

HYPERBOLIC DEEP LEARNING FOR COMPUTER VISION:A SURVEY

Addis Ababa University
Mahlet Nigussie
GSR/3758/16



Contents

- 1 Introduction
- 2 Background
- 3 Applications in Computer Vision
- 4 Discussion and Future Directions
- 5 Conclusion

Introduction

The Human Advantage in Visual Perception

The human visual system excels at understanding complex scenes with hierarchical structures.

- We can effortlessly identify objects, their parts, and their relationships within an environment.

Deep learning has revolutionized computer vision, but limitations exist

- Euclidean geometry, the traditional mathematical framework, struggles to represent hierarchical relationships effectively.

Hyperbolic deep learning addresses limitations of Euclidean geometry in computer vision by efficiently representing hierarchical structures.

Background

Euclidean vs. Hyperbolic Geometry

Euclidean Geometry (Flat Space)

- Familiar distance calculations (Pythagorean theorem)
- Well-suited for representing simple, non-hierarchical relationships
- Limited in capturing complex hierarchies found in visual data

Hyperbolic Geometry (Curved Space)

- Exponential distance growth as points move further apart
- More natural representation for hierarchical structures with nested relationships.

Con..

Analogy: Library Classification System

Imagine a library classification system with different levels of categories (books, genres, subgenres).

- Euclidean space might struggle to depict the relationships effectively.
- Hyperbolic space allows for a more intuitive representation, where closely related subgenres are positioned closer together, while broader categories like "books" reside farther away.

Advantages of Hyperbolic Deep Learning

Efficient Modeling of Hierarchical Structures:

- 3D Scene Understanding: Classify objects within a scene (furniture, vehicles) and model their relationships using scene graph representations with hyperbolic graph convolutions.
- Object Detection: Identify objects and their locations in images, leveraging the ability of hyperbolic space to capture hierarchical relationships between parts and wholes

Handling Large Datasets with Numerous Objects

- Hyperbolic embeddings can efficiently manage complex scenes with many objects, potentially improving scalability and accuracy.

Improved Performance with Limited Data (Few-Shot Learning)

- Hyperbolic deep learning models may exhibit better performance in scenarios with limited training data, making them valuable for tasks where acquiring large datasets is challenging.

Supervised and Unsupervised Learning

Supervised Learning:

- Hyperbolic CNNs: Efficiently classify objects using hierarchical features in images.
- Salt-and-pepper noise: random pixels set to either 0 or 255.
- Hyperbolic Attention: Focus on relevant regions based on their importance within the scene hierarchy (better object detection).

Unsupervised Learning:

- Hyperbolic Autoencoders: Learn hierarchical data structures without labels (useful for anomaly detection).
- Hyperbolic Clustering: Group data points based on their similarities in the hyperbolic space (better for hierarchical data segmentation).

Applications in Computer Vision

Research Areas

The survey Focus on 2-3 Key Areas, Revolutionizing Tasks with Hierarchical Structures

3D Scene Understanding:

- Hyperbolic embeddings: Efficiently classify objects within a scene (e.g., furniture, vehicles).
- Hyperbolic graph convolutions: Represent relationships between objects in a scene graph, capturing their hierarchical structure.

Scene Perception:

- Hyperbolic scene graph attention networks: Improve fine-grained object recognition by focusing on relevant regions based on their relationships within the scene (e.g., distinguishing bird species).

Action Recognition in Videos:

- Hyperbolic representations: Capture temporal relationships between video frames, aiding in understanding actions and their sequences.

Discussion and Future Directions

Addressing Challenges and Unlocking Potential

Limitations of Hyperbolic Deep Learning:

- Theoretical Underpinnings: Ongoing research is needed to fully understand the theoretical foundations of hyperbolic deep learning.
- Computational Efficiency: Optimizing algorithms for real-world applications with large datasets is crucial.
- Limited Datasets: Techniques for adapting existing Euclidean datasets or creating specialized hyperbolic datasets are important areas of exploration.

Future Research Directions:

- Strengthening theoretical foundations to establish a more robust framework. Developing computationally efficient algorithms for practical applications.
- Exploring techniques for leveraging existing datasets or creating new ones specifically suited for hyperbolic deep learning.

Conclusion

Conclusion

- Hyperbolic deep learning offers a promising new direction for computer vision.
- This approach has the potential to revolutionize tasks involving complex hierarchical structures.
- Further research can unlock the full potential of this exciting field and empower computer vision systems with a deeper understanding of the world around us.

Thank you!