

# Towards Low-Distortion Graph Representation Learning

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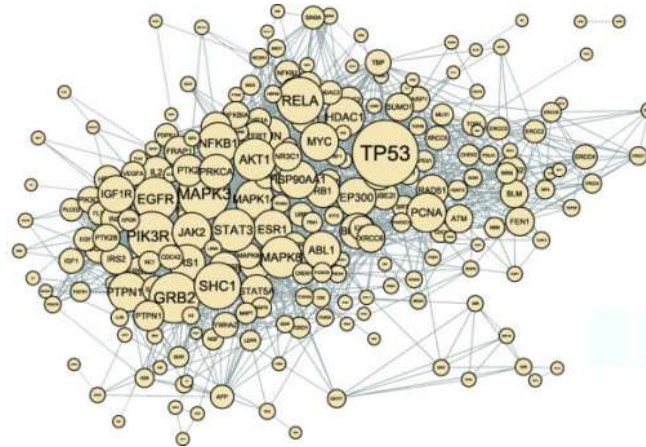
# Outline

- Introduction (20min)
- Invariance-guided Graph Representation Learning (40min)
- Information-theoretic Graph Representation Learning (40min)
- Geometry-guided Graph Representation Learning (40min)
- Advanced Directions (30min)
- QA

# Networks/Graphs



# Social Network



# Biology



## Logistics



# Internet of Things

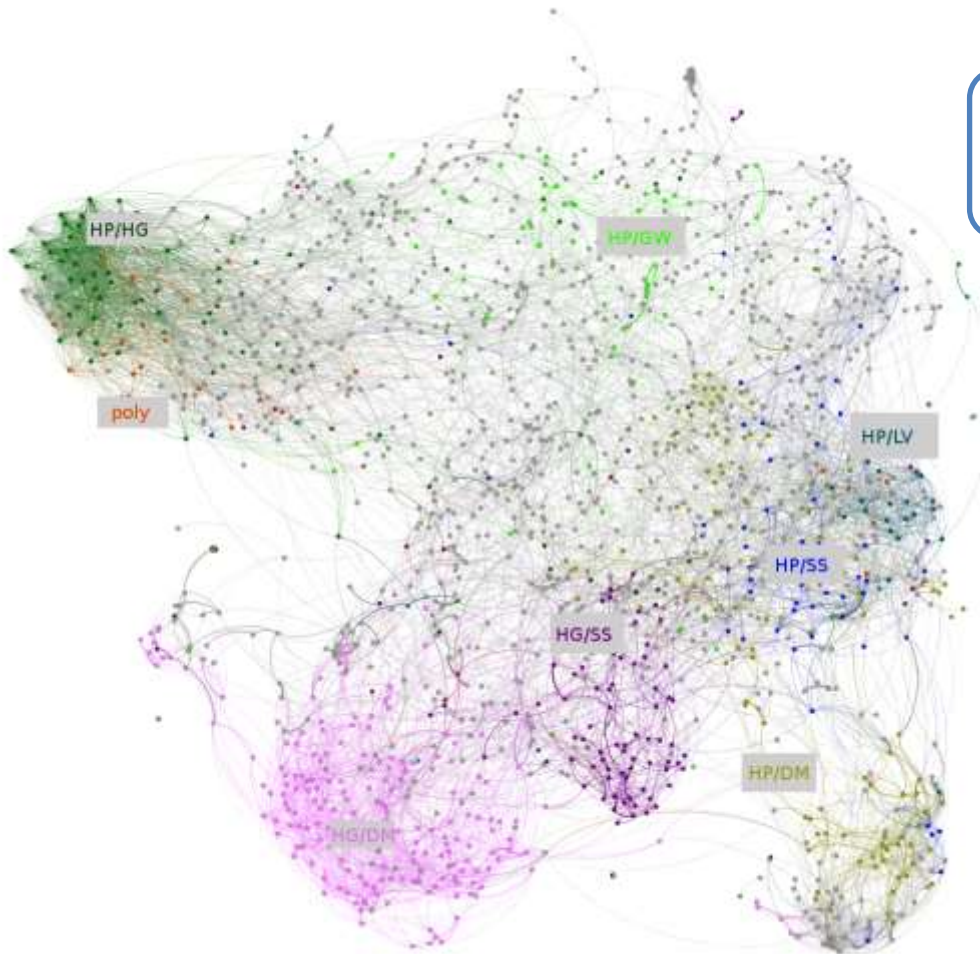


# Transaction



# Knowledge Graphs

# Graph Tasks



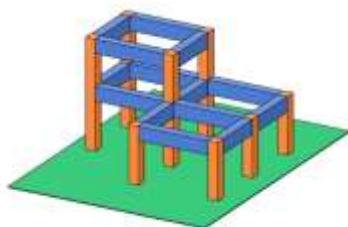
## Descriptive and Predictive

- ❑ Node classification
- ❑ Link prediction
- ❑ Graph Classification
- ❑ Node importance
- ❑ Community detection
- ❑ Network distance
- ❑ Network evolution
- ❑ ...

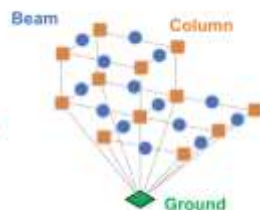


Encoding Sentences with Graph Convolutional Networks for Semantic Role Labeling, *EMNLP 2017*  
Neural Motifs: Scene Graph Parsing with Global Context, *CVPR 2018*  
Learning by Abstraction: The Neural State Machine. *NeurIPS 2019*

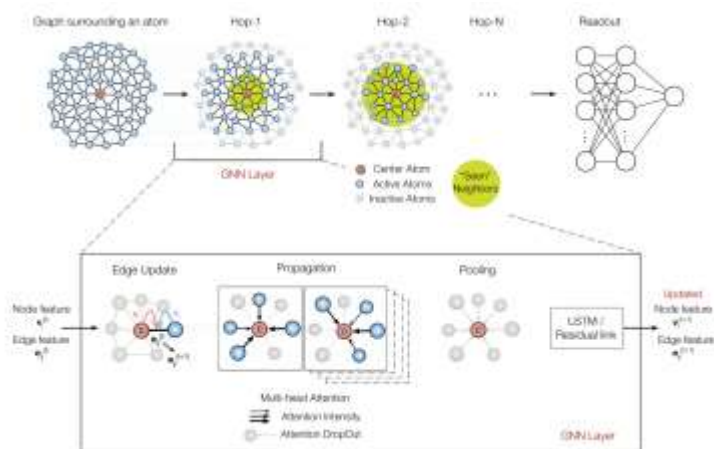
# Graph Applications beyond Computer Science



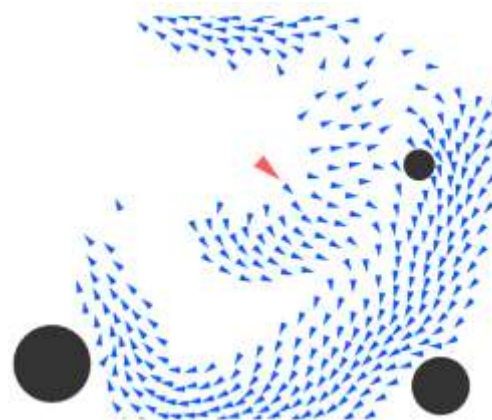
Structural Engineering



Drug repurposing for Covid-19



Material Science

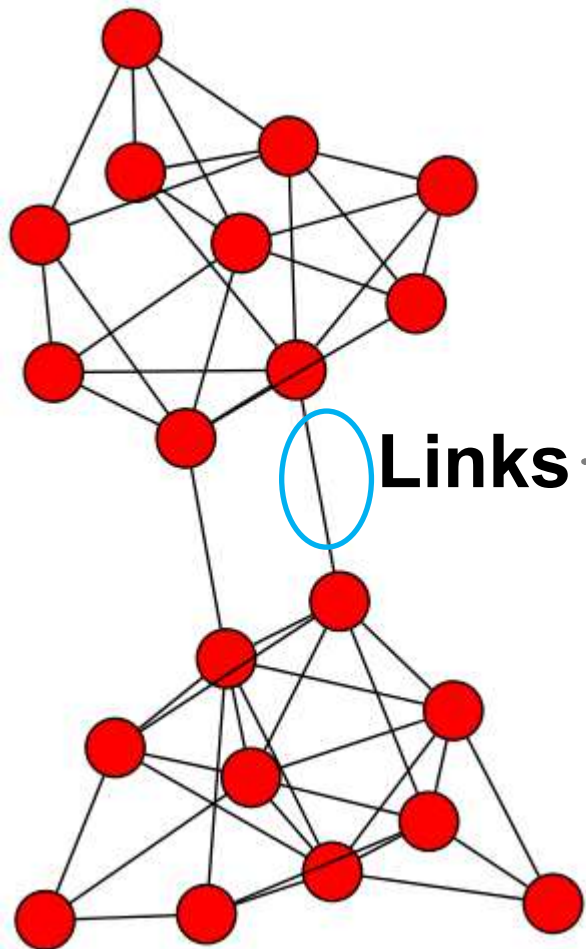


Physical Simulation

**Graph is a common and general tool for modeling relational data!**

# Graph Machine Learning is Challenging

$$G = (V, E)$$



**Links**

Iterative &  
Combinatorial

Complexity

Coupling

Parallelizability

Dependency  
among nodes

Applicability of  
ML methods

# Graph Representation Learning (GRL)

$$G = (V, E)$$



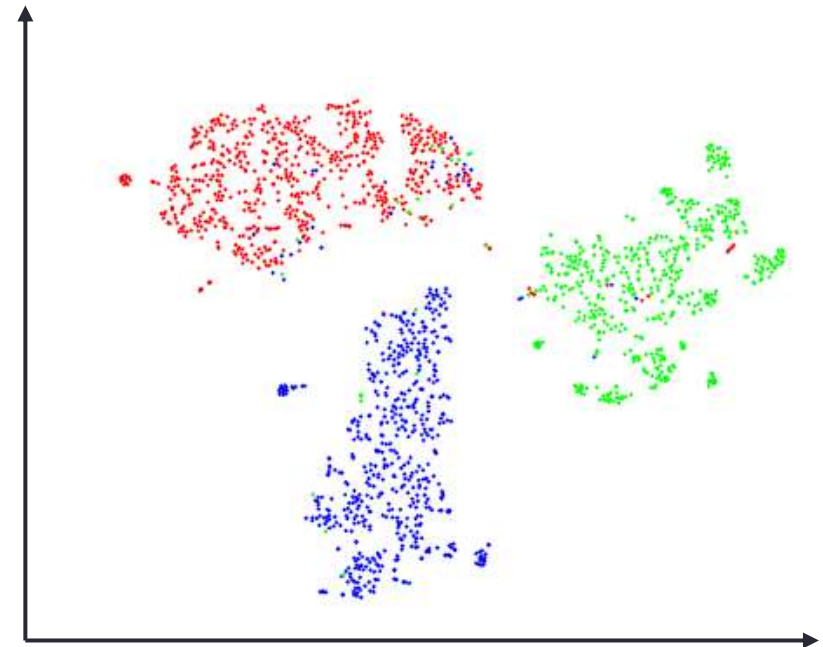
Links

generate

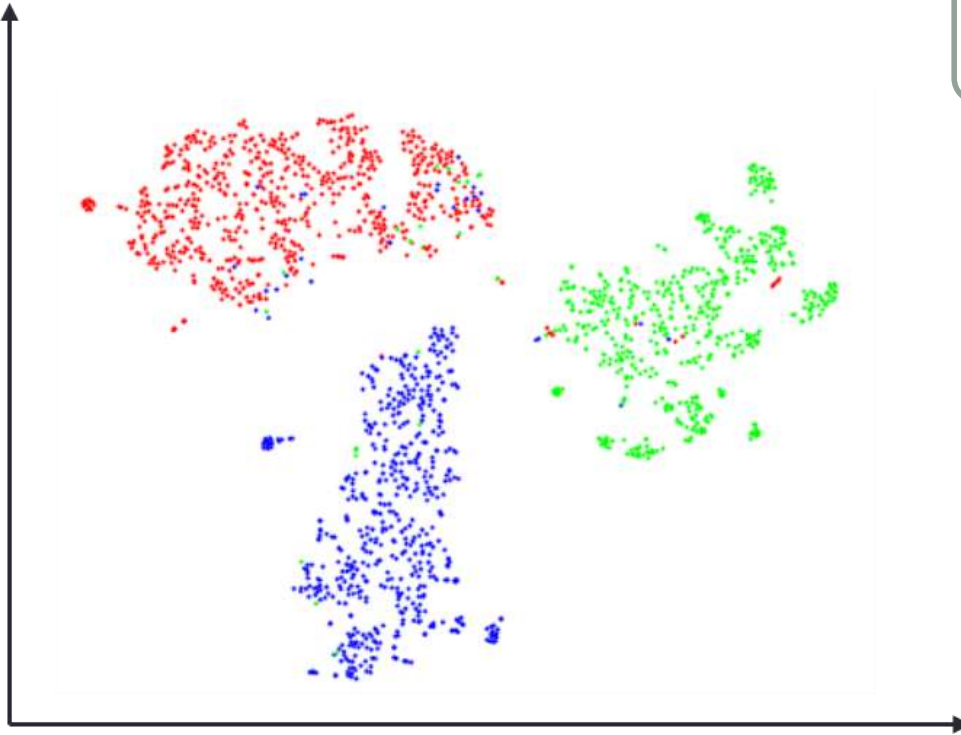
embed

$$G = (V)$$

Vector Space



# The ultimate goal of Graph Representation Learning



## Descriptive and Predictive

- ❑ Node classification
- ❑ Link prediction
- ❑ Graph Classification
- ❑ Node importance
- ❑ Community detection
- ❑ Network distance
- ❑ Network evolution
- ❑ ...

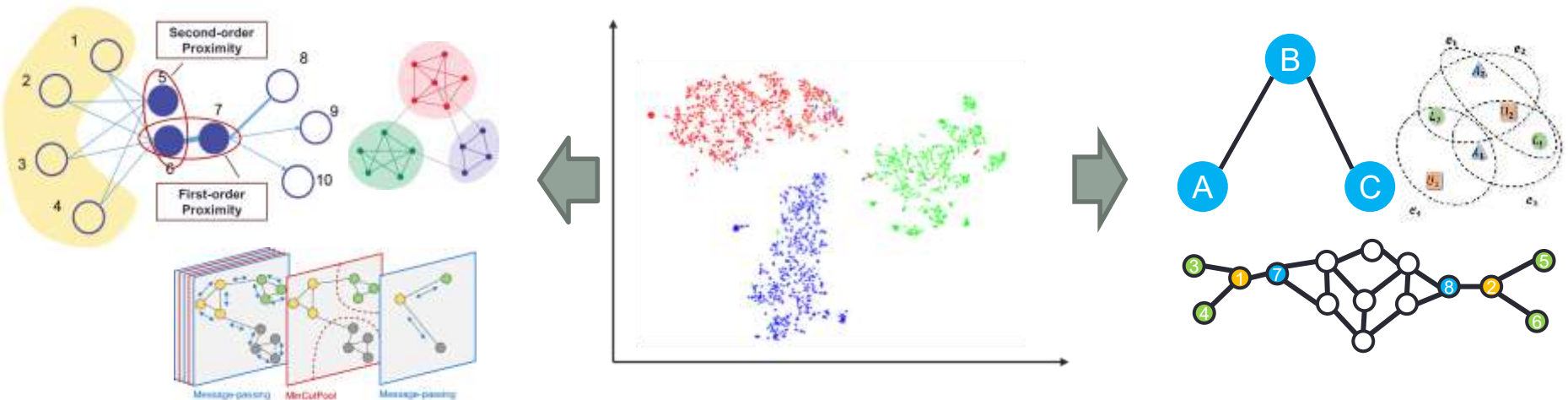
in the *Vector Space*

# Requirement of Graph Representation Learning

**Goal:** Support various graph analytical tasks

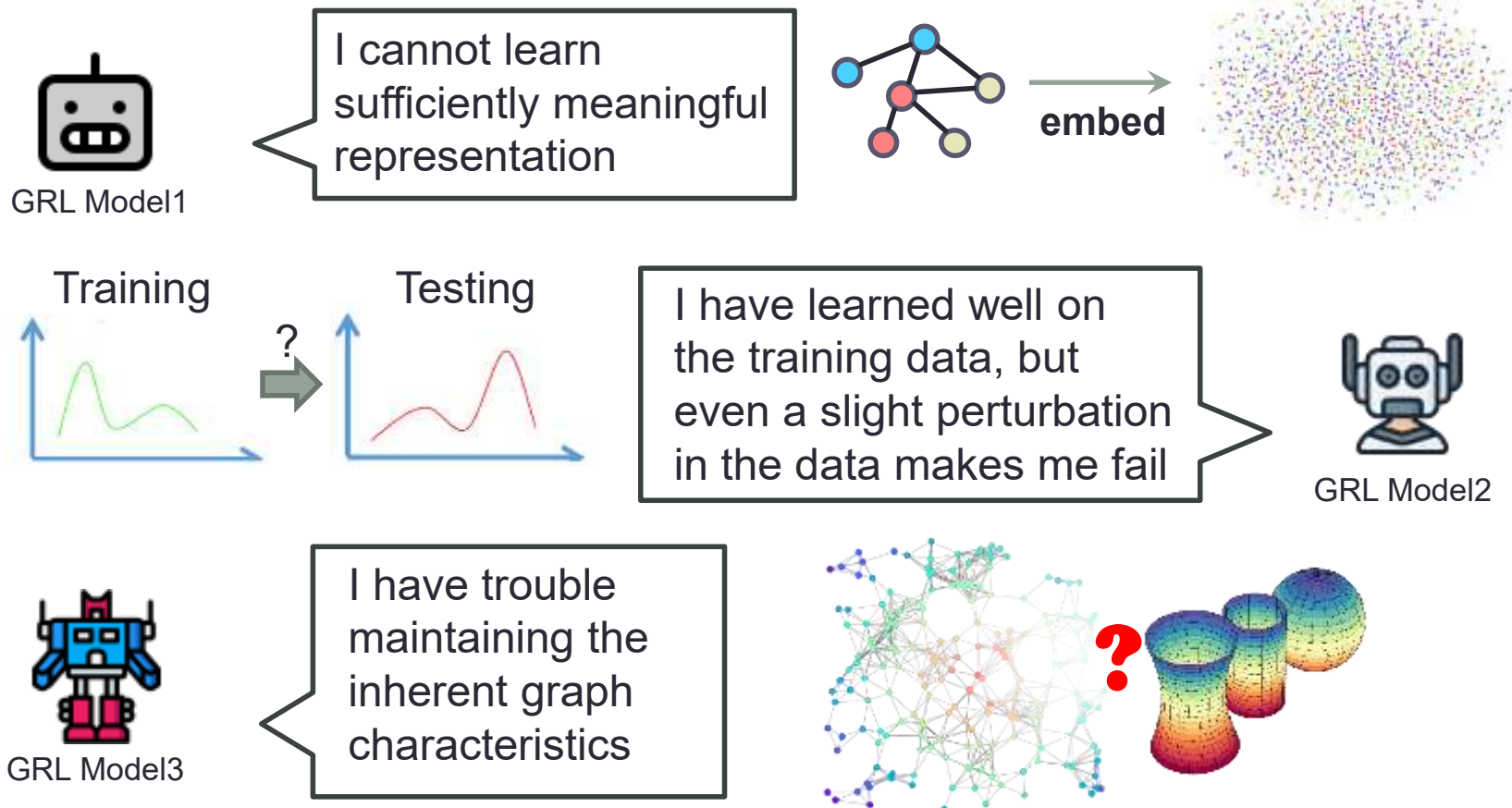
Reflect graph structure

Maintain graph Properties



**GRL should preserve essential characteristics of graphs**

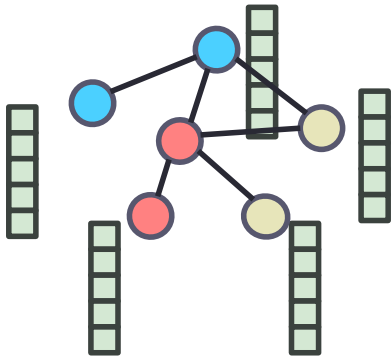
# However, GRL is usually imperfect ...



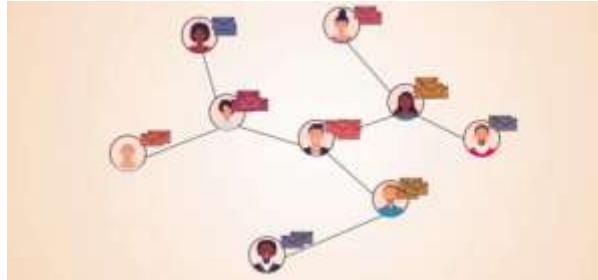
**We generally refer to these phenomenon as “distortion”**

# What Causes Distortion in Graph Representation?

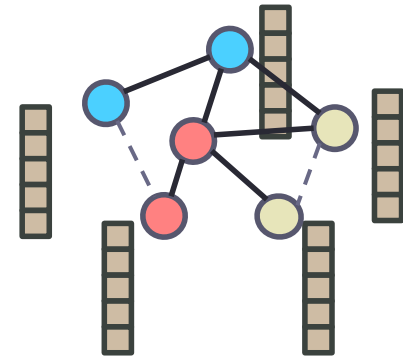
Graph Data



GRL Models



Representation



Spurious relationship  
Imbalance (label, topology)  
Noise (label, structure)  
...

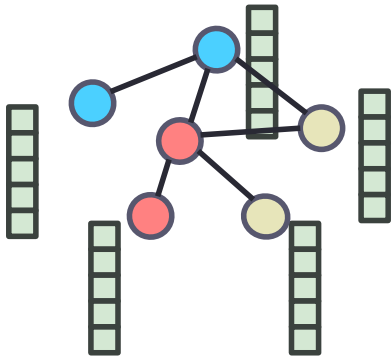
Over-smoothing  
Over-squashing  
Structural simplification  
...

Limited dimensionality  
Representation bias  
Low discriminability  
...

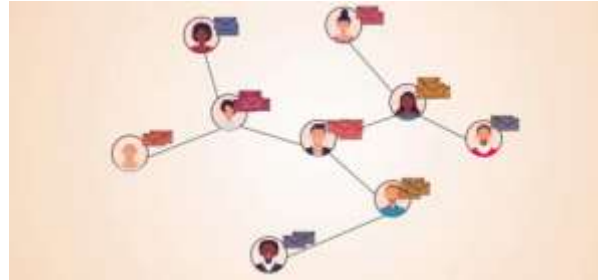
**!! Distortion !!**

# Understanding and Addressing Distortion

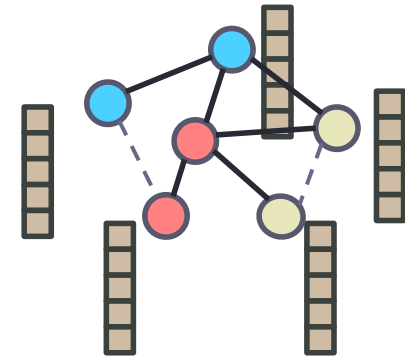
Graph Data



GRL Models



Representation



**Low-Distortion Graph Representation Learning**

**Invariance-guided**  
Graph Representation  
Learning

**Information-theoretic**  
Graph Representation  
Learning

**Geometry-guided**  
Graph Representation  
Learning

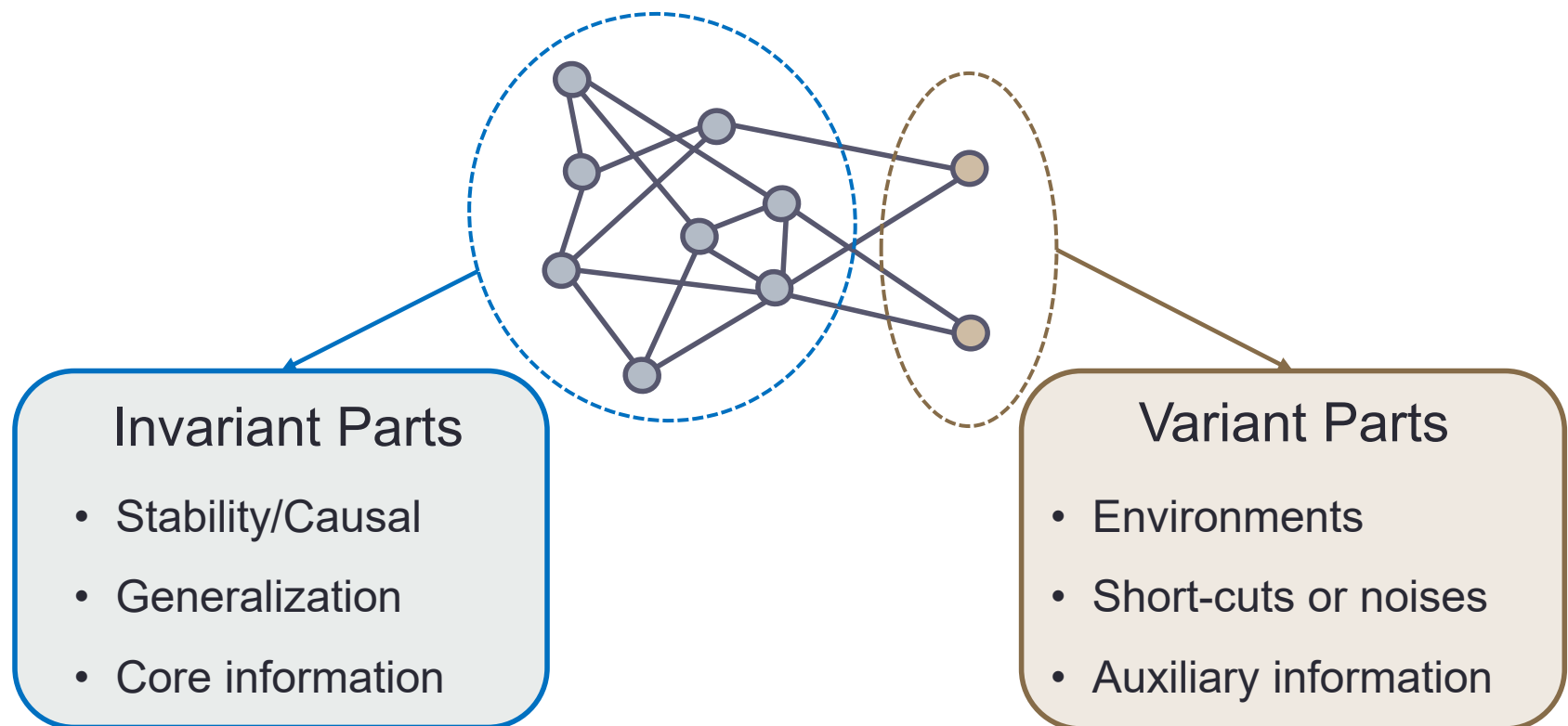
# Understanding and Addressing Distortion

① Invariance-guided

② Information-theoretic

③ Geometry-guided

Distinguish the **invariant/variant structures/features** in the graph data



# Understanding and Addressing Distortion

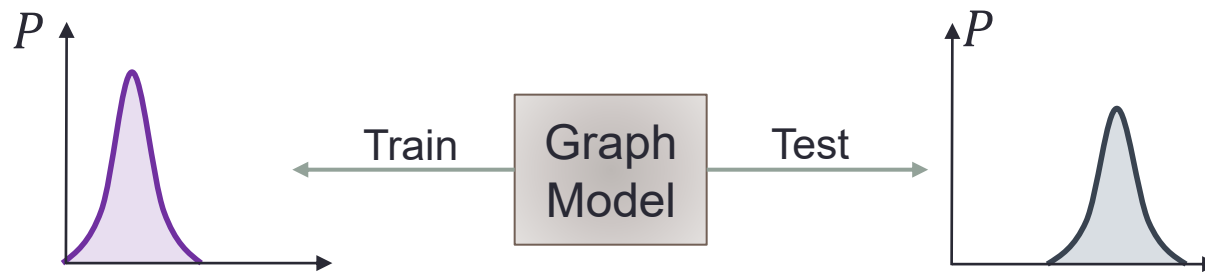
① Invariance-guided

② Information-theoretic

③ Geometry-guided

**Distortion:** Learned representations **fail** to fully capture **invariant features**, which makes them struggle with **distribution shift** problem.

- ❑ E.g., train on small graphs, test on large graphs.
- ❑ Mislead by spurious correlations.



Distinguish invariant and variant structures/features under distribution shift



**Reduce distortion and improve generalization**

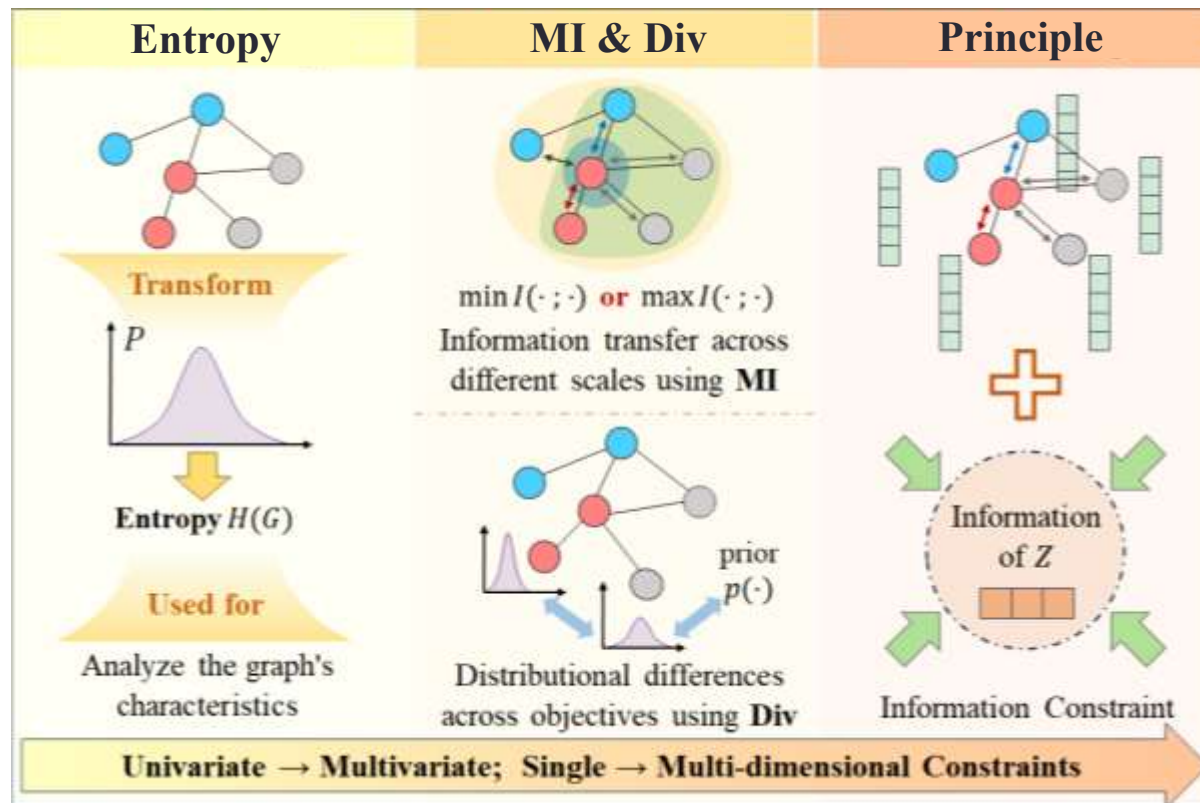
# Understanding and Addressing Distortion

① Invariance-guided

② **Information-theoretic**

③ Geometry-guided

**Analyze** and **extract information** from complex node features and irregular structure



# Understanding and Addressing Distortion

① Invariance-guided

② **Information-theoretic**

③ Geometry-guided

**Distortion:** The model **loses information** during encoding, message passing, or decoding

- ❑ Message passing causes feature information loss
- ❑ Structure simplification causes structural information loss



Formulate the trade-off between information acquisition and compression in graph learning



**Reduce distortion and improve interpretability**

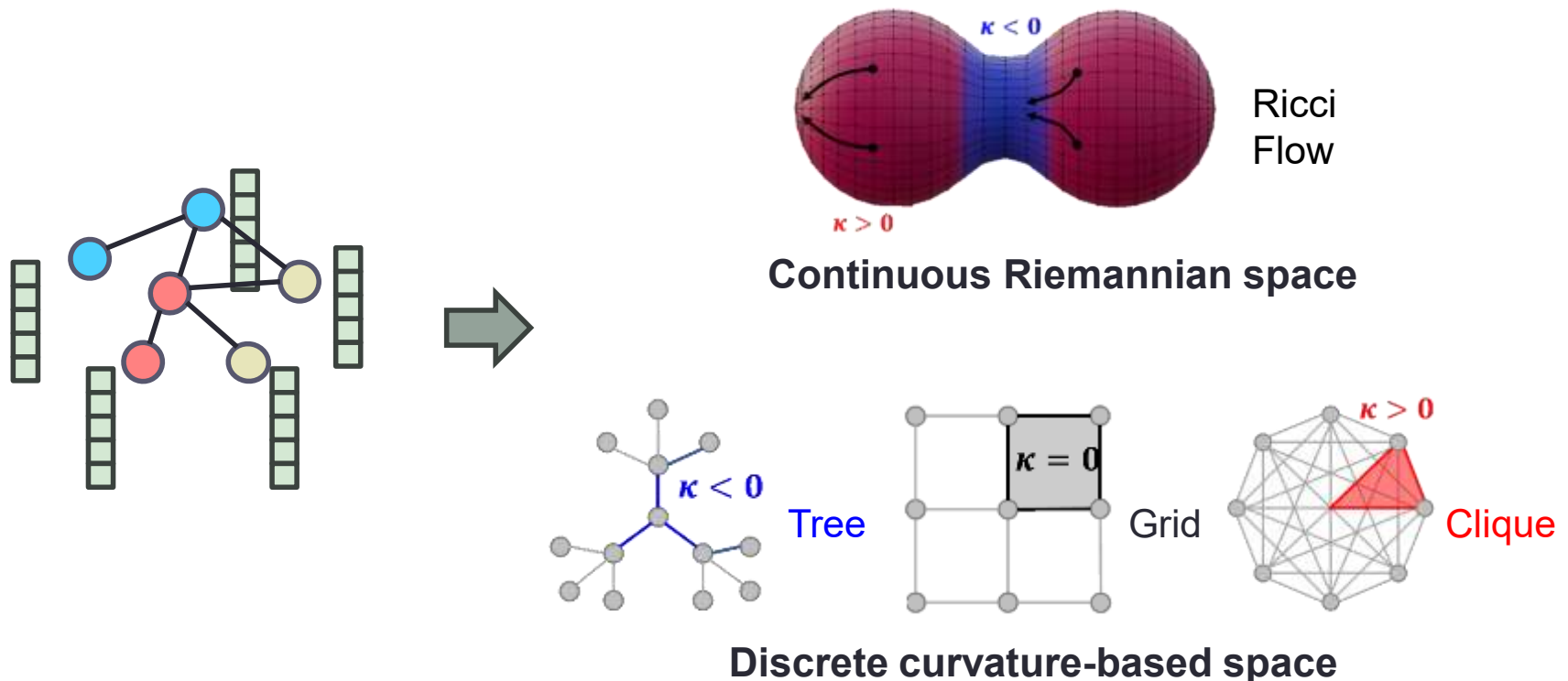
# Understanding and Addressing Distortion

① Invariance-guided

② Information-theoretic

③ **Geometry-guided**

**Extend** graph learning to the **continuous** Riemannian / **discrete** curvature space



# Understanding and Addressing Distortion

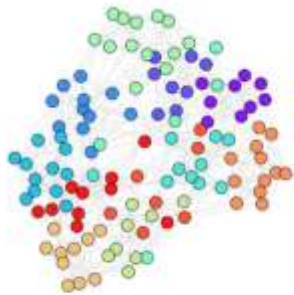
① Invariance-guided

② Information-theoretic

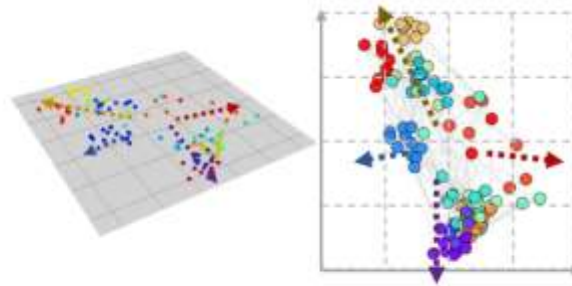
③ **Geometry-guided**

**Distortion:** The embedding space **mismatches** the geometric relations

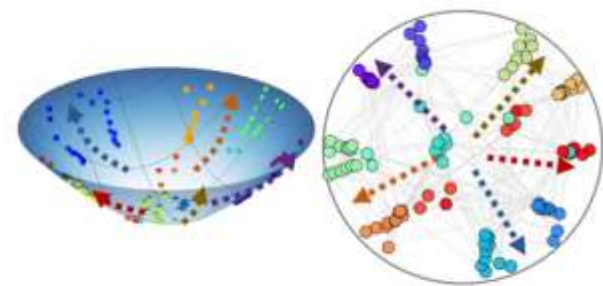
- ❑ Mapping to Euclidean space without considering graph characteristics
- ❑ Insufficient information storage capacity in low-dimensional space



(a) Original structure.



(b) Euclidean latent space.



(c) Hyperbolic latent space.

Learn representations in non-Euclidean spaces (Riemannian space & curvature-based space)

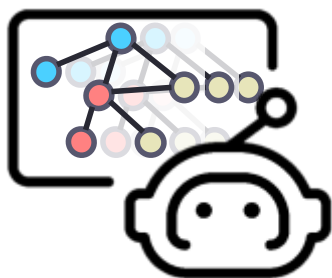


**Reduce distortion and improve expressiveness**

# Advanced Directions

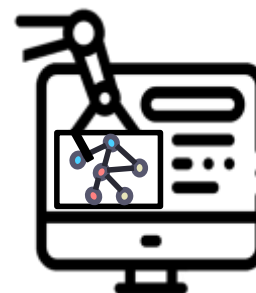
## Graph Foundation Model

- Inspired by LLMs, GNNs with cross-task zero-shot generalization
- One pre-train, use everywhere
- Scaling Law



## Graph RAG

- Construct knowledge graphs
- Capture complex relations across documents and across facts
- Enhance multi-hop reasoning



**Graph World Model**

**Now, let's move towards  
low-distortion graph representation!**