PPT-01(0:00-0:20)
Good afternoon, Professors.
It is my great honor to participate in the ICGNC Best Paper Defense.
I am Jiawen Chen, come from School of Mathematics, Southeast University.
My research topic is "Investigating Hypernode Classification of Complex System Based on High-Order Graph Neural Networks".

PPT-02(0:20-1:10)
Research of the complex interactions in swarm control in networks motivates effective decision-making.
High-order graph can be defined as Hyperedges and Simplex. Multiple nodes interact with a hyperedge.
Hypergraph models can solve combinatorial optimization problems with high dimension
It can be decomposed into sub-problems, making it easier to manage and analyze.

However, There are two main difficulties,
First , Interactions between nodes are interrupted, some unobserved labels are usually missing.
Second , Modeling of high-order interactions among different individuals lacks explicit mathematical formulation.

PPT-03(1:10-2:30)
Existing research on GNN focuses on binary relationships between nodes, which limits the expression ability and can't capture high-order interactions.
Meanwhile,
High-order GNNs address this limitation of high-order relationships, but suffer from low hypernode classification accuracy and poor representation, which fails distinguish non-isomorphic hypergraphs.
Therefore, Our work focuses on the Uniqueness of Hypergraph structure and Higher representation ability. Fill the Gap of Hypergraph Isomorphic Neural Networks in Hypernode Classification.

PPT-04(2:30-3:00)
So, What's Hypernode Classification?
Infering unlabeled nodes based on observed labels
GNN aggregates neighborhood l information by first-order WL-test to the predict unlabeled nodes.
Meanwhile, on higher-order graphs,

We consider Hypergraph WL test aggregate hyperedge nodes to infer node labels, and it can also distinguish non-isomorphic hypergraphs

PPT-05 (3:00-3:30)
According to Hypergraph Weisfeiler-Lehman Test,
~~we~~ solved the hypergraph isomorphism problem.
In details,

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To solve the hypergraph isomorphism problem,

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Lemma one, if two hypergraphs maintain consistent labels and features over a series of iterations, and if the labels remain unchanged, they will continue to have the same feature in the next iteration.

Furthermore, we propose a necessary condition Lemma two, which states that if a HGNN maps two hypergraphs to inconsistent representations, then they are non-isomorphic.

PPT-06(3:30-5:30)

To enable HGNN ~~distinguish non-isomorphic hypergraphs and~~ have higher expressive power, this paper proposes the equivalent condition between hypergraph isomorphic neural network and hypergraph WL-test

We prove that, In the first stage, the iterative aggregation can be expressed as follows: \phi_two aggregates the high-order interactions , \phi_one updates the feature of node by iterations it is a sufficient condition that two functions are injective.
In the second stage, Readout Function is also guaranteed to be injective.

Based on lemmas, the equivalent conditions enable HGNN achieve the theoretical upper bound of the hypergraph WL test,

Therefore, we propose Self-hypergraph Isomorphic Network model, employ Muti-layer Linear Perceptron learn function \phi one,   and hyperedges aggregation models function \phi two, to improve HGNNs' representation ability

PPT-07(5:30-6:10)
To demonstrate the effectiveness of our theory, we tested the model on high-order graph datasets, including co-authorship and co-citation networks.
As shown in the table,
Our method achieved higher hypernode classification accuracy compared to GNN and HGNN models, validating the superiority of SHGIN in handling complex interactions in these networks.

PPT-08(5:30-6:10)
In brief, the contributions and innovations of our work are as follows:
Our key contributions include:
First we propose SHGIN model to the limitations of structural isomorphism, achieve higher accuracy than existing methods.
Second we establish an upper bound on the expressive ability demonstrating its equivalence to hypergraph Weisfeiler-Lehman (WL) test.

PPT-09(6:15-7:00)
In conclusion, we have presented an explicit mathematical formulation of high-order interactions

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and defined the equivalent conditions for Hypergraph Neural Networks (HGNN) to the hypergraph Weisfeiler-Lehman test.

Our model demonstrates higher the hypernode classification accuracy on real-world datasets.

Looking forward, there are two directions for future research:

Dynamic high-order relationship evolution. Heterogeneous hypergraph node importance estimation to solve high-dimensional problems.

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PPT-09 (7:05-7:35)

Thank you for your attention. I would be glad to address any questions you may have.

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