Part 5:
Future Directions

Conclusion

Hyperbolic Neural Networks

- Hyperbolic space is better at capturing hierarchical features due to its exponential growth in volume (depth ≈ radius).
- Hyperbolic space can simultaneously capture spatial and hierarchical structure information by pseudo-querying the knowledge graphs (HyPE).
- Attention mechanism can be used to capture intersection and union operations in search queries.
- HypE's representation, in congruence with matching architecture can be utilized for downstream tasks (query matching).
- The hyperbolic space can also be visualized for better human comprehension.

However, further study in the field shows certain interesting challenges.

Challenges

Hyperbolic Neural Networks

- As we mentioned previously, hyperbolic networks suffer from practical implementation challenges.
  - Non-availability of specific objective functions (or) normalization layers.
  - Unstable training and non-closure of hyperbolic networks.
- Application to complex tasks in Natural Language Processing and Computer Vision
  - Currently only limited to representation learning
- Development of scalable pre-trained architectures.
  - Hyperbolic networks are not able to leverage the GPU operations.
- Standardization of hyperbolic architectures as libraries for easy access.
  - Currently, a lot of theoretical background is required for development of hyperbolic networks, certain level of abstraction and standardization will help the initiation of new researchers in the area.

Future Directions
Implementational Challenges

We see development of new models of hyperbolic formulation such as; Pseudo-Poincaré and HNN++.

However, the following problems remain:

- Objective functions remains limited to hyperbolic distance, which is equivalent to L1-norm. There is scope for development of more complex classification and regression objectives.
- Along the lines of development of AdaM for Euclidean spaces, further study into the hyperbolic gradient descent is needed to provide new techniques for stable training.
- Not all Euclidean points are hyperbolic points. There is scope for practical development of specific hyperbolic libraries or theoretical development to satisfy the bound limitation of hyperbolic space.

Future Directions
Extension to Complex Applications

While graph research into hyperbolic spaces has been extended to complex problems such as logical reasoning. The scope in other domains has been limited to representation learning. Following are the possibilities in other domains;

- Natural Language Processing: The dependency tree structure of sentences can be used towards machine translation, question-answering, and document search.

- Computer Vision: The power of exponential volume growth can be used to hierarchically preserve both high-level features, such as object type, and low-level details for object identification.

- Networks: Hyperbolic space can hierarchically aggregate information from network clusters to process high-level details.

Future Directions

Scalable Pre-trained architectures

Due to the complexity of addition and multiplication operations, hyperbolic networks cannot properly utilize the power of GPUs. This limits our ability to develop architectures for effective training paradigms such as transfer learning and curriculum learning.

- Development of scalable formulation for GPUs is required.

- Subsequently, further development of large networks that can then utilize;
  - pretraining and finetuning approach of transfer learning and,
  - continuous improvements through curriculum learning

Future Directions

Standardization of Hyperbolic Neural Networks

Abstraction and Standardization of hyperbolic network theory and architectures is required.

GraphZoo* and this tutorial are a step in that direction.

The abstraction, especially, helps application-oriented research that would prefer black-box frameworks.

Interpretability frameworks such as LINE and SHAP also need to be developed for hyperbolic spaces to improve the trust in hyperbolic networks.

This will also improve human comprehension of the networks, so researchers can conduct targeted studies into the problem areas of hyperbolic networks.

* https://github.com/reddy-lab/GraphZoo

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Thanks!

Any questions?

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The toolkit is available at:

https://github.com/reddy-lab/GraphZoo