## Graph Learning Network A Structure Learning Algorithm

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\& $\downarrow$ https:/ / gitlab.com/mipl/graph-learning-network/

## - Context

A Problem. Current deep learning graphmodels do not support extreme variations: complete changes in the structure of graphs in each layer.
? Proposal. Use graph convolutions to propose expected node features, and predict the best structure based on them. Recursively repeat these steps to enhance the prediction and the embeddings.

## CONTRIBUTIONS

i Two prediction functions: nodes' features and adjacency
ii A recurrent architecture
iii An end-to-end learning framework for predicting graphs' structure
iv Introduction of new synthetic datasets, i.e., 3D surface functions and geometric images


Dissimilarity MMD between pred. and GT (smaller is better) on the 3D Surface.


MMD varying the input structure on Community $C=4$ (left) and $C=2$ (right).

| Losses |  |  | Metrics |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| IoU | HED | Reg | Acc $\uparrow$ | IoU $\uparrow$ | Dice $\uparrow$ | Deg $\downarrow$ | Clus $\downarrow$ | Orb $\downarrow$ |
| - | $\checkmark$ | - | 0.9997 | 0.9747 | 0.9872 | 0.0068 | 0.0011 | 0.1069 |
| - | $\checkmark$ | $\checkmark$ | 0.9997 | 0.9749 | 0.9872 | 0.0065 | 0.0010 | 0.0972 |
| $\checkmark$ | - | - | 0.7997 | 0.0524 | 0.0996 | 1.8624 | 1.9980 | 0.9827 |
| $\checkmark$ | - | $\checkmark$ | 0.8938 | 0.0953 | 0.1740 | 1.7689 | 1.9491 | 1.1862 |
| $\checkmark$ | $\checkmark$ | - | 0.9997 | 0.9749 | 0.9872 | 0.0063 | 0.0002 | 0.0619 |
| $\checkmark$ | $\checkmark$ | $\checkmark$ | 0.9997 | 0.9749 | 0.9872 | 0.0062 | 0.0002 | 0.0053 |

Ablation of GLN using Geometric Figures.

## I Proposed Method: GLN



## Loss Functions

Intersection over Union (IoU) of adjacency
$\Delta \sqrt{\Delta}$ Class-balanced Cross-Entropy (HED)
ㅡㅡ Regularization

$$
\begin{aligned}
H_{\mathrm{int}}^{(l)} & =\sum_{i=1}^{k} \sigma_{l}\left(\hat{A}^{(l)} H_{i}^{(l)} W_{i}^{(l)}\right) \\
H_{\mathrm{local}}^{(l)} & =\sigma_{l}\left(\hat{A}^{(l)} H_{\mathrm{int}}^{(l)} U^{(l)}\right) \\
H_{\text {global }}^{(l)} & =\sigma_{l}\left(H_{\text {local }}^{(l)} Z^{(l)}\right) \\
A^{(l+1)} & =\sigma_{l}\left(M^{(l)} H_{\text {local }}^{(l)} Q^{(l)} H_{\text {global }}^{(l)} M^{(l)^{\top}}\right)
\end{aligned}
$$

(i) Learnable matrices

Non linearities
Embedding functions

## © Results

Elliptic hyperboloid Elliptic paraboloid


Saddle

(i) Not predicted edges (FN), extra predicted edges (FP), and correctly predicted ones.

Community $\mathrm{C}=4$


Geometrical Figures dataset segmentation


