**Computer Vision by Learning** 

# Hyperbolic Deep Learning

# **Pascal Mettes**

University of Amsterdam

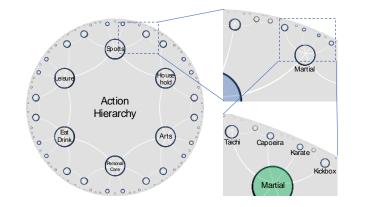


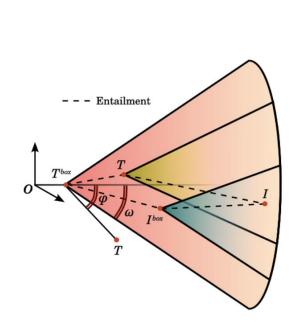


**Pascal Mettes** Assistant Professor - University of Amsterdam

> Computer vision Hierarchical knowledge Hyperbolic geometry

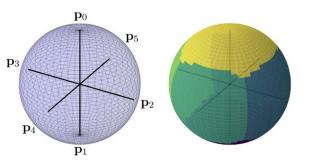


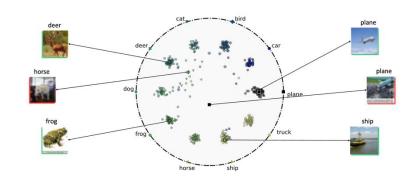




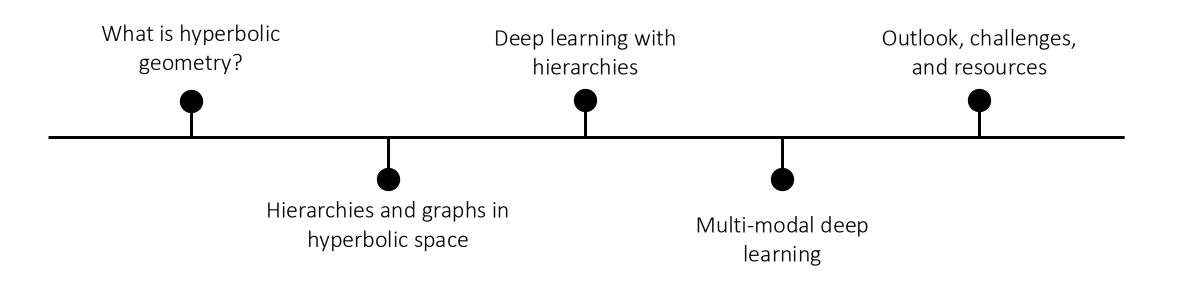
Segmentation

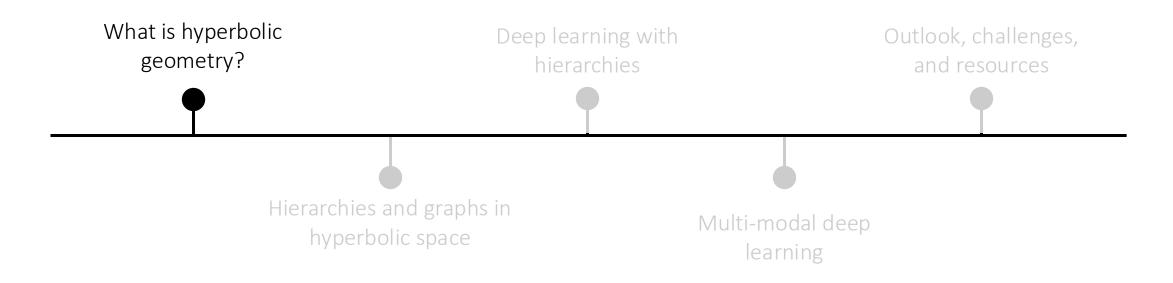
0.2 0.4 0.6 0.8 Confidence Map





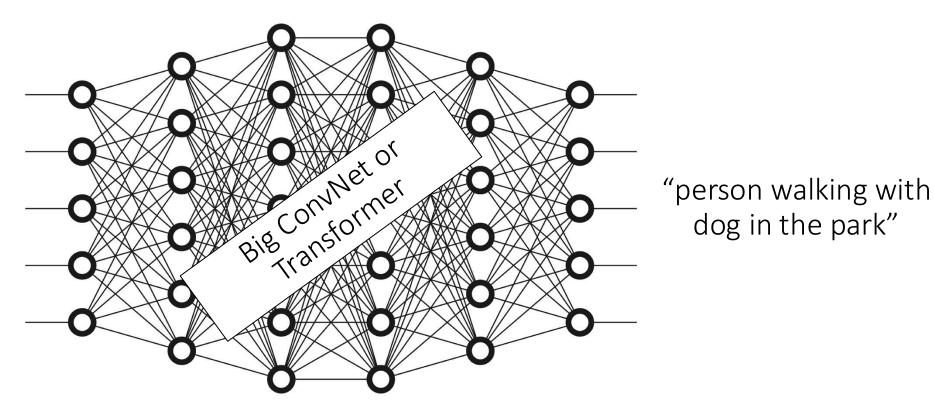
# Journey of the lecture



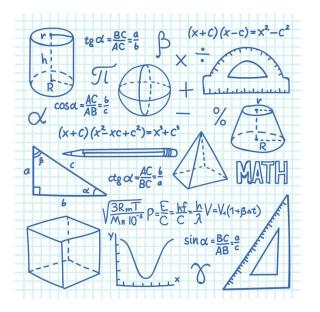


#### Canonical deep learning

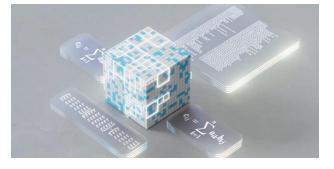




### Why are we so Euclidean?



**O** PyTorch



**TensorFlow** 

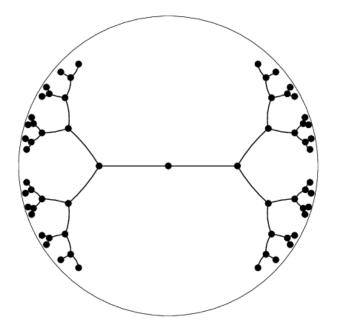
sign exponent (8 bits) fraction (7 bits)										s)						
	0	0	1	1	1	1	1	0	0	0	1	0	0	0	0	0
15 14						<b>?</b>	<b>6</b>	(t	oit	inc	le>	()	o			

Our school curricula are Euclidean

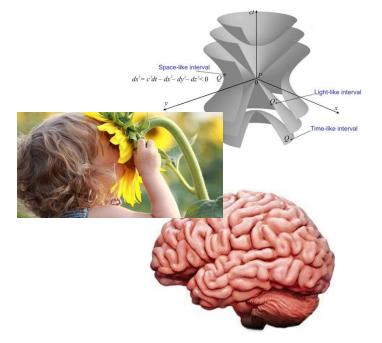
Our deep learning tools are Euclidean

Our computers are built for Euclidean space

# But is Euclidean always the answer?





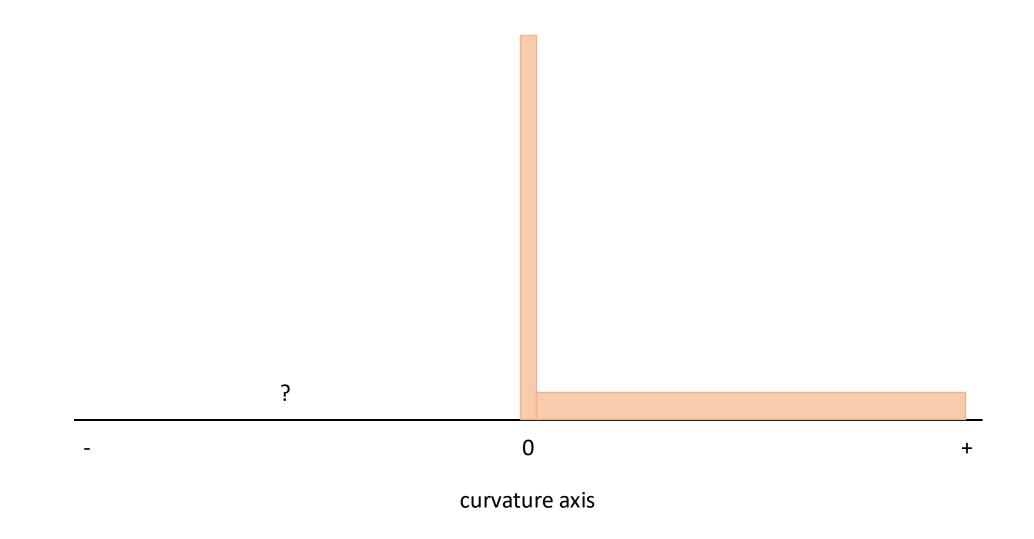


Euclidean is not hierarchical

Euclidean is not compact

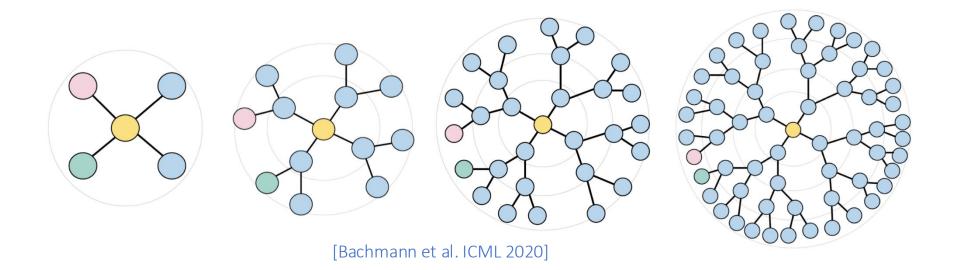
The world is not always Euclidean

# The blindspots in deep learning research

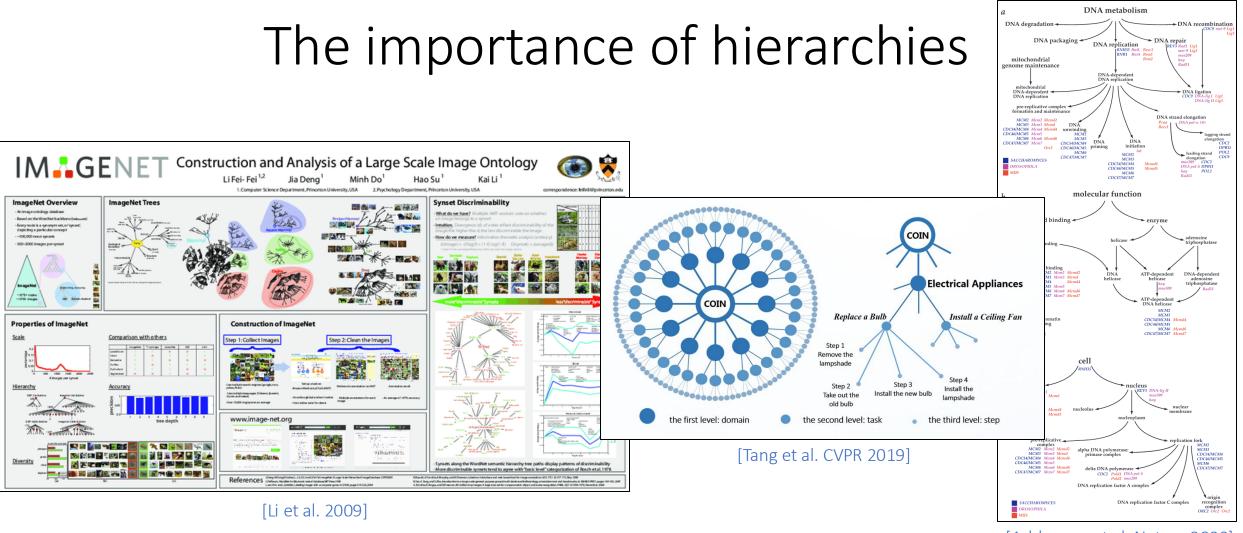


# The geometry of hierarchies

Euclidean space and hierarchies are a mismatch: linear vs. exponential growth.



What we need is a hierarchical geometry for representation learning!



[Ashburner et al. Nature 2000]

Hierarchies allow us to look beyond samples and their individual labels.

# Origins of hyperbolic geometry

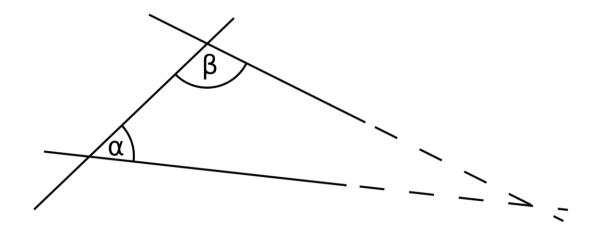
Euclid's 5 postulates:

- 1. A straight-line segment can be drawn joining any two points.
- 2. Any straight-line segment can be extended indefinitely in a straight line.
- 3. Given any straight lines segment, a circle can be drawn having the segment as radius and one endpoint as center.
- 4. All Right Angles are congruent.

5. If two lines are drawn which intersect a third in such a way that the sum of the inner angles on one side is less than two Right Angles, then the two lines inevitably must intersect each other on that side if extended far enough. This postulate is equivalent to what is known as the Parallel Postulate.

# Origins of hyperbolic geometry

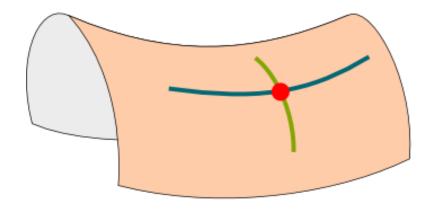
Euclid's 5th postulate:



Did Euclid make a mistake by making it a postulate? Shouldn't it be a theorem?

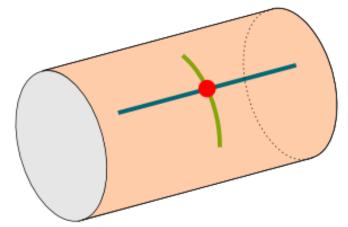
# The rise of non-Euclidean geometry

Extremal directions curve in opposite directions

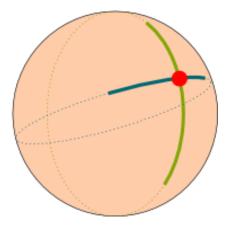


Negative Curvature

One extremal direction has zero curvature



Extremal directions curve in the same directions

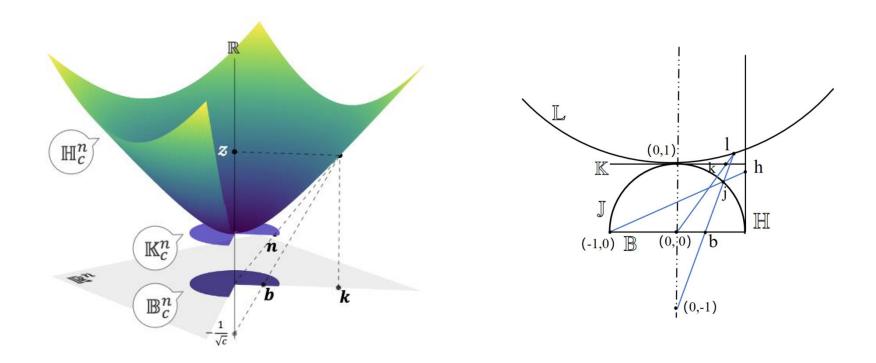


#### Zero Curvature

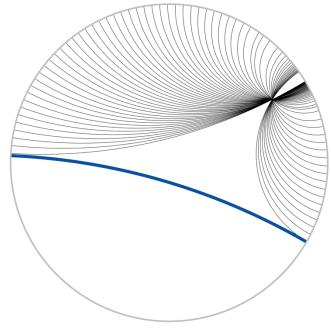
Positive Curvature

# Models of hyperbolic geometry

To perform numerical operations, we need to operate in a model of hyperbolic geometry.



Multiple isometric models exist, with different pros and cons for numerical complexity, stability, and visualization prowess.



#### Poincaré ball model

\ D1

D

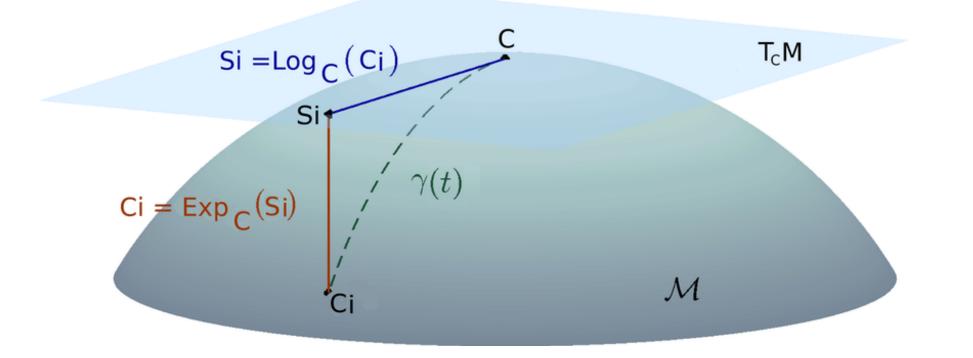


#### Numerical operation in Poincaré model

Points inside unit ball Tensor metric  $\mathbb{D}^n = \{ x \in \mathbb{R}^n : \|x\| < 1 \} \qquad g_x^{\mathbb{D}} = \lambda_x^2 g^E, \quad \text{where } \lambda_x := \frac{2}{1 - \|x\|^2}$ Distance between two points: D D1  $d_{\mathbb{D}}(x,y) = \cosh^{-1}\left(1 + 2\frac{\|x-y\|^2}{(1-\|x\|^2)(1-\|y\|^2)}\right)$ Möbius addition:

$$x \oplus_{c} y := \frac{(1 + 2c\langle x, y \rangle + c \|y\|^{2})x + (1 - c \|x\|^{2})y}{1 + 2c\langle x, y \rangle + c^{2} \|x\|^{2} \|y\|^{2}}$$

# From tangent space to Poincaré ball (and back)



$$\log_{\mathbf{0}}^{c}(y) = \tanh^{-1}(\sqrt{c}\|y\|) \frac{y}{\sqrt{c}\|y\|}$$

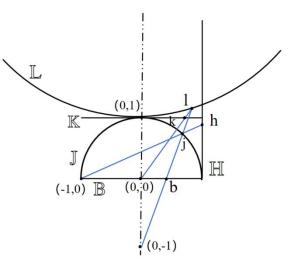
$$\exp_{\mathbf{0}}^{c}(v) = \tanh(\sqrt{c}\|v\|) \frac{v}{\sqrt{c}\|v\|}$$

# Models of hyperbolic geometry

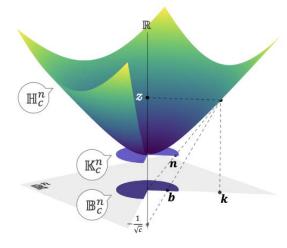
Different models shine in different aspects.

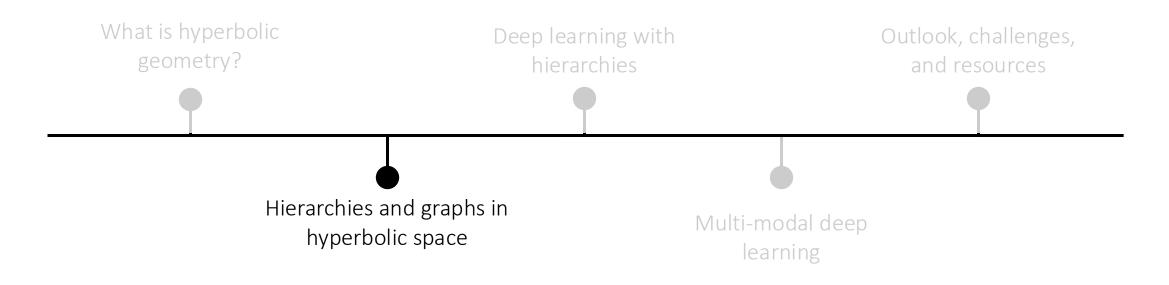
Poincaré most intuitive, Lorentz most stable, Klein fastest average operator

Many open questions about which models are best for deep learning.



Poincaré ball and Lorentz model default choices.

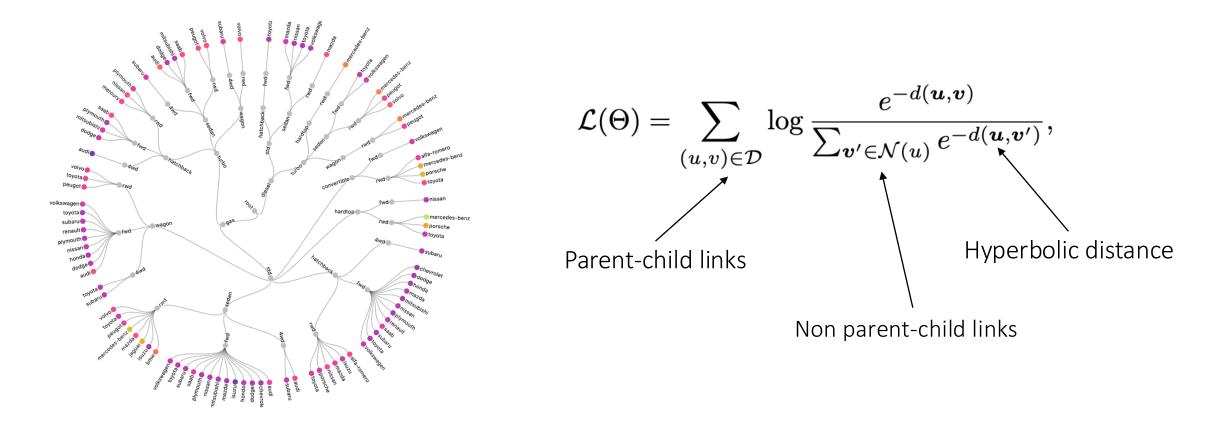




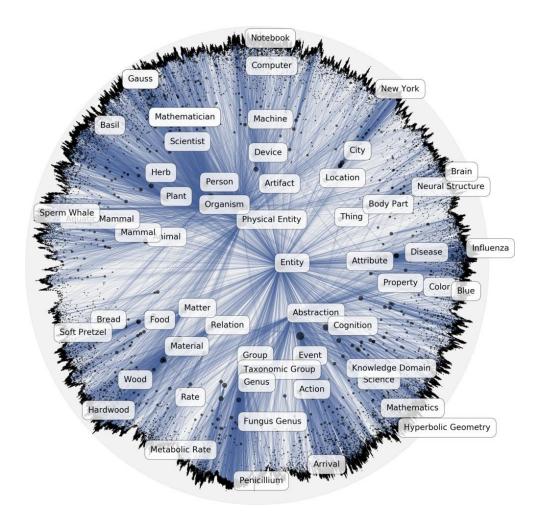
### Poincaré Embeddings

[Nickel and Kiela. NeurIPS 2017]

Embed nodes as hyperbolic points and optimize with contrastive learning.



# Poincaré Embeddings



			Dimensionality						
			5	10	20	50	100	200	
WORDNET Reconstruction	Euclidean	Rank MAP	3542.3 0.024	2286.9 0.059	1685.9 0.087	1281.7 0.140	1187.3 0.162	1157.3 0.168	
	Translational	Rank MAP	205.9 0.517	179.4 0.503	95.3 0.563	92.8 0.566	92.7 0.562	91.0 0.565	
	Poincaré	Rank MAP	4.9 0.823	4.02 0.851	3.84 0.855	3.98 0.86	3.9 0.857	3.83 0.87	
WORDNET Link Pred.	Euclidean	Rank MAP	3311.1 0.024	2199.5 0.059	952.3 0.176	351.4 0.286	190.7 0.428	81.5 0.490	
	Translational	Rank MAP	65.7 0.545	56.6 0.554	52.1 0.554	47.2 0.56	43.2 0.562	40.4 0.559	
	Poincaré	Rank MAP	5.7 0.825	<b>4.3</b> 0.852	4.9 0.861	4.6 <b>0.863</b>	4.6 0.856	4.6 0.855	

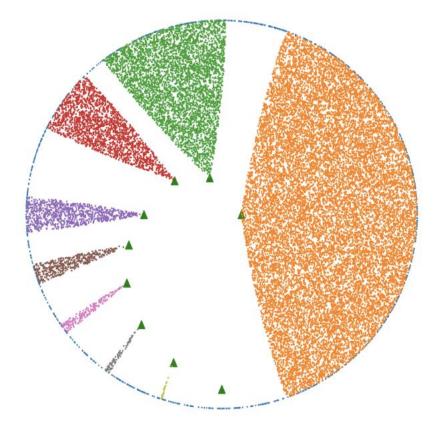
# Hyperbolic Entailment Cones

[Ganea et al. ICML 2018]

Pairwise contrastive learning has trouble enforcing hierarchical depth. They propose to view points as cones of entailment.

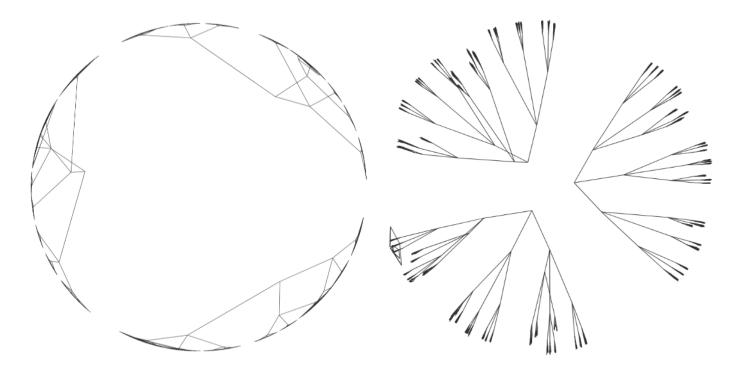
#### Required properties:

- 1. Axial symmetry
- 2. Rotation invariance
- 3. Aperture of cone is continuous function
- 4. Nested angular cones preserve partial order



### Hyperbolic Entailment Cones

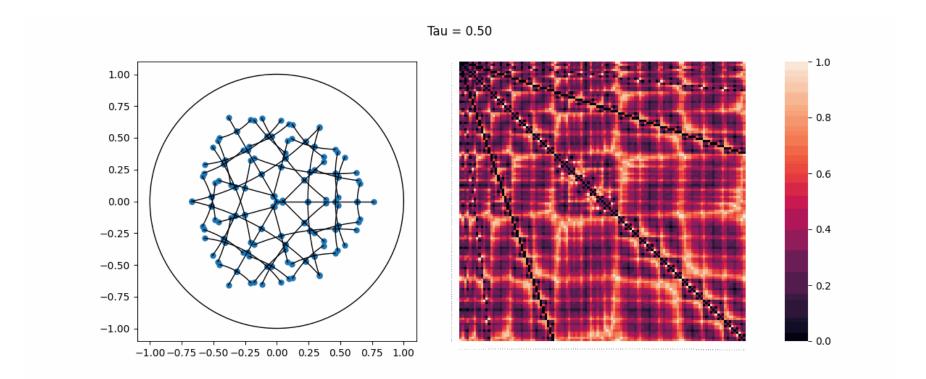
[Ganea et al. ICML 2018]



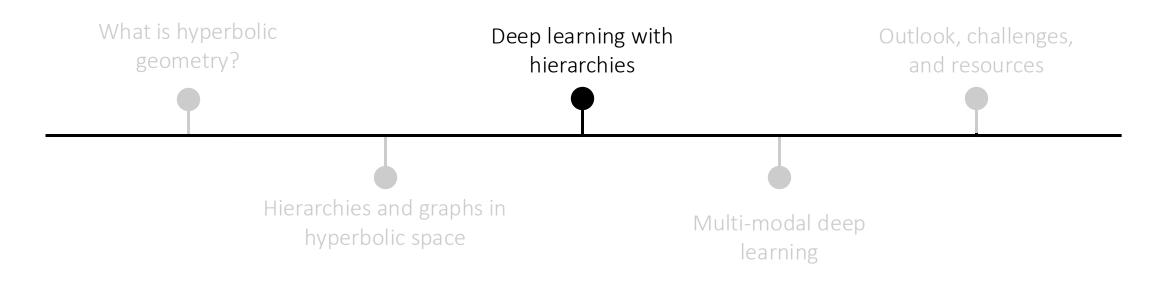
Poincaré Embeddings (left) vs Hyperbolic Entailment Cones (right)

# **Closed-form Embeddings**

[Sarkar et al. 2012]



In 2D, it is possible to embed hierarchies through uniform spreading and projections. No direct higher-dimensional generalization feasible, only approximate solutions.



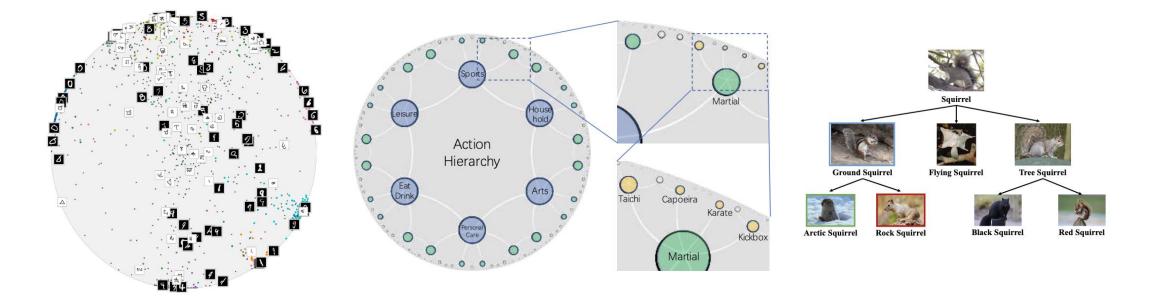
# Hyperbolic embeddings for vision

[Liu et al, Long et al., Khrulkov et al. CVPR 2020]

#### CVPR 2020

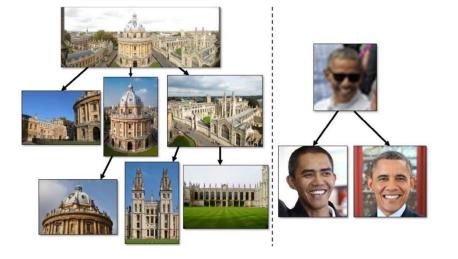
Three papers with the exact same question:

What happens when we place hyperbolic embeddings on top of deep networks?

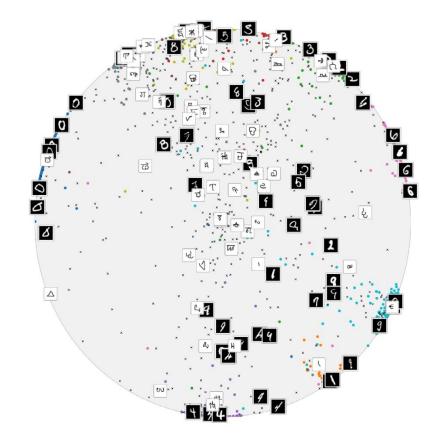


# Hyperbolic Image Embeddings

[Khrulkov et al. CVPR 2020]



Encodor	Dataset						
Encoder	CIFAR10	CIFAR100	CUB	<i>Mini</i> ImageNet			
Inception v3 [49]	0.25	0.23	0.23	0.21			
ResNet34 [14]	0.26	0.25	0.25	0.21			
VGG19 [42]	0.23	0.22	0.23	0.17			



Images are naturally hierarchical, hyperbolic embeddings improve few-shot learning.

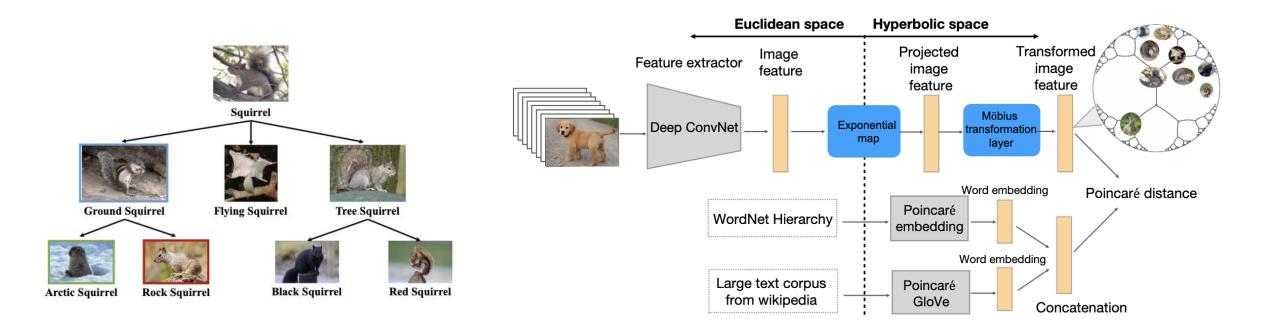
# Hyperbolic actions

[Long et al., CVPR 2020] 0 0 1 High Low 0 Leisur 0 Action Hierarchy 0 Eat Drink Capoeira Taichi Karate O Kickbox (a) One-hot. (b) Hyperbolic (ours). Martial Hyperbolic video embedding Hyperbolic action embedding  $T_x\mathcal{M}$ x $exp_x(v)$  $\mathcal{M}$ Discriminative Action hierarchy Hyperbolic matching Exponential mapping Video representation hyperbolic embedding Action videos

Videos are naturally hierarchical, hyperbolic embeddings improve action recognition.

# Hyperbolic zero-shot learning

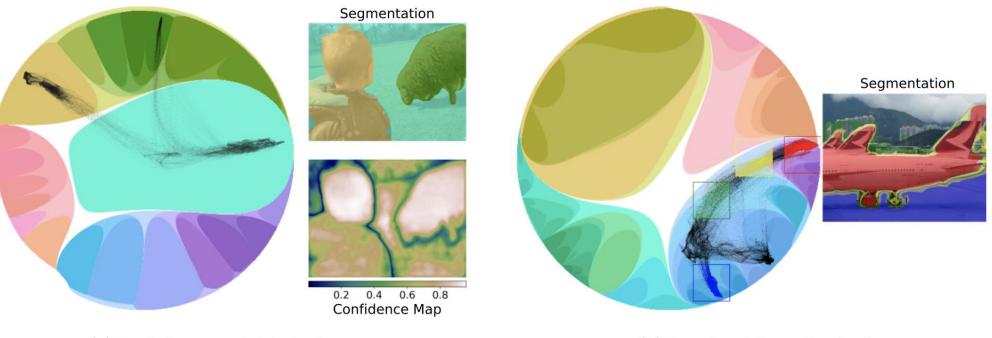
[Liu et al. CVPR 2020]



Semantics is naturally hierarchical, hyperbolic embeddings improve zero-shot recognition.

# Hyperbolic Image Segmentation

[Ghadimi Atigh et al. CVPR 2022]

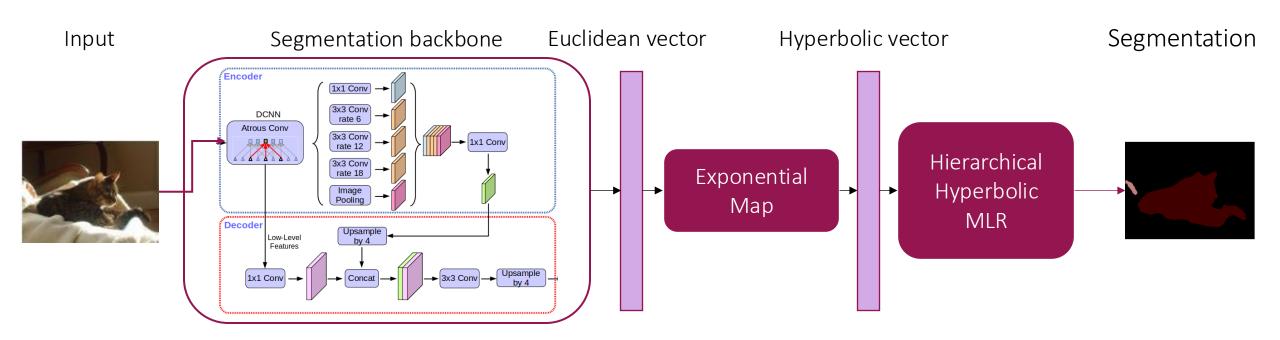


(a) Prediction uncertainty for free

(b) Boundary information for free

What happens when the final pixel classification is done in hyperbolic space?

# Hyperbolic Image Segmentation

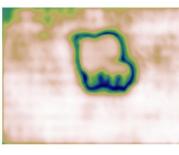


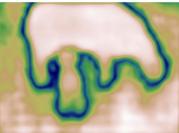
#### Hyperbolic Image Segmentation

Hyperbolic Segmentation

Hyperbolic Uncertainty 1 pass

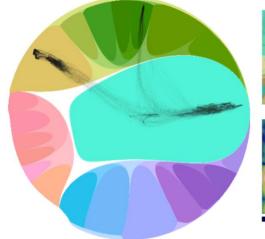










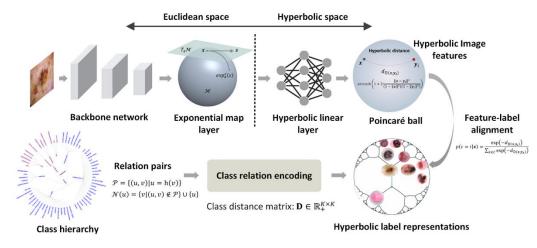




COCO-Stuff-10k									
Manifold	Hierarchical	Class Acc	Pixel Acc	mIOU					
$\mathbb{R}$		0.44	0.33	0.23					
$\mathbb R$	$\checkmark$	3.29	48.65	18.53					
$\mathbb{D}$	$\checkmark$	3.46	51.70	21.15					

Pascal VOC										
Manifold	Hierarchical	Class Acc	Pixel Acc	mIOU						
$\mathbb{R}$		4.88	10.84	2.59						
$\mathbb{R}$	$\checkmark$	7.80	31.04	16.15						
$\mathbb{D}$	$\checkmark$	12.15	47.92	34.87						

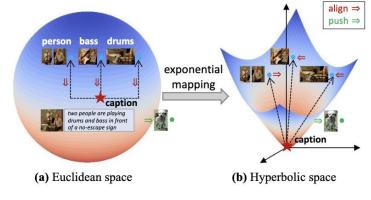
# Too many hyperbolic vision papers to mention



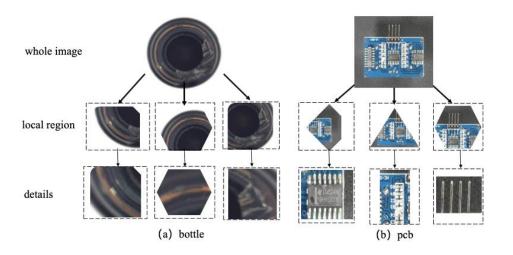
[Yu et al. MICCAI 2022]



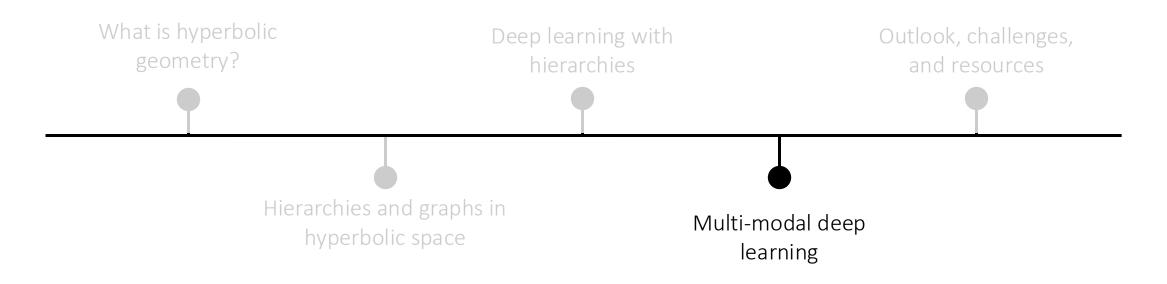
[Ge et al. CVPR 2023]



[Kong et al. CVPR 2024]



#### [Li et al. CVPR 2024]



# Hyperbolic vision-language models

[Desai et al. ICML 2023]

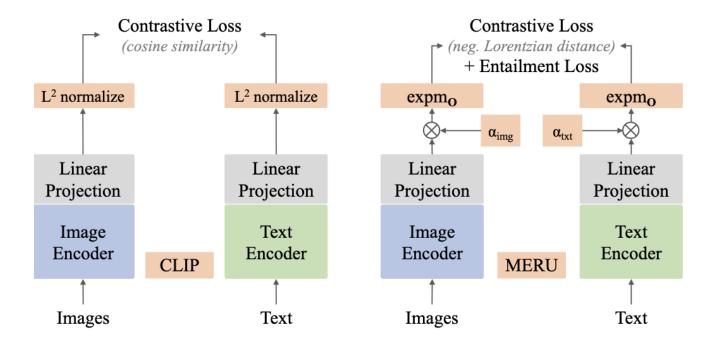
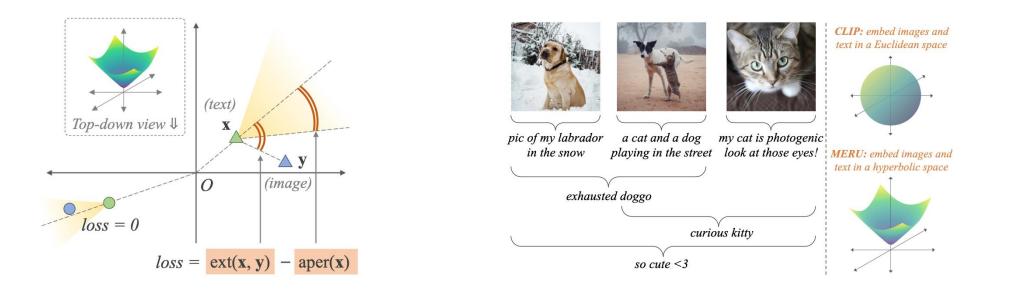


Image-text representation learning wants to collapse image and text embeddings.

# Hyperbolic vision-language models

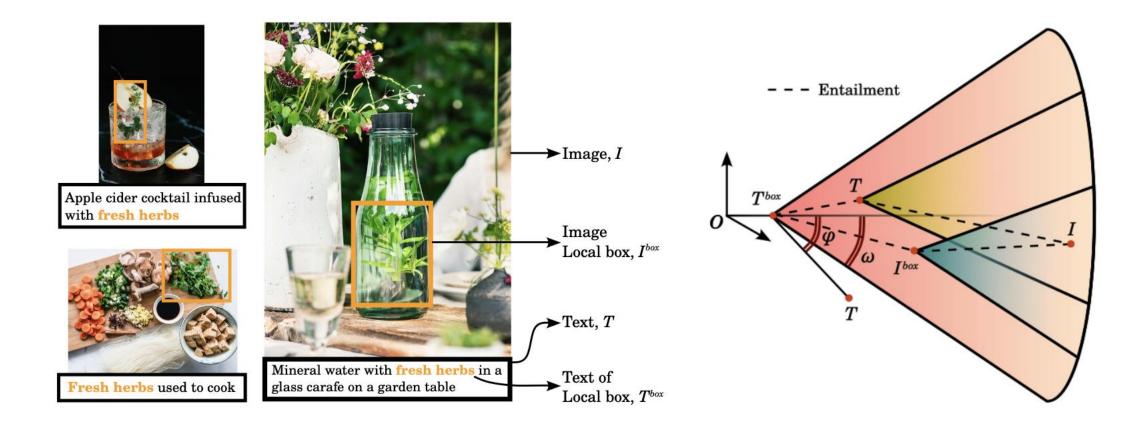
Intuitively, image and text embeddings are unequal!



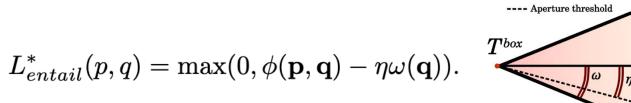
Hyperbolic entailments allow to model this imbalance and learn the hierarchical nature of image-text representations.

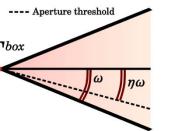
## Vision-language models and compositions

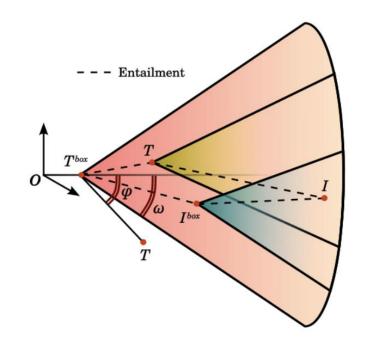
[under submission]



## Vision-language models and compositions







$$\begin{aligned} hCE(I,T,I^{box},T^{box}) = \underbrace{L^*_{entail}(I^{box},T^{box}) + L^*_{entail}(I,T)}_{\text{inter-modality entailment}} \\ + \underbrace{L^*_{entail}(I,I^{box}) + L^*_{entail}(T,T^{box})}_{\text{intra modality entailment}}. \end{aligned}$$

intra-modality entailment

### Multi-modal network

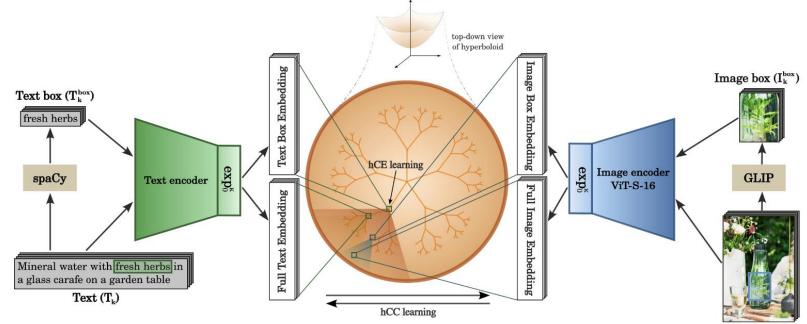
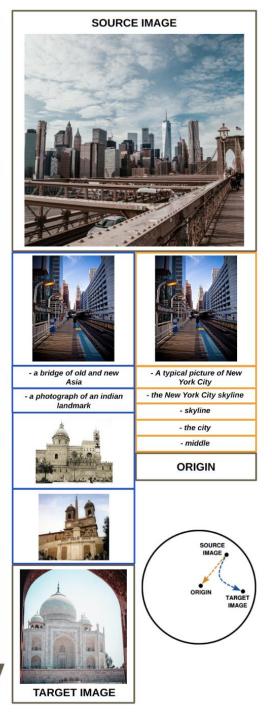
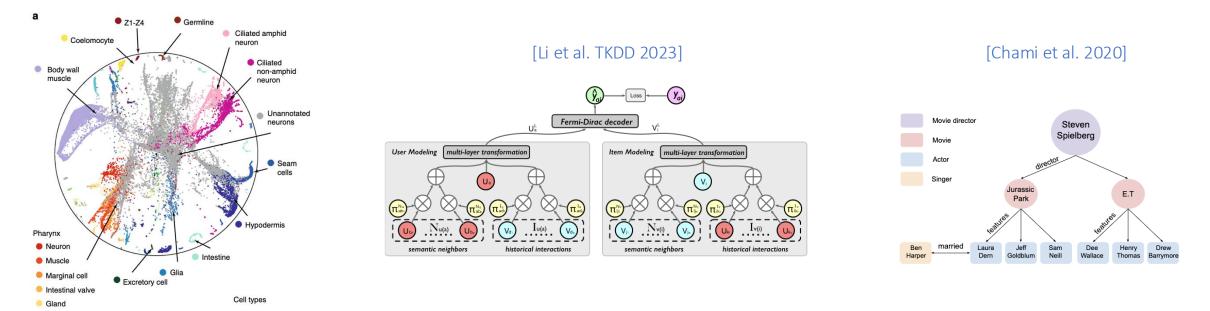


Image  $(I_k)$ 



# Hyperbolic embeddings for other data types

#### [Klimovskaia et al. Nature Comm. 2020]



Hyperbolic embeddings of single-cell data.

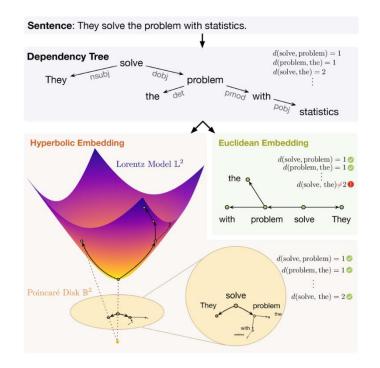
Hyperbolic recommender systems Hyperbolic knowledge graphs

And for text, music, 3D skeletons, phylogenetic placement, social networks, clustering...

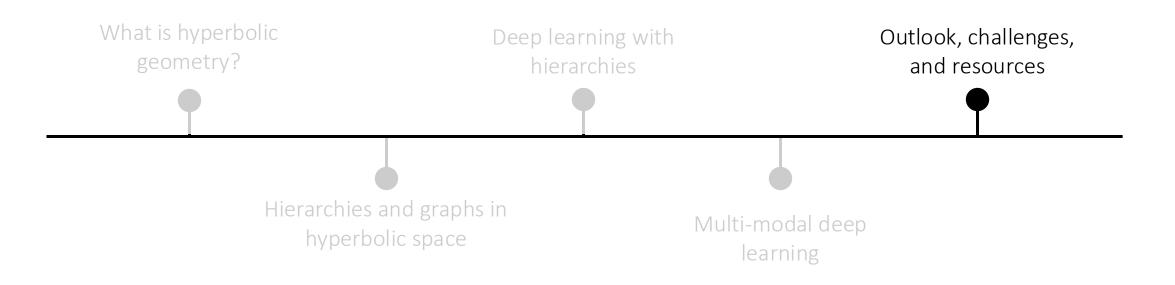
# Hyperbolic large language models?

[Chen et al. TASLP 2024]

Large language models are Euclidean, but should they be?



Very recent work is making the first step, but no big companies dare to make the step (yet?).



# The big potential of hyperbolic learning

**Hierarchical learning** model the hierarchies of semantics and data.

**Robust learning** handle new distributions and adversarial samples.

Low-dimensional learning hyperbolic space is dense, allowing for smaller networks.

Brain-like networks

brains are likely hyperbolic, big links with neuroscience Zhang et al. Nature Communications 2022

## The grand challenges of hyperbolic learning

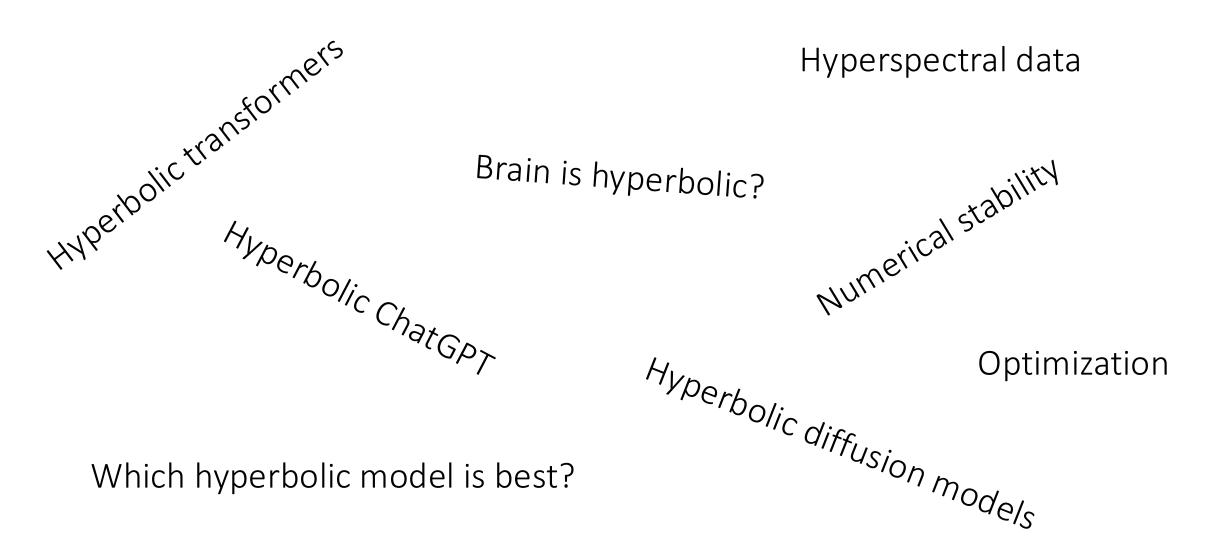
**Fully hyperbolic learning** which hyperbolic model is best? and how to optimize?

**Computational challenges** numerical stability and speed of computation.

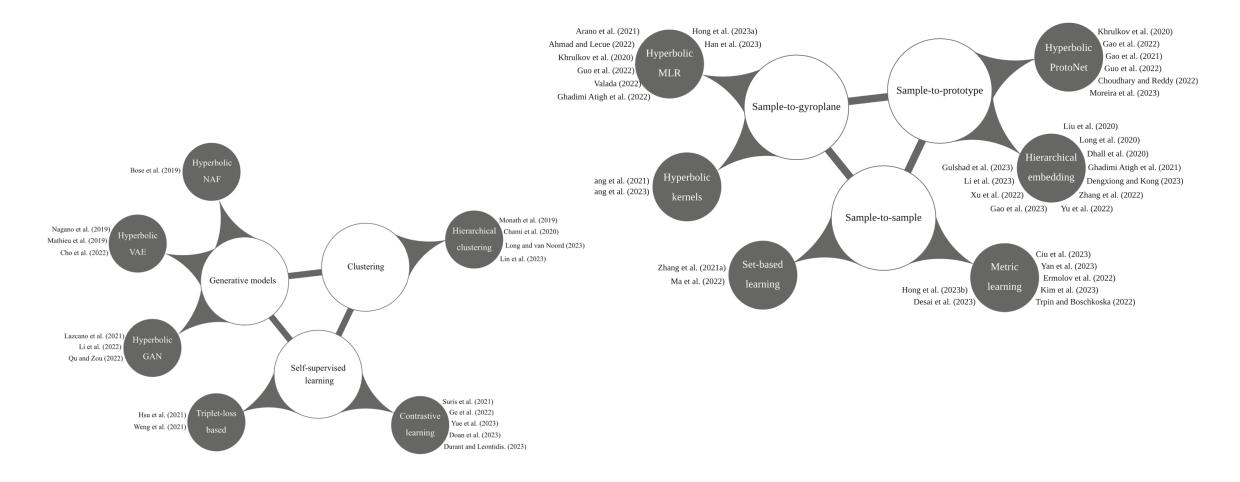
**Open source community** where is hyperbolic PyTorch?

**Learning at scale** we need an ImageNet/CLIP moment for hyperbolic learning.

## Unexplored territories



Pascal Mettes, Mina Ghadimi, Martin Keller-Ressel, Jeffrey Gu, Serena Yeung. IJCV 2024 Hyperbolic Deep Learning in Computer Vision: A Survey



Max van Spengler, Philipp Wirth, Pascal Mettes. ACM MM 2024 HypLL: The Hyperbolic Learning Library



ball = PoincareBall(Curvature(1.0))
class HNet(nn.Module):
 def \_\_init\_\_(self):
 super().\_\_init\_\_()
 self.conv1 = hnn.HConvolution2d(3, 6, 5, ball)
 self.pool = hnn.HMaxPool2d(2, ball, 2)
 self.conv2 = hnn.HConvolution2d(6, 16, 5, ball)
 self.fc1 = hnn.HLinear(16 \* 5 \* 5, 120, ball)
 self.fc2 = hnn.HLinear(120, 84, ball)
 self.fc3 = hnn.HLinear(84, 10, ball)
 self.relu = hnn.HReLU(ball)

def forward(self, x): x = self.pool(self.relu(self.conv1(x))) x = self.pool(self.relu(self.conv2(x))) x = x.flatten(1) x = self.relu(self.fc1(x)) x = self.relu(self.fc2(x)) x = self.fc3(x) return x

#### import torch.nn as nn class Net(nn.Module): def init (self): super().\_\_init\_\_() self.conv1 = nn.Conv2d(3, 6, 5)self.pool = nn.MaxPool2d(2, 2) self.conv2 = nn.Conv2d(6, 16, 5)self.fc1 = nn.Linear(16 \* 5 \* 5, 120) self.fc2 = nn.Linear(120, 84)self.fc3 = nn.Linear(84, 10) self.relu = nn.ReLU() def forward(self, x): x = self.pool(self.relu(self.conv2(x))) x = x.flatten(1) x = self.relu(self.fc1(x)) x = self.relu(self.fc2(x)) x = self.fc3(x)return x

https://github.com/maxvanspengler/hyperbolic\_learning\_library

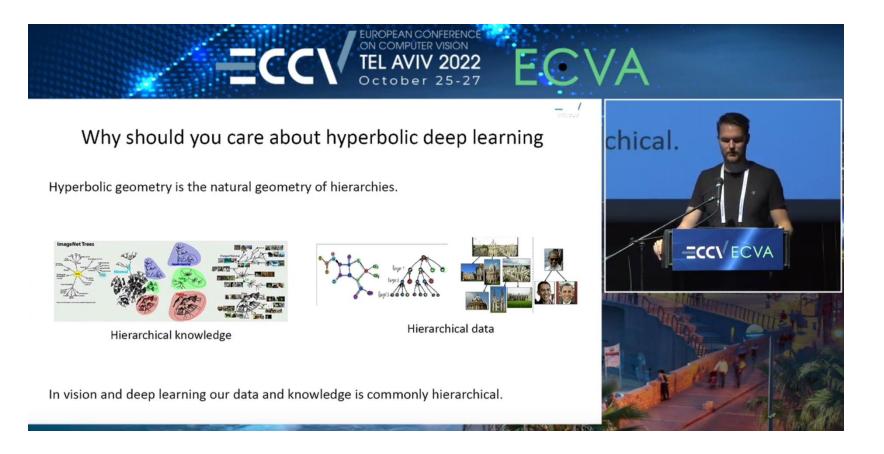
Max van Spengler, Philipp Wirth, Pascal Mettes. ACM MM 2024

*HypLL: The Hyperbolic Learning Library* 



https://github.com/maxvanspengler/hyperbolic\_learning\_library





https://www.youtube.com/@hyperboliclearningforcv/playlists