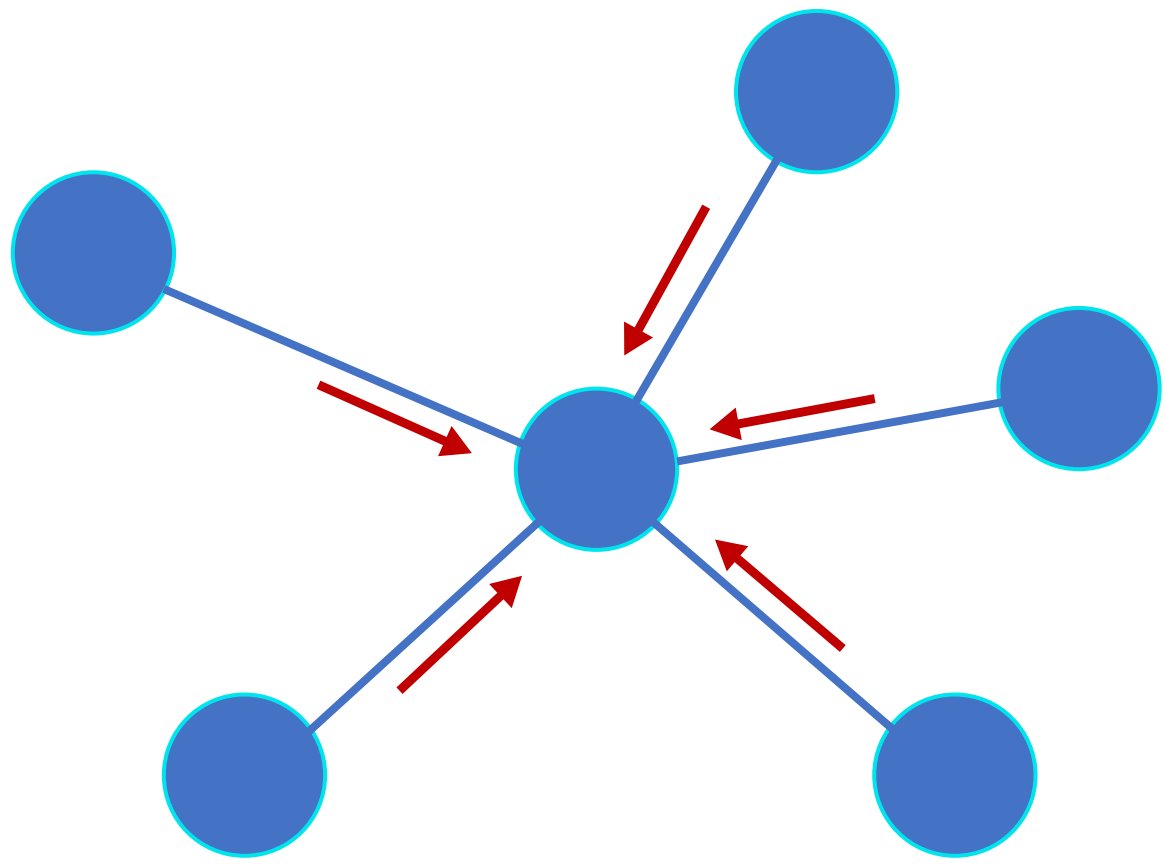
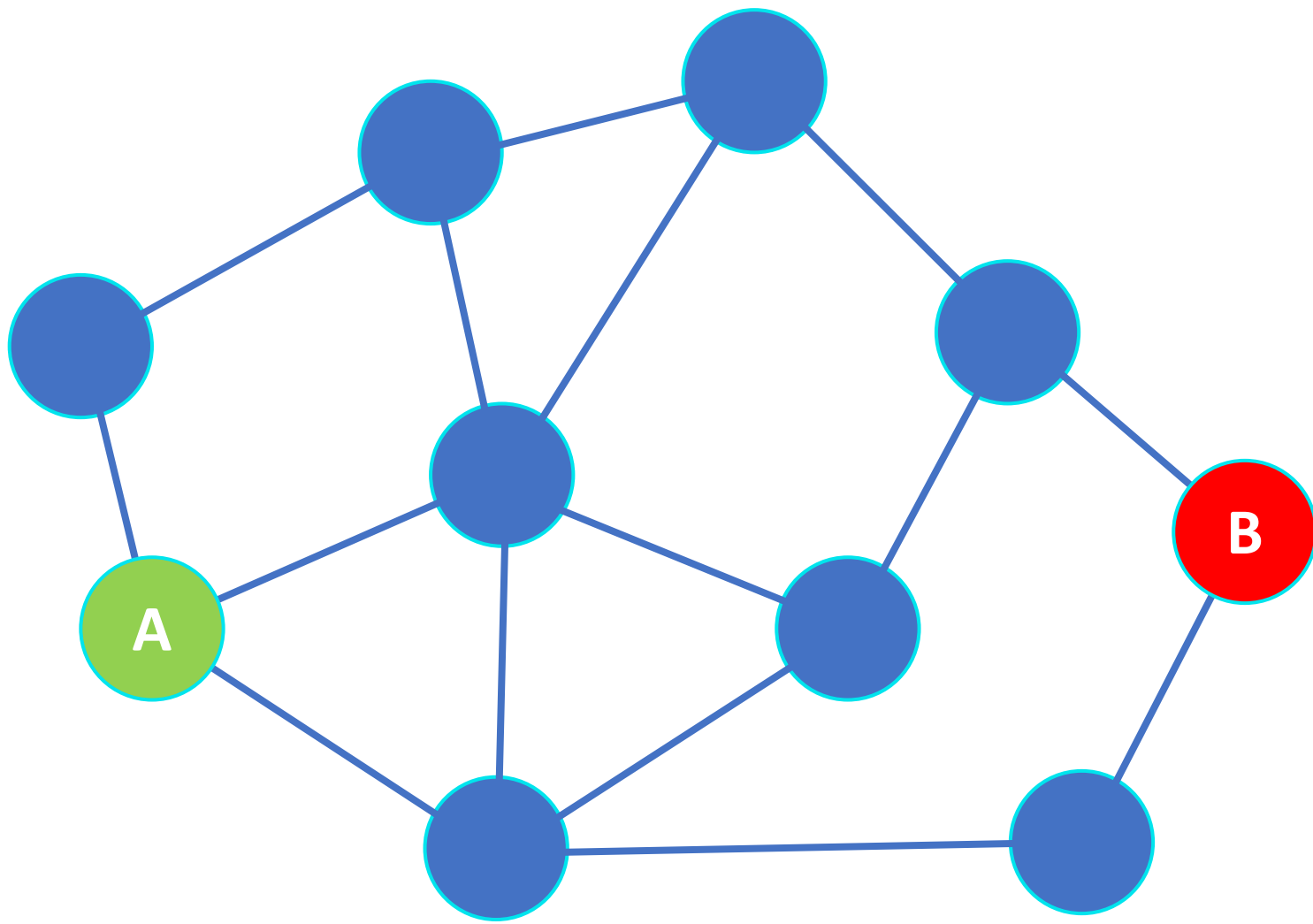


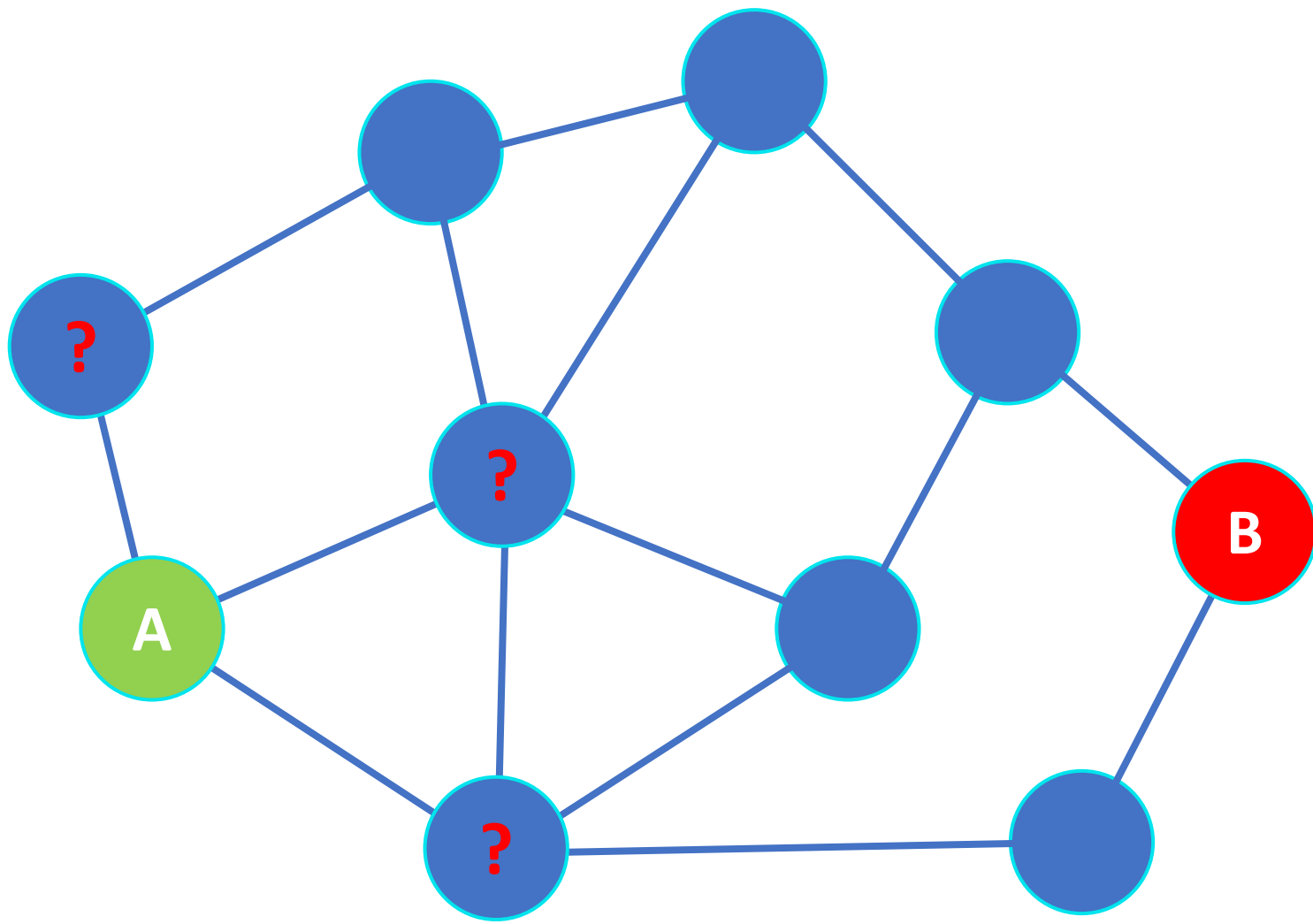
Graph U-Nets

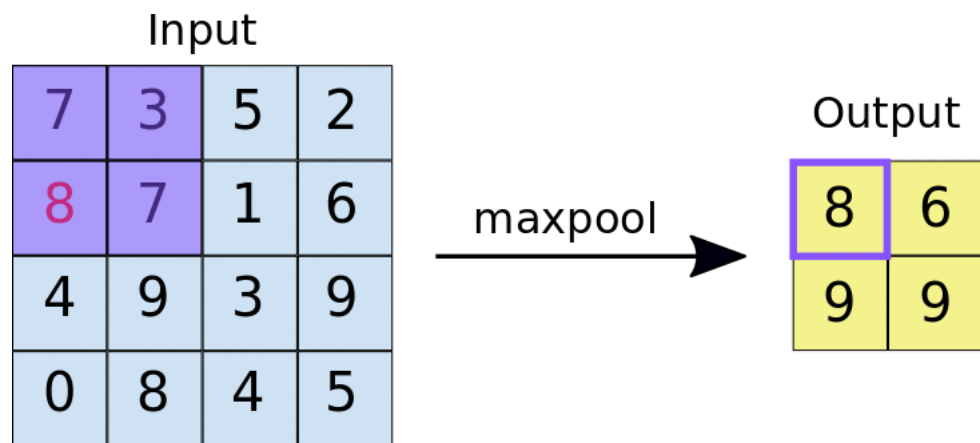
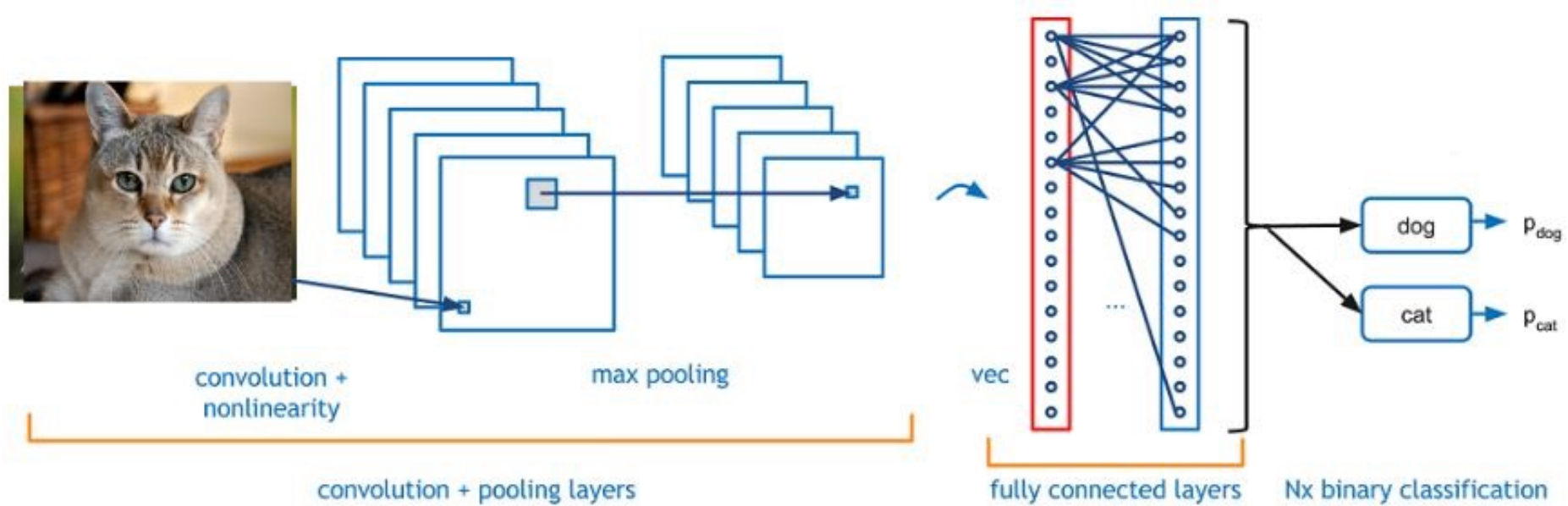
Hongyang Gao

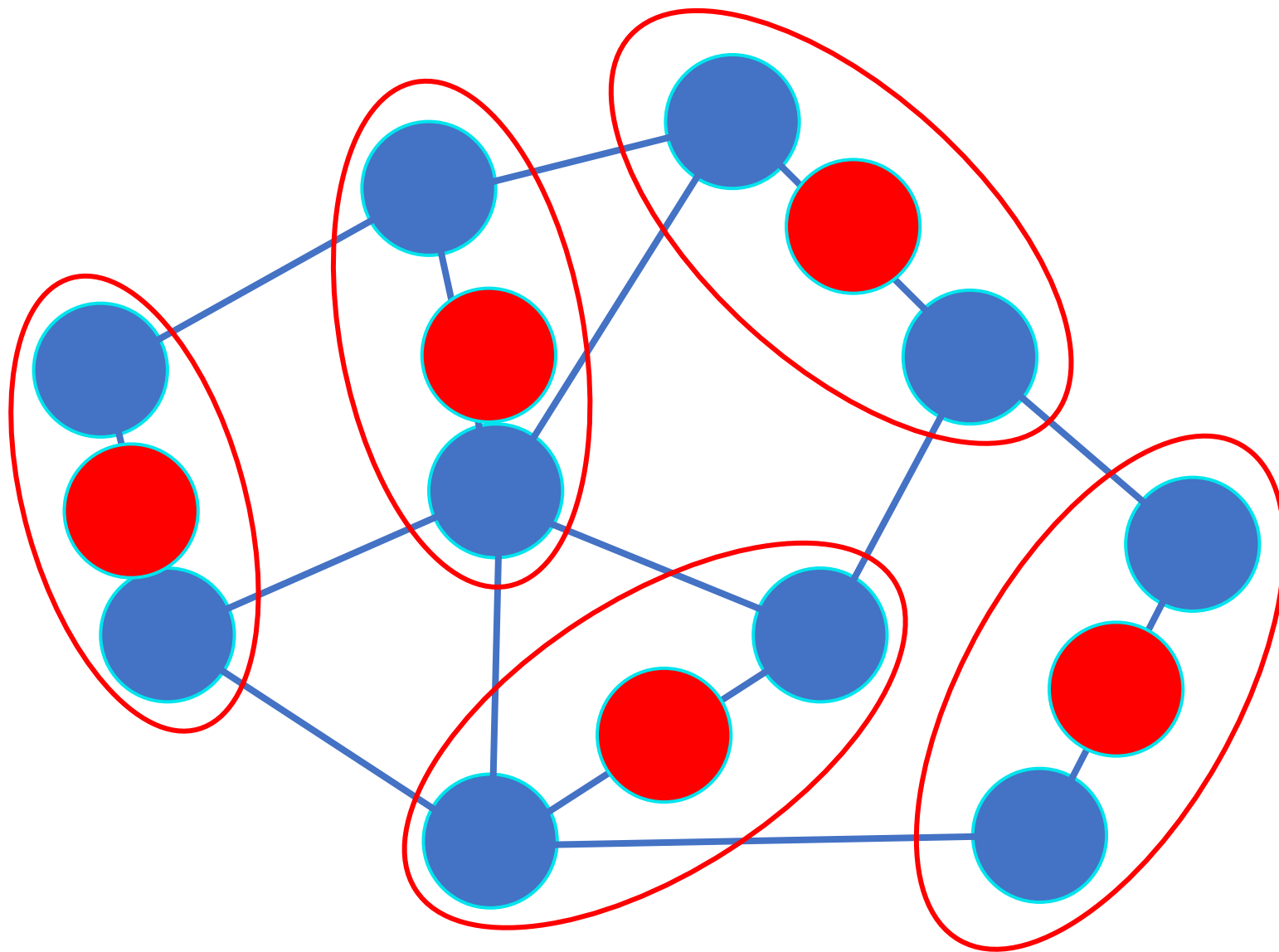
Shuiwang Ji

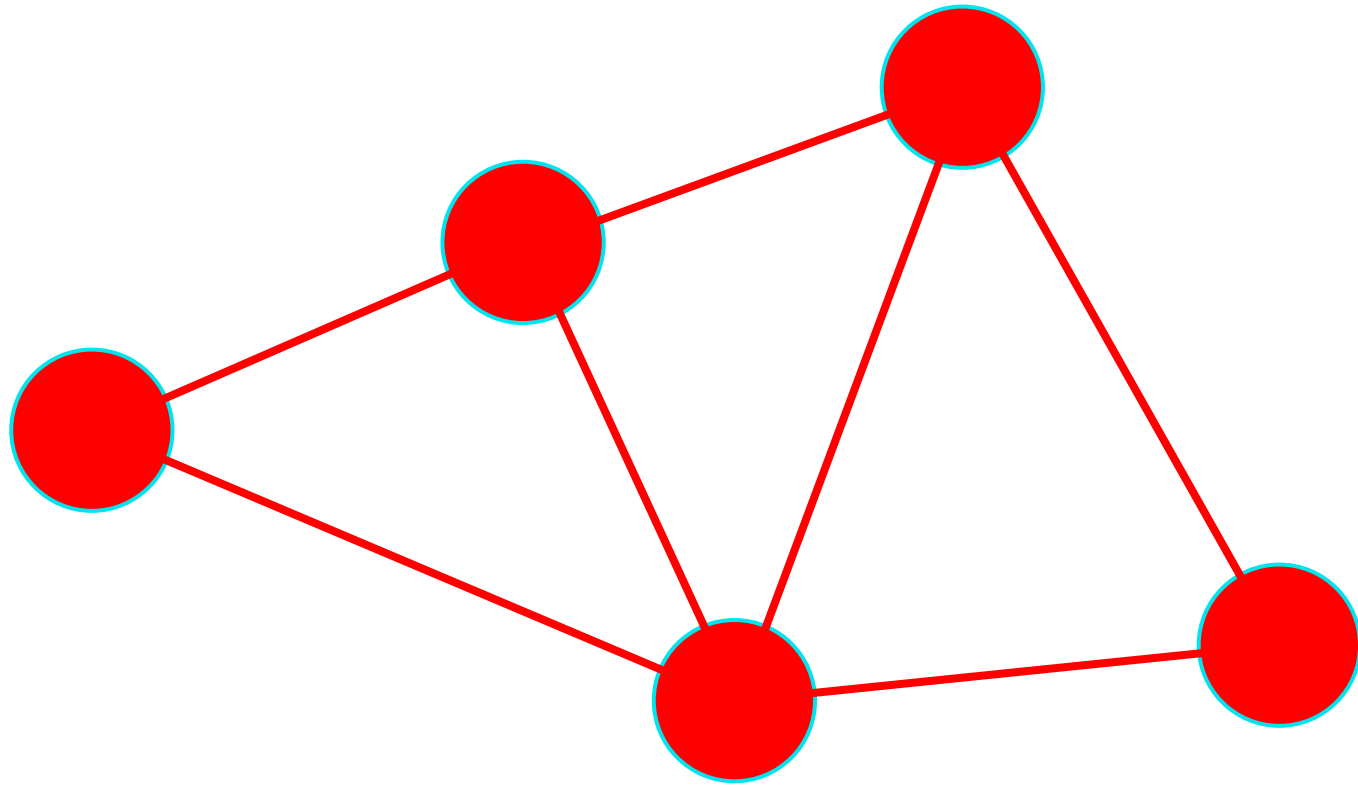










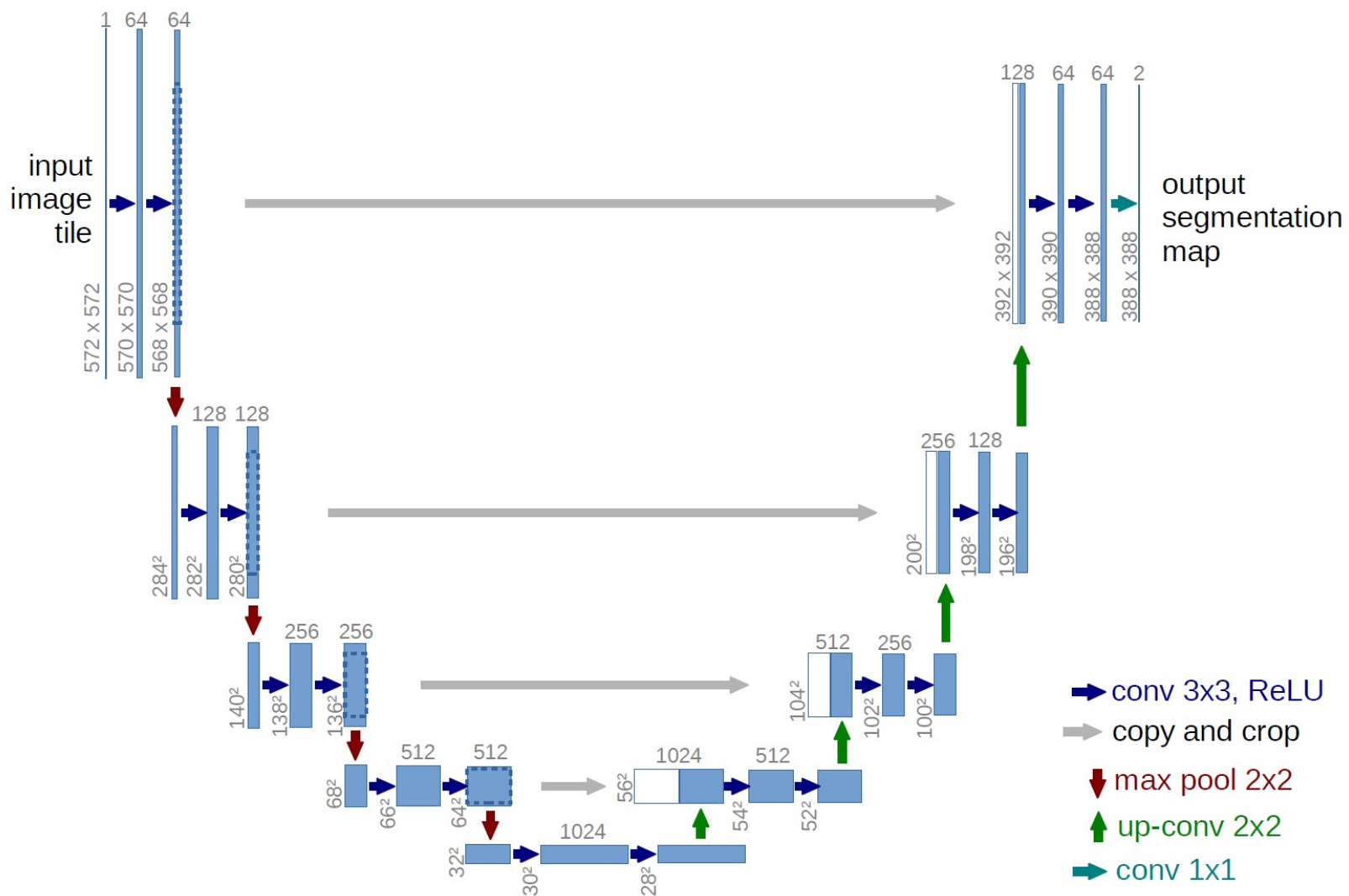


Graph U-Nets

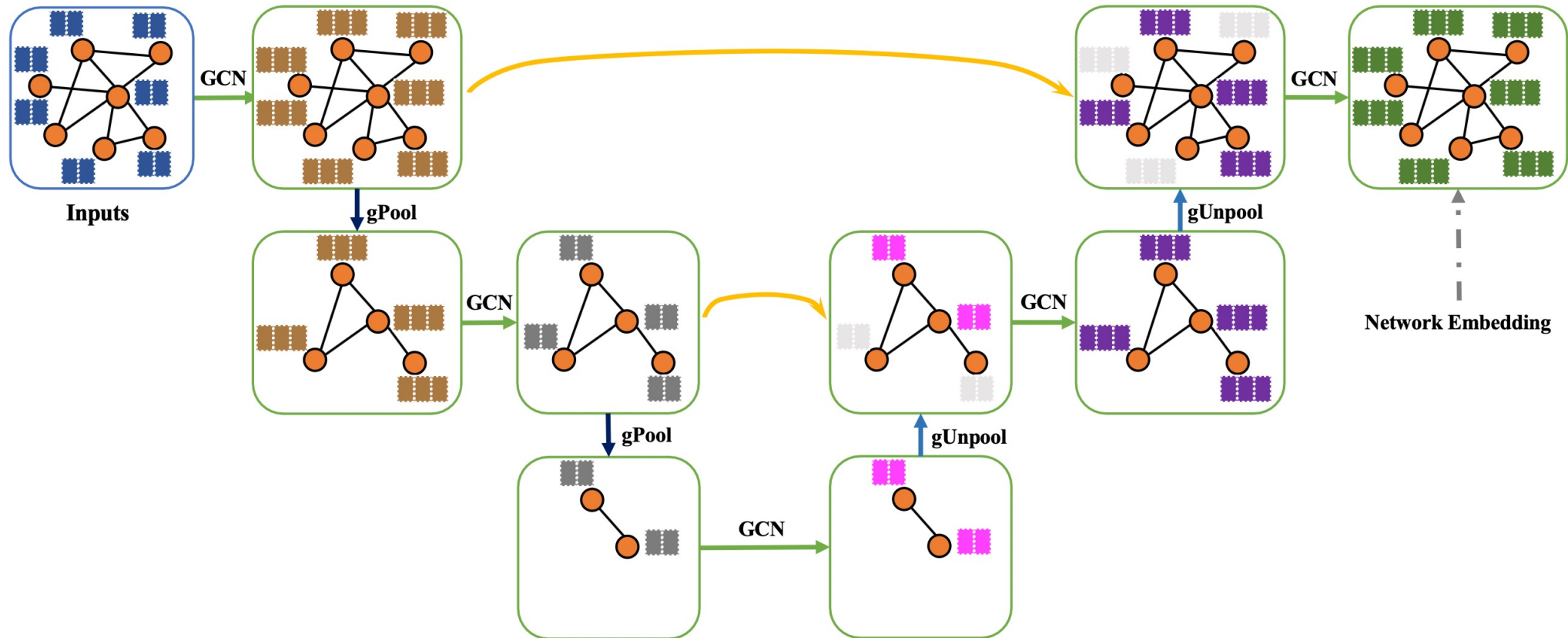
Hongyang Gao

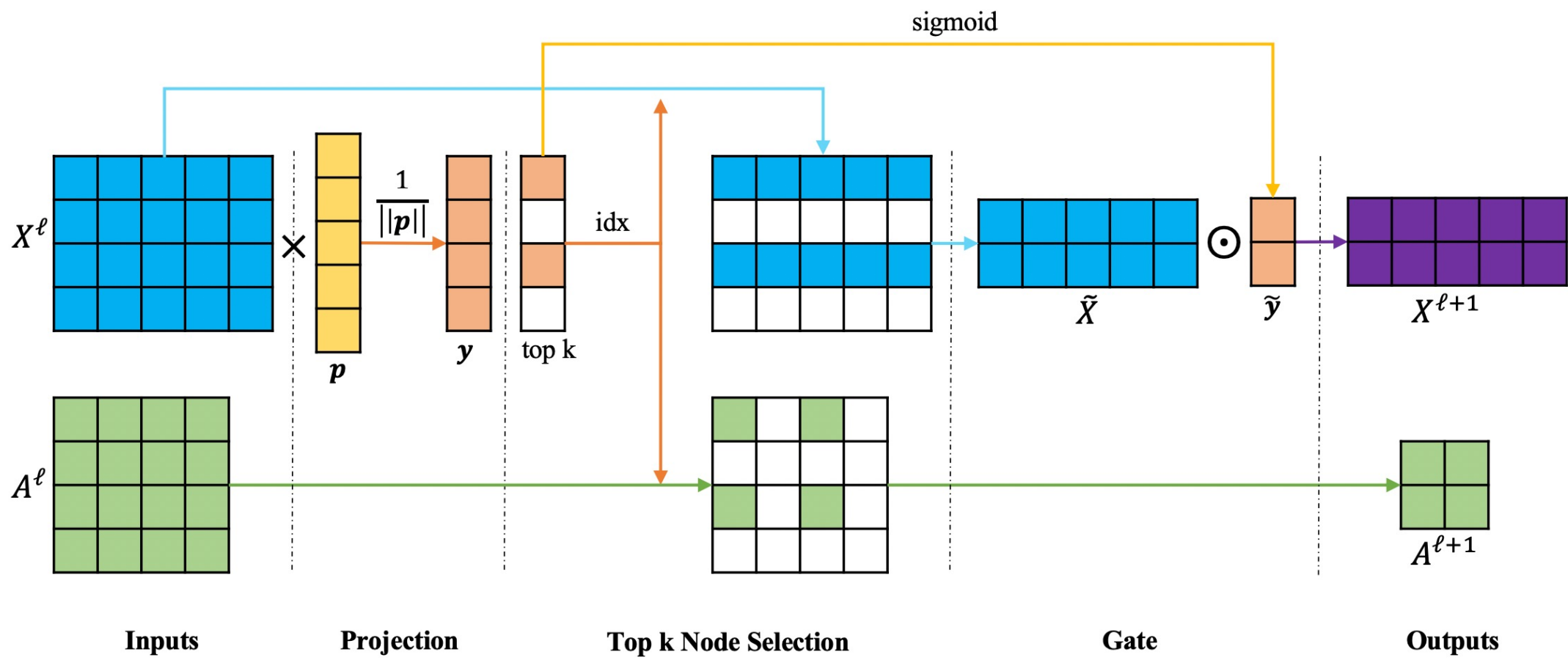
Shuiwang Ji

U-Net :



Graph U-Net :





$$\begin{aligned}
 \mathbf{y} &= X^\ell \mathbf{p}^\ell / \|\mathbf{p}^\ell\|, \\
 \text{idx} &= \text{rank}(\mathbf{y}, k), \\
 \tilde{\mathbf{y}} &= \text{sigmoid}(\mathbf{y}(\text{idx})), \\
 \tilde{X}^\ell &= X^\ell(\text{idx}, :), \\
 A^{\ell+1} &= A^\ell(\text{idx}, \text{idx}), \\
 X^{\ell+1} &= \tilde{X}^\ell \odot (\tilde{\mathbf{y}} \mathbf{1}_C^T),
 \end{aligned}$$

Table 3. Results of transductive learning experiments in terms of node classification accuracies on Cora, Citeseer, and Pubmed datasets. g-U-Nets denotes our proposed graph U-Nets model.

Models	Cora	Citeseer	Pubmed
DeepWalk (Perozzi et al., 2014)	67.2%	43.2%	65.3%
Planetoid (Yang et al., 2016)	75.7%	64.7%	77.2%
Chebyshev (Defferrard et al., 2016)	81.2%	69.8%	74.4%
GCN (Kipf & Welling, 2017)	81.5%	70.3%	79.0%
GAT (Veličković et al., 2017)	83.0 \pm 0.7%	72.5 \pm 0.7%	79.0 \pm 0.3%
g-U-Nets (Ours)	84.4 \pm 0.6%	73.2 \pm 0.5%	79.6 \pm 0.2%

Table 4. Results of inductive learning experiments in terms of graph classification accuracies on D&D, PROTEINS, and COLLAB datasets. g-U-Nets denotes our proposed graph U-Nets model.

Models	D&D	PROTEINS	COLLAB
PSCN (Niepert et al., 2016)	76.27%	75.00%	72.60%
DGCNN (Zhang et al., 2018)	79.37%	76.26%	73.76%
DiffPool-DET (Ying et al., 2018)	75.47%	75.62%	82.13%
DiffPool-NOLP (Ying et al., 2018)	79.98%	76.22%	75.58%
DiffPool (Ying et al., 2018)	80.64%	76.25%	75.48%
g-U-Nets (Ours)	82.43%	77.68%	77.56%