Part 1: Motivation

Motivation

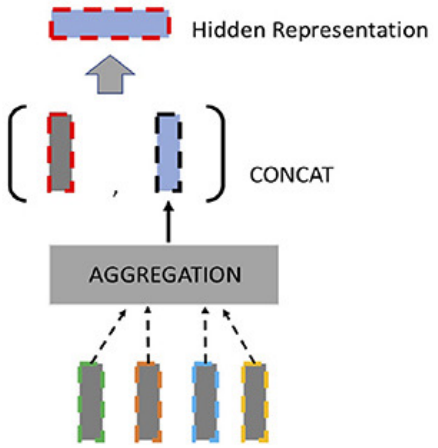
Neural Networks and Applications

Neural networks have been applied to a wide range of problems with different types of datasets such as graphs, text and images.

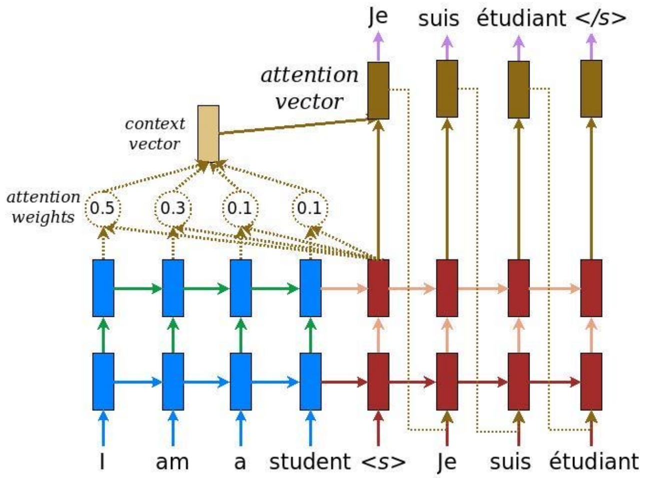
Motivation

Euclidean Spaces

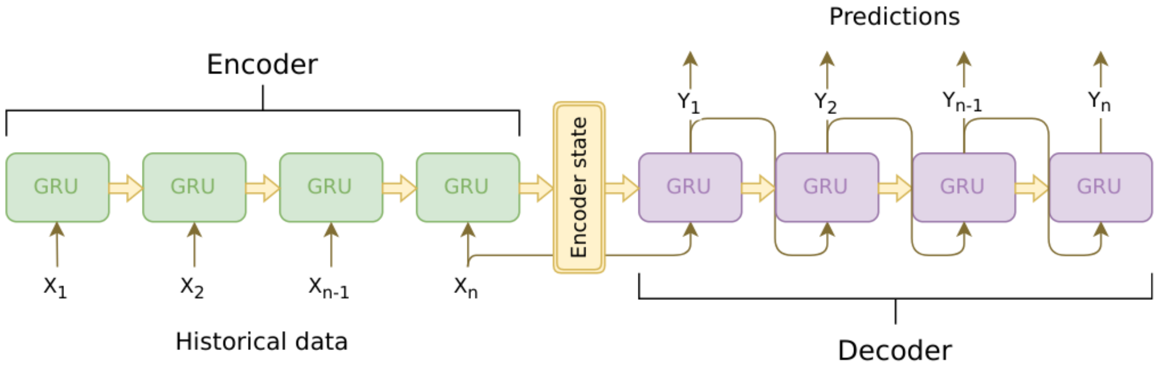
The difference in the inherent properties required to solve these tasks is handled with different types of models, generally based on Euclidean spaces.



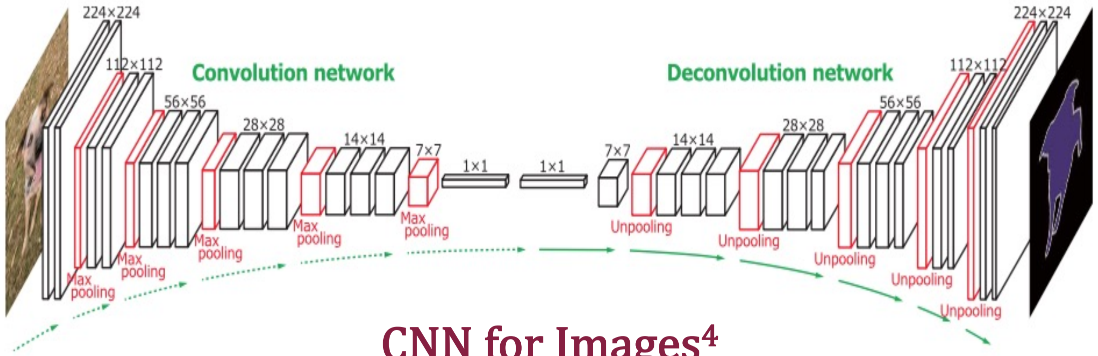
GNN for Graphs[1]



Transformers for Text[2]



RNN for Timeseries[3]



CNN for Images[4]

1. Tan, et al., "Deep representation learning for social network analysis." *Frontiers in big Data* 2 (2019):
2. Bahdanau et al., "Neural machine translation by jointly learning to align and translate." ICLR (2015).
3. Chatbot Tutorial — PyTorch Tutorials 1 (Lasylife.top).
4. https://towardsdatascience.com/review-deconvnet-unpooling-layer-semantic-segmentation-55cf8a6e380e.

Motivation

Where to apply?

- **Graph Analysis:**

Using hierarchies in graph relations.

- **Knowledge Graphs:**

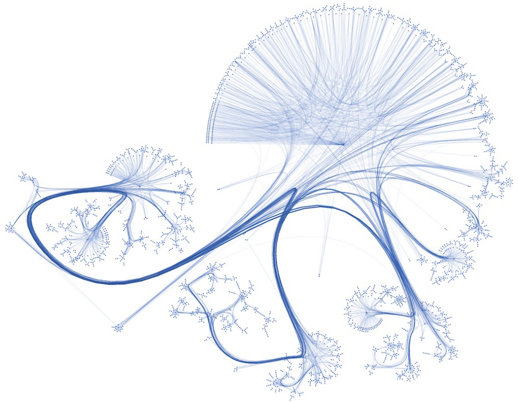
Using hierarchies in knowledge graph representation.

- **Search:**

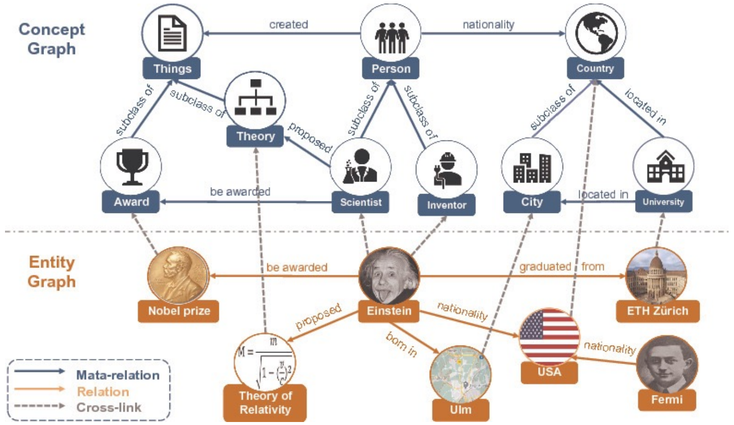
Using hierarchies in retrieval entities.

- **Natural Language Processing**

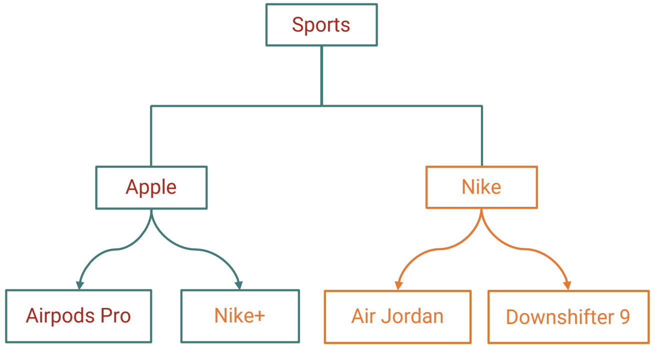
Using hierarchal relations between words of a sentence.



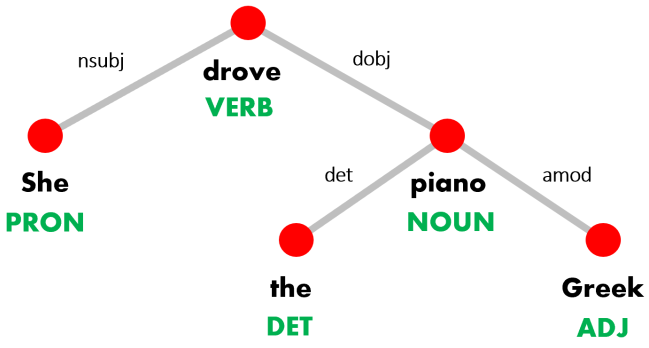
Graph Analysis[1]



Knowledge Graph Representation[2]



Product Search Catalogues



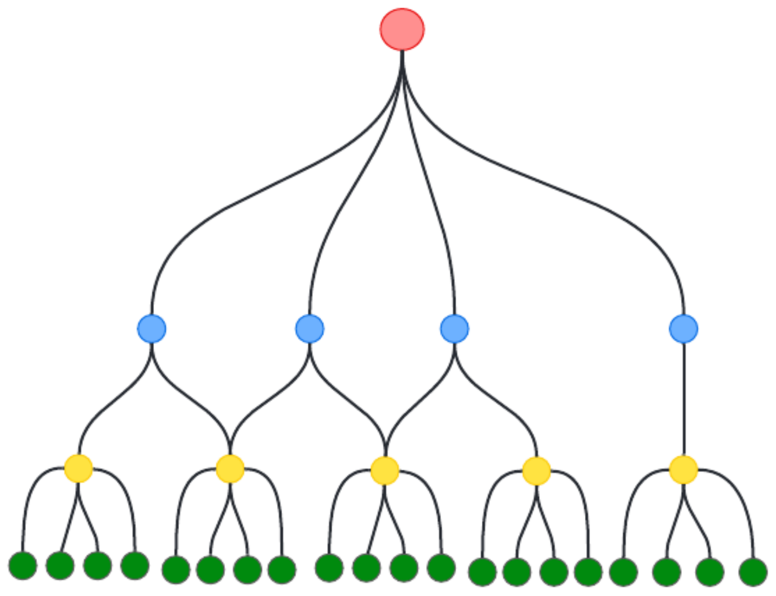
Syntax tree of a Sentence[3]

1. https://graphsandnetworks.com/category/graph-machine-learning/ [Cora Dataset]
2. Dong, J., Gu, B., Qu, J., Liu, A., Zhao, L., Chen, Z., & Li, Z. (2021, October). HyperJOIE: Two-View Hyperbolic Knowledge Graph Embedding with Entities and Concepts Jointly. In International Conference on Web Information Systems Engineering (pp. 305-320). Springer, Cham.
3. Getting to grips with parse trees, Vered Zimmerman (Towards Data Science, 2019).

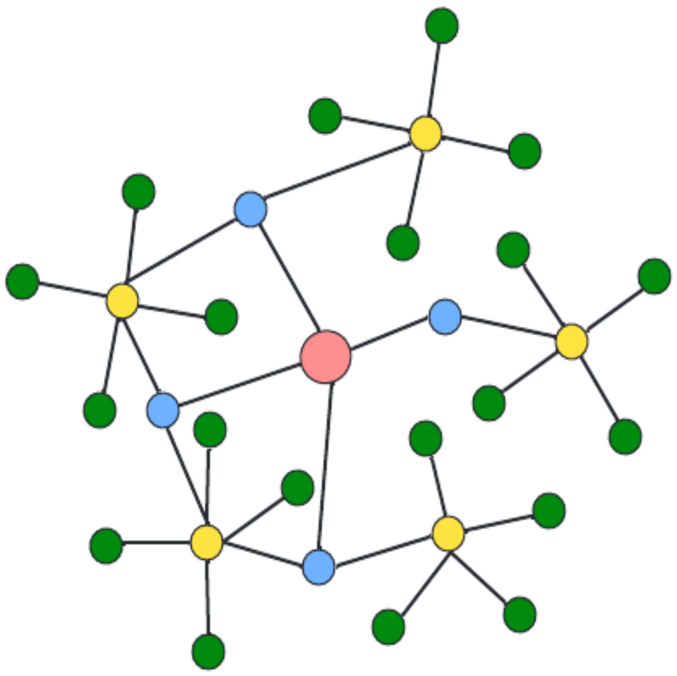
Motivation

Peculiar Case of Hierarchical Problems

With increasing depth, the number of nodes grow exponentially, however Euclidean space grows linearly (L1-norm, Euclidean distance).
Thus, Euclidean representational volume is not sufficient. Points get clustered together.



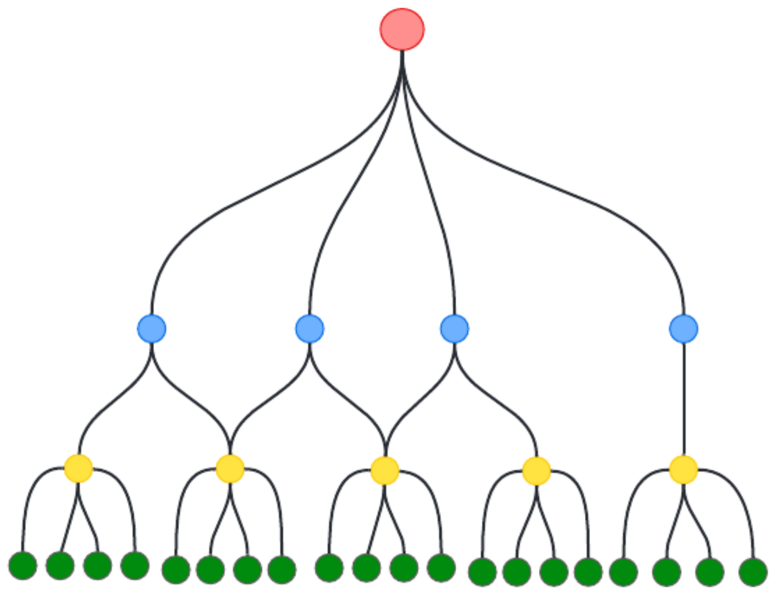
Hierarchical Dataset



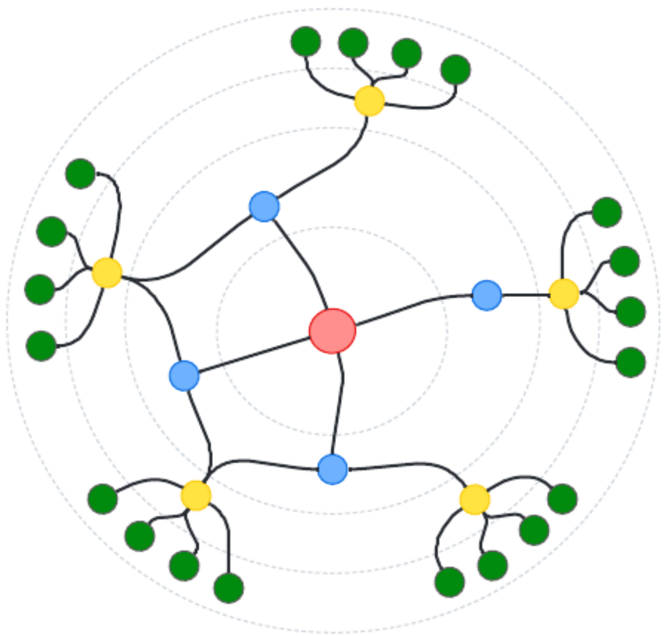
Euclidean Embeddings

Motivation
Why Hyperbolic Space?

Thus, recent research has shifted to non-Euclidean hyperbolic spaces for capturing hierarchical dependencies in the datasets.



Hierarchical Dataset



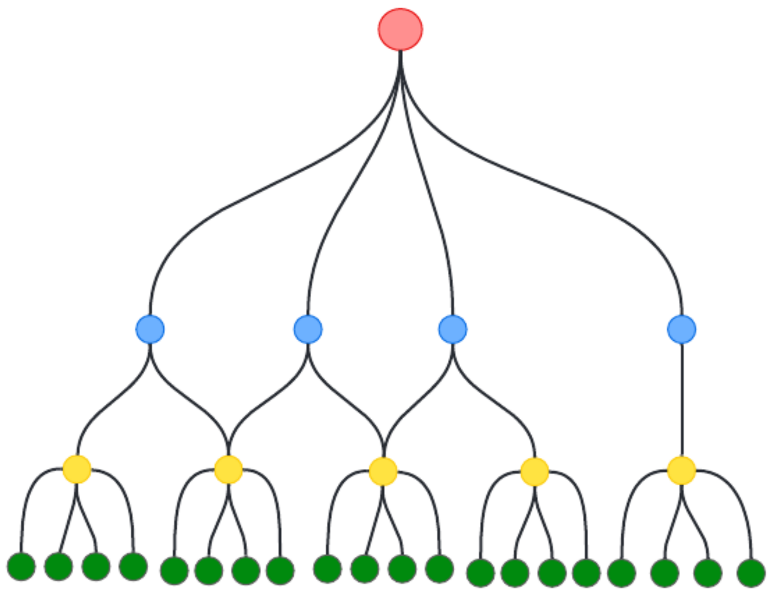
Hyperbolic Embeddings

Motivation

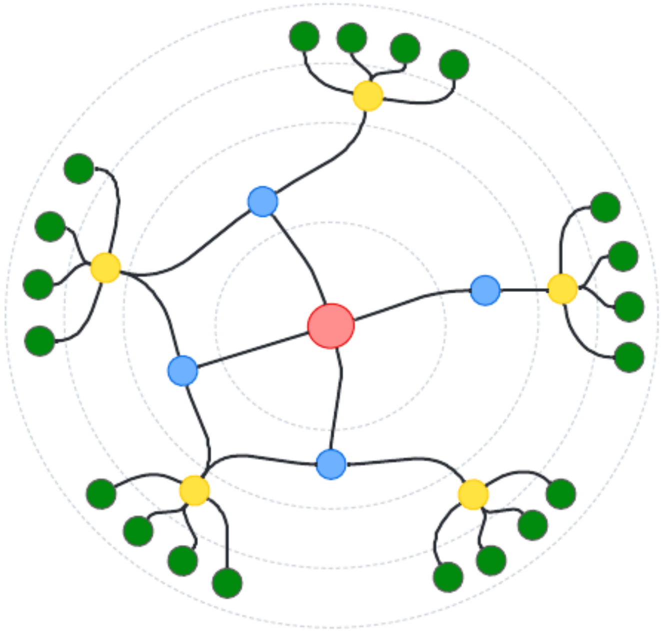
Why Hyperbolic Space?

Recently, research has shifted to non-Euclidean hyperbolic spaces for capturing hierarchical dependencies in the datasets.

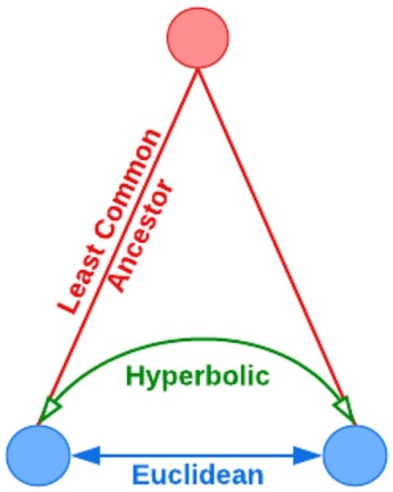
Hyperbolic spaces more closely resemble hierarchical structures than Euclidean space.



Hierarchical Dataset



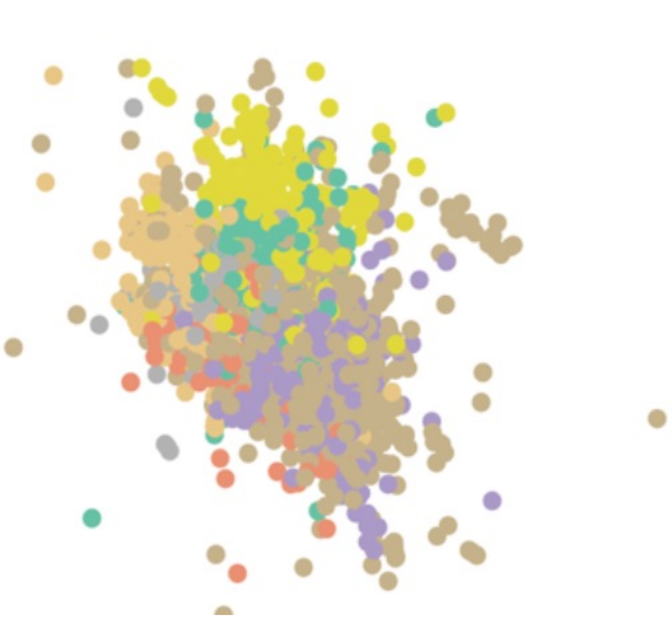
Hyperbolic Embeddings



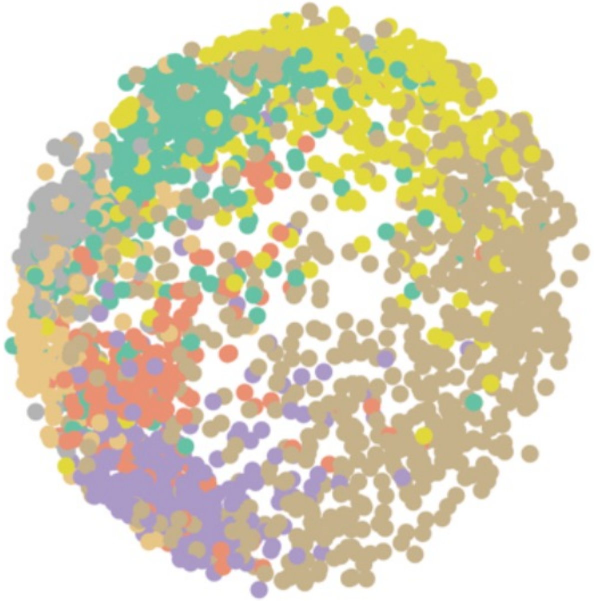
Motivation

How to use?

In such problem settings, hyperbolic models generate better representations.



Euclidean Embeddings*
(GCN, Cora dataset)



Poincaré Embeddings*
(HGCN, Cora dataset)

In the above problem of node classification, hyperbolic model HGCN generates more separable representations, compared to its Euclidean counterpart GCN.

*Chami, Ines, et al. "Hyperbolic graph convolutional neural networks." Advances in neural information processing systems 32 (2019).

Motivation

How to use?

Node Classification (F1 Score)									
	Shallow		Neural Nets		Graph Neural Nets				
Dataset	EUC	HYP	MLP	HNN	GCN	GAT	SAGE	HGCN	HGAT
CORA	23.8 ± 0.7	22.0 ± 1.5	51.5 ± 1.0	54.6 ± 0.4	81.3 ± 0.3	83.0 ± 0.7	77.9 ± 2.4	79.9 ± 0.2	79.6 ± 0.3
PubMed	48.2 ± 0.7	68.5 ± 0.3	72.4 ± 0.2	69.8 ± 0.4	78.1 ± 0.2	79.0 ± 0.3	77.4 ± 2.2	80.3 ± 0.3	79.2 ± 0.3
DISEASE	32.5 ± 1.1	45.5 ± 3.3	28.8 ± 2.5	41.0 ± 1.8	69.7 ± 0.4	70.4 ± 0.4	69.1 ± 0.6	74.5 ± 0.9	73.4 ± 0.9
PPI	-	-	55.3+0.4	59.3 ± 0.4	69.7 ± 0.3	70.5 ± 0.4	69.1 ± 0.3	74.6 ± 0.3	73.6 ± 0.3
AIRPORT	60.9 ± 3.4	70.2 ± 0.1	68.6 ± 0.6	80.5 ± 0.5	81.4 ± 0.6	81.5 ± 0.3	82.1 ± 0.5	90.6 ± 0.2	89.4 ± 0.2

Just a teaser to the power of hyperbolic networks, entire experiment shall be discussed in the Applications section of the tutorial.

Tutorial Objective

Make it easy to use

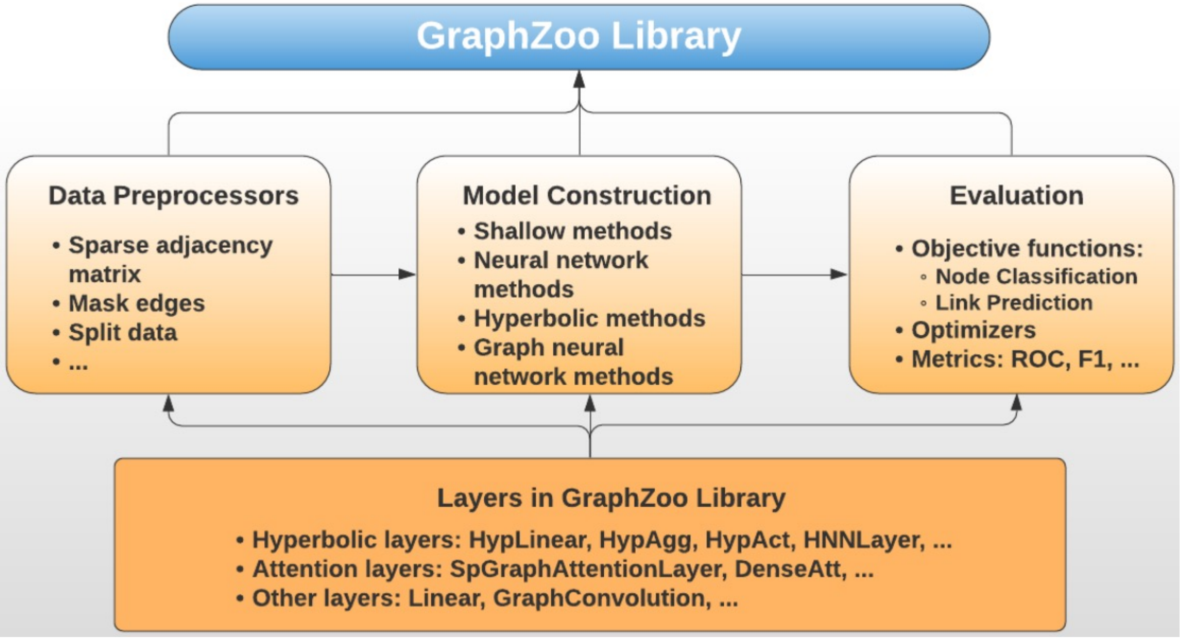
One-Stop-Shop for Hyperbolic Networks

Theoretical Underpinnings of Hyperbolic geometry

Architectural Design Choices and Implementation

Successful Application Scenarios

GraphZoo Toolkit



Tutorial Objective

Make it easy to use

In majority of the cases, to change a Euclidean architecture, we just need to:

1. Change operators

Euclidean:

$w_1 x_1 + w_2 x_2 + w_3 x_3 + \mathrm{b}$

Hyperbolic: Replace with gyrovector operations

$w_1 \otimes_c x_1 \oplus_c w_2 \otimes_c x_2 \oplus_c w_3 \otimes_c x_3 \oplus_c b$

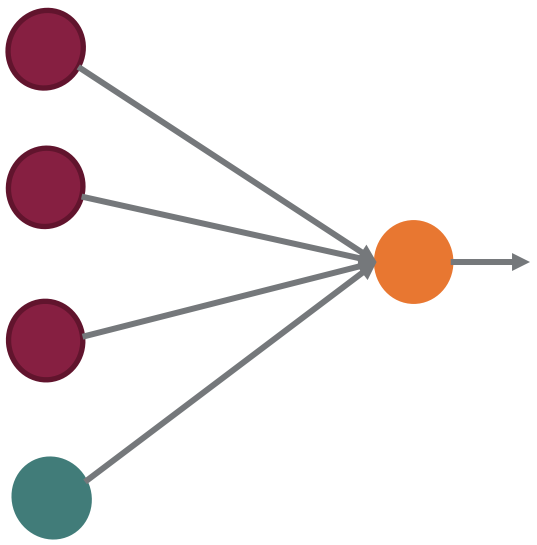
2. Call manifold versions of the Euclidean layers:

Euclidean:

nn.Linear

Hyperbolic: Replace with manifold library

manifolds.hyperbolic.Linear



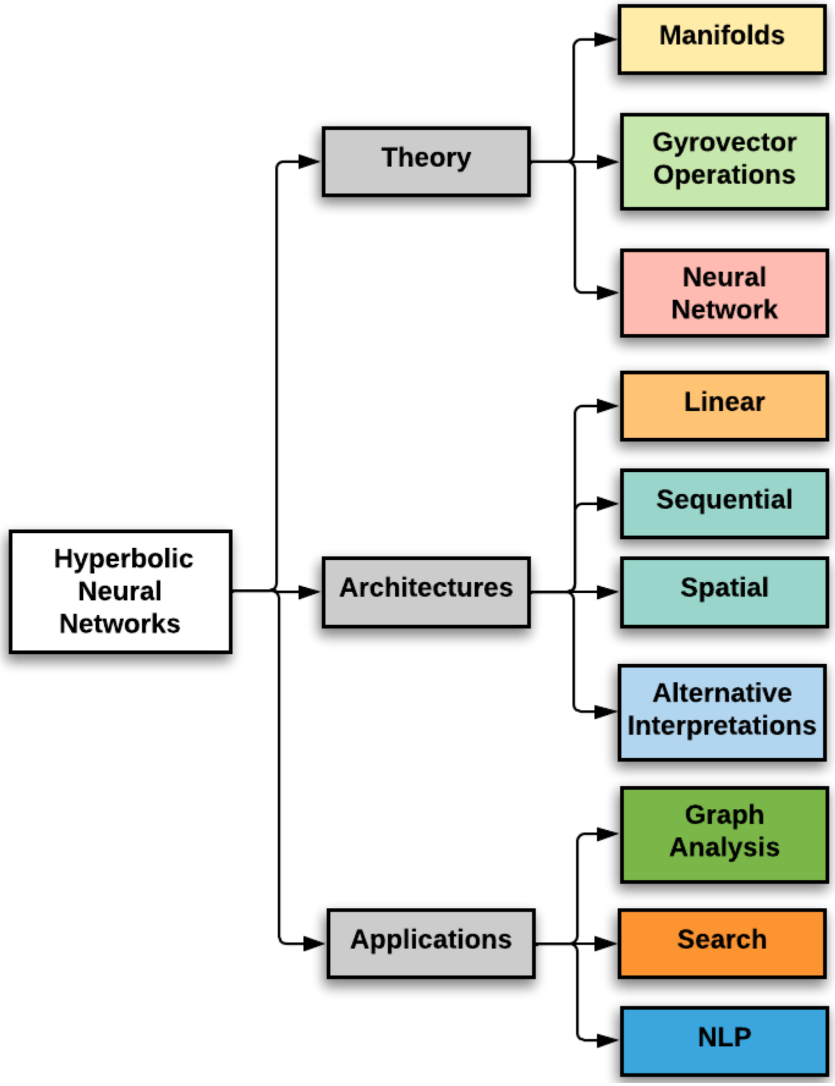
Note that the overarching network structure remains the same, only some components change.

Tutorial

Overview

Our goal is to introduce:

1) Hyperbolic geometry
2) Implementation techniques
3) Existing applications
4) Advantages over Euclidean architectures.

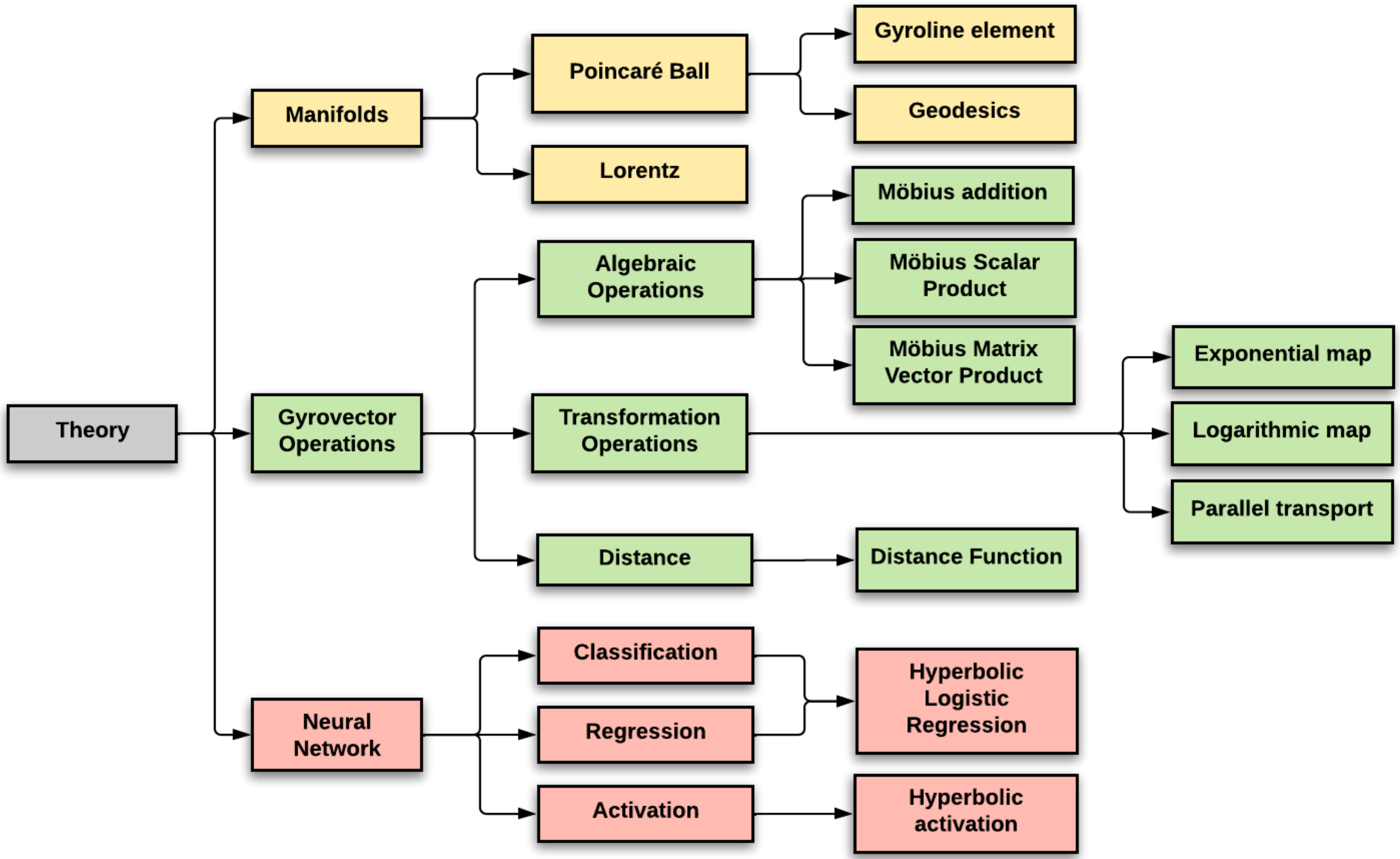


Tutorial

Details: Hyperbolic Geometry

Hyperbolic geometry

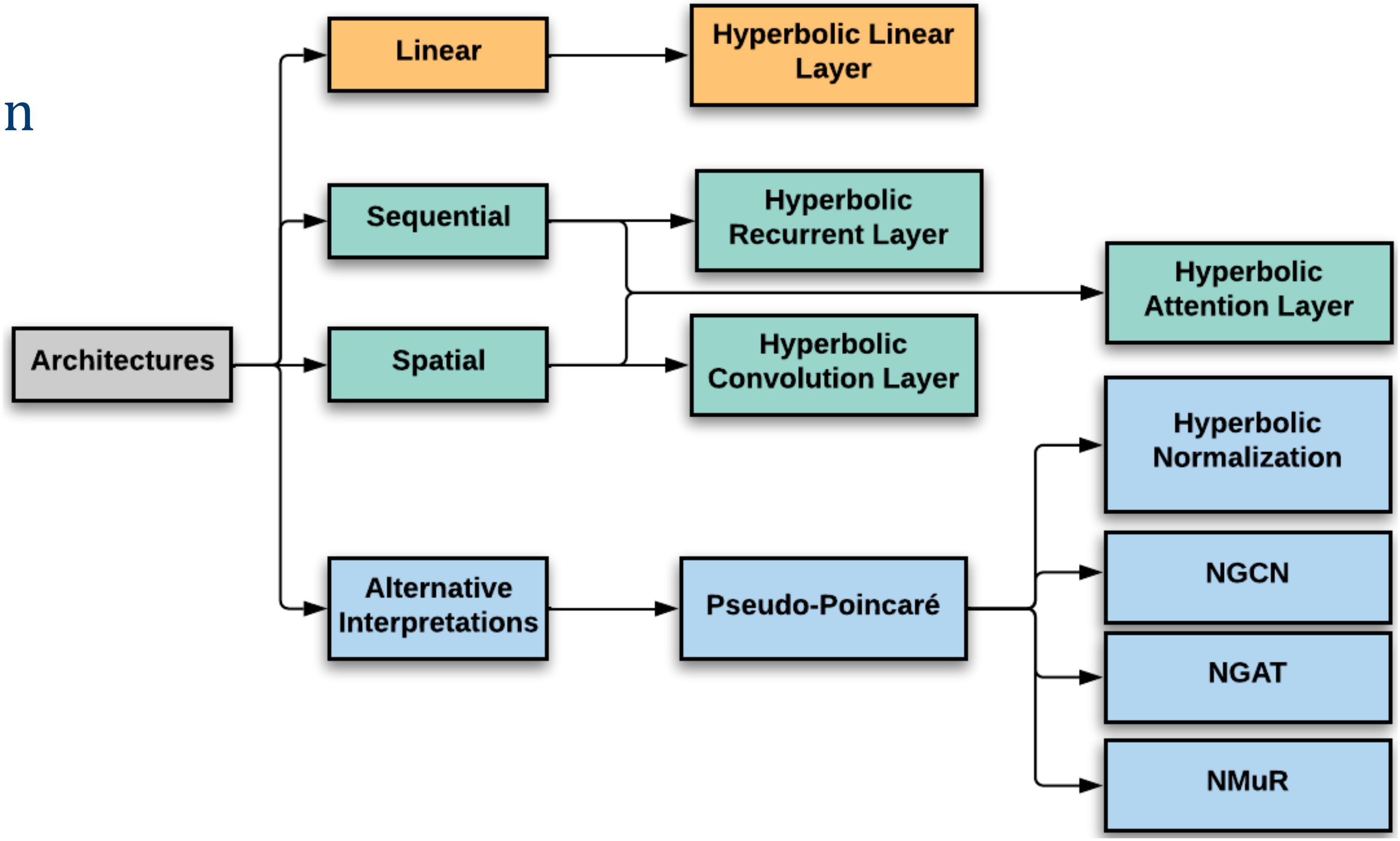
- Manifolds
- Gyrovector Operations
- Neural Networks



Tutorial
Details: Architectures

Architectures/ Implementation

- Linear layer
- Sequential data
- Spatial data
- Other formulations

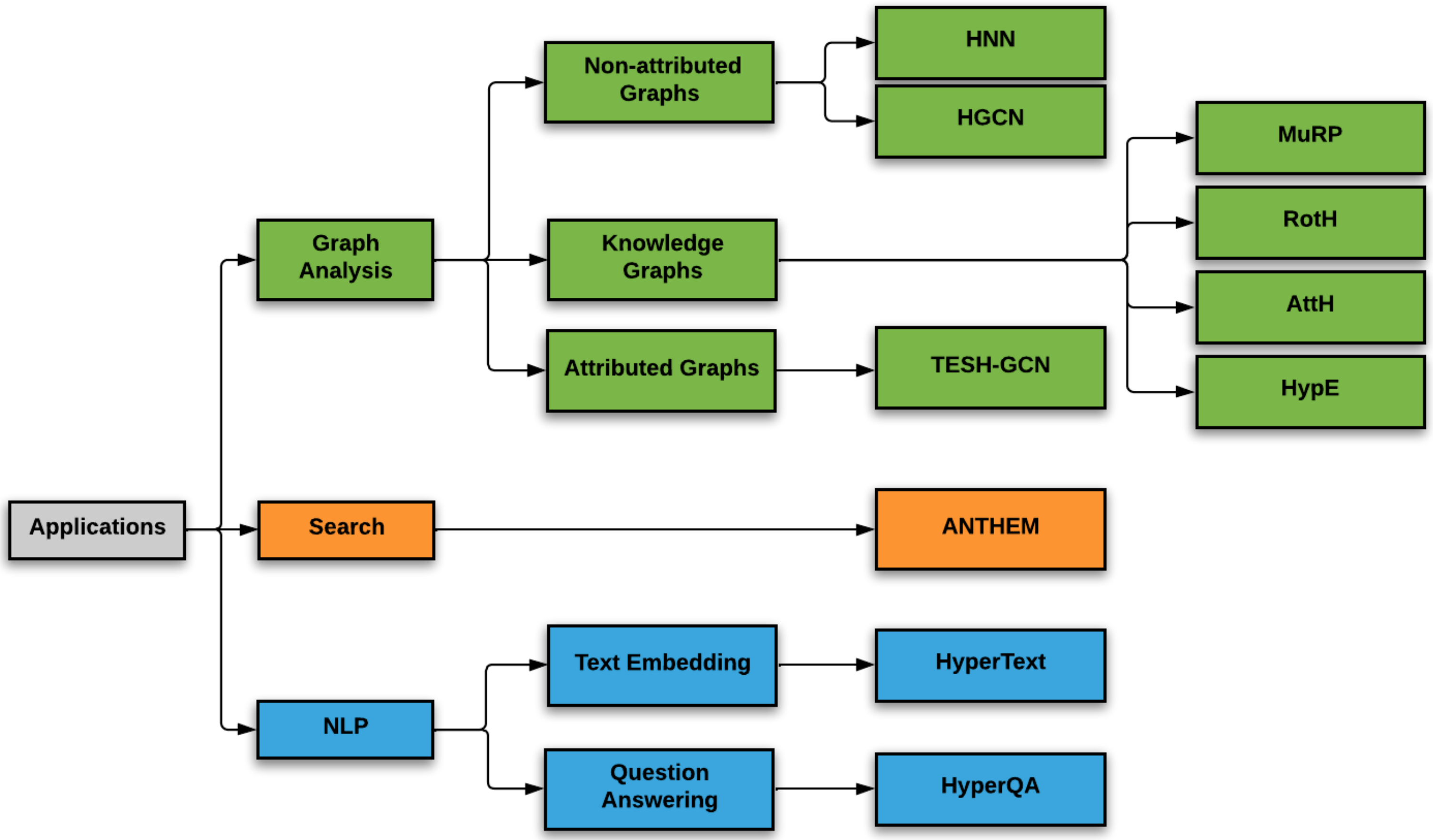


Tutorial

Details: Applications

Real-World Applications

- Graph Analysis
- Knowledge Graph Mining
- Search
- Natural Language Processing



Q&A

Please provide your feedback at:

https://bit.ly/feedback-hyperbolic-tutorial