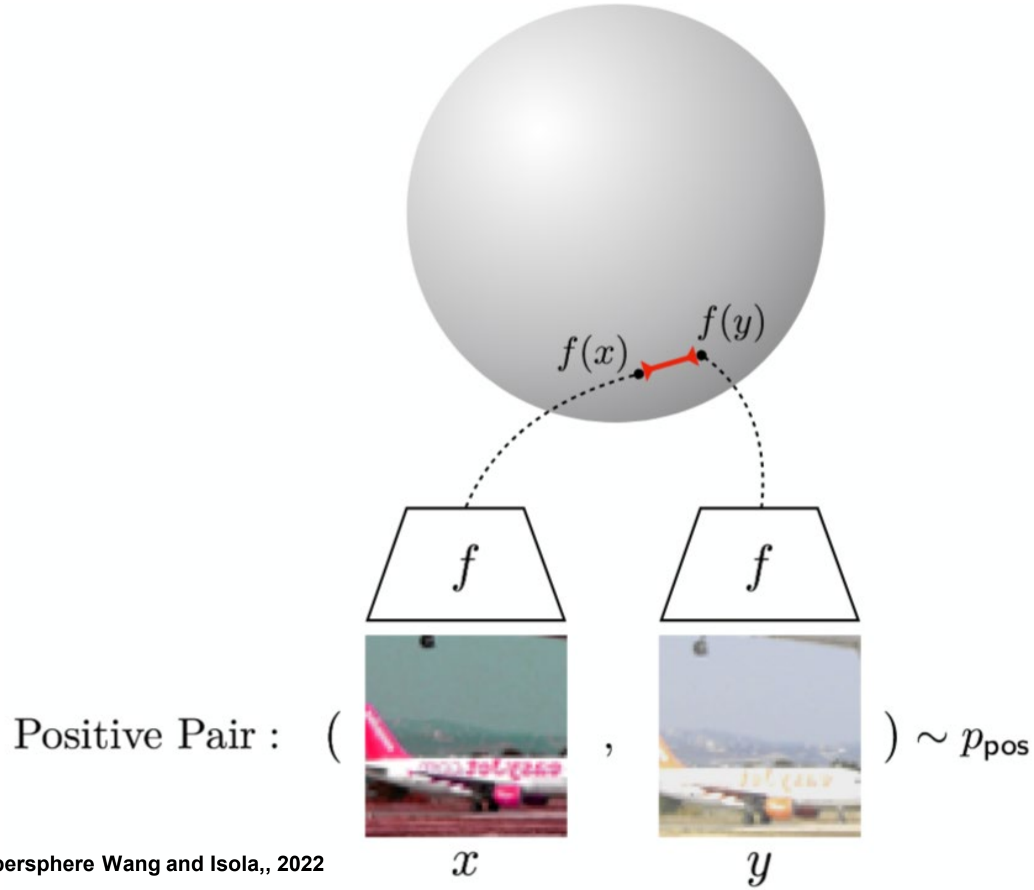
Constant 0 curvature
Exactly one set of parallel lines

Constant positive curvature
No sets of parallel lines

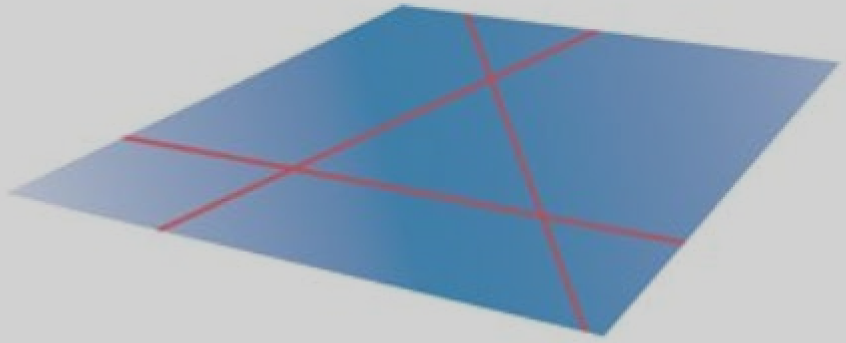
Contrastive Learning is Hyperspherical Learning

→ Contrastive Learning is often applied by measuring cosine similarity of unit vectors

→ All embeddings lie on a unit hypersphere



Understanding Contrastive Representation Learning through Alignment and Uniformity on the Hypersphere Wang and Isola,, 2022

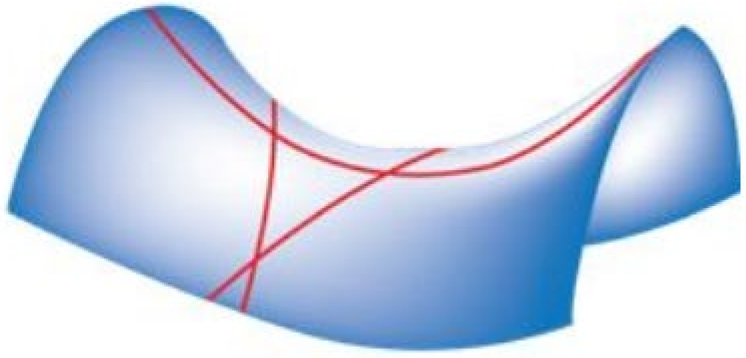


Euclidean

Constant 0 curvature
Exactly one set of parallel lines

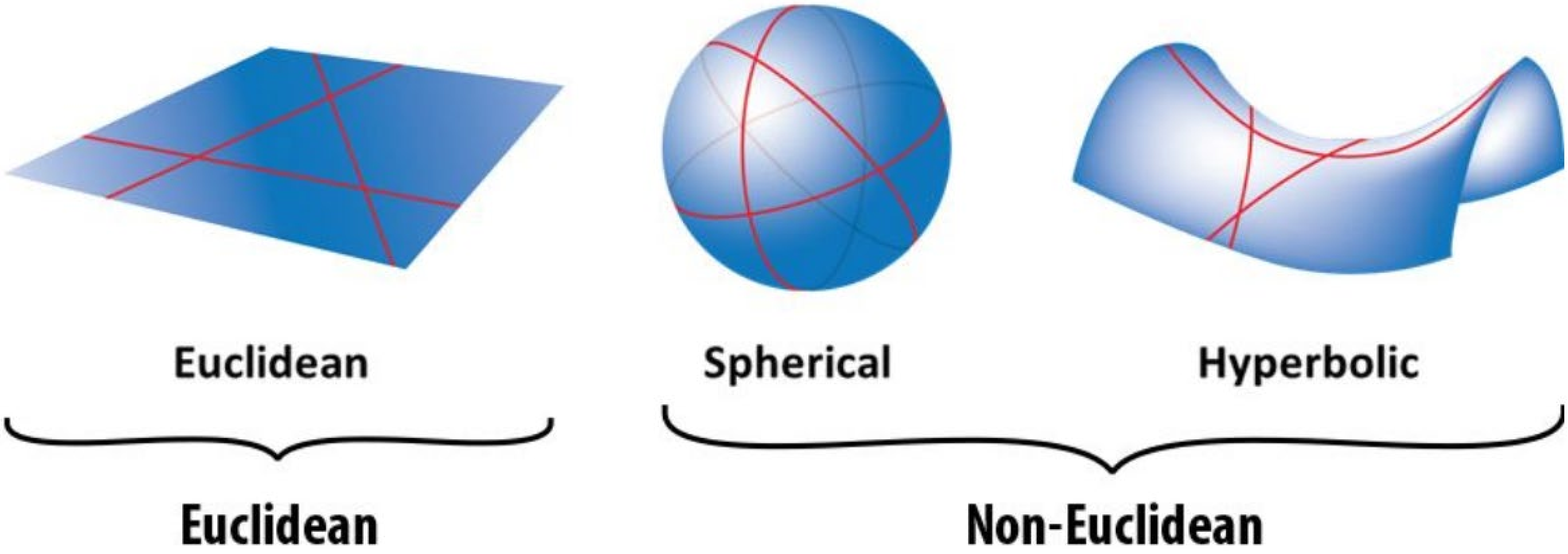
Spherical

Constant positive curvature
No sets of parallel lines



Hyperbolic

Constant negative curvature
Infinite sets of parallel lines


Euclidean
Spherical
Hyperbolic
Euclidean
Non-Euclidean

But why is Hyperbolic Geometry interesting?

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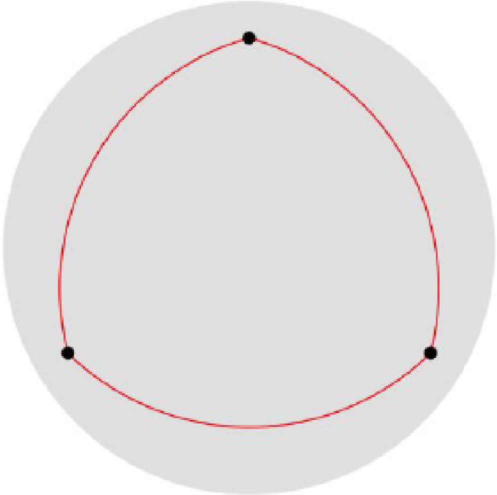
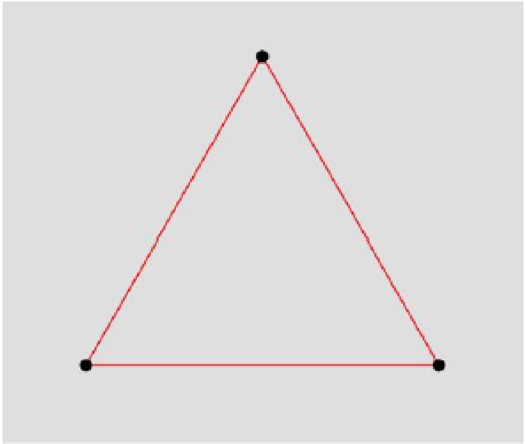
Spherical
($\kappa = +1$)



Euclidean
($\kappa = 0$)



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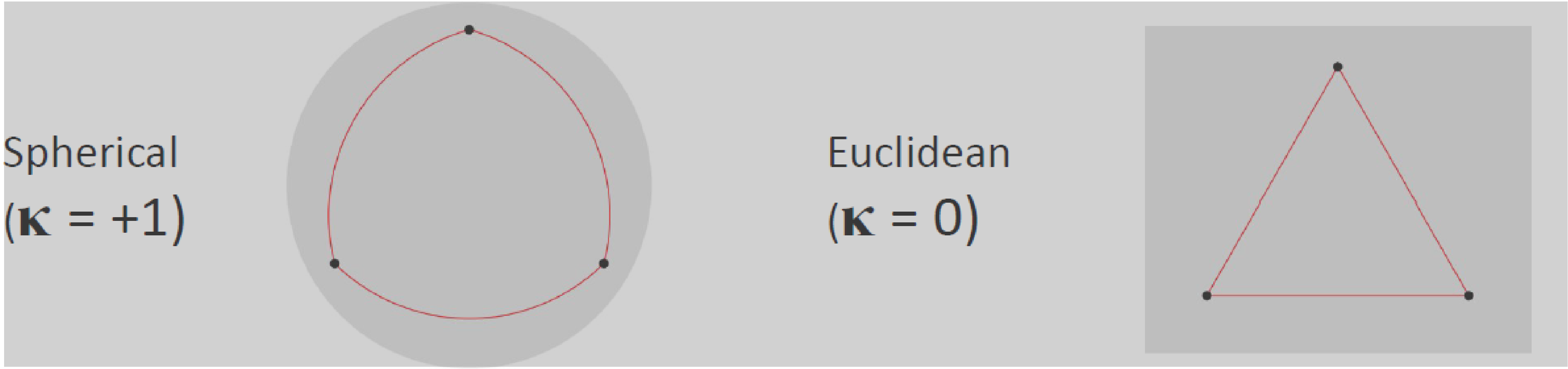
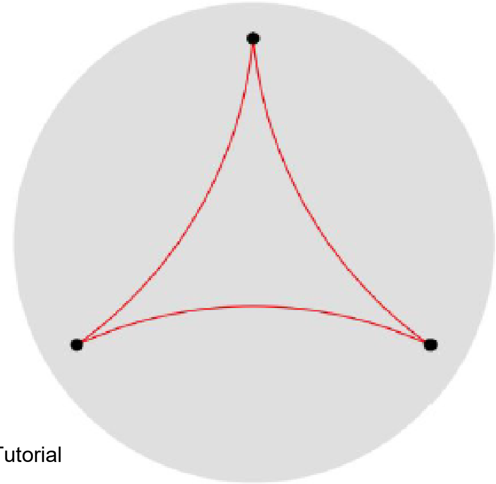


Hyperbolic
(κ = -1)



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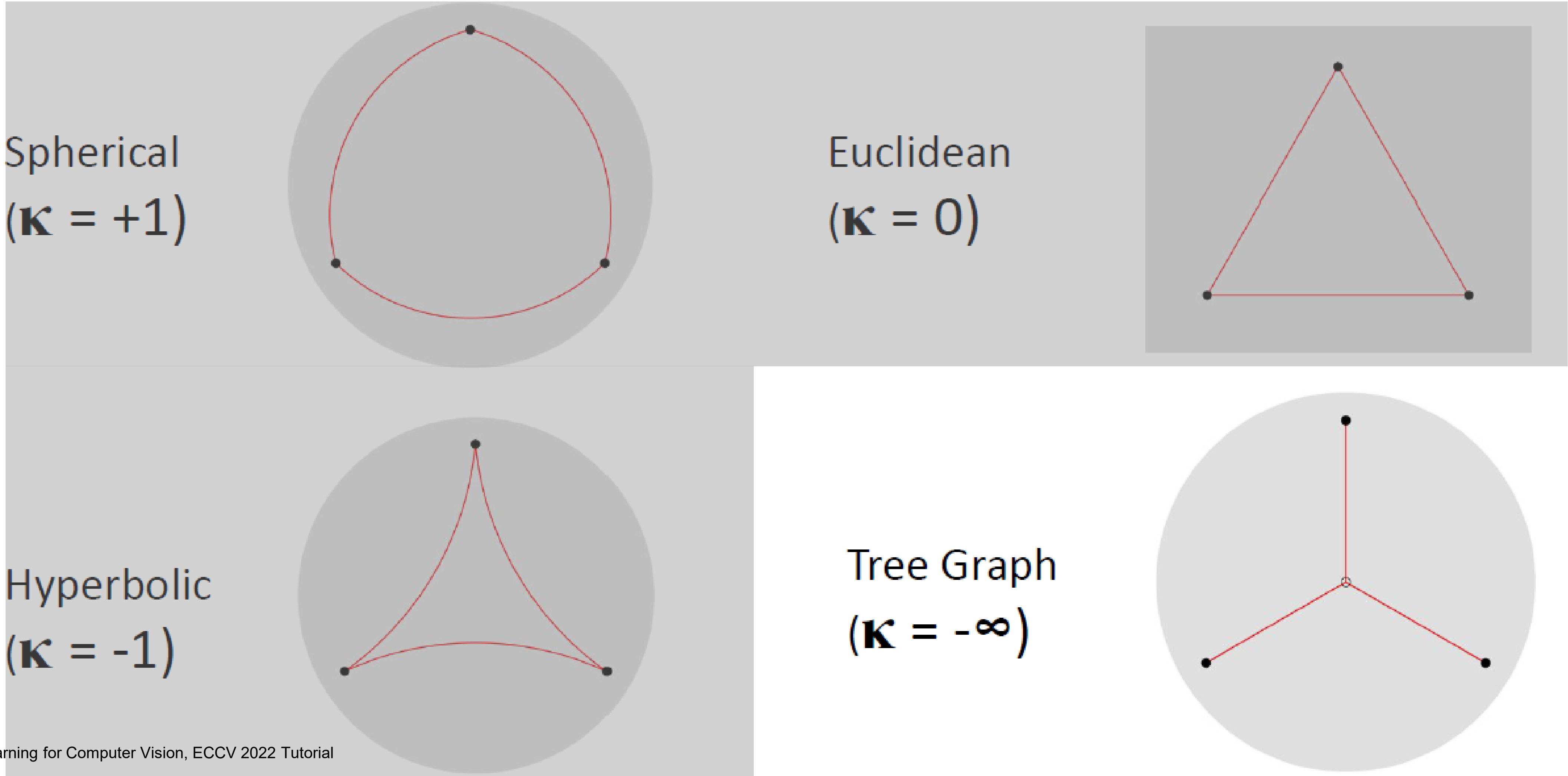

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→ There are several options!

→ The two most commonly used are:

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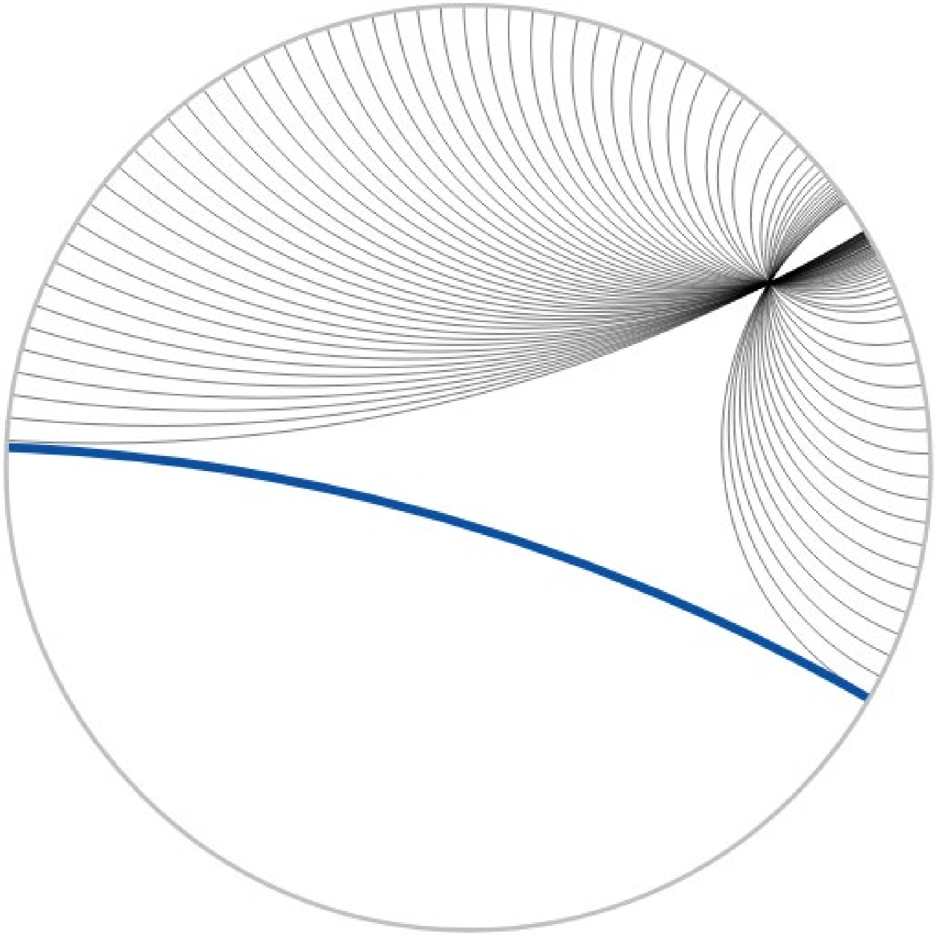
→ The **Poincaré disk model**
- → Conformal to Euclidean space
- → Restricted to a unit disc

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



How do we represent Hyperbolic spaces?

→ There are several options!

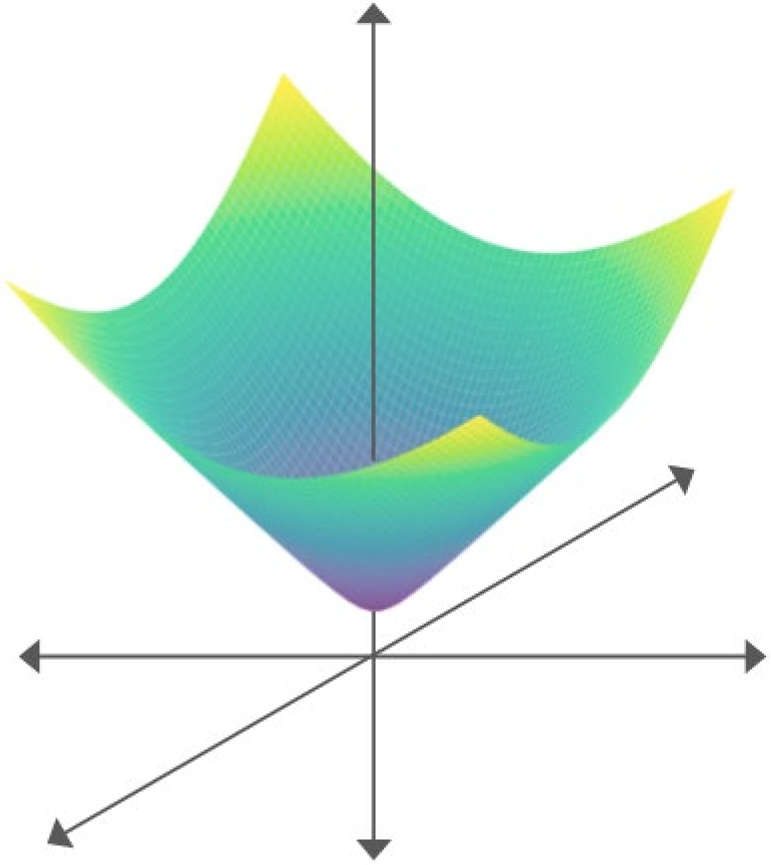
→ The two most commonly used are:

→ The **Poincaré disk model**

→ The **Hyperboloid / Lorentzian model**

  → Embeds a d-dimensional Euclidean space into a d+1 hyperbolic space

$$\mathbb{H}_d = \{x \in \mathbb{R}^{d+1} : x_0^2 - \left(x_1^2 + \cdots + x_d^2\right) = 1, x_0 > 0\}$$



Key concepts of Hyperbolic Geometry

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Distance: Measure how far two points and are from each other in hyperbolic space.

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Poincaré

$$d_{\mathbb{D}}(p,q) = \frac{1}{\sqrt{\kappa}} \operatorname{arcosh}\left(1 + \frac{2|p-q|^2}{(1-|p|^2)(1-|q|^2)}\right)$$

Lorentz

$$d_{\mathbb{H}}(x,y) = \frac{1}{\sqrt{\kappa}} \operatorname{arcosh}\left(x \circ y\right)$$

$$x \circ y = x_0 y_0 - (x_1 y_1 + \cdots + x_d y_d)$$

Key concepts of Hyperbolic Geometry

Distance: Measure how far two points and are from each other in hyperbolic space.

Geodesic arc: The shortest (=distance-minimizing) curve from x to y.

Geodesic: A geodesic arc, extended as far as possible.

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Poincaré

$$\exp_x^\kappa(v) = x \oplus_\kappa \left(\tanh\left(\frac{\sqrt{\kappa}\,||v||}{1-\kappa||x||^2}\right) \frac{v}{\sqrt{\kappa}\,||v||} \right)$$

Lorentz

$$\exp_x^\kappa(v) = \cosh\left(\sqrt{\kappa}\,||v||_L\right) x + \frac{\sinh\left(\sqrt{\kappa}\,||v||_L\right)}{\sqrt{\kappa}\,||v||_L} v$$

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This is how you map from Euclidean spaces to Hyperbolic space!

Hyperbolic Representation Learning

So what has been done?

Hyperbolic Action Recognition

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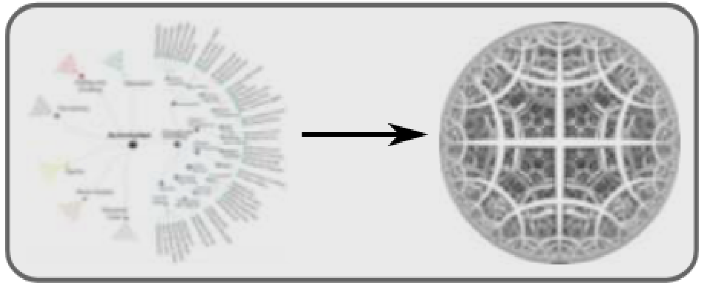
Hyperbolic action embedding



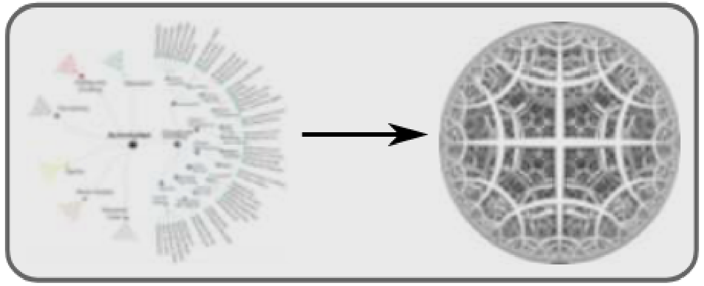
Action hierarchy

Discriminative hyperbolic embedding

Searching for Actions on the Hyperbole, Long et al., 2020

Hyperbolic Action Recognition

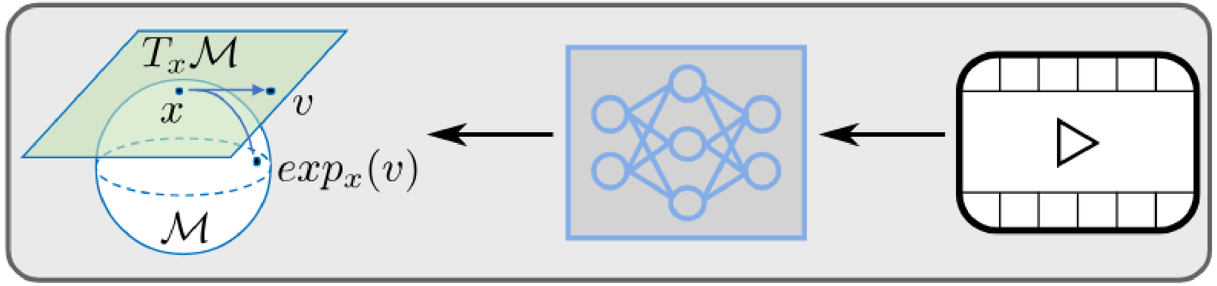
Hyperbolic action embedding



Action hierarchy

Discriminative hyperbolic embedding

Hyperbolic video embedding



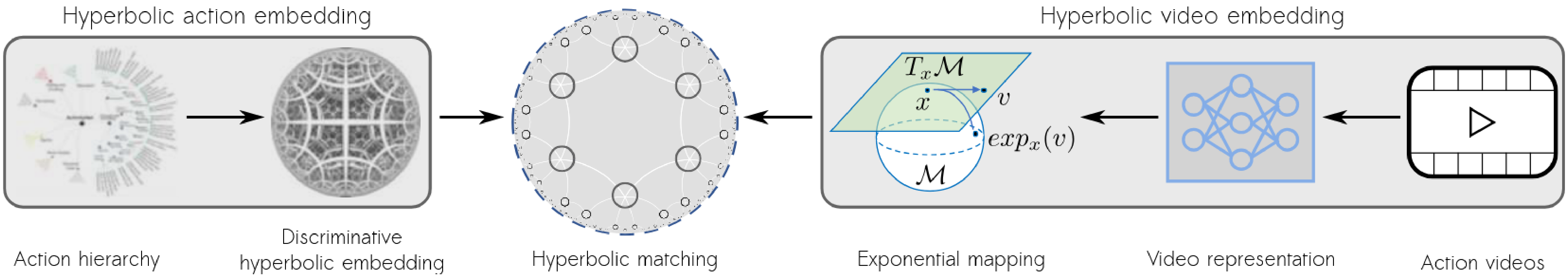
Exponential mapping

Video representation

Action videos

Searching for Actions on the Hyperbole, Long et al., 2020

Hyperbolic Action Recognition



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Hyperbolic Image Segmentations

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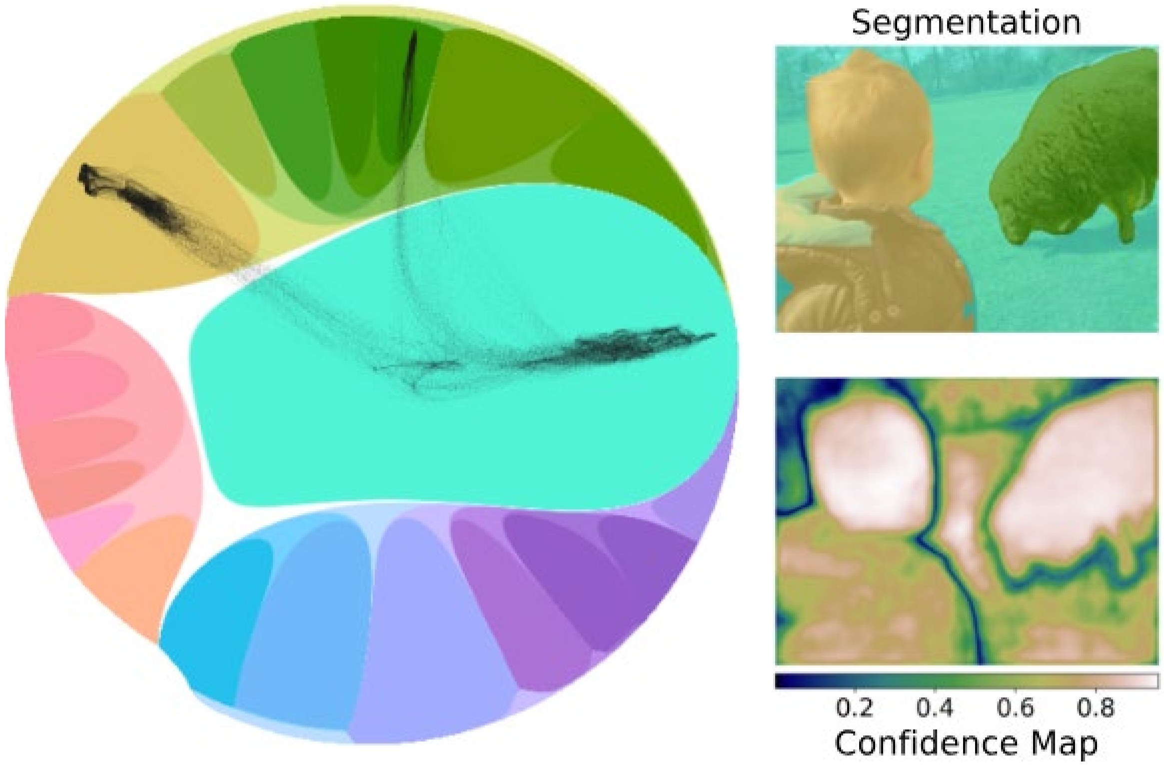

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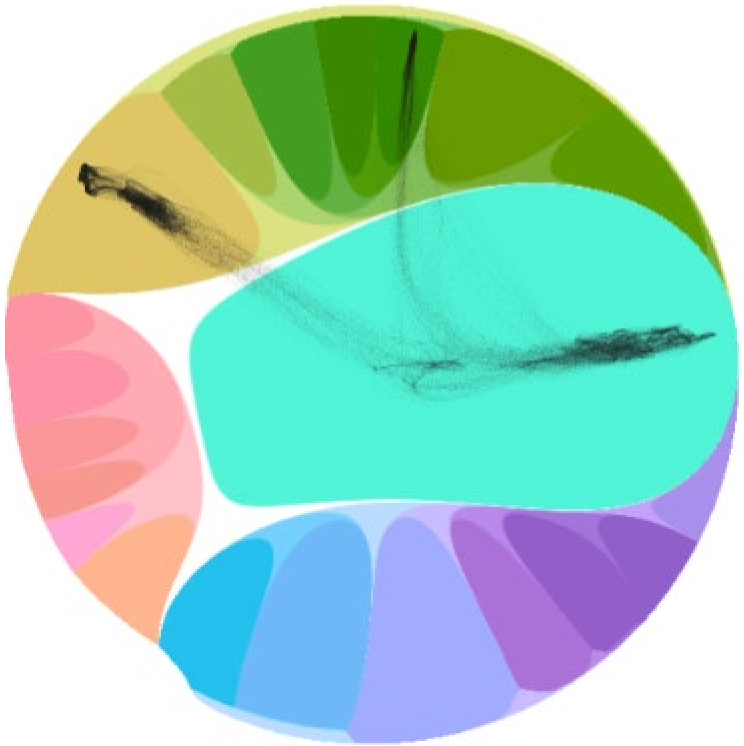

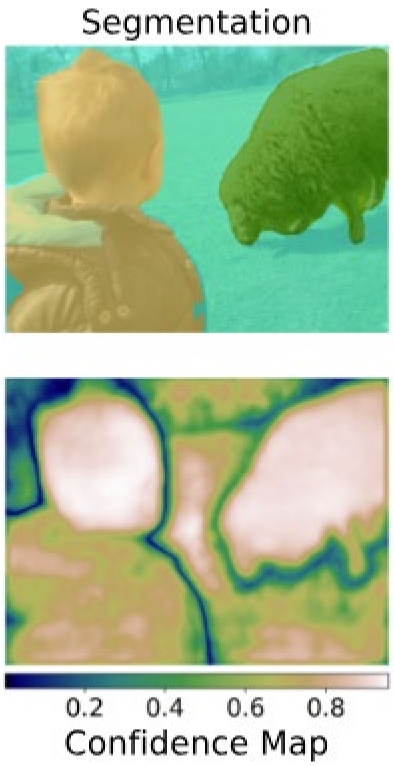

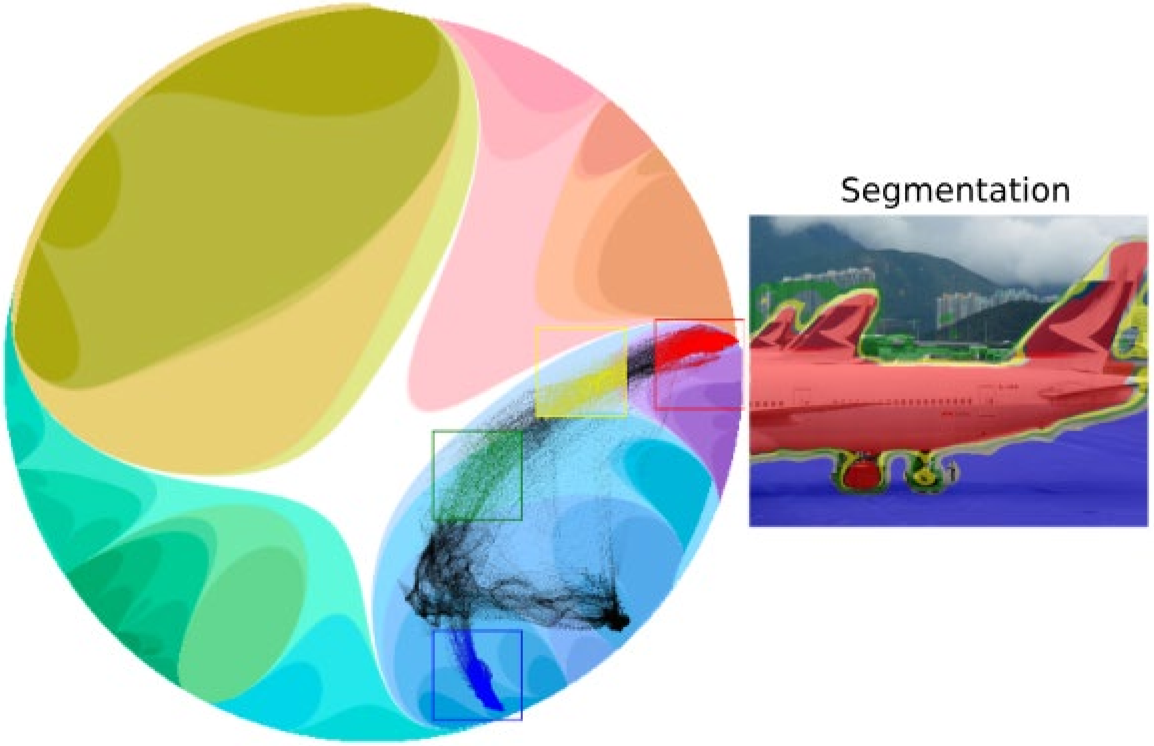

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Hyperbolic Image-Text Embeddings

Hyperbolic Image-Text Representations

Karan Desai [1] Maximilian Nickel [2] Tanmay Rajpurohit [3] Justin Johnson [1 2] Ramakrishna Vedantam [4]

Abstract

Visual and linguistic concepts naturally organize themselves in a hierarchy, where a textual concept "dog" entails all images that contain dogs. Despite being intuitive, current large-scale vision and language models such as CLIP (Radford et al., 2021) do not explicitly capture such hierarchy. We propose MERU, a contrastive model that yields hyperbolic representations of images and text. Hyperbolic spaces have suitable geometric properties to embed tree-like data, so MERU can better capture the underlying hierarchy in image-text datasets. Our results show that MERU learns a highly interpretable and structured representation space while being competitive with CLIP's performance on standard multi-modal tasks like image classification and image-text retrieval. Our code and models are available at: https://github.com/facebookresearch/meru

Figure 1. **Hyperbolic image-text representations. Left:** Images and text depict *concepts* and can be jointly viewed in a *visual-semantic hierarchy*, wherein text *'exhausted doggo'* is more generic than an image (which might have more details like a cat or snow). Our method MERU embeds images and text in a hyperbolic space that is well-suited to embed tree-like data. **Right:** Representation manifolds of CLIP (*hypersphere*) and MERU (*hyperboloid*) illustrated in 3D. MERU assumes the origin to represent the *most generic concept*, and embeds text closer to the origin than images.

1. Introduction

Visual-semantic hierarchy. It is commonly said that *'an image is worth a thousand words'* – consequently, images contain a lot more information than the sentences which typically describe them. For example, given the middle image in Figure 1 one might describe it as *'a cat and a dog playing in the street'* or with a less specific sentence like *'exhausted doggo'* or *'so cute <3'*. These are not merely diverse descriptions but contain varying levels of detail about the underlying semantic contents of the image.

As humans, we can reason about the relative detail in each caption, and can organize such concepts into a meaningful visual-semantic hierarchy (Vendrov et al., 2016), namely, *'exhausted doggo'* → *'a cat and a dog playing in the street'* → (Figure 1 middle image). Providing multimodal models access to this inductive bias about vision and language has the potential to improve generalization (Radford et al., 2021), interpretability (Selvaraju et al., 2017) and enable better exploratory data analysis of large-scale datasets (Radford et al., 2021; Schuhmann et al., 2022).

Vision-language representation learning. Approaches such as CLIP (Radford et al., 2021) and ALIGN (Jia et al., 2021) have catalyzed a lot of recent progress in computer vision by showing that Transformer-based (Vaswani et al., 2017) models trained using large amounts of image-text data from the internet can yield transferable representations, and such models can perform *zero-shot* recognition and retrieval using natural language queries. All these models represent images and text as vectors in a high-dimensional Euclidean, affine space and normalize the embeddings to unit L^2 norm. However, such a choice of geometry can find it hard to capture the visual-semantic hierarchy.

An affine Euclidean space treats all embedded points in the same manner, with the same distance metric being applied to all points (Murphy, 2013). Conceptually, this can cause issues when modeling hierarchies – a *generic* concept (closer to the *root node* of the hierarchy) is close to many other concepts compared to a *specific* concept (which is only close to its immediate neighbors). Thus, a Euclidean space can find it hard to pack all the images that say a generic

KD and Rama did this work while at Meta. [1]University of Michigan [2]Meta AI [3]Independent Researcher [4]New York University. Correspondence to: Karan Desai <kdexd@umich.edu>.

Proceedings of the 40th International Conference on Machine Learning, Honolulu, Hawaii, USA. PMLR 202, 2023.

Hyperbolic Image-Text Representations, Desai et al., 2023

Hyperbolic Image-Text Embeddings

→ Proposes a CLIP style setup in Hyperbolic space

→ Uses the Lorentzian space due to *numerical instabilities* in Poincaré space

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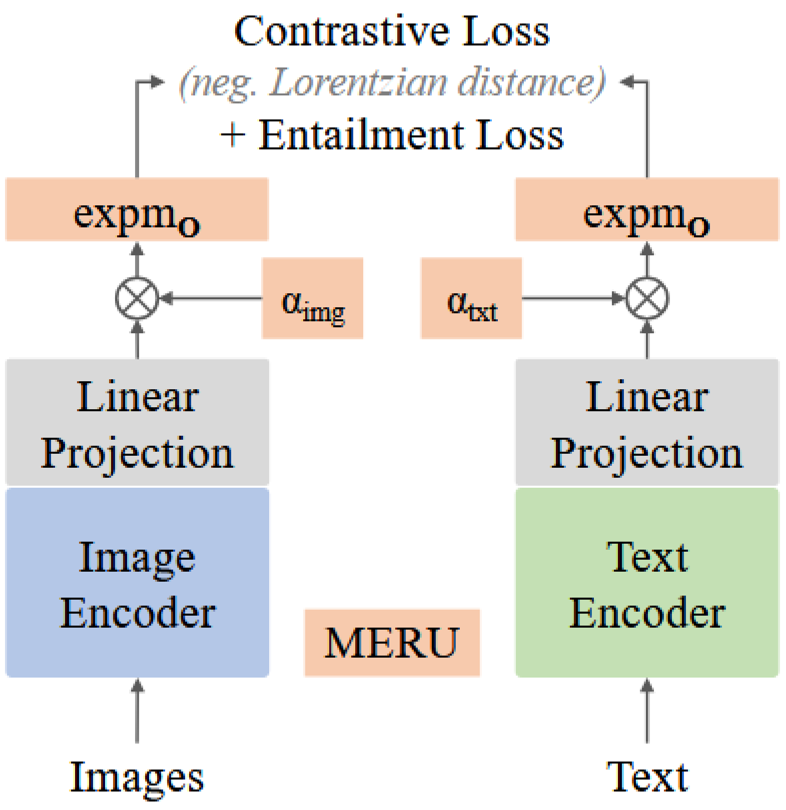

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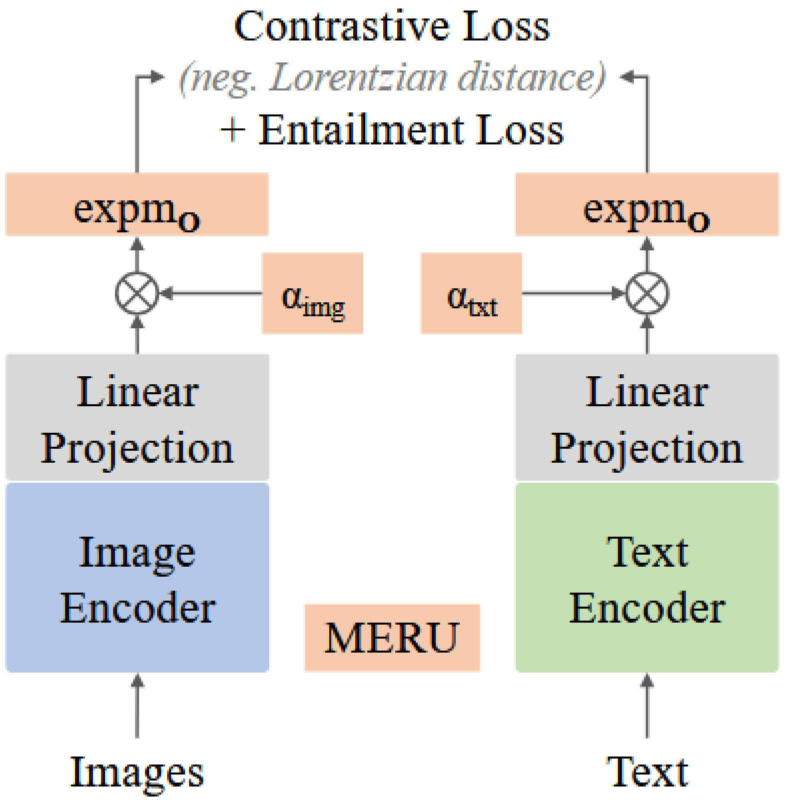
→ Two losses: Contrastive and *Entailment loss*



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→ However, uses Lorentzian distance instead of cosine similarity

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→ Lorentzian inner product: $\langle x, y \rangle_L = x \circ y = x_0 y_0 - (x_1 y_1 + \cdots + x_d y_d)$

→ Lorentzian distance: $d_L(x, y) = \sqrt{\frac{1}{c}} \cosh^{-1}(c \langle x, y \rangle_L)$

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Minimize distance for positive pairs
Maximize distance for negative pairs

Entailment Loss

→ Key concept: Fine-grained concepts should be embedded *deeper* into the space

Hyperbolic Image-Text Representations, Desai et al., 2023

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→ Enforced by making sure the fine-grained concept is within the *entailment cone* of a parent concept

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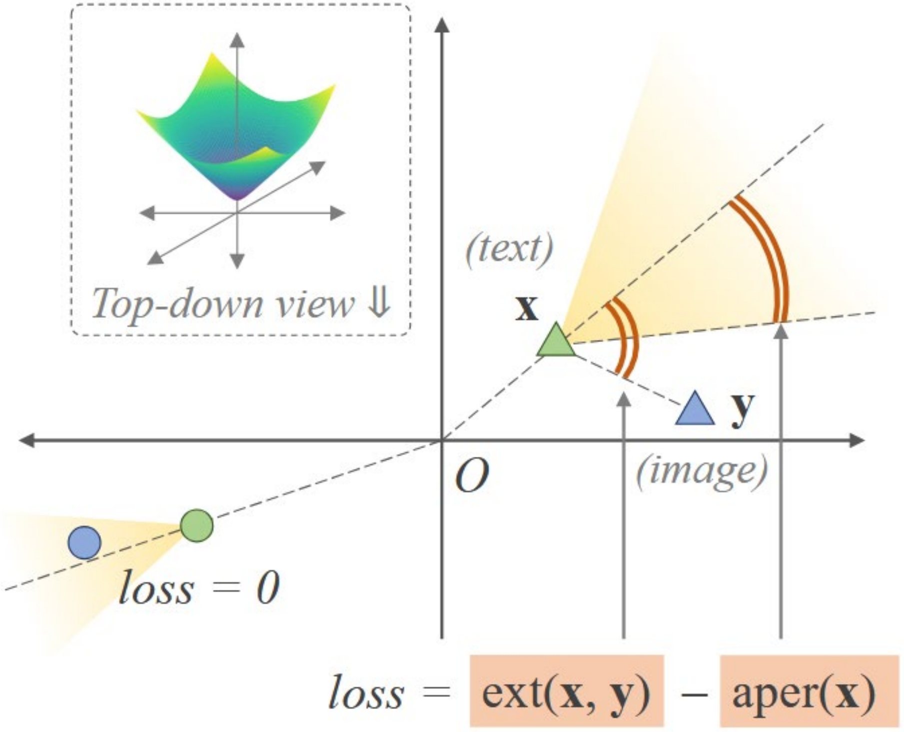

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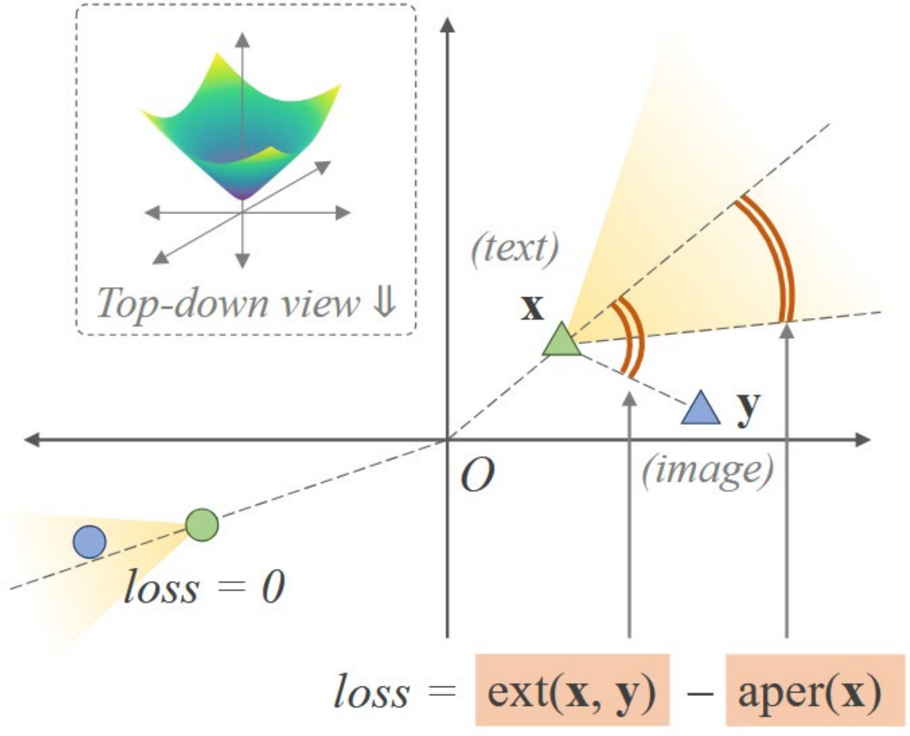
Angle between parent and child nodes



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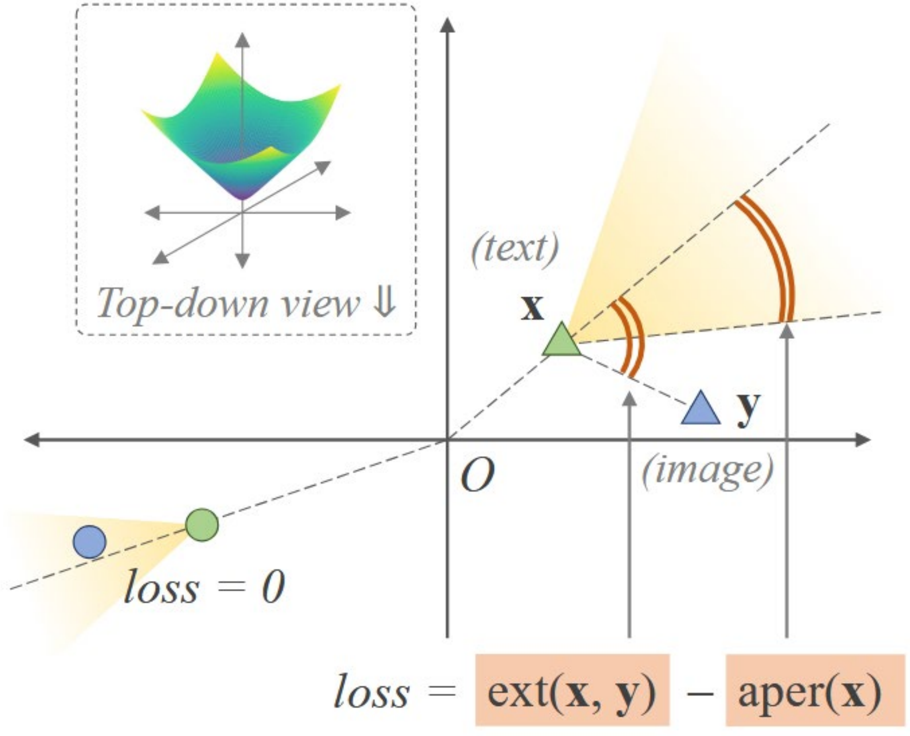
Angle between parent and child nodes

Entailment cone of parent node



Hyperbolic Image-Text Representations, Desai et al., 2023

Entailment Loss Effect

Entailment Loss Effect

MERU	CLIP
brooklyn bridge	*photo of brooklyn bridge, new york*
new york city	*new york city*
city	*new york*
outdoors	↓
day	↓
[ROOT]	[ROOT]

Hyperbolic Image-Text Representations, Desai et al., 2023

Entailment Loss Effect

MERU	CLIP
brooklyn bridge	*photo of brooklyn bridge, new york*
new york city	*new york city*
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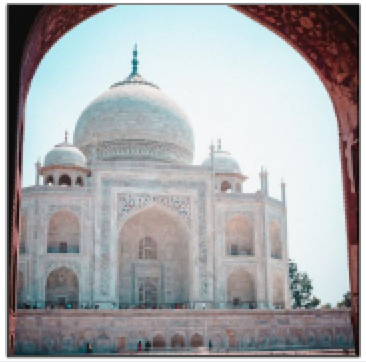
day	↓
[ROOT]	[ROOT]

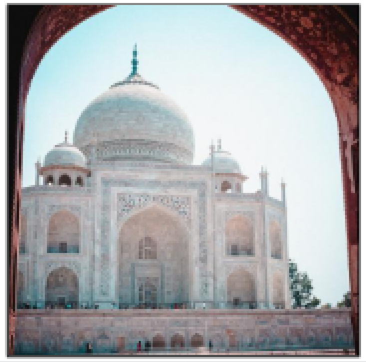


MERU	CLIP
taj mahal	*taj mahal through an arch*
monument	*travel*
architecture	*inspiration*
travel	↓
day	↓
[ROOT]	[ROOT]

Hyperbolic Image-Text Representations, Desai et al., 2023

Entailment Loss Effect

MERU	CLIP
brooklyn bridge	*photo of brooklyn bridge, new york*
new york city	*new york city*
city	*new york*
outdoors	↓
day	↓
[ROOT]	[ROOT]



MERU	CLIP
taj mahal	*taj mahal through an arch*
monument	*travel*
architecture	*inspiration*
travel	↓
day	↓
[ROOT]	[ROOT]

MERU	CLIP
sydney opera house	*sydney opera house*
opera house	*opera house*
holiday	*gift*
day	*beauty*
[ROOT]	[ROOT]

Hyperbolic Image-Text Representations, Desai et al., 2023

Stacked Entailment Loss

How is this used for Taxonomic Classification?

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→ Assume paired multi-modal data, with expert textual labels

→ The textual labels contains the full hierarchy!

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Diptera Psychodidae Psychoda Psychoda grisescens

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→ Assume paired multi-modal data, with expert textual labels

→ The textual labels contains the full hierarchy!

Diptera	Psychodidae	Psychoda	Psychoda grisescens
Order	***Family***	***Genus***	***Species***

Stacked Entailment Loss

Hyperbolic Multimodal Representation Learning for Biological Taxonomies

ZeMing Gong[1] Chuanqi Tang[1] Xiaoliang Huo[1] Nicholas Pellegrino[2]
Austin T. Wang[1] Graham W. Taylor[3,4] Angel X. Chang[1,5]
Scott C. Lowe[3†] Joakim Bruslund Haurum[6†]
Simon Fraser University[1] University of Waterloo[2] Vector Institute[3]
University of Guelph[4] Alberta Machine Intelligence Institute (Amii)[5] Aalborg University[6]
{zmgong, ctal56, xiaoliang_huo, atw7, angelx}@sfu.ca,{nicholas.pellegrino}@uwaterloo.ca,
{gwtaylor}@uoguelph.ca {scott.lowe}@vectorinstitute.ai, {joha}@create.aau.dk

Abstract

Taxonomic classification in biodiversity research involves organizing biological specimens into structured hierarchies based on evidence, which can come from multiple modalities such as images and genetic information. We investigated whether hyperbolic networks provide a better embedding space for such hierarchical models. Our method embeds multimodal inputs into a shared hyperbolic space using contrastive and novel entailment-based objectives. Experiments on the BIOSCAN-1M dataset show that hyperbolic embedding gs achieve competitive performance with Euclidean baselines, and outperforms all other models on unseen species classification using DNA barcodes. However, fine-grained classification and open-world generalization remain challenging. This framework offers a scalable and structure-aware foundation for biodiversity modelling, with potential applications to species discovery, ecological monitoring, and conservation efforts.

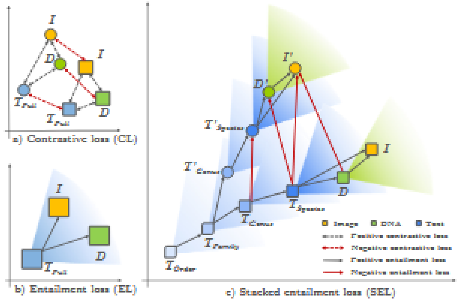

Figure 1. (a) **Contrastive loss**: instance-level alignment between modalities. (b) **Entailment loss**: enforces hierarchy within the text modality using entailment cones. (c) **Stacked entailment loss**: combines EL and cross-modal constraints by aligning image and DNA embeddings to multiple levels of the text hierarchy.

1. Introduction

Taxonomic classification is essential for monitoring and mitigating biodiversity loss, requiring accurate identification of specimens across diverse ecosystems. DNA barcodes [1, 7] provide a way to classify specimens to known taxa or identify them as novel to science, but classification to the species level remains challenging when barcodes are unavailable. To tackle this, Gong et al. [5] showed that using contrastive learning to align DNA barcode embeddings to image embeddings can improve classification at the species level even when only using images as input at inference.

However, a key limitation of CLIBD [5] and other recent biodiversity-focused multimodal methods [17] is that the methods do not utilize the known taxonomic hierarchy of the input data. To address this, we explore whether embeddings in hyperbolic space can better capture the hierarchical structure of taxonomic relationships, enabling better fine-grained classification. While training, the model takes inputs from multiple modalities—DNA barcodes, specimen images, and hierarchical taxonomic labels—and co-aligns their embeddings into a shared hyperbolic space to promote taxonomic alignment across modalities.

Our experimental results show that our hyperbolic multimodal learning framework achieves strong performance in taxonomic classification and retrieval, especially at higher taxonomic ranks. The approach consistently matches or outperforms Euclidean baselines and better preserves the hierarchical relationships among modalities. However, all methods—including ours—face challenges in fine-grained species classification, particularly for previously unseen taxa. These results highlight both the potential of hyperbolic learning for hierarchical biological data, and the ongoing difficulty of open-world classification for biodiversity.

Stacked Entailment Loss

→ Core ideas:

1. Enforce entailment loss between consecutive taxonomic ranks
2. Also apply a negative entailment loss

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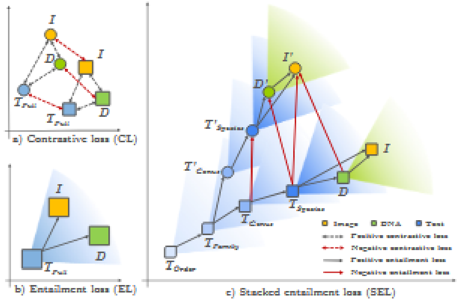

Figure 1. (a) **Contrastive loss**: instance-level alignment between modalities. (b) **Entailment loss**: enforces hierarchy within the text modality using entailment cones. (c) **Stacked entailment loss**: combines EL and cross-modal constraints by aligning image and DNA embeddings to multiple levels of the text hierarchy.

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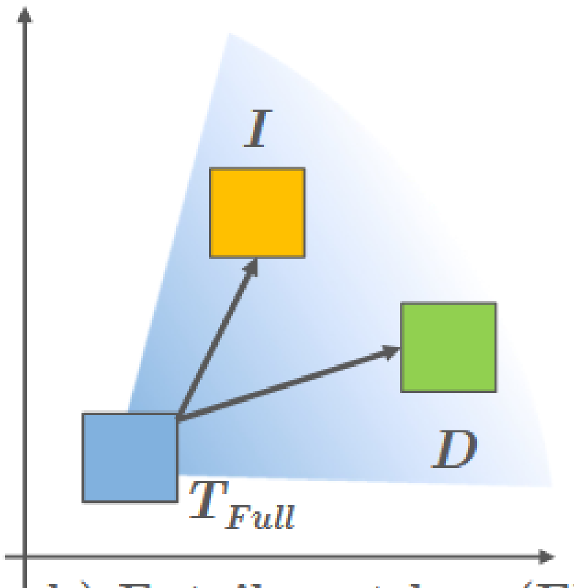
1. Enforce entailment loss between consecutive taxonomic ranks
2. Also apply a negative entailment loss



b) Entailment loss (EL)

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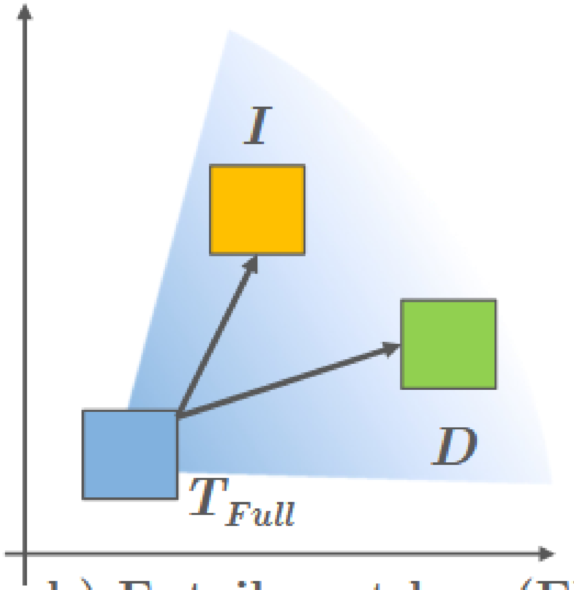

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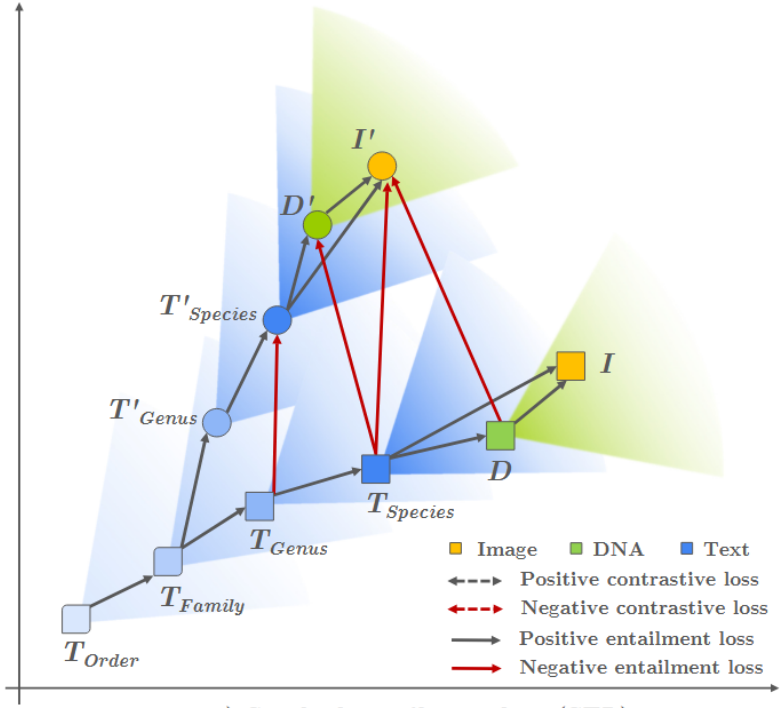

c) Stacked entailment loss (SEL)

Postive and Negative Entailment loss:

$$L_{\text{ent}}^{+} = \frac{1}{|\mathcal{P}|} \sum_{(i,j)\in\mathcal{P}} \max\left(0,\ \text{ext}(x_i, y_j) - \text{aper}(x_i)\right)$$

$$L_{\text{ent}}^{-} = \frac{1}{|\mathcal{N}|} \sum_{(i,j)\in\mathcal{N}} \max\left(0,\ \text{aper}(x_i) - \text{ext}(x_i, y_j) + m\right)$$

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$$L_{\text{ent}} = {}^{1}\!/_{2}\left(L_{\text{ent}}^{+} + L_{\text{ent}}^{-}\right)$$

Inter- and Intra-modal Entailment Losses

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$$L_{\text{SEL-intra}} = \frac{1}{\sum_{r=2}^{R} \mathbb{1}_r} \sum_{r=2}^{R} \mathbb{1}_r \times L_{\text{ent}}(T_r, T_{r-1})$$

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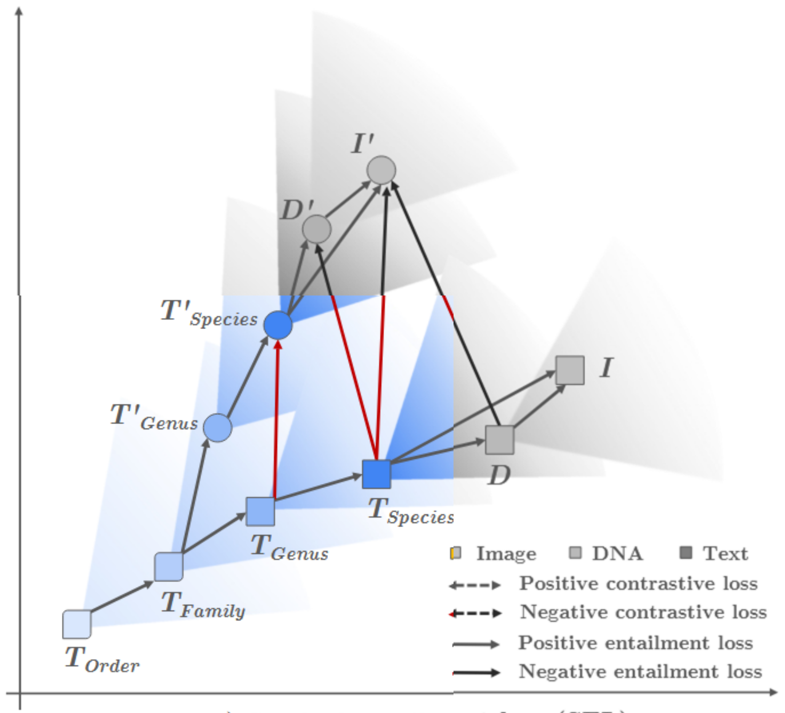

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$$L_{\text{SEL-inter}} = \frac{1}{3}\Big(L_{\text{ent}}(I, T_{R'}) + L_{\text{ent}}(D, T_{R'}) + L_{\text{ent}}(I, D)\Big)$$

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Deepest annotated taxonomic rank

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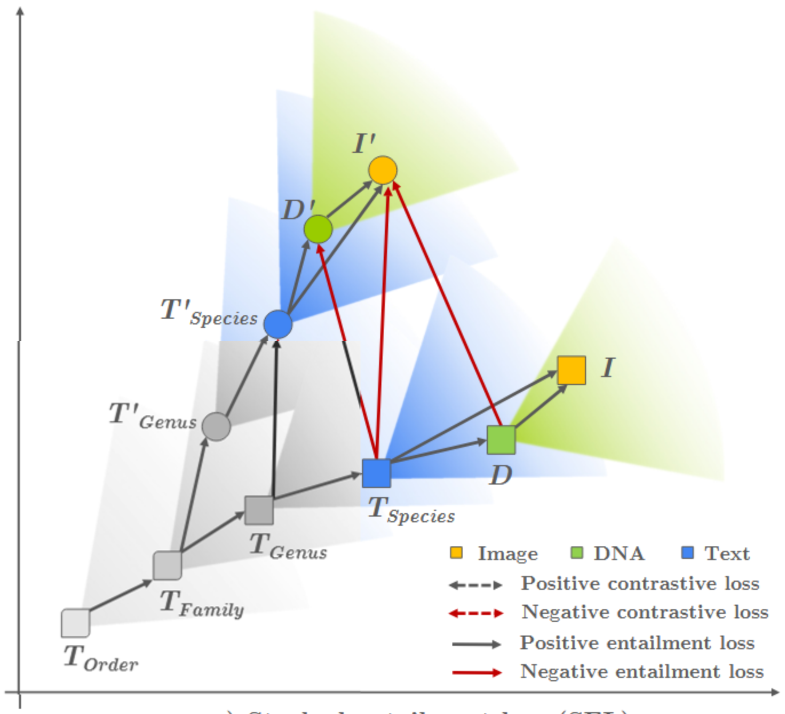

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Inter- and Intra-modal Entailment Losses

$$L_{\text{SEL-intra}} = \frac{1}{\sum_{r=2}^{R} \mathbb{1}_r} \sum_{r=2}^{R} \mathbb{1}_r \times L_{\text{ent}}(T_r, T_{r-1})$$

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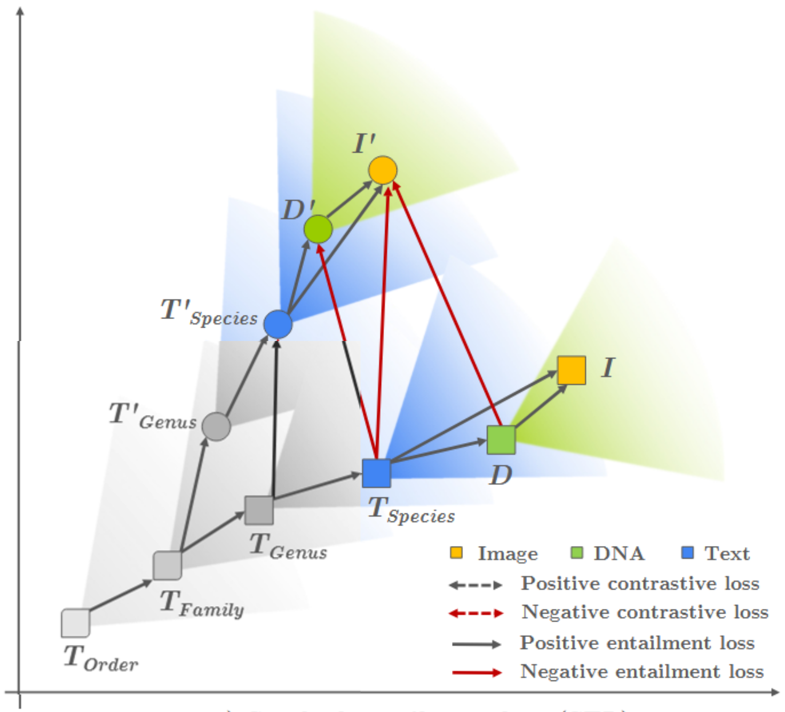
$$L_{\text{SEL}} = L_{\text{SEL-intra}} + L_{\text{SEL-inter}}$$



c) Stacked entailment loss (SEL)

Preliminary Results

BIOSCAN-1M Results

					DNA-to-DNA			Image-to-Image			Image-to-DNA		
Rank	Method	EL config.	Full Text	Space	Seen	Unseen	H.M.	Seen	Unseen	H.M.	Seen	Unseen	H.M.
Order	CLIBD	–	✓	$\mathbb{R}^n$	**89.1**	87.8	88.4	**99.5**	**66.4**	**79.6**	**98.7**	**49.5**	**65.9**
	CL	–	✓	$\mathbb{H}^n_L$	**89.1**	85.6	87.3	98.5	61.2	75.5	89.1	47.8	62.2
	EL+CL	Pos.	✓	$\mathbb{H}^n_L$	88.6	86.5	87.5	98.6	56.9	72.1	77.8	48.4	59.7
	SEL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	88.4	**90.8**	**89.6**	79.3	62.3	69.8	**98.7**	<u>48.9</u>	<u>65.4</u>
	SEL+CL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	88.7	86.3	87.5	<u>99.4</u>	<u>65.9</u>	<u>79.3</u>	78.6	48.2	59.7
	SEL+CL	Pos.+Neg.	✓	$\mathbb{H}^n_L$	88.9	<u>88.2</u>	<u>88.5</u>	99.0	60.9	75.4	78.6	<u>48.9</u>	60.3

Rank	Method	EL config.	Full Text	Space	DNA-to-DNA			Image-to-Image			Image-to-DNA		
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Family	CLIBD	–	✓	$\mathbb{R}^n$	90.8	75.8	82.6	**89.2**	**52.2**	**65.9**	**83.6**	**19.3**	**31.4**
	CL	–	✓	$\mathbb{H}^n_L$	90.3	76.6	82.9	83.9	48.5	61.4	79.6	18.8	30.4
	EL+CL	Pos.	✓	$\mathbb{H}^n_L$	89.3	74.9	81.4	81.9	37.6	51.5	76.7	16.8	27.6
	SEL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	86.8	**78.8**	82.6	79.0	41.8	54.7	78.9	18.4	29.9
	SEL+CL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	89.0	76.9	82.5	79.6	46.6	58.8	78.7	17.3	28.4
	SEL+CL	Pos.+Neg.	✓	$\mathbb{H}^n_L$	**91.2**	77.0	**83.6**	82.4	41.5	55.2	78.1	17.4	28.4

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Genus	CLIBD	–	✓	$\mathbb{R}^n$	85.2	64.3	73.3	**71.3**	**35.0**	**47.0**	**70.8**	**7.1**	**12.9**
	CL	–	✓	$\mathbb{H}^n_L$	**86.4**	64.9	74.1	65.6	32.4	43.4	66.9	6.5	11.8
	EL+CL	Pos.	✓	$\mathbb{H}^n_L$	84.7	63.1	72.3	63.0	22.8	33.5	64.2	6.6	11.9
	SEL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	82.7	65.9	73.4	62.1	29.2	39.7	63.1	6.6	12.0
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	SEL+CL	Pos.+Neg.	✓	$\mathbb{H}^n_L$	**91.2**	77.0	**83.6**	82.4	41.5	55.2	78.1	17.4	28.4
Genus	CLIBD	–	✓	$\mathbb{R}^n$	85.2	64.3	73.3	**71.3**	**35.0**	**47.0**	**70.8**	**7.1**	**12.9**
	CL	–	✓	$\mathbb{H}^n_L$	**86.4**	64.9	74.1	65.6	32.4	43.4	66.9	6.5	11.8
	EL+CL	Pos.	✓	$\mathbb{H}^n_L$	84.7	63.1	72.3	63.0	22.8	33.5	64.2	6.6	11.9
	SEL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	82.7	65.9	73.4	62.1	29.2	39.7	63.1	6.6	12.0
	SEL+CL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	83.6	**66.9**	**74.3**	63.3	33.1	43.5	67.6	6.4	11.7
	SEL+CL	Pos.+Neg.	✓	$\mathbb{H}^n_L$	85.8	64.8	73.9	64.8	27.5	38.6	64.8	6.2	11.4
Species	CLIBD	–	✓	$\mathbb{R}^n$	81.8	60.6	69.7	**55.1**	**24.3**	**33.7**	**55.8**	0.7	1.4
	CL	–	✓	$\mathbb{H}^n_L$	**84.4**	61.8	**71.4**	48.2	22.6	30.8	53.7	0.9	1.7
	EL+CL	Pos.	✓	$\mathbb{H}^n_L$	82.5	60.1	69.6	45.4	14.3	21.8	50.5	0.9	1.8
	SEL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	79.5	62.3	69.9	45.5	20.0	27.8	52.0	**1.1**	**2.1**
	SEL+CL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	80.5	**63.2**	70.8	46.8	22.8	30.7	54.2	0.7	1.4
	SEL+CL	Pos.+Neg.	✓	$\mathbb{H}^n_L$	82.6	62.0	70.8	47.8	19.0	27.2	51.4	1.0	**2.1**

Rank	Method	EL config.	Full Text	Space	DNA-to-DNA			Image-to-Image			Image-to-DNA		
					Seen	Unseen	H.M.	Seen	Unseen	H.M.	Seen	Unseen	H.M.
Order	CLIBD	–	✓	$\mathbb{R}^n$	**89.1**	87.8	88.4	**99.5**	**66.4**	**79.6**	**98.7**	**49.5**	**65.9**
	CL	–	✓	$\mathbb{H}^n_L$	**89.1**	85.6	87.3	98.5	61.2	75.5	89.1	47.8	62.2
	EL+CL	Pos.	✓	$\mathbb{H}^n_L$	88.6	86.5	87.5	98.6	56.9	72.1	77.8	48.4	59.7
	SEL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	88.4	**90.8**	**89.6**	79.3	62.3	69.8	**98.7**	48.9	65.4
	SEL+CL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	88.7	86.3	87.5	99.4	65.9	79.3	78.6	48.2	59.7
	SEL+CL	Pos.+Neg.	✓	$\mathbb{H}^n_L$	88.9	88.2	88.5	99.0	60.9	75.4	78.6	48.9	60.3
Family	CLIBD	–	✓	$\mathbb{R}^n$	90.8	75.8	82.6	**89.2**	**52.2**	**65.9**	**83.6**	**19.3**	**31.4**
	CL	–	✓	$\mathbb{H}^n_L$	90.3	76.6	82.9	83.9	48.5	61.4	79.6	18.8	30.4
	EL+CL	Pos.	✓	$\mathbb{H}^n_L$	89.3	74.9	81.4	81.9	37.6	51.5	76.7	16.8	27.6
	SEL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	86.8	**78.8**	82.6	79.0	41.8	54.7	78.9	18.4	29.9
	SEL+CL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	89.0	76.9	82.5	79.6	46.6	58.8	78.7	17.3	28.4
	SEL+CL	Pos.+Neg.	✓	$\mathbb{H}^n_L$	**91.2**	77.0	**83.6**	82.4	41.5	55.2	78.1	17.4	28.4
Genus	CLIBD	–	✓	$\mathbb{R}^n$	85.2	64.3	73.3	**71.3**	**35.0**	**47.0**	**70.8**	**7.1**	**12.9**
	CL	–	✓	$\mathbb{H}^n_L$	**86.4**	64.9	74.1	65.6	32.4	43.4	66.9	6.5	11.8
	EL+CL	Pos.	✓	$\mathbb{H}^n_L$	84.7	63.1	72.3	63.0	22.8	33.5	64.2	6.6	11.9
	SEL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	82.7	65.9	73.4	62.1	29.2	39.7	63.1	6.6	12.0
	SEL+CL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	83.6	**66.9**	**74.3**	63.3	33.1	43.5	67.6	6.4	11.7
	SEL+CL	Pos.+Neg.	✓	$\mathbb{H}^n_L$	85.8	64.8	73.9	64.8	27.5	38.6	64.8	6.2	11.4
Species	CLIBD	–	✓	$\mathbb{R}^n$	81.8	60.6	69.7	**55.1**	**24.3**	**33.7**	**55.8**	0.7	1.4
	CL	–	✓	$\mathbb{H}^n_L$	**84.4**	61.8	**71.4**	48.2	22.6	30.8	53.7	0.9	1.7
	EL+CL	Pos.	✓	$\mathbb{H}^n_L$	82.5	60.1	69.6	45.4	14.3	21.8	50.5	0.9	1.8
	SEL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	79.5	62.3	69.9	45.5	20.0	27.8	52.0	**1.1**	**2.1**
	SEL+CL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	80.5	**63.2**	70.8	46.8	22.8	30.7	54.2	0.7	1.4
	SEL+CL	Pos.+Neg.	✓	$\mathbb{H}^n_L$	82.6	62.0	70.8	47.8	19.0	27.2	51.4	1.0	**2.1**

Rank	Method	EL config.	Full Text	Space	DNA-to-DNA			Image-to-Image			Image-to-DNA		
					Seen	Unseen	H.M.	Seen	Unseen	H.M.	Seen	Unseen	H.M.
Order	CLIBD	–	✓	$\mathbb{R}^n$	**89.1**	87.8	88.4	**99.5**	**66.4**	**79.6**	**98.7**	**49.5**	**65.9**
	CL	–	✓	$\mathbb{H}^n_L$	**89.1**	85.6	87.3	98.5	61.2	75.5	89.1	47.8	62.2
	EL+CL	Pos.	✓	$\mathbb{H}^n_L$	88.6	86.5	87.5	98.6	56.9	72.1	77.8	48.4	59.7
	SEL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	88.4	**90.8**	**89.6**	79.3	62.3	69.8	**98.7**	48.9	65.4
	SEL+CL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	88.7	86.3	87.5	99.4	65.9	79.3	78.6	48.2	59.7
	SEL+CL	Pos.+Neg.	✓	$\mathbb{H}^n_L$	88.9	88.2	88.5	99.0	60.9	75.4	78.6	48.9	60.3
Family	CLIBD	–	✓	$\mathbb{R}^n$	90.8	75.8	82.6	**89.2**	**52.2**	**65.9**	**83.6**	**19.3**	**31.4**
	CL	–	✓	$\mathbb{H}^n_L$	90.3	76.6	82.9	83.9	48.5	61.4	79.6	18.8	30.4
	EL+CL	Pos.	✓	$\mathbb{H}^n_L$	89.3	74.9	81.4	81.9	37.6	51.5	76.7	16.8	27.6
	SEL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	86.8	**78.8**	82.6	79.0	41.8	54.7	78.9	18.4	29.9
	SEL+CL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	89.0	76.9	82.5	79.6	46.6	58.8	78.7	17.3	28.4
	SEL+CL	Pos.+Neg.	✓	$\mathbb{H}^n_L$	**91.2**	77.0	**83.6**	82.4	41.5	55.2	78.1	17.4	28.4
Genus	CLIBD	–	✓	$\mathbb{R}^n$	85.2	64.3	73.3	**71.3**	**35.0**	**47.0**	**70.8**	**7.1**	**12.9**
	CL	–	✓	$\mathbb{H}^n_L$	**86.4**	64.9	74.1	65.6	32.4	43.4	66.9	6.5	11.8
	EL+CL	Pos.	✓	$\mathbb{H}^n_L$	84.7	63.1	72.3	63.0	22.8	33.5	64.2	6.6	11.9
	SEL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	82.7	65.9	73.4	62.1	29.2	39.7	63.1	6.6	12.0
	SEL+CL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	83.6	**66.9**	**74.3**	63.3	33.1	43.5	67.6	6.4	11.7
	SEL+CL	Pos.+Neg.	✓	$\mathbb{H}^n_L$	85.8	64.8	73.9	64.8	27.5	38.6	64.8	6.2	11.4
Species	CLIBD	–	✓	$\mathbb{R}^n$	81.8	60.6	69.7	**55.1**	**24.3**	**33.7**	**55.8**	0.7	1.4
	CL	–	✓	$\mathbb{H}^n_L$	**84.4**	61.8	**71.4**	48.2	22.6	30.8	53.7	0.9	1.7
	EL+CL	Pos.	✓	$\mathbb{H}^n_L$	82.5	60.1	69.6	45.4	14.3	21.8	50.5	0.9	1.8
	SEL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	79.5	62.3	69.9	45.5	20.0	27.8	52.0	**1.1**	**2.1**
	SEL+CL	Pos.+Neg.	✗	$\mathbb{H}^n_L$	80.5	**63.2**	70.8	46.8	22.8	30.7	54.2	0.7	1.4
	SEL+CL	Pos.+Neg.	✓	$\mathbb{H}^n_L$	82.6	62.0	70.8	47.8	19.0	27.2	51.4	1.0	**2.1**

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→ Across all ranks Hypebolic models match or outperform Euclidean CLIBD

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→ But Euclidean CLIBD is better at image retrieval tasks

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→ This is still ongoing research, so we hope to further improve results within the coming months