A Hypergraph Partitioner Utilizing a Novel Graph Generative Model

Magi Chen, Ting-Chi Wang

National Tsing-Hua University, Taiwan

Introduction

- Hypergraph partitioning is essential for VLSI design.
- Traditional methods (spectral, multi-level) lose structure or compromise cut size quality.
- GenPart introduces a generative model that improves embeddings and optimizes partitions.

Problem Formulation

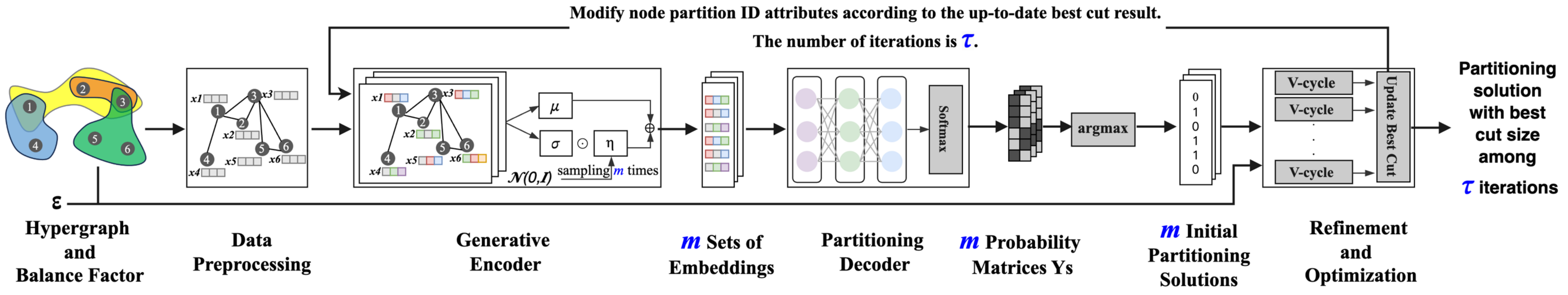
- **Task**: Divide hypergraph's vertex set V into k disjoint subsets.
- **Objective**: Minimize cut size while maintaining balance constraints.
- Simplified with uniform weights on vertices and hyperedges.

GenPart Framework Overview

- **Data Preprocessing**: Clique expansion, node feature preparation.
- **Generative Encoder**: Variational GNN for embeddings.
- **Partitioning Decoder**: Outputs partition assignments.
- **Refinement**: V-cycle for iterative optimization.

GenPart Framework Overview

GenPart: A hypergraph partitioner combining neural network and heuristic techniques



Data Preprocessing

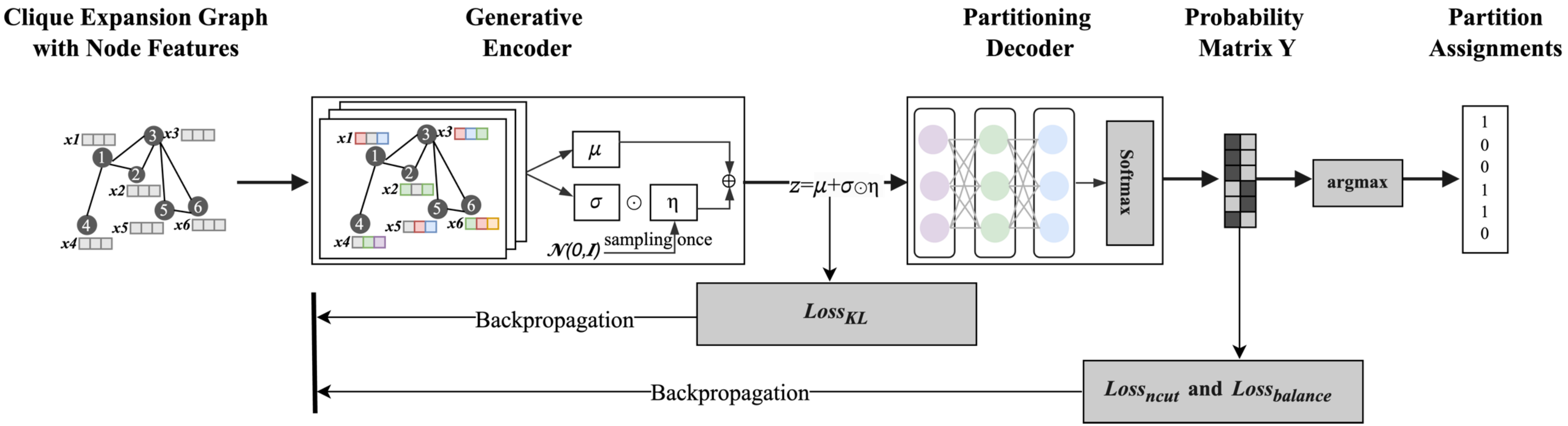
- Graph transformation
  - Transform the hypergraph into a clique expansion graph by replacing each hyperedge with a clique.
  - In the clique corresponding to a hyperedge e, each of its edge weight is assigned to be $\frac{1}{|e|-1}$
- Node features
  - Eigen vectors associated with the two largest eigenvalues
  - Degree
  - Pin count
  - Partition ID

Model Structure

- Generative Encoder
  - Five GraphConv layers, each with a hidden dimension of 256
  - Following these layers, the output is processed using a variational approach, which yields the mean and standard deviation of the sampling distribution.
- Partitioning Decoder
  - A three-layer dense network
  - It ends with a softmax output layer to produce the probability matrix Y, each $Y[i][g]$ indicating the probability that node i is assigned to sub-circuit g.

Model Training

- Supervised learning limits exploration due to label reliance, while GenPart's *unsupervised learning* optimizes partitioning based on intrinsic graph structures, enhancing flexibility and generalization.



Loss Function Components

- Three loss function components
  - $Loss_{KL}$ (KL divergence): Regularizes the embedding space, keeping distributions close to a standard normal distribution.
  - $Loss_{ncut}$ (normalized cut loss): Reduces edges across sub-circuits, improving partitioning quality.
  - $Loss_{balance}$ (size balance loss): Maintains balanced sub-circuit sizes, preventing uneven splits.
- A composite loss function is employed to guide the model toward optimal partitioning results.

$$L = \alpha Loss_{KL} + \beta Loss_{ncut} + \gamma Loss_{balance}$$

Experimental Results

- Comparison with hMETIS [DAC 1997], SpecPart [ICCAD 2022], K-SpecPart [TCAD 2024], MedPart [ISPD 2024].

	Statistics		ε=2%					ε=10%			
Benchmark	|V|	|E|	*hMETIS*	*SpecPart*	*K-SpecPart*	*MedPart*	*Ours*	*hMETIS*	*SpecPart*	*MedPart*	*Ours*
IBM01	12752	14111	203	202	203	202	203	190	171	166	166
IBM02	19601	19584	354	336	333	339	327	262	262	262	262
IBM03	23136	27401	957	959	957	955	952	960	952	954	950
IBM04	27507	31970	595	593	580	583	580	388	388	388	388
IBM05	29347	28446	1733	1720	1716	1744	1706	1733	1688	1668	1645
IBM06	32498	34826	978	963	976	1000	964	760	733	760	733
IBM07	45926	48117	951	935	935	913	883	796	760	772	760
IBM08	51309	50513	1141	1146	1140	1146	1140	1145	1140	1131	1120
IBM09	53395	60902	629	620	620	623	620	535	519	520	519
IBM10	69429	75196	1333	1318	1257	1295	1254	1284	1261	1257	1244
IBM11	70558	81454	1071	1062	1051	1067	1051	782	764	765	763
IBM12	71076	77240	1982	1920	1937	1949	1920	1940	1842	1872	1841
IBM13	84199	99666	859	848	832	850	831	721	693	696	655
IBM14	147605	152772	1865	1859	1850	1876	1842	1665	1768	1605	1530
IBM15	161570	186608	2833	2741	2741	2855	2741	2262	2235	2166	2135
IBM16	183484	190048	2059	1915	1921	1972	1846	1708	1619	1645	1619
IBM17	185495	189581	2403	2354	2307	2336	2300	2300	1989	2024	1989
IBM18	210613	201920	1587	1535	1523	1587	1521	1550	1537	1550	1520
Average Cut Size Improvement Over hMETIS			0%	1.83%	2.48%	1.12%	**3.32%**	0%	2.92%	3.27%	**4.79%**

Experimental Results

- Comparison with hMETIS on ISPD2005 benchmarks.

	Statistics		ε=2%		ε=10%	
Benchmark	|V|	|E|	hMETIS	Ours	hMETIS	Ours
adaptec1	211447	221142	2790	2752	2234	2233
adaptec2	255023	266009	1153	1101	1113	1101
adaptec3	451650	466758	2804	2550	1947	1903
adaptec4	496045	515951	4140	4125	3445	3411
bigblue1	278164	284479	4217	4201	4133	4110
bigblue2	557866	577235	2179	2140	2199	2173
bigblue3	1096812	1123170	2859	2799	2652	2612
bigblue4	2177353	2229886	5655	5346	4902	4831
Average Cut Size Improvement Over hMETIS			0%	**3.13%**	0%	**1.13%**

Thank You