Recent papers in hypergraph

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18/10/2023 - University of Utah

Exact Inference in High-order Structured Prediction (Chuyang Ke - Jean Honorio) - ICML 2023

- "Exact Inference in High-order Structured Prediction" suggests that the focus is on developing methods or algorithms that can accurately compute predictions for complex structured outputs, which may involve high-dimensional or complex dependencies between variables. This problem could be a challenging problem in machine learning, where exact solutions are not always readily available, and approximations are often used.

    - Pairwise Markov Random Field

- As the name suggests, pairwise MRFs primarily model pairwise interactions between variables. In the context of graphical models, a variable's conditional probability distribution depends on its neighboring variables. In pairwise MRFs, these pairwise interactions are the main focus, and they often lead to more computationally tractable models than higher-order interactions.

- In this paper, the author first considers traditional structure prediction inference problems in the Markov Random field, such as:

- $$\text{Maximize} \sum_{v \in V} \sum_{l \in L} c_v(l).1[y_v = l] + \sum_{v_1, V_2 \in V} \sum_{l_1 \in L} \sum_{l_2 \in L} c_{v_1,v_2}(l_1, l_2).1[y_{v_1} = l_1, y_{v_2} = l_2]$$

- where L is the space of labels, $c_v(l)$is the score of assigning label l to node v, and $c_{v1,v2}(l1,l2)$ is the score of assigning labels l_1 and l_2 to neighboring nodes v_1 and v_2. The terms in (1) are often referred to as unary and pairwise potentials in the MRF and inference literature. The inference formulation above allows one to recover the global structure, by finding a configuration that maximizes the summation of unary and pairwise local scores.

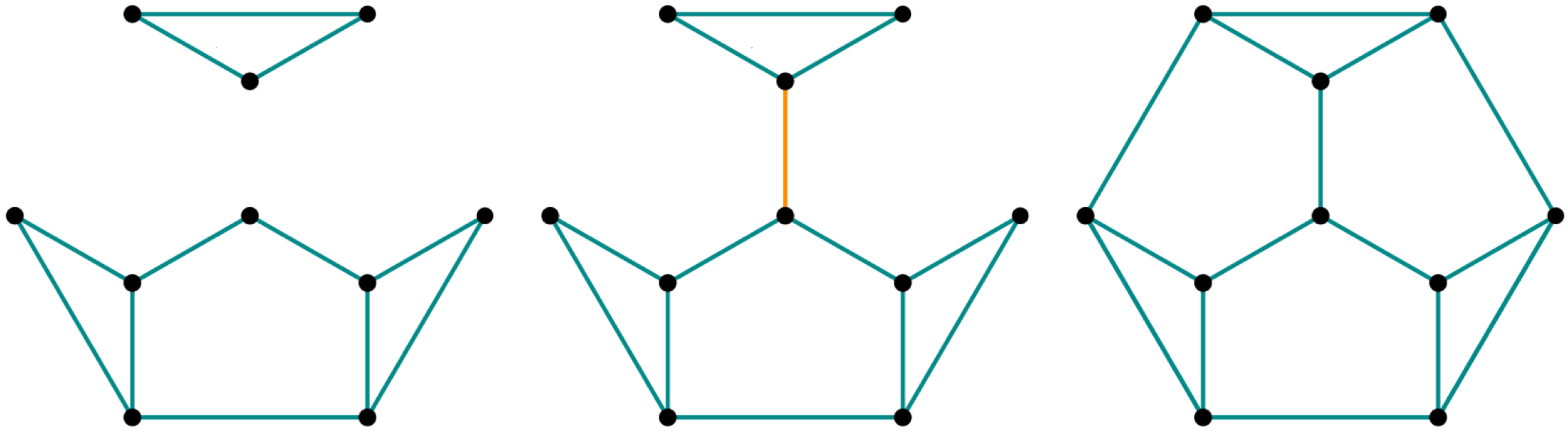
- This paper studies the problem of high-order structured prediction, in which high-order potentials are considered instead of pairwise potentials.
- Maximize $\sum_{v \in V} \sum_{l \in L} c_v(l).1[y_v = l] + \sum_{l_1,\ldots,l_m \in L} c_e(l_1, \ldots, l_m).1[y_{v_1} = l_1, \ldots, y_{v_m} = l_m]$

Model Setting

- They consider the task of predicting a set of n vertex labels $y* = (y_1^*, \ldots, y_n^*)$, where $y_i^* \in (+1, -1)$, from a set of observations X and z. X and z are noisy observations generated from some underlying m-uniform hypergraph G = (V, E). In particular, V is the set of vertices (nodes) with |V| = n, and E is the set of hypergraphs.

- For every possible m-vertex tuple $e = (i_1, \ldots., i_m)$, if $e \in E$, the hypergraph observation $X_{i_1,\ldots i_m}$ (and all corresponding symmetric entries $X_{(i_1,\ldots i_m)}$) is sampled with probability 1 - p and probability p independently. If e is not in E, $X_{i_1,\ldots i_m}$ it is set to 0.

- For every node v_i in V, the node observation z_i is sampled y_i^* with probability 1 - q, and $-y_i^*$ with probability q independently.



(a) Disconnected graph (zero edge expansion)

(b) Graph with a bottleneck (small edge expansion)

(c) Graph without bottlenecks (large edge expansion)

- In pairwise MRFs, such connectivity property can be characterized by the graph’s edge expansion (Cheeger constant) (Bello and Honorio 2019) showed that exact inference can be achieved with graphs that are "good" expanders, or "bad" expanders plus Erdos-Reny edges.

- **Research question: Under what topological conditions will a convex relaxation work correctly, with a small probability of error?**

High-order Structured Prediction with Partial Observation

Unknown: True node labeling vector $y^* = (y_1^*, \ldots, y_n^*)$

Observation: partial and noisy hyperedges observation tensor $X \in (-1,0,+1)^{n^{\otimes m}}$.

Task: Infer and recover the correct node labeling vector y^* from the observations X and z.

- ζ-function: $\zeta : R_m \to R$ is a function defined as:

$$\zeta(v_1, \ldots, v_m) = \sum_{l \subset [m],\ l = m/2} \left(\sum_{i \in l} v_i - \sum_{j \notin l} v_j \right)^m$$

- L is a Hypergraph Laplacian. Given an m-uniform hypergraph G = (V, E), we use $L \in R^{n^{\otimes m}}$ it to denote its Laplacian tensor, which fulfills the following:

$$< L, v^{\otimes m} > = \frac{1}{m!\binom{m}{m/2}} \sum_{(i_1, \ldots, i_m) \in m} \zeta(v_1, \ldots, v_m)$$

Algorithm

- Stage One: Use the observed hyperedge information X to solve a convex conic-form optimization problem:

$$\begin{aligned} \max_{y} \quad & < X, y^{\otimes m} > \\ \text{Subject to} \quad & y \in (-1, +1)^n \end{aligned}$$

- The problem with this optimization formulation is that the problem is not convex, making the analysis hard and intractable. Instead, they consider:

$$\begin{aligned} \max_{Y} \quad & < X, Y > \\ \text{Subject to} \quad & y \in S_{+}^{*,n,m} \\ & -1 \leq Y_{odd} \leq 1, \forall odd \in \bar{\sigma}_2^{n,m} \\ & Y_{even} = 1, \forall even \in \sigma_2^{n,m} \end{aligned}$$

Recall that $S_{+}^{*,n,m}$ is a convex cone of rank-one tensors. The motivation is that they use a rank-one tensor Y instead of the outer product $y^{\otimes n}$ so that the problem becomes convex in the objective function and the constraints. We have $-1 \leq Y_{\bar{\sigma}_2^{n,m}} \leq 1$ because the product of y's is either −1 or +1, and we have $Y_{\sigma_2^{n,m}}= 1$ because if every y_i repeats an even number of times, we know the product must be +1.

- Stage two: The above narrows down our solution space to two possible solutions. With the help of the vertex information z, we can infer the correct labeling:

$$z^T y* = max_{y\in(y*,-y*)} z^T y$$

Main Theoreim

- The solution of the convex conic-form optimization problem is a rank-one tensor and it is correct with the probability of error(Proof by Karush-Kuhn-Tucker conditions):

$$\epsilon_1(\phi_{\mathcal{G}}, n, p) = 2n^m \exp\left(-\frac{(1-2p)^2\phi_{\mathcal{G}}^{2m}}{8n^m \cdot \max(|\mathcal{E}|, n^{m-1})}\right) + \frac{16(1-p)|\mathcal{E}|}{(1-2p)^2\phi_{\mathcal{G}}^{2m}}.$$

- Stage Two Correctness: The returned labeling is correct, with the probability of error:

$$1 - \epsilon_1(\phi_{\mathcal{G}}, n, p) - \epsilon_2(n, q)\,.$$

From Hypergraph Energy Functions to Hypergraph Neural Networks - (Yuxin Wang - Quan Gan - Xipeng Qiu - Xuanjing Huang - David Wipf) - ICML 2023

- This scientific article introduces a new approach called PhenomNN for hypergraph node classification. Hypergraphs are powerful tools for representing higher-order interactions between entities, and previous work has proposed hypergraph neural network architectures for making predictions based on these relationships. However, these architectures often rely on specific hypergraph expansions, such as cliques or star expansions.

- PhenomNN takes a different approach by incorporating multiple expansions and exploring their integrated role within a unified framework. The authors first define a family of parameterized hypergraph energy functions that closely align with popular existing expansions. They then show how the minimizers of these energy functions can be treated as learnable node embeddings and trained via a bilevel optimization process.

- The proposed energy function in this paper is as follows:

$$\ell(Y, Z; \Psi) = g_1(Y, X; \Psi) + g_2(Z, U; \Psi) + g_3(Y, Z, G; \Psi)$$

- Where g_1 and g_2 terms are non-structural regularization factors over node and edge representations, the g_3 term incorporates hypergraph structure. This paper aims to develop energy functions based on hypergraphs to obtain embeddings whose minima can be applied effectively in subsequent predictive tasks.

$$g_1(Y, X; \Psi) = \sum_{i=1}^{n} \left\| y_i - f(x_i; W_x) \right\|_2^2$$

- The authors define g_1(Y, X; Ψ) as a non-structural regularization factor over node representations.
- Y represents the node embeddings, and X represents the original node features.
- For each node i (i ranging from 1 to n), they calculate the L2 norm (Euclidean distance) between the learned embedding y_i and the embedding predicted by a function $f(x_i; W_x)$. This is done for all nodes and summed up.
- The goal of this term is to regularize the node embeddings Y, making them close to the embeddings predicted by the function $f(x_i; W_x)$.

$$g_2(Z, U; \Psi) = \sum_{k=1}^{m} \left\| z_k - f(u_k; W_u) \right\|_2^2$$

- Exactly as g_1

$$g_3(Y, Z, G; \Psi) = \sum_{i=1}^{n} \phi(y_i) + \sum_{k=1}^{m} \phi(z_i) + \lambda_0 \sum \sum \sum \quad y_i H_0 - y_i \quad {}_2^2 + \lambda_0 \sum \sum \quad y_i H_1 - z_k \quad {}_2^2$$

- The authors define g_3(Y, Z, G; Ψ) as a term incorporating hypergraph structure.
- Y represents node embeddings, Z represents edge embeddings, and G represents the hypergraph structure.
- The term g_3 involves several components:
- The first two sums in g_3 involve the function $\phi(y_i)$ for nodes and $\phi(z_i)$ for edges. These components likely define some form of regularizing the embeddings based on their individual properties.
- The next two sums involve regularization terms that enforce similarity constraints between nodes and edges. Specifically, they penalize the difference between y_i , H_0 and y_i between y_i H_1 and z_k, where H_0 and H_1 are related to hypergraph structures. These terms encourage nodes and edges to be similar when projected into the appropriate spaces according to the hypergraph structure.

- To incorporate clique expansion and star expansion in our general form of energy function as a specified condition. By removing g_2, $H_0 = H_1 = I$ and we have

$$min_z \ell(Y, Z; \psi) = g_1(Y, X; \psi) + \sum_{i=1}^{n} \phi(y_i) + 2\lambda_0 tr[Y^T L_C Y] + \lambda_1 tr(\frac{Y}{Z*} L_S \frac{Y}{Z*})$$

- Then, applying proximal gradient descent to get the hypergraph neural network layers (PhenomNN):

$$Y^{(t+1)} = ReLU((1-\alpha)Y^(t) + \alpha\tilde{D}^{-1}[f(X; W) + \lambda_0 \tilde{Y}_c^{(t)} + \lambda_1(\overline{L}_s Y^{(t)}) + \tilde{Y}_s^{(t)}])$$

- They also present another simpler model $PhenomNN_{simple}$

$$\alpha \tilde{D}^{-1} \left[(\lambda_0 A_C + \lambda_1 \bar{A}_S) Y^{(t)} + f\left(X; W\right) \right] \Big)$$

Optimal LP Rounding and Linear-Time Approximation Algorithms for Clustering Edge-Colored Hypergraphs (ICML, 2023)

- The article discusses the approximability of clustering in edge-colored hypergraphs, specifically focusing on chromatic correlation clustering. Chromatic correlation clustering is a specific clustering approach used in the context of hypergraphs. This approach is designed to cluster objects or entities based on their interactions in a way that considers multi-way interactions between different categories or types of entities.

- This technique involves an optimization process in itself.

- The input of this problem is an edge-colored hypergraph.
- The goal of edge color clustering is to color the nodes to minimize the number of unsatisfied edges.
- The paper wants to color the nodes of this hypergraph for node colors to match as much as possible to the edge colors.
- This problem is NP-hard problem. The main question of this paper is how to use approximation algorithms to tackle this NP-hard problem by finding near-optimal solutions in a reasonable amount of time.

- The author discussed using the LP rounding algorithm to solve this problem and we mentioned that we can get a good result but at the same time, the LP rounding algorithm can be slow. How can we find the faster approximation algorithm?
- The question that arises here is how fast is fast enough? The author mentioned that how about as fast as just reading the hypergraph input.
- They present a 2-approximation algorithm that can achieve this goal regardless of the value of the number of colors and maximum hyperedge size.

How this algorithm works

- First, delete the minimum number of edges so there are no “bad” or “unsatisfied” edges.

- For the remaining edges, this is equivalent to vertex cover which means finding the minimum number of nodes to “cover” all edges. So now they can apply a 2-approximation algorithm. So, the idea is first to transfer the problem to the vertex cover and then apply a 2-approximation algorithm.

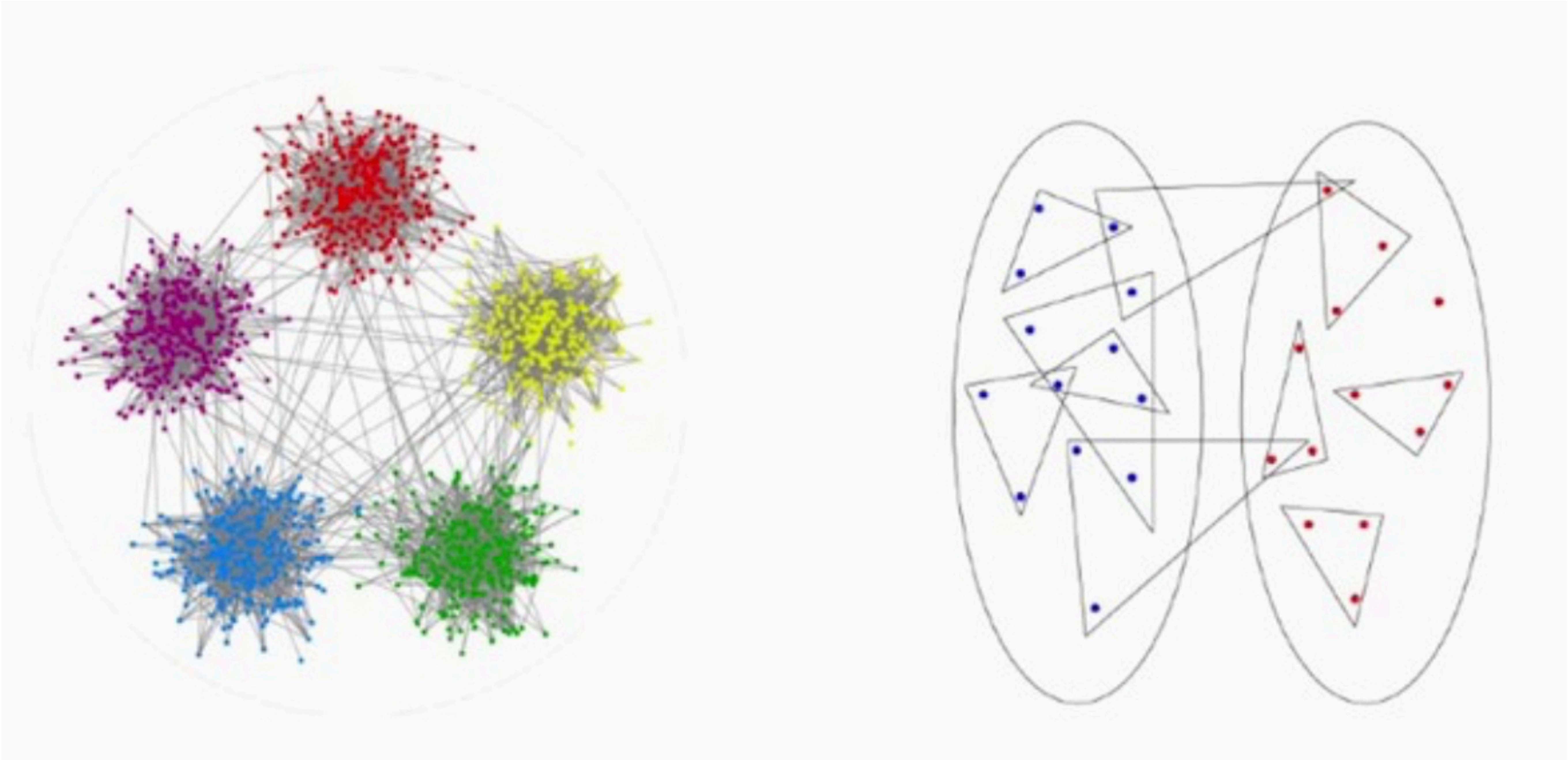
Projected Tensor Power Method for Hypergraph Community Recovery ICML, 2023

- The goal of this paper is community recovery over hypergraph.

- In this paper, the authors propose a method called the Projected Tensor Power Method (PTPM) for exact community recovery in hypergraphs. The Projected Tensor Power Method is an optimization algorithm for solving complex mathematical problems, particularly those involving high-dimensional tensors.

- The PTPM is applied to the symmetric d-uniform hypergraph stochastic block model (d-HSBM), which captures high-order relations among multiple objects. The goal is to identify the community structures based on a random hypergraph.

- In the left figure, colors represent communities; these communities are unknown to us, and our observation is the edge connection between those communities. In the right figure, we have two communities and the observations are triangles which we call hyperedges. In this paper, they are supposed to have n nodes that are divided by k equal-sized communities.



- So in this paper, their observation is that the adjacency tensor $A \in s^d(R^n)$

- The paper aims to recover the underlying communities, which means uncovering groups or clusters of entities within a network or dataset that share common characteristics.

- They use a statistical generative model. These models are used to capture the underlying probability distribution of the dataset.

- If d different nodes belong to the same community < there exists a hypergraph with probability p, otherwise with probability q which is:

$$p = \frac{\alpha \log n}{n^{d-1}} \qquad\qquad q = \frac{\beta \log n}{n^{d-1}}$$

- If $I(\alpha, \beta) > 1$, exact recovery is possible.

- One of the questions in this paper is how we can achieve exact recovery from the computational aspect.

- To recover the underlying communities they use MLE and the input is $A \in s^d(R^n)$ adjacency tensor and our output should be $H^{\otimes d}$. To solve the MLE problem, you often use optimization techniques to find the parameter values that maximize the likelihood function. The optimization process that they use is non-convex polynomial optimization.

- They use tensor power methods to recover or identify hidden community structures within a dataset.

- PTPM is an iterative method, which means it works through a series of steps or iterations to refine its estimates. It combines two primary steps: the tensor power step and the projection step. These steps are applied iteratively to improve the estimate of the hidden community structure.

- Power Step:
  - The power step involves taking tensor products of certain matrices or vectors.
  - The power step is usually applied iteratively. The more iterations, the more the method can highlight the relevant information.
  - This step aims to improve the estimate of the hidden community structure by leveraging the properties of the tensor products.
  - Projection Step:
  - The projection step involves projecting the results obtained from the power step onto a specific space or set of constraints that reflect the characteristics of the problem.
  - This step ensures that the estimates conform to the problem's requirements and constraints, thus refining the estimate and aligning it with the underlying community structure.

- The method also has a competitive time complexity of O(n log2 n/ log log n)
- Numerical Experiments: The authors conduct numerical experiments to validate their theoretical findings. They first examine the PTPM and compare it with two existing methods. The results show that the PTPM achieves the optimal recovery threshold and is faster than the other methods. They also test the convergence performance of the PTPM and show that it achieves exact community recovery within a small number of iterations.

Nonlinear Feature Diffusion on Hypergraphs (ICML, 2022)

- In this paper, the authors propose a new method for semi-supervised learning on hypergraphs, called HyperND. Semi-supervised learning aims to predict labels for the remaining nodes given a small number of labeled nodes.

Classical Techniques for Semi-Supervised Learning on Graphs and Their Limitations on Hypergraphs

- What is the nonlinear diffusion process?
- Existing methods do not incorporate node features for making predictions.

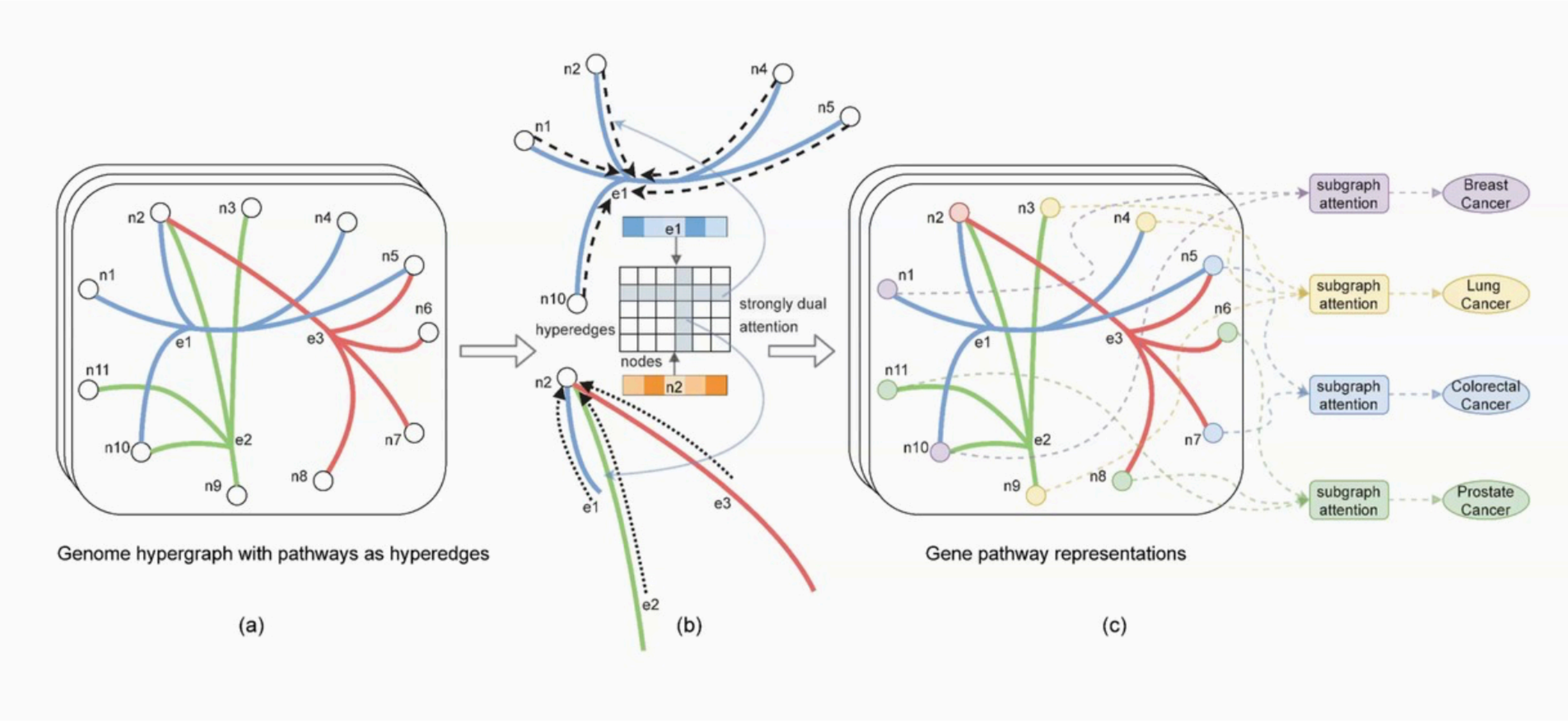
comparison with Graph and Hypergraph Neural Network

- The authors compare their approach to popular graph and hypergraph neural network baselines and find that it is competitive in accuracy while taking less time to train. They also evaluate their method on several real-world hypergraph datasets, showing that it outperforms the baselines.

Conclusion

- The proposed HyperND method can incorporate node features in the prediction process for semi-supervised learning on hypergraphs. It achieves competitive results, takes less training time, and performs well on real-world datasets.

SHINE: SubHypergraph Inductive Neural nEtwork (NeurIPS, 2022)



- Existing hypergraph models focus on node-level or graph-level inference, but there is a need for powerful representations of subgraphs in real-world applications.
- It highlights the importance of learning subgraph representations in hypergraphs and the need for inductive inference for varying-sized sub hypergraphs. The article explains the SHINE framework, including hyperedge attention over nodes, node attention over hyperedges, hypergraph regularization, and subgraph representation learning.
- We have an incidence matrix H_{ij} which takes value 1 if node $g_i \in p_j$. p_j is a hyperedge.

Strongly dual attention message passing

- In order to update this representation they aggregate information from the nodes using the attention mechanism

$$\alpha_E(p_j, g_i) = \frac{exp(c^T s(p_j, g_i))}{\sum exp(c^T s(p_j, g_i))}$$

- C is a trainable context vector as this attention writing state is computed by this:

$$s(p_j, g_i) = leakyReLU((w_N h_N^{k-1} g(i) + b_N) * (w_E H_E^{k-1}(p_i) + b_E))$$

- Also we can update hyperedge representation:

- $h_E^k(p_j) = \alpha(\sum \alpha_e(p_j, g_i) h_N^{k-1}(g_i))$

Evaluation of SHINE against state-of-the-art models

- The authors evaluated SHINE against various state-of-the-art models using large-scale genetic datasets. SHINE outperformed all comparison models significantly in disease-type prediction and cancer-type prediction tasks.

Sparse Hypergraph Community Detection Thresholds in Stochastic Block Model (NeurIPS, 2022)

- This scientific article discusses community detection in random graphs or hypergraphs. The authors focus on the hypergraph stochastic block model (HSBM), used to model higher-order relationships in complex data. The HSBM is a generalization of the stochastic block model (SBM) used for graph community detection.

Challenges in Analyzing Hypergraphs and Spectral Analysis

- The article discusses the challenges in analyzing hypergraphs, as they are more complex than graphs and the spectral properties of hypergraphs are more difficult to study. The authors propose using a hypergraph's incidence matrix and adjacency tensor to analyze its spectral properties.

Main Results

- The paper's main results include the confirmation of the positive part of the conjecture for the HSBM, the derivation of consistent estimators for the model parameters, and the discussion of the negative part of the conjecture, which concerns non-reconstruction of community structures. It means that the negative part of the conjecture deals with situations where it is not possible to accurately reconstruct or identify the community structures within a network using the HSBM or the model being studied. This could be due to certain limitations or conditions under which the model fails to perform well.

Augmentations in Hypergraph Contrastive Learning: Fabricated and Generative (NeurIPS, 2022)

- In this paper the authors focus on label scarcity. This paper introduces a contrasting learning approach called HyperGCL to improve the generalizability of hypergraph neural networks (HyperGNNs) in low-label scenarios. The authors explore the question of how to construct contrastive views for hypergraphs via augmentations. They propose two solutions: fabricated augmentations using domain knowledge and generative augmentations learned during contrastive learning.

Fabricated Augmentations

- In the fabricated augmentations, the authors propose two schemes to augment hyperedges and three strategies to augment vertices. They find that augmenting hyperedges provides the most improvement, indicating that higher-order information in structures is usually more downstream-relevant. They also find that vertex augmentations for graph-structured data are applicable to hypergraphs.

Generative Augmentations

- For generative augmentations, the authors propose a variational hypergraph auto-encoder architecture to parameterize the augmentation space of hypergraphs. They use an end-to-end differentiable pipeline to learn hypergraph augmentations and model parameters jointly. The generative augmentations perform better in preserving higher-order information and improve the generalizability of HyperGNNs.

Equivariant Hypergraph Diffusion Neural Operators

- In existing HNNs using clique expansion. These methods expand hypergraphs to a simple graph and then run GNNs.
- Another method is to set function-based HNNs. In this technique, this idea by transforming a hypergraph to a bipartite graph.
- Formally hypergraph diffusion aims to minimize the total potential function that defines energy over each node.

$$min \sum f(h_v) + \sum g(h_v \quad v \in e)$$

The first term in the node potential function and the second term is the hyperedge potential function.

- To minimize this problem we can use gradient decent-based diffusion for differentiable functions and proximal gradient descent for non-differentiable functions.

- The gradient of hyperedge potential in term of a node can be regarded as a function

- $h_v^{(t+1)} = h_v^{(t)} - \mu \nabla f(h_v^{(t+1)}) + \sum \nabla_v g(h_v^{(t)})$

- The directional derivative of the G that aggregate its neighborhood and dispaches the summarized information to each node.

- In this paper, ED-HNN combines star expansions of hypergraphs with message-passing neural networks.

Evaluation of ED-HNN on real-world datasets

- The authors evaluate ED-HNN on nine real-world hypergraph datasets for node classification tasks. ED-HNN consistently outperforms baseline models, achieving over 2 percent improvement in prediction accuracy on four datasets.

ou are AllSet: A Multiset Function Framework for Hypergraph Neural Networks (ICLR, 2022)

- The article introduces AllSet, a new framework for hypergraph neural networks that aims to improve performance in learning hypergraph properties and structure. Existing methods for learning on hypergraphs often use heuristic propagation rules and offer suboptimal performance. Here, heuristic propagation rules are approaches for spreading information or influence through a hypergraph that are based on practical or intuitive guidelines rather than a well-founded mathematical framework.

Evaluation of AllSet's performance on benchmark and challenging datasets

- To evaluate AllSet's performance, extensive experiments were conducted on ten benchmark datasets and three new datasets that represent significant challenges for hypergraph node classification. The results consistently showed that AllSet outperformed all other hypergraph neural network methods on the tested datasets. For example, it achieved performance improvements of up to 4 percent on the Yelp and Zoo datasets and 3 percent on the Walmart dataset compared to existing methods.

Comparison of AllSet with baseline models and identification of top-performing instance

- The article also compared AllSet with several baseline models, including MLP, CE+GCN, CE+GAT, HGNN, HCHA, HyperGCN, HNHN, UniGCNII, and HAN. Among the tested methods, AllSetTransformer, a specific instance of the AllSet framework, was found to be the most robust and highest performing model.

Hypergraph Simultaneous Generators (AISTATS, 2022)

- HySGen: A Probabilistic Generative Model for Detecting Overlapping Communities in Hypergraphs

- The scientific article proposes an efficient probabilistic generative model called HySGen for detecting overlapping communities in hypergraphs. Unlike existing models, HySGen does not make unrealistic assumptions, such as working only on regular graphs or enforcing restrictions on the size of hyperedges. HySGen can handle hyperedges of any size and captures the higher-order connections between nodes in hypergraphs.

Challenges in Community Detection in Hypergraphs

- The article discusses the use of graph theory to model connections in various domains. While graphs are suitable for pairwise connections, some problems involve larger units of connection. Hypergraphs, an extension of regular graphs, can capture higher-order connection information using hyperedges that can connect any number of nodes. However, community detection in hypergraphs has been limited, with most methods transforming hypergraphs into regular graphs or making simplifications and approximations.

Reformulation of Likelihood Function and Transformation Function in HySGen

- To overcome the computational burden, the authors propose a reformulation of the likelihood function that reduces exponential computations. They introduce a transformation function Ψ that allows for efficient access and updating of values related to hyperedges. The authors provide detailed mathematical formulations and updated algorithms.

- The effectiveness of HySGen is demonstrated through experiments on both synthetic and real-world hypergraphs. In a synthetic example, HySGen successfully discovers communities based on hyperedges without being influenced by the size of hyperedges. In comparison with real-world datasets' baseline methods, HySGen consistently outperforms other methods regarding F1 score and Jaccard Index.

Conclusion

- Overall, HySGen offers a scalable and efficient solution for detecting overlapping communities in hypergraphs, overcoming the limitations of existing methods. The model can be extended and modified for different types of hypergraphs, providing a basis for further research in community detection.

Statistical and computational thresholds for the planted k-densest sub-hypergraph problem (AISTATS, 2022)

- This scientific article focuses on the problem of recovering a planted sub-hypergraph on a d-uniform hypergraph. The problem arises in various contexts such as community detection, average-case complexity, and neuroscience applications. Using the maximum-likelihood estimator, the article provides statistical upper and lower bounds for the exact recovery threshold. It also presents algorithmic bounds based on approximate message-passing algorithms.

- The bounds reveal a statistical-computational gap that widens with increasing sparsity of the problem. The location of the statistical and computational phase transition is influenced by the signal structure, which is not captured by existing bounds for the tensor PCA model. The article investigates the recovery problem for different problem dimensions and explores the existence of statistical-computational gaps.

- The recovery problem is closely related to community detection and the planted clique problem in graph settings. It is also connected to tensor PCA and higher-order interactions in various applications such as neuroscience and computer vision.

- The article provides tight information-theoretic recovery bounds for the problem. It also proposes a new algorithmic threshold based on approximate message-passing algorithms, specifically the AMP algorithm. The AMP algorithm approximates belief propagation in the large system limit and has been shown to be optimal for several other high-dimensional statistical estimation problems. The article presents the AMP algorithm for the recovery problem and analyzes its performance.

- Conclusion
- Overall, the article provides insights into the recovery problem of a planted sub-hypergraph and establishes statistical and computational thresholds for its solution. The analysis and experiments contribute to the understanding of high-dimensional inference problems and the development of efficient algorithms for recovery tasks.

Nested Named Entity Recognition as Building Local Hypergraphs (AAAI, 2023)

- The article proposes a novel method called the Local Hypergraph Builder Network (LHBN) for nested named entity recognition. This task involves identifying named entities within text with nested structures, such as entities within entities. The LHBN model builds local hypergraphs, which are simpler than previous complex hypergraphs used in other methods. The model has three main properties: (1) it captures named entities with shared boundaries in the same local hypergraph, (2) it enhances boundary information by building local hypergraphs, and (3) it can build hypergraphs bidirectionally to take advantage of different named entity recognition preferences.

Experimental Results and Performance of the LHBN Model

- The experiments demonstrate that the proposed LHBN model outperforms previous state-of-the-art methods on four widely used datasets for nested named entity recognition.

Multi-Modal Knowledge Hypergraph for Diverse Image Retrieval (AAAI, 2023)

- This scientific article introduces a new method for keyword-based diverse image retrieval. The goal of diverse image retrieval is to retrieve various relevant images based on a given keyword query. Existing methods for diverse image retrieval either rely on multi-stage ranking strategies or multi-semantic representation approaches. However, these methods have limitations regarding accuracy, diversity, and explainability.

- To address these limitations, the authors propose a new method that leverages a multi-modal knowledge graph (MMKG) to capture sub-semantics in an explicit manner. The MMKG contains rich entities and relations, providing a more diverse and explainable representation. However, there are challenges in fusing the MMKG with retrieval datasets due to the domain and semantic gaps between them.

Proposed Solution: Multi-Modal Knowledge Hyper Graph (MKHG

- To overcome these challenges, the authors propose a solution called Multi-Modal Knowledge Hyper Graph (MKHG), which models many-to-many relations using a degree-free hypergraph. MKHG consists of four key components: hypergraph construction, multi-modal instance bagging, diverse concept aggregator, and semantic space optimizer. The hypergraph construction module customizes various hyperedges to link the MMKG and retrieval databases. The multi-modal instance bagging module selects instances to diversify the semantics, while the diverse concept aggregator adapts key sub-semantics. Finally, several losses are used to optimize the semantic space.

Experimental Verification

- The effectiveness and explainability of the proposed method are verified through extensive experiments on two real-world datasets. The results show that the proposed method outperforms existing state-of-the-art methods in terms of accuracy and diversity.

Contribution

- Contribution 1: Introducing a Multi-Modal Knowledge Graph}
- Contribution 2: Solution for Fusing Knowledge Graph and Retrieval Database}
- Contribution 3: Architecture Design

Conclusion

- In conclusion, the proposed Multi-Modal Knowledge Hypergraph (MKHG) method provides a more diverse and explainable solution for keyword-based diverse image retrieval. The experiments show that MKHG achieves better accuracy and diversity compared to existing methods and demonstrates the effectiveness and explainability of the proposed method.

Hypergraph Modeling via Spectral Embedding Connection: Hypergraph Cut, Weighted Kernel k-Means, and Heat Kernel (AAAI, 2022)

- This scientific article proposes a framework for modeling real-valued data as hypergraphs, in particular: Matching in hypergraphs; Vertex cover in hypergraphs (also known as: transversal); Line graph of a hypergraph; Hypergraph... for clustering. The authors introduce a biclique kernel to formulate multi-way similarity by exploiting the kernel function's ability to model similarity. They establish a theoretical foundation for the biclique kernel, showing that it is equivalent to a semi-definite even-order tensor. The authors also connect their formulation to established hypergraph cut problems, such as weighted kernel k-means and heat kernels. They provide a fast spectral clustering algorithm based on their formulation, outperforming existing graph and heuristic embedding methods.

- The authors demonstrate the effectiveness of their algorithm through numerical experiments on various datasets. They also observe that the performance of spectral clustering improves with increasing order of the hypergraph until a certain point, beyond which it slightly degrades. This study contributes to the field by providing a framework for modeling multi-way relationships in real-valued data, connecting it to hypergraph cut problems, and developing a fast clustering algorithm

Contribution

- Formulating real-valued data as an even order m-uniform hypergraph using a biclique kernel.
- Theoretical connection of the formulation to established hypergraph cuts through weighted kernel k-means and heat kernels.
- Development of a fast spectral clustering algorithm that outperforms existing methods.

MS-HGAT: Memory-Enhanced Sequential Hypergraph Attention Network for Information Diffusion Prediction (AAAI, 2022)

- In this scientific article, the authors propose a Memory-enhanced Sequential Hypergraph Attention Network (MSHGAT) for predicting information diffusion on social networks. Specifically, it focuses on understanding how information diffuses and is shared among users on these networks. Previous methods have focused on the order or structure of the infected users in a single cascade, ignoring the global dependencies of users and cascades. The proposed MS-HGAT model aims to address this issue by considering both user friendships and their interactions at the cascade level.

Model Description

- The MS-HGAT model utilizes graph-based representation learning techniques to capture the co-occurrence relationship between users and cascades. It incorporates both the user friendships and the diffusion hypergraphs to learn the global dependencies of users. The diffusion hypergraphs divide the cascades into several subsets based on timestamps, which allows for the modeling of dynamic connections between users and cascades. The model uses sequential hypergraph attention networks to learn the interactions between users and cascades, and a memory-enhanced module to capture the learned representations and emphasize the interactions within the cascade.

Experimental Results

- The authors conduct experiments on four real datasets to evaluate the performance of the MS-HGAT model. The results show that MS-HGAT outperforms state-of-the-art diffusion prediction models

Conclusion

- In conclusion, the MS-HGAT model proposed in this article provides a novel approach for predicting information diffusion on social networks. By considering global dependencies of users and capturing dynamic interactions, the model achieves better performance compared to existing methods. The experiments demonstrate the effectiveness and robustness of the model in predicting information diffusion.

Adaptive Hypergraph Neural Network for Multi-Person Pose Estimation (AAAI, 2022)

- This scientific article proposes a novel framework called Adaptive Hypergraph Neural Network (AD-HNN) for estimating multiple human poses from a single image. The framework consists of a keypoint localization network and an Adaptive-Pose Hypergraph Neural Network (AP-HNN). The keypoint localization network uses a Semantic Interaction Convolution (SIC) module to improve predictions (Within the first stage, the keypoint localization network employs a specialized module called the Semantic Interaction Convolution (SIC). This module is utilized to enhance the accuracy of the predictions made by the network regarding the locations of key points on the human body.), while the AP-HNN uses an adaptive hypergraph to capture high-order semantic relations among joints (The adaptive hypergraph is a flexible structure that can dynamically adjust the relationships between different joints based on the specific pose being estimated. This adaptability helps the network handle various and variable human poses effectively). The hypergraph can adjust the relations between joints and find the most reasonable structure for variable poses. The two stages are trained together in an end-to-end fashion. Experimental results show that AD-HNN outperforms other methods on multiple datasets, including MS-COCO, MPII, and CrowdPose.

- The article also discusses the limitations of existing methods for human pose estimation, such as the inability to capture high-order semantic dependencies and the lack of adaptability to different poses. It introduces the concept of hypergraphs, which are used to model the relations between joints. Hypergraphs allow for more flexible and complex relationships among joints, improving the accuracy of pose estimation. The article further discusses the use of graph convolutional networks (GCNs) and hypergraph neural networks (HNNs) in pose estimation and the advantages of using HNNs over GCNs.

Conclusion

- This. article presents a novel framework for human pose estimation using a combination of keypoint localization and adaptive hypergraph modeling. The framework achieves state-of-the-art performance on multiple datasets and addresses the limitations of existing methods in capturing high-order semantic dependencies and adapting to different poses. The proposed framework has the potential to improve various applications, such as action recognition and 3D pose estimation.