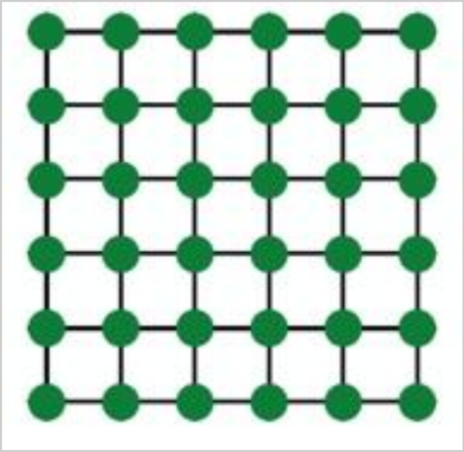
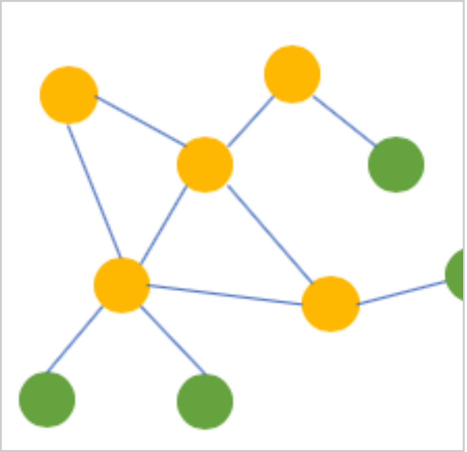
Graph U-Nets

Hongyang Gao and Shuiwang Ji

Texas A&M University

IMAGE VS. GRAPH





- Image can be treated as a special graph with well-defined locality. There is no locality information on normal graph, which makes it hard to define pooling and un-pooling operation on graph data.

- Node classification problems can be considered as image segmentation problems. Both predict for each node or pixel.

U-NET ON GRAPH

Node classification ⟷ Image segmentation

Conv layer

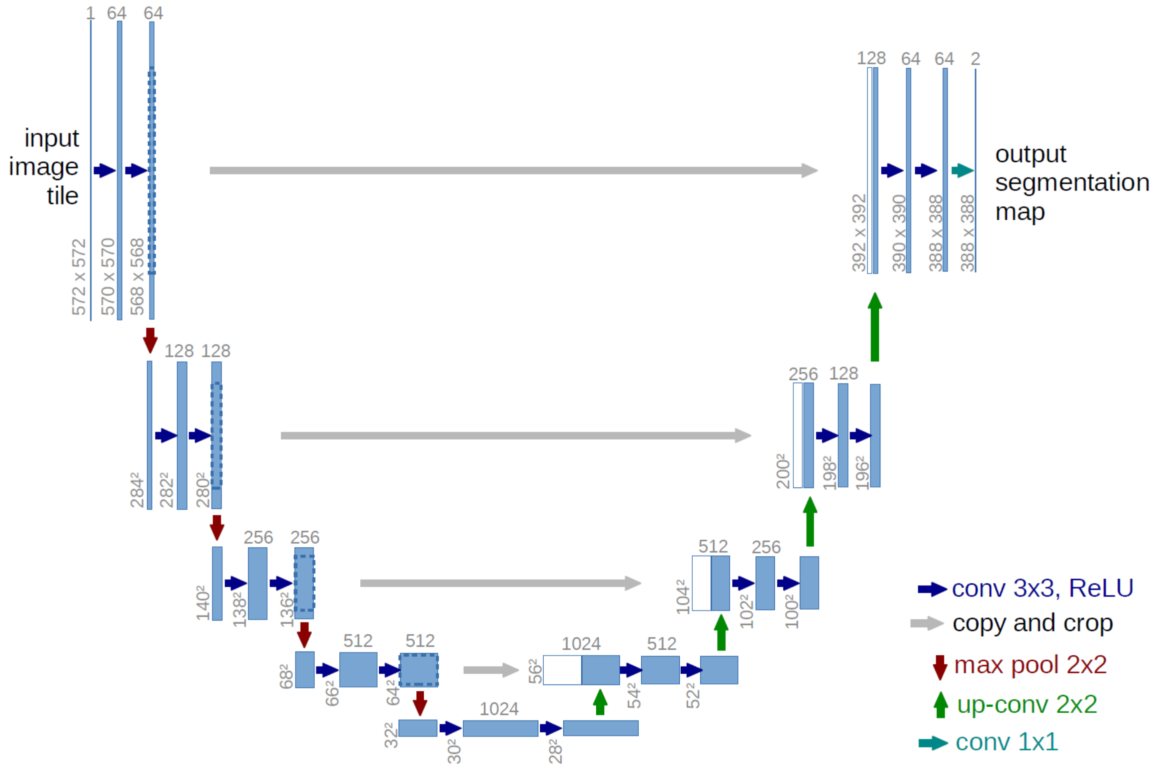
- GCN layer

Pooling layer

- ?

Un-pooling layer

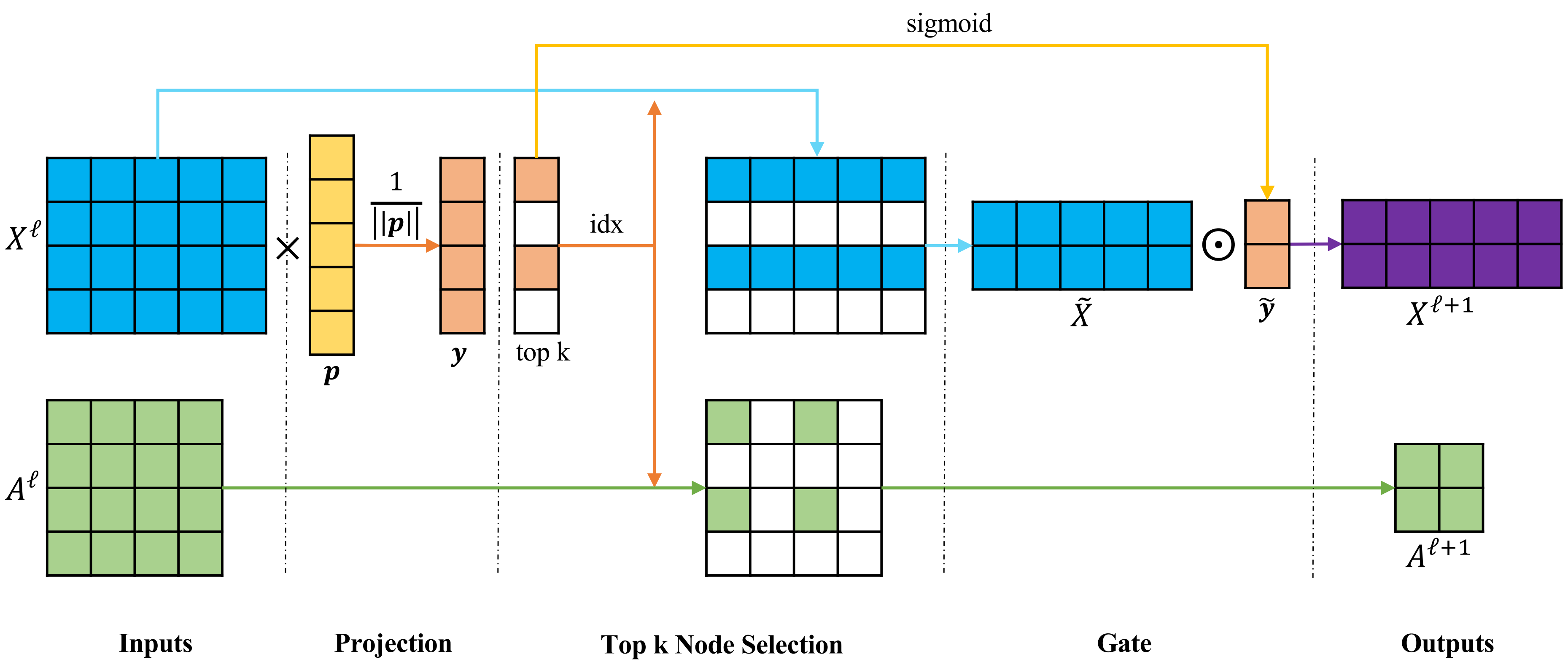
- ?



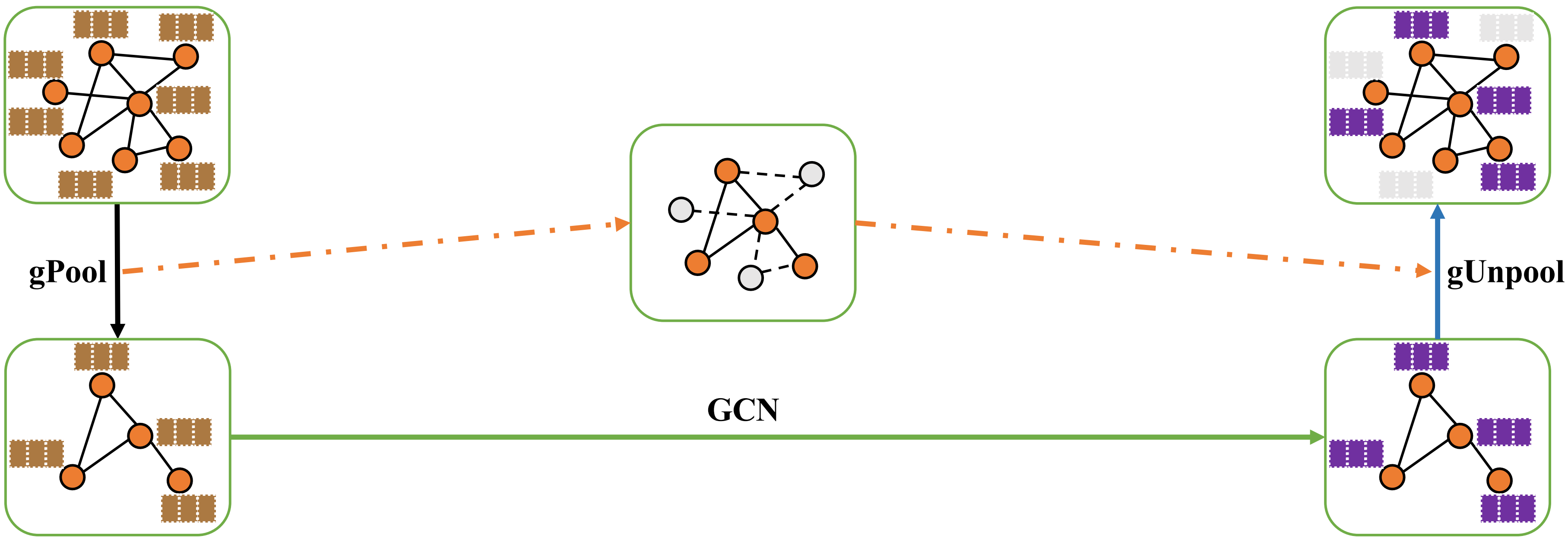
https://lmb.informatik.uni-freiburg.de/people/ronneber/u-net/

ENGINEERING
TEXAS A&M UNIVERSITY
TEXAS A&M ENGINEERING EXPERIMENT STATION

GRAPH POOLING LAYER (GPOOL)

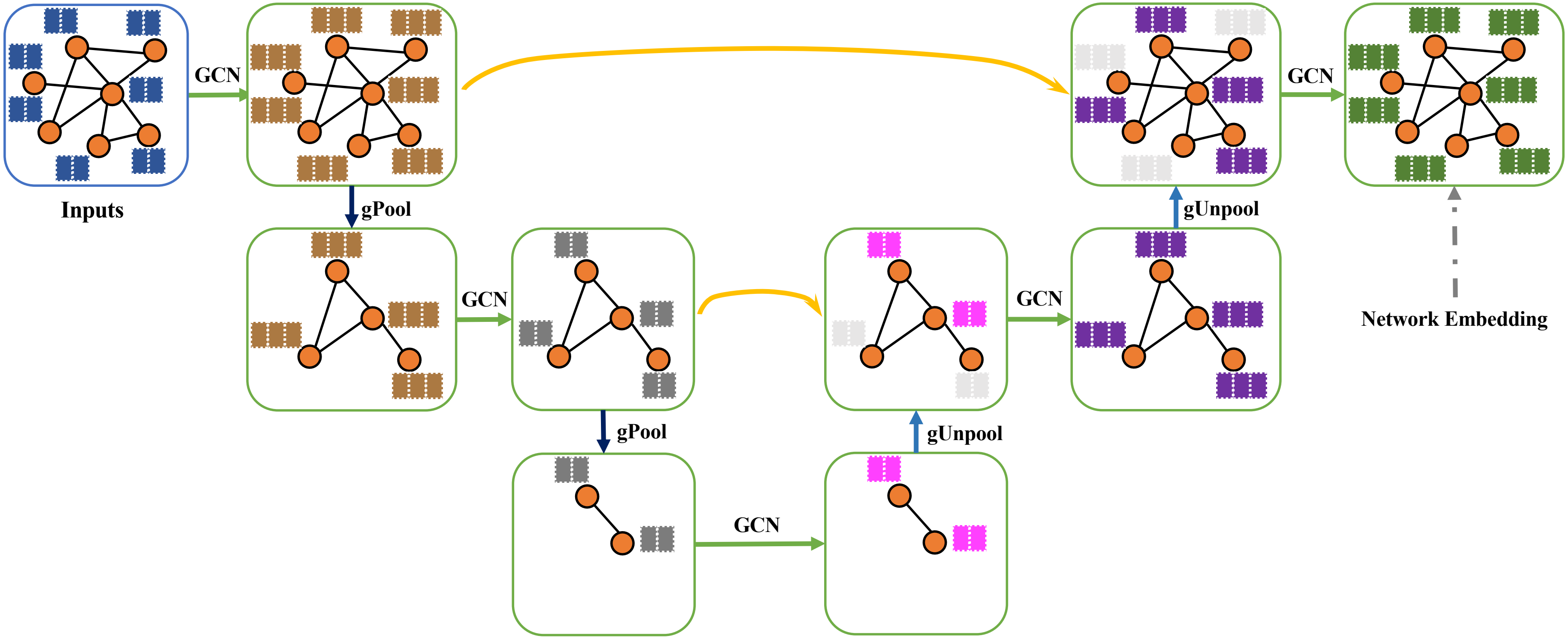


GRAPH UN-POOLING LAYER (GUNPOOL)



gUnpool layer uses position information from gPool layer to reconstruct original graph structure.

GRAPH U-NET


GCN
Inputs
gPool
GCN
gPool
GCN
gUnpool
GCN
gUnpool
GCN
Network Embedding

NETWORK REPRESENTATION LEARNING RESULTS

Results on node classification tasks:

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-Net (Ours)	$\mathbf{84.4 \pm 0.6\%}$	$\mathbf{73.2 \pm 0.5\%}$	$\mathbf{79.6 \pm 0.2\%}$

Results on graph classification tasks:

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%

ENGINEERING
TEXAS A&M UNIVERSITY

TEXAS A&M ENGINEERING EXPERIMENT STATION

GRAPH U-NETS

Come to poster

#25

for more details!