

Total Variation Graph Neural Networks

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Balanced K-cut Problem

- The optimal cluster assignment is the solution of the following (combinatorial) problem:

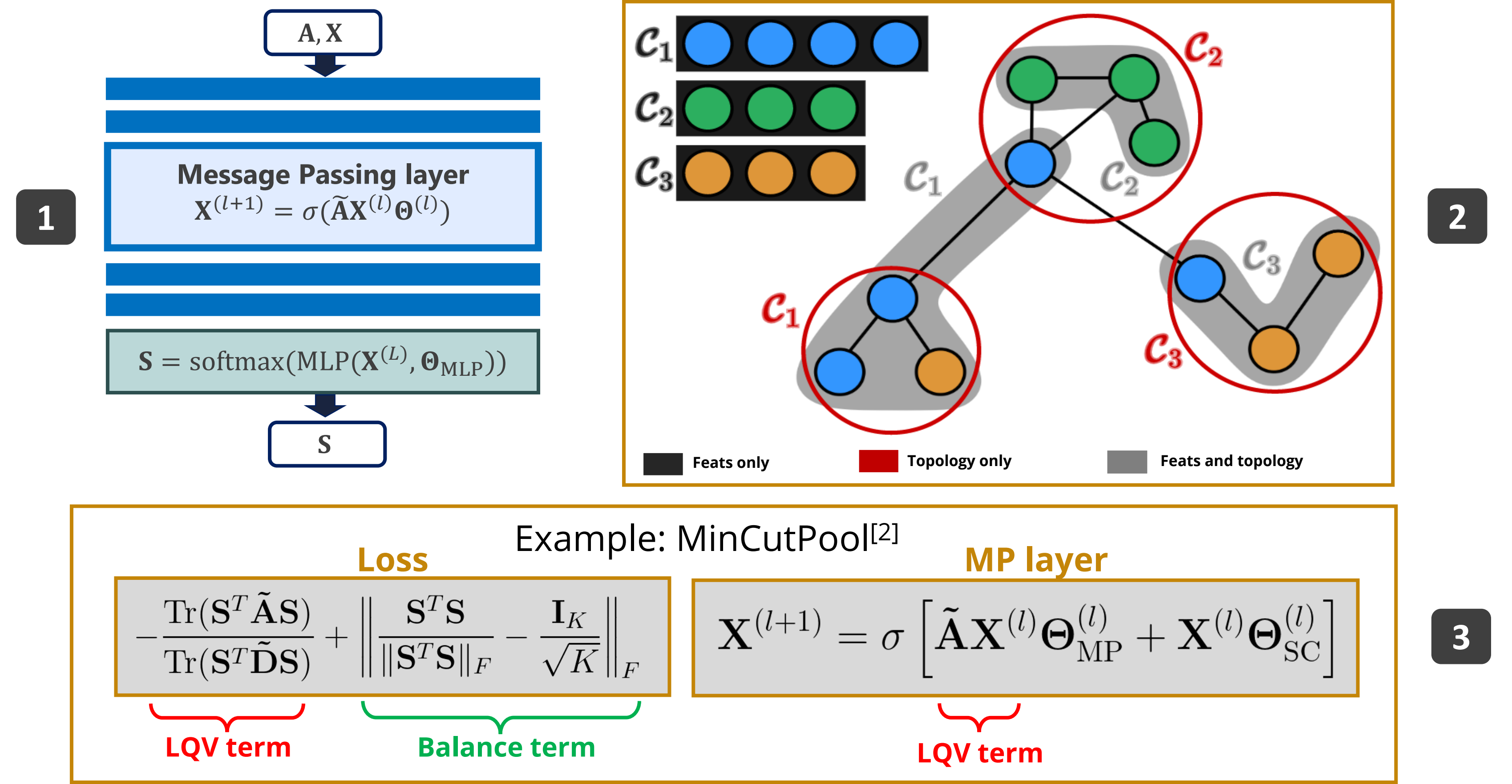
$$\min_{C_1, \dots, C_K} \sum_{k=1}^K \frac{\text{cut}(C_k, \bar{C}_k)}{\hat{S}(C_k)}$$

- The **numerator** minimizes the volume of edges between clusters
- The **denominator** ensures balanced partitions and avoids degenerate solutions
- Spectral clustering adopts a continuous relaxation that replaces the numerator with a local quadratic variation (**LQV**) term: $\|s\|_{LQV} = \sum_{(i,j) \in E} a_{ij} (s_i - s_j)^2$
- Tighter relaxations adopt a graph total variation (**GTV**) term: $\|s\|_{GTV} = \sum_{(i,j) \in E} a_{ij} |s_i - s_j|$, but do not admit closed form solutions^[1]

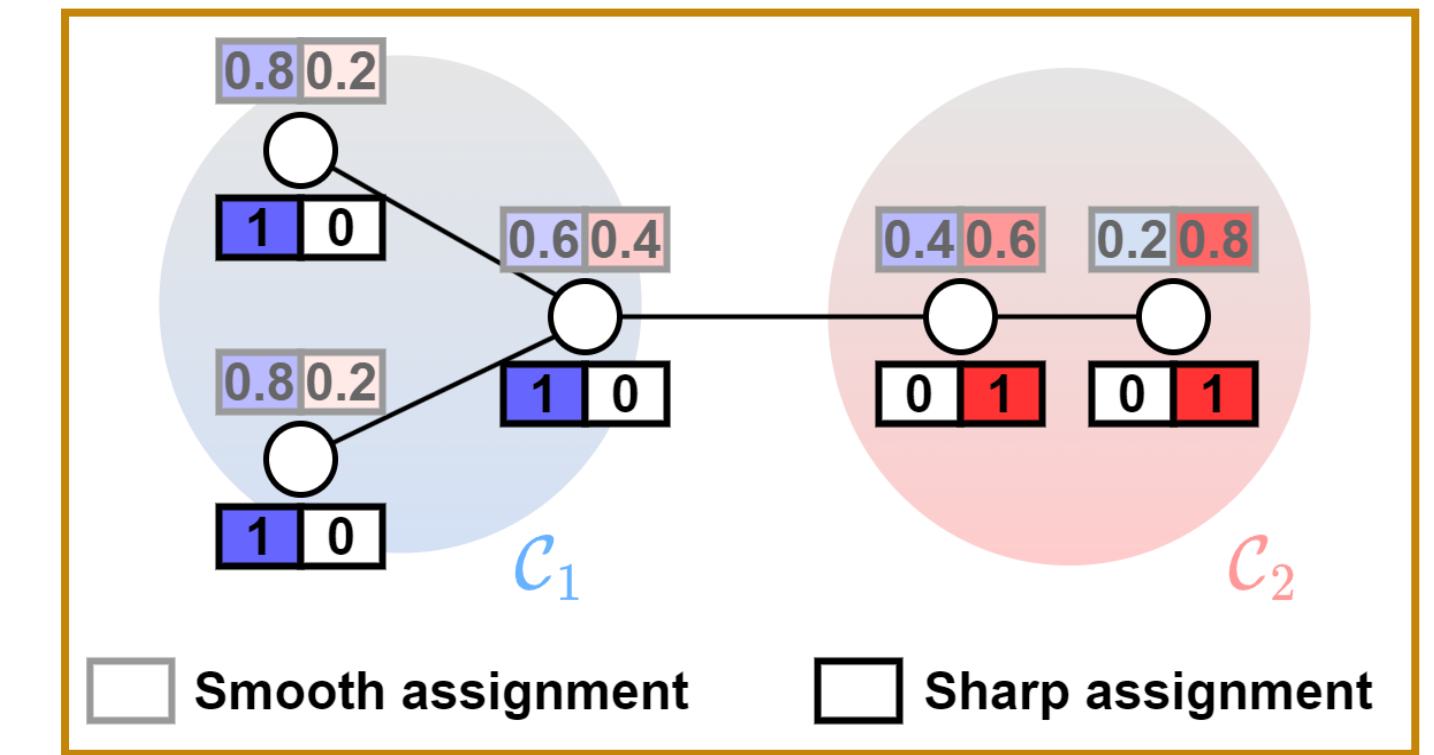
Notation

$\mathbf{X} \in \mathbb{R}^{N \times F}$: node features
 $\mathbf{A} \in \mathbb{R}^{N \times N}$: adjacency matrix
 $\mathbf{D} \in \mathbb{R}^{N \times N}$: degree matrix
 $\mathbf{S} \in \mathbb{R}^{N \times K}$: cluster assignments

Clustering with GNNs



- The GNN Computes *soft assignments* \mathbf{S} using MP layers and an MLP
- GNN's clusters account both for *topology* and *node features*
- Current approaches are based on loose graph cut relaxations with **LQV** terms
- This results in *smooth* cluster assignments



Total Variation GNN (TVGNN)

Loss based on a **tighter relaxation** of the minimum K-cut

$$\|\mathbf{S}\|_{GTV} - \sum_{k=1}^K \|\mathbf{s}_{:,k} - \text{quantile}_{K-1}(\mathbf{s}_{:,k})\|_{1,K-1}$$

Legend: GTV term (red), Balance term (green)

Message passing layer derived from the **gradient descent step** of GTV

$$\mathbf{X}^{(l+1)} = \sigma \left[\left(\mathbf{I} - 2\delta \mathbf{L}_\Gamma^{(l)} \right) \mathbf{X}^{(l)} \Theta^{(l)} \right]$$

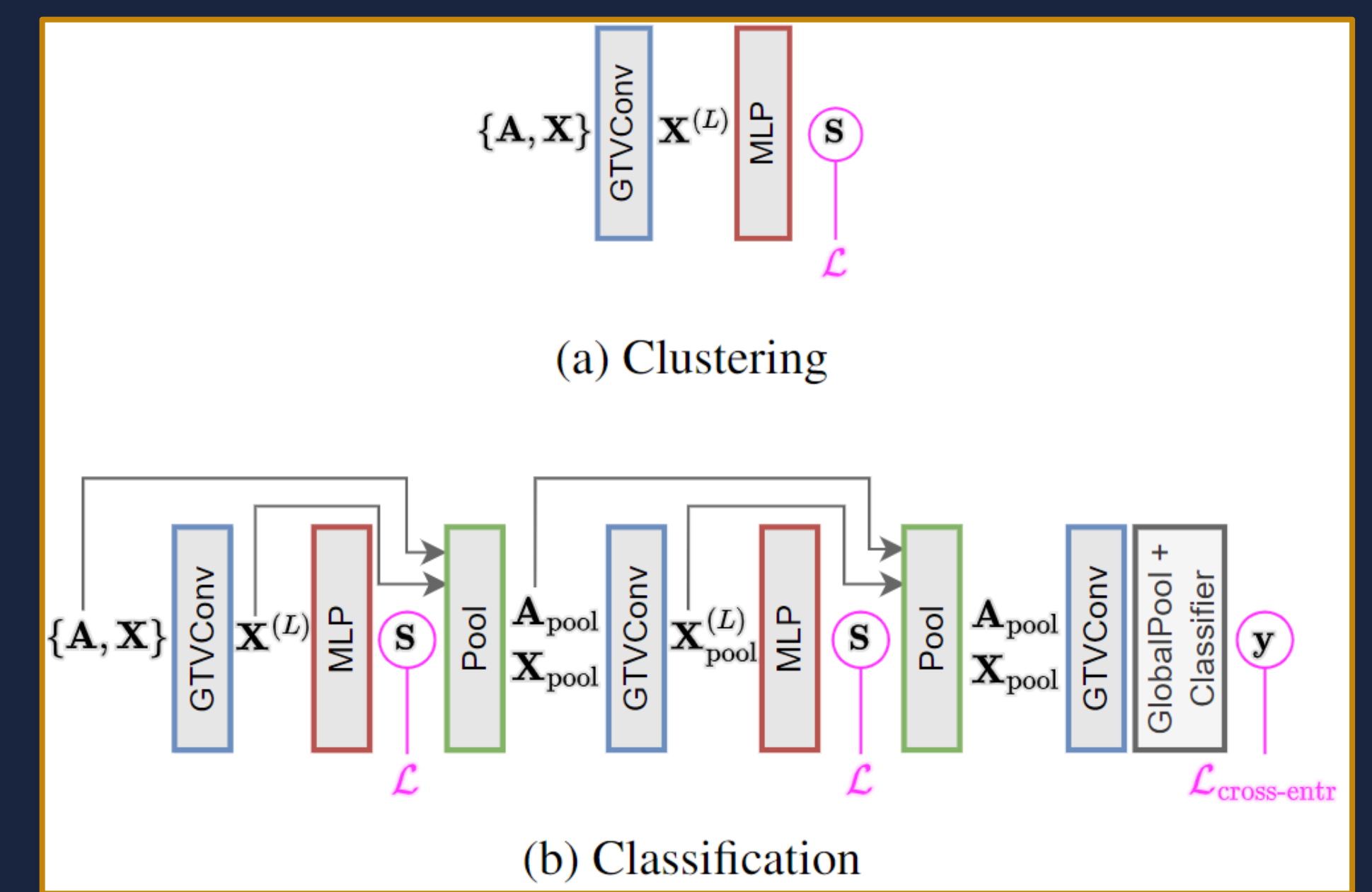
Legend: GTV term (red)

Properties

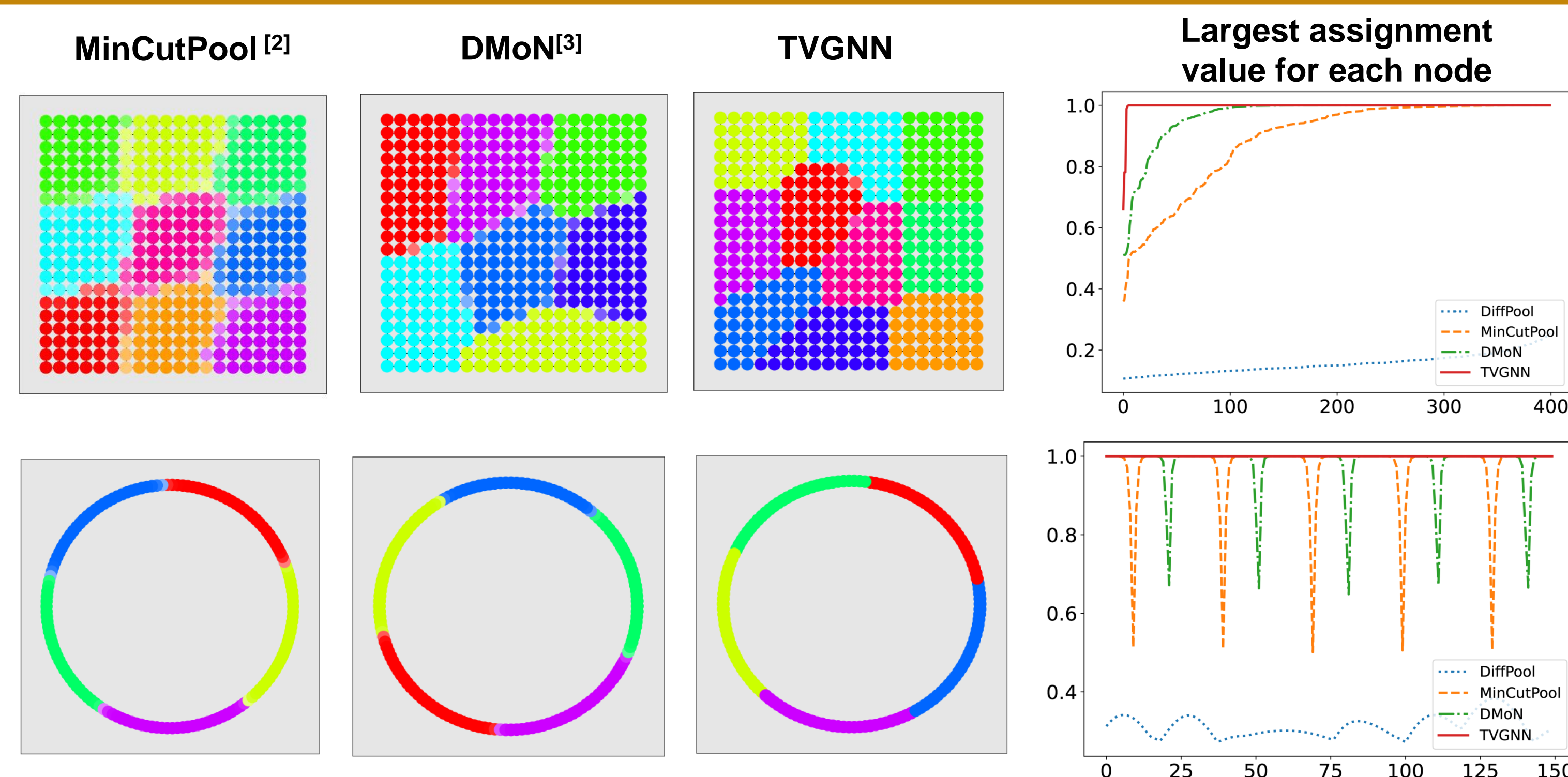
- Yields **sharper assignments** compared to methods that minimize LQV
- Implicitly **learns connectivity weights** given by $\mathbf{L}_\Gamma = \mathbf{D}_\Gamma - \Gamma$ where

$$[\Gamma]_{ij} = \frac{[\mathbf{A}]_{ij}}{\max\{\|\mathbf{x}_i - \mathbf{x}_j\|_1, \epsilon\}}$$

Architecture

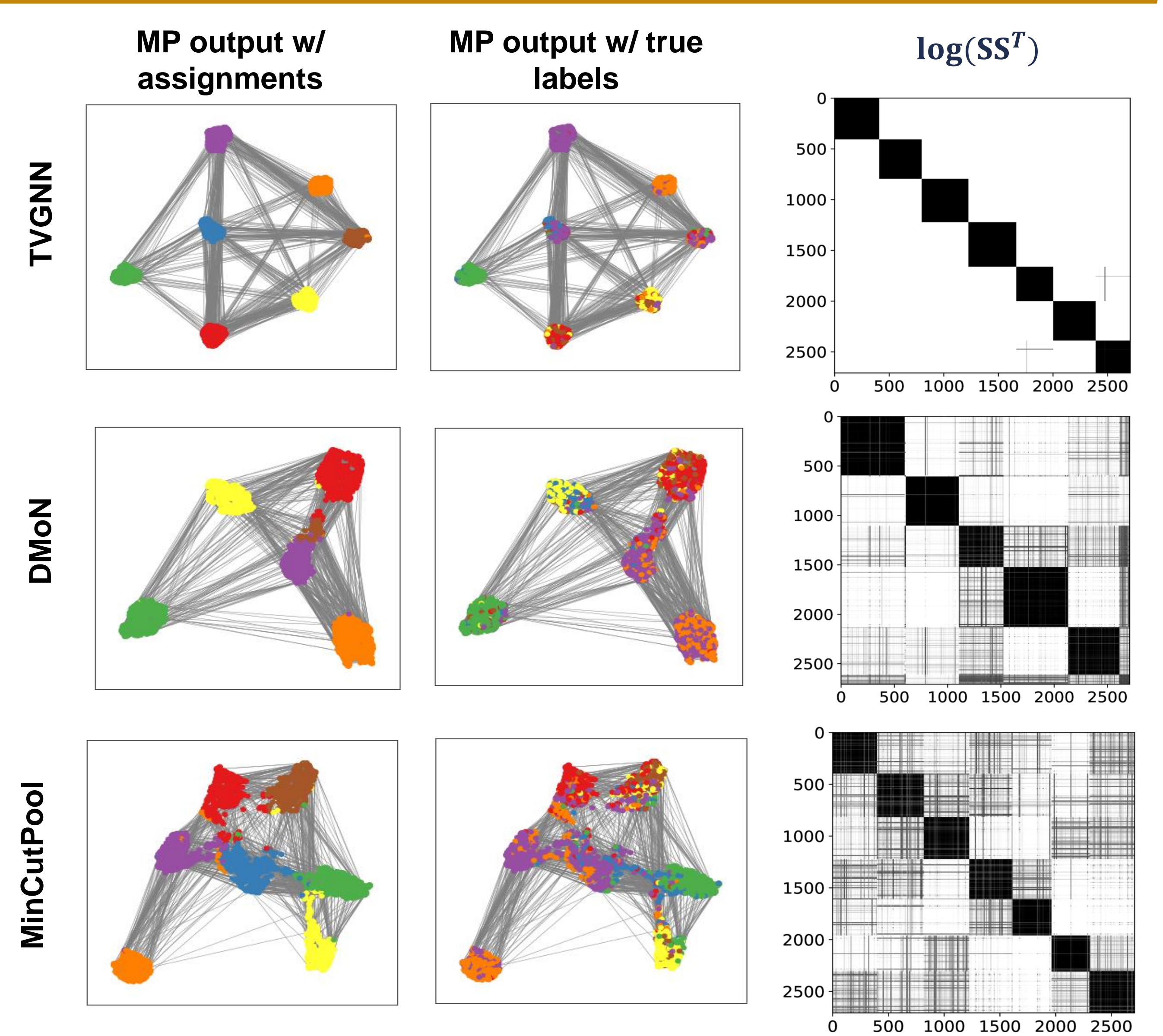


Results



Dataset	Top-K	SAGPool	DiffPool	MinCutPool	DMoN	TVGNN	p-value
Bench-easy	53.8±31.8	53.8±31.8	99.0±0.3	99.0±0.3	98.8±0.5	99.6±0.6	.011*
Bench-hard	30.5±0.7	29.5±0.0	72.8±0.2	70.9±1.7	71.8±1.9	75.3±0.8	.001**
MUTAG	77.5±8.4	76.8±9.7	86.4±7.6	85.2±7.2	86.7±7.0	88.4±7.5	.606
Mutagenicity	68.4±8.4	68.2±7.8	78.5±1.5	78.4±1.4	77.1±1.3	80.0±1.3	.028*
NCI	54.0±4.1	59.2±7.7	74.1±1.8	75.2±1.8	74.3±1.3	77.3±1.8	.018*
Proteins	69.6±2.7	70.4±2.5	74.6±4.2	75.7±3.0	75.2±3.3	77.1±2.9	.302
D&D	62.0±5.6	64.2±7.0	77.7±3.0	78.2±3.4	78.0±3.3	79.5±2.2	.323
COLLAB	73.4±6.9	75.6±2.5	78.4±1.6	79.3±1.1	79.5±0.7	79.8±1.1	.476
REDDIT-BINARY	54.0±10.0	50.0±0.1	80.9±2.7	82.3±3.2	82.6±2.9	86.5±2.8	.007**

Graph classification performance



Latent features and cluster assignments for Cora

References

- Bresson, X., Laurent, T., Uminsky, D. and Von Brecht, J. *Multiclass total variation clustering*. Advances in Neural Information Processing Systems, 2013.
- F. M. Bianchi, D. Grattarola, and C. Alippi. *Spectral clustering with graph neural networks for graph pooling*. International Conference on Machine Learning, 2020.
- A. Tsitsulin, J. Palowitch, B. Perozzi, and E. Muller. *Graph clustering with graph neural networks*. arXiv preprint arXiv:2006.16904, 2020.

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