





# A Tutorial on Hypergraph Neural Networks: An In-Depth and Step-by-Step Guide Part 1. Introduction



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#### Part 1. Introduction

Part 1. Introduction Part 2. Inputs

Part 3. Message **Passing** 

Part 4. **Training Strategies**  Part 5. **Applications** 

Part 6. **Discussions** 













#### **Presenter**



Kijung Shin. Associate Professor @ **KAIST** 

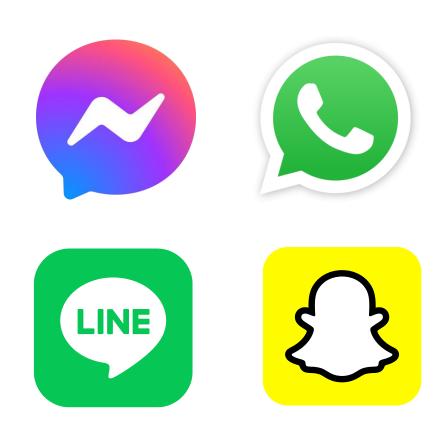


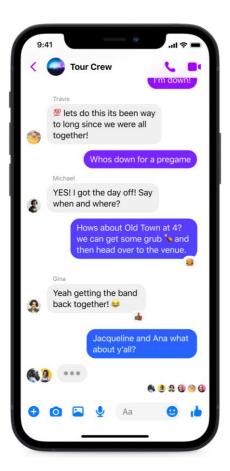




#### **Higher-Order Interactions are Everywhere**

• [Example 1] Group chats on social messaging apps













• [Example 2] Co-authorship of researchers





ResearchGate

#### A Survey on Hypergraph Neural Networks: An In-Depth and Step-by-Step Guide

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HYPEBOY: GENERATIVE SELF-SUPERVISED REPRE-SENTATION LEARNING ON HYPERGRAPHS

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# Higher-Order Interactions are Everywhere (cont.)

• **[Example 3]** Co-purchase of items









Today 6:08 PM	NEW ORDER #45790: 1 x Nike Air Printed 1 page(s) on Epson TMT88 The file #Agreement.pdf is not processed because you set a condition in the action	Success	Actions 🗸
Today 6:05 PM	NEW ORDER #45790: 1 x Nike Air Printed 1 page(s) on Epson TMT88 The file #Agreement.pdf is not processed because you set a condition in the action	Success	Actions 🗸
Today 3:33 PM	NEW ORDER #45789: 2 x adidas Superstar Printed 2 page(s) on Epson TMT88 The file #Agreement.pdf is not processed because you set a condition in the action	Success	Actions 🗸
Today 3:30 PM	NEW ORDER #45789: 2 x adidas Superstar Printed 2 page(s) on Epson TMT88 The file #Agreement.pdf is not processed because you set a condition in the action	Success	Actions 🗸
Yesterday 5:03 PM	NEW ORDER #45788: 50 x Flag adidas Printed 5 page(s) on Epson TMT88 The file #Agreement.pdf is not processed because you set a condition in the action	Success	Actions 🗸



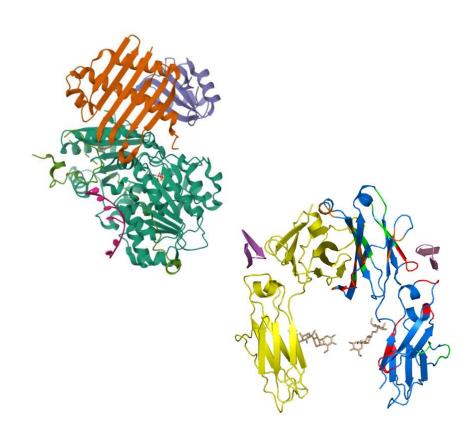
#### **Higher-Order Interactions are Everywhere (cont.)**

• [Example 4] Interactions of proteins





Johnson&Johnson

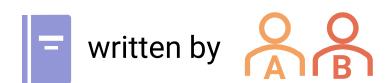








- Higher-order interactions are commonly modeled as a hypergraph.
  - A hypergraph consists of a node set and a hyperedge set.
  - A hyperedge (i.e., a subset of nodes) models a higher-order interaction.







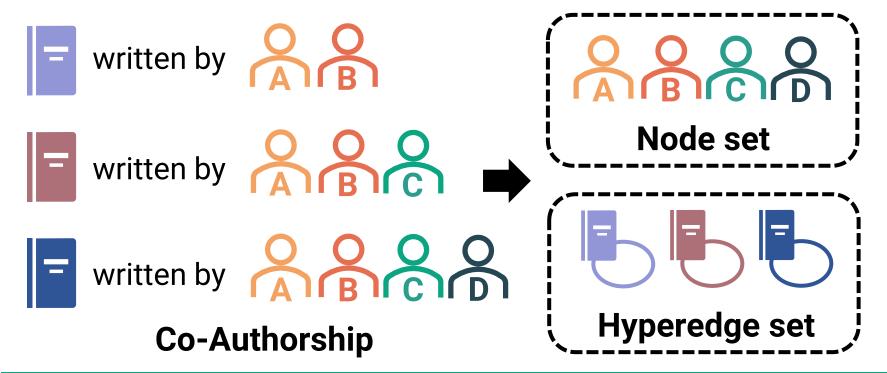
**Co-Authorship** 





#### **Hypergraphs Model Higher-Order Interactions**

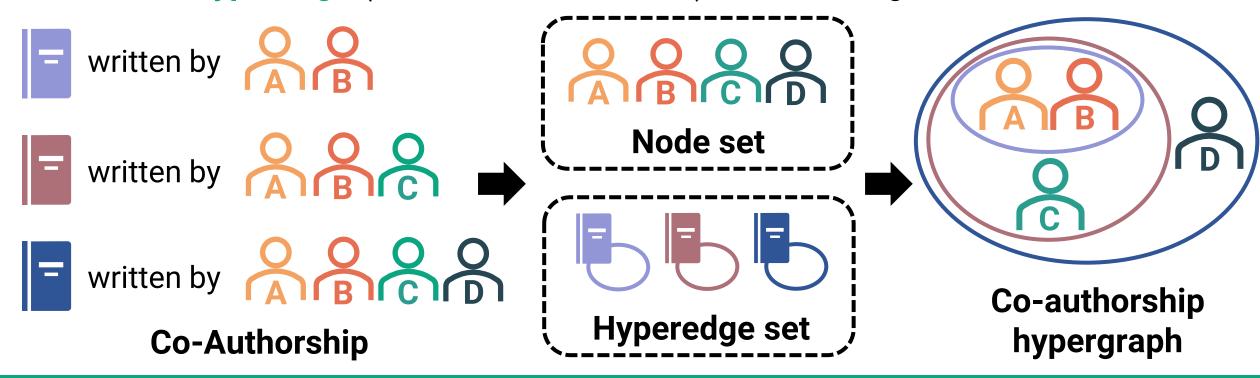
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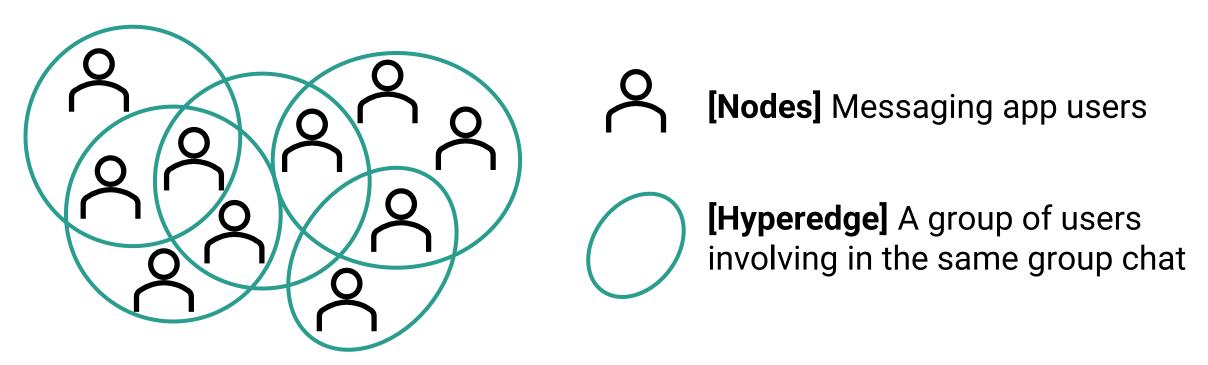
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- There are various machine learning tasks on hypergraphs.
  - The first example is a **node classification** task.

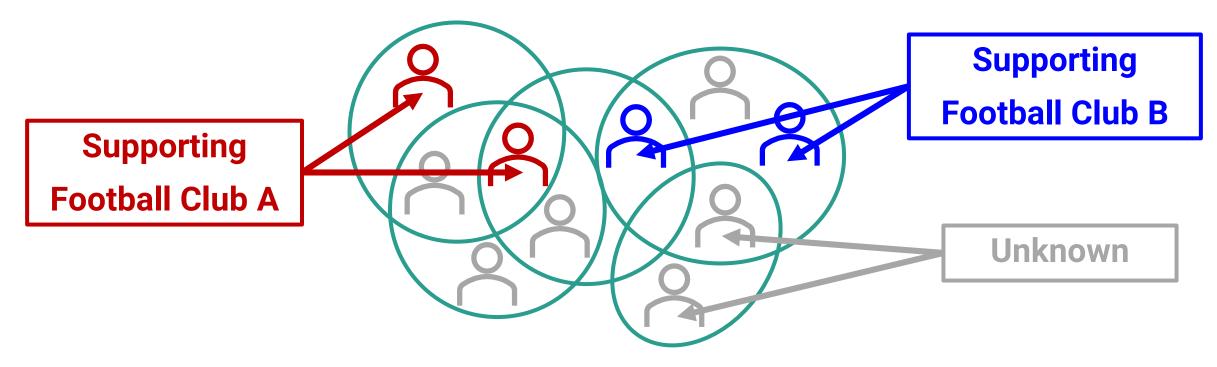


Messaging app hypergraphs





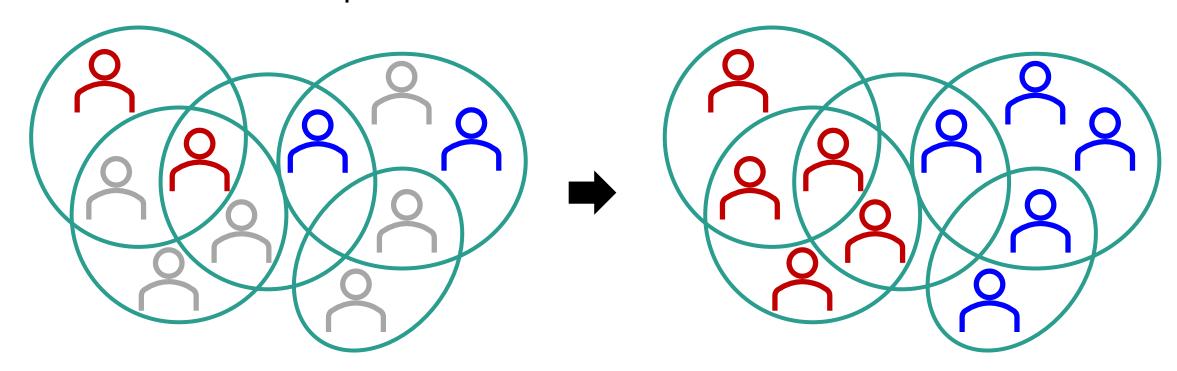
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  - The first example is node classification.



Which club does each user support?



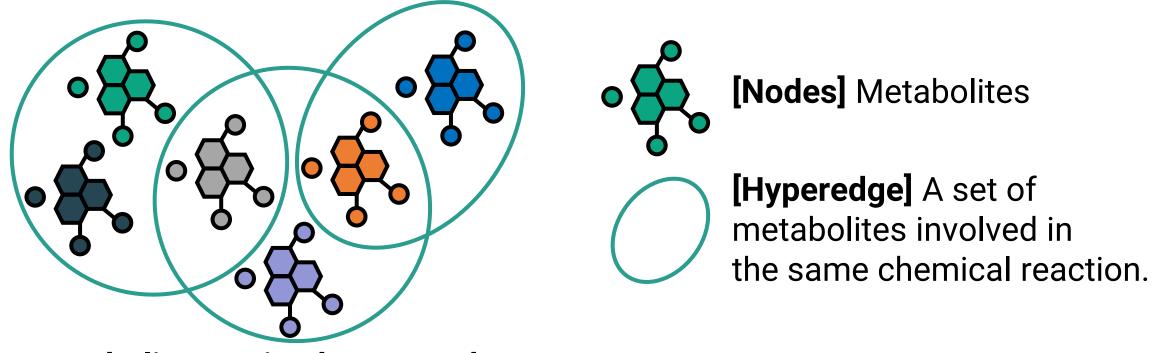
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The node classification task formalizes this user profiling.

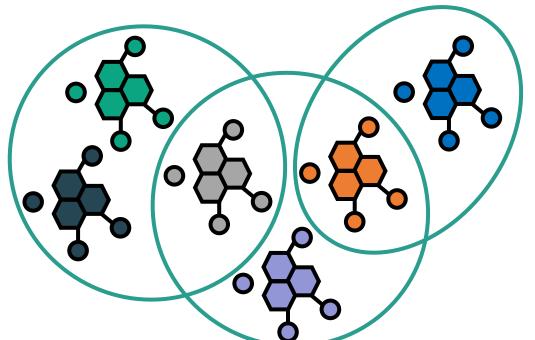


- There are various machine learning tasks on hypergraphs.
  - The second example is hyperedge prediction.

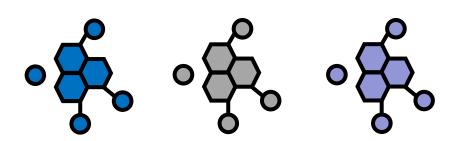




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Metabolic reaction hypergraph

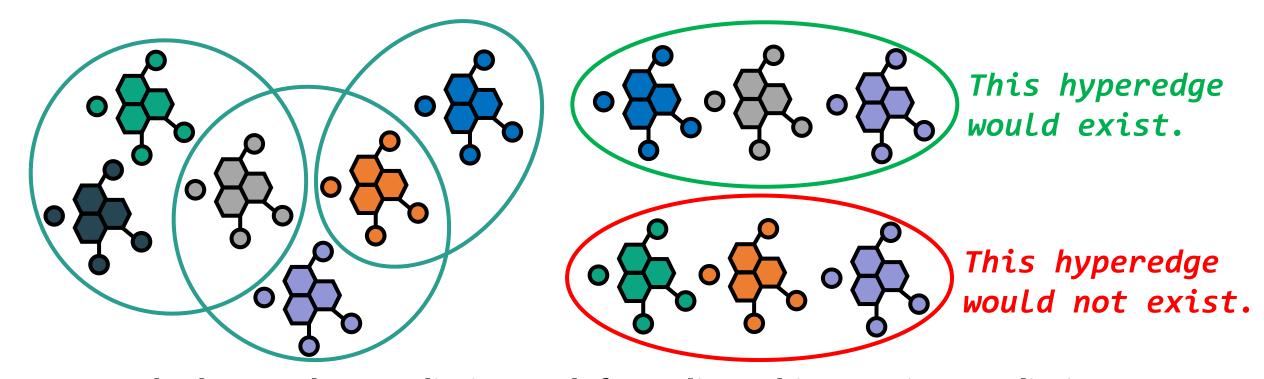


Would these three metabolites react together?





- There are various machine learning tasks on hypergraphs.
  - The second example is hyperedge prediction.

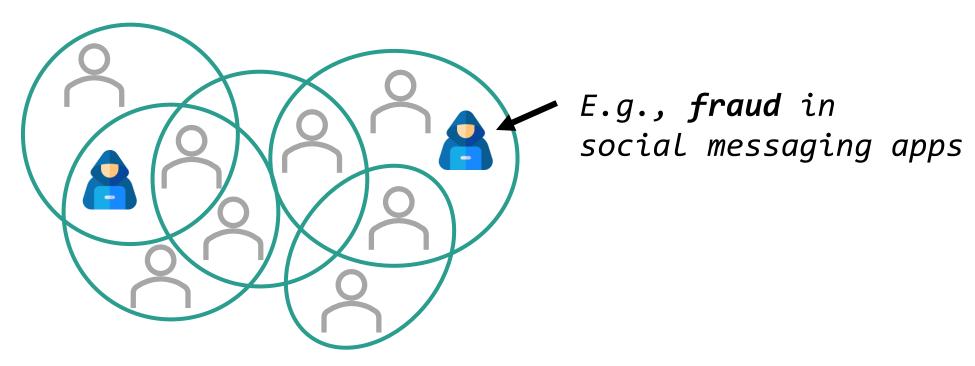


The hyperedge prediction task formalizes this reaction prediction.





- There are various machine learning tasks on hypergraphs.
  - More examples include anomaly detection, ranking, and alignment.

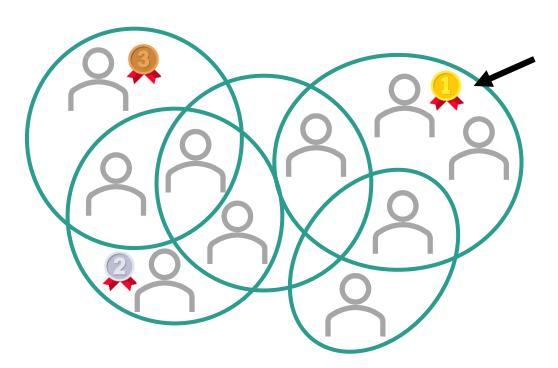


Messaging app hypergraphs





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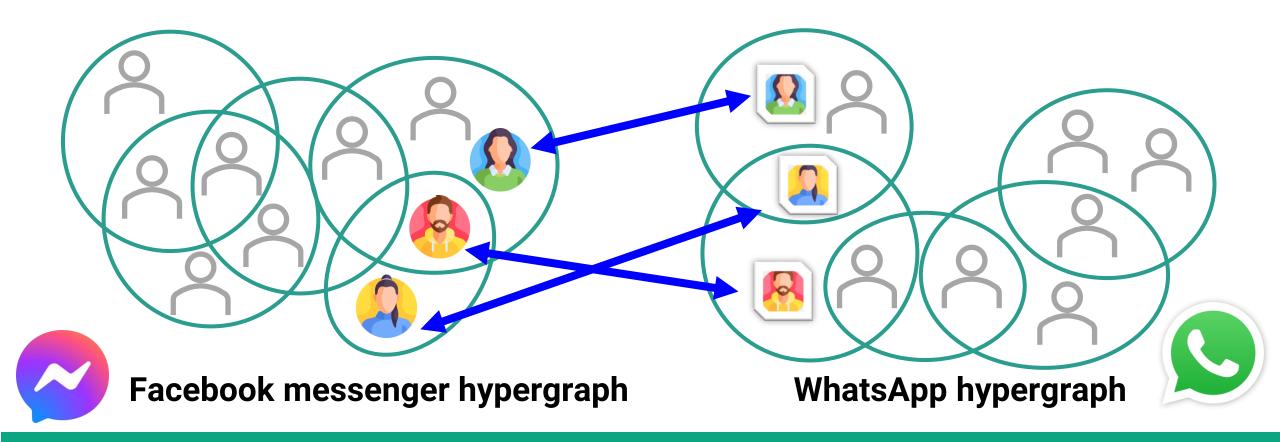
E.g., most influential user in social messaging apps

Messaging app hypergraphs





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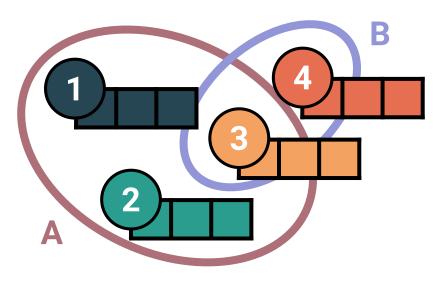




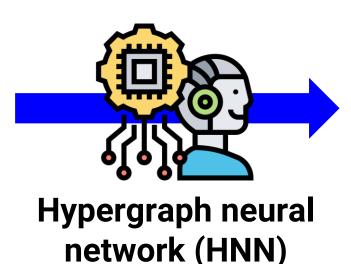


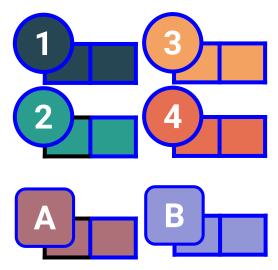
# **Hypergraph Neural Network (HNN)**

 Hypergraph neural networks (HNNs) are family of neural networks specialized for machine learning on hypergraphs.



Hypergraph and node (and hyperedge) features





Node (and hyperedge) embeddings



 Hypergraph neural networks (HNNs) have achieved state-of-the-art performance in many machine learning tasks on hypergraphs.

Hypergraph Node Classification Leader Board

Dataset: DBLP

1. HNN

2. GNN

Dataset: Trivago

1. HNN 🧡

2. **SVM** 

Dataset: House

1. HNN

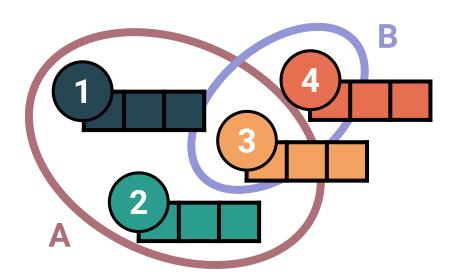
2. GNN

•••



#### Why Hypergraph Neural Networks?

- For hypergraph learning, one might consider using graph neural networks:
  - [Step 1] Represent higher-order interactions as a pairwise graph.
  - [Step 2] Apply graph neural networks to the pairwise graph.

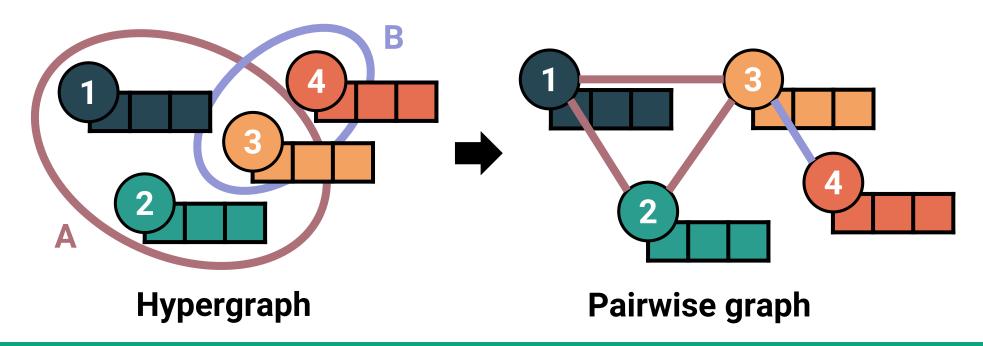


Hypergraph



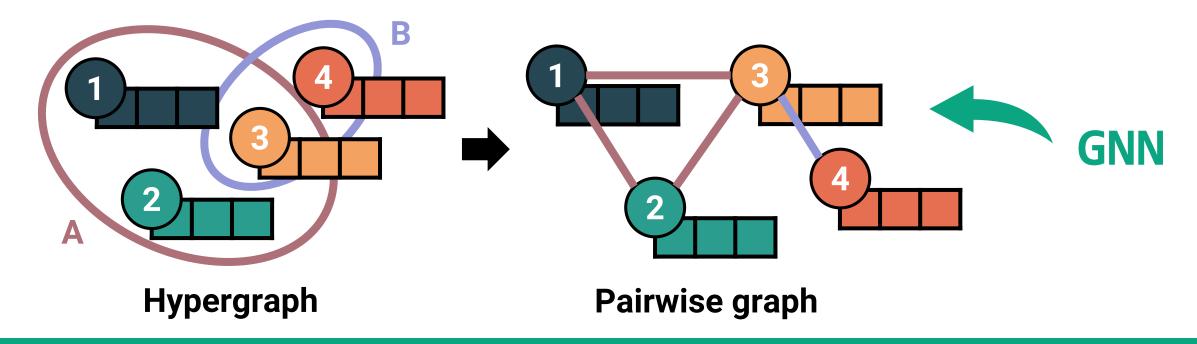


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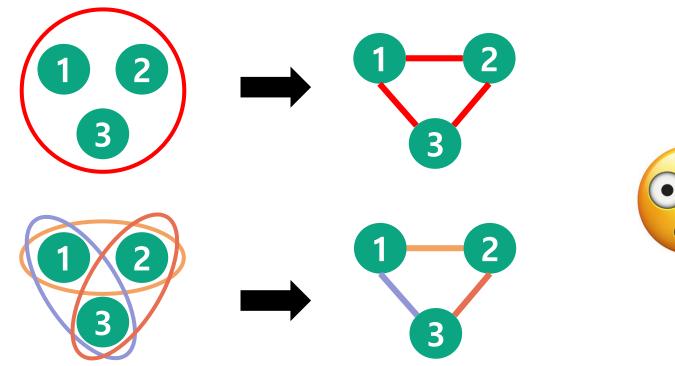
- For hypergraph learning, one might consider using graph neural networks:
  - [Step 1] Represent higher-order interactions as a pairwise graph.
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 However, expressing higher-order interactions with a pairwise graph may cause an information loss [Zhou et al., 2006].





**Resulting in the** Sanulting in the same structure.

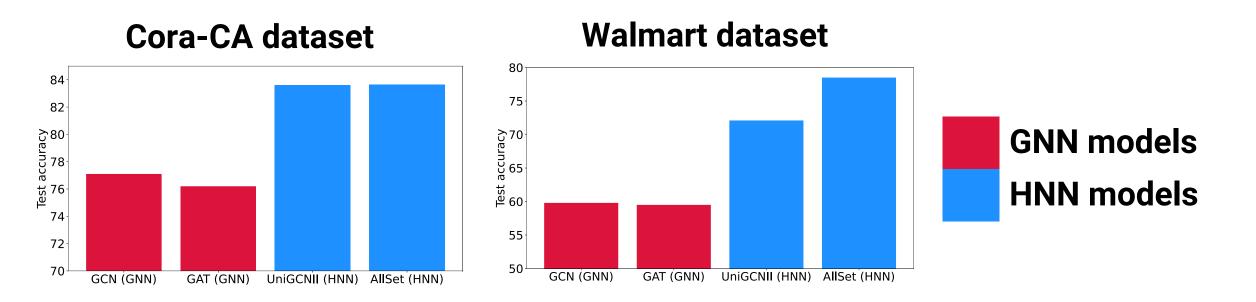
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- Such information loss can result in a significant performance degradation.
- → Hypergraph neural networks are crucial for hypergraph learning.



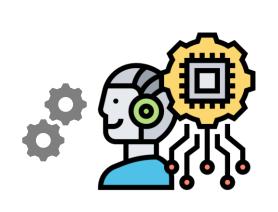
Node classification performance on hypergraph benchmark datasets

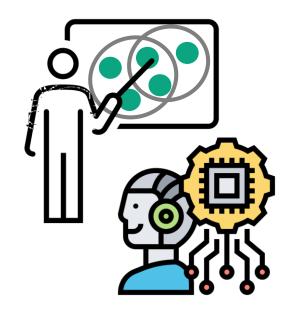


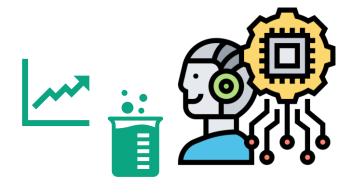


#### **Tutorial Overview**

• In this tutorial, we provide an overview of how hypergraph neural networks are designed, trained, and utilized for various applications.







**Design choice** 

**Training strategy** 

**Application** 





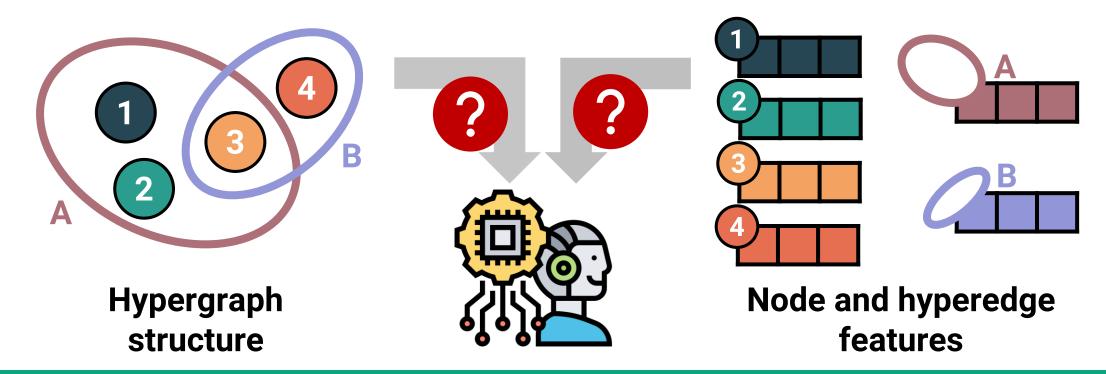
The remainder of our tutorial is divided into the five parts.







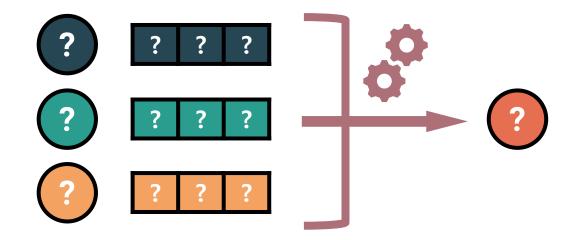
- [Part 2] We cover inputs of hypergraph neural networks.
  - 2.1. How can hypergraph structures be represented?
  - 2.2. What input features can be used for nodes and hyperedges?



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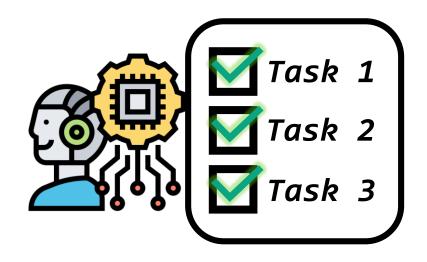


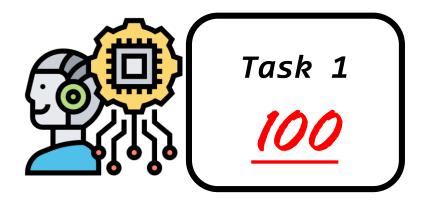
- [Part 3] We cover message passing in hypergraph neural networks.
  - 3.1. Whose messages to aggregate
  - 3.2. What messages to aggregate
  - 3.3. How to aggregate messages





- [Part 4] We cover training strategies for hypergraph neural networks.
  - 4.1. Task-agnostic training
  - 4.2. Task-targeted training







- [Part 5] We cover practical applications of hypergraph neural networks.
  - **5.1.** Recommender systems
  - 5.2. Bioinformatics and medical science
  - **5.3.** Time series analysis
  - **5.4.** Computer vision











- [Part 6] We discuss open questions related to hypergraph neural networks.
  - 6.1. What are theoretical foundation of HNNs in hypergraph learning?
  - 6.2. When is using HNNs especially advantageous?
  - 6.3. How should HNNs encode more complex hypergraphs?
  - 6.4. How to utilize large language models to empower HNNs.



