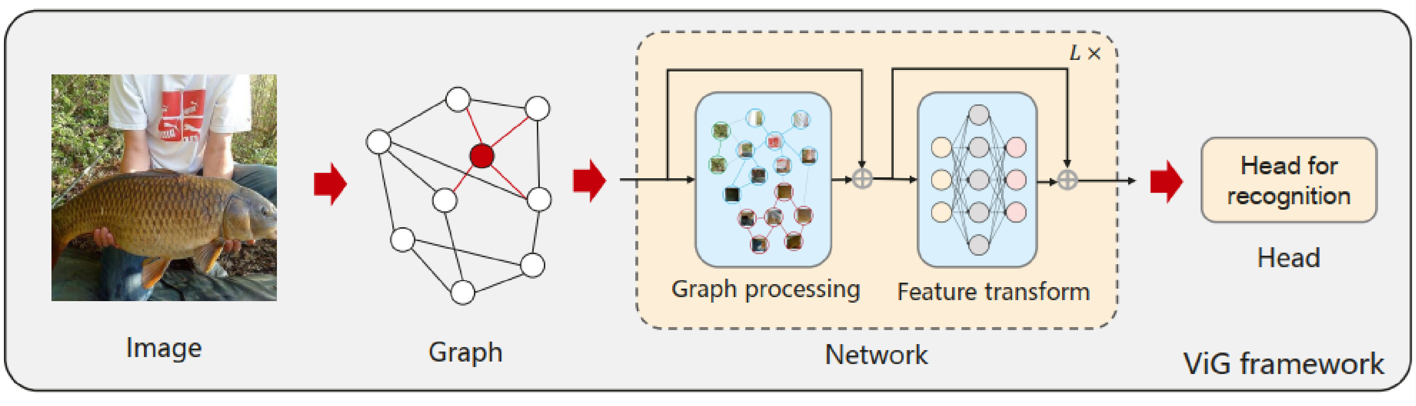
Vision GNN-Powered Object Detection

Sagar Prakash Barad

Harnessing Vision GNNs as Backbone Feature Extractors for RetinaNet and Mask R-CNNs

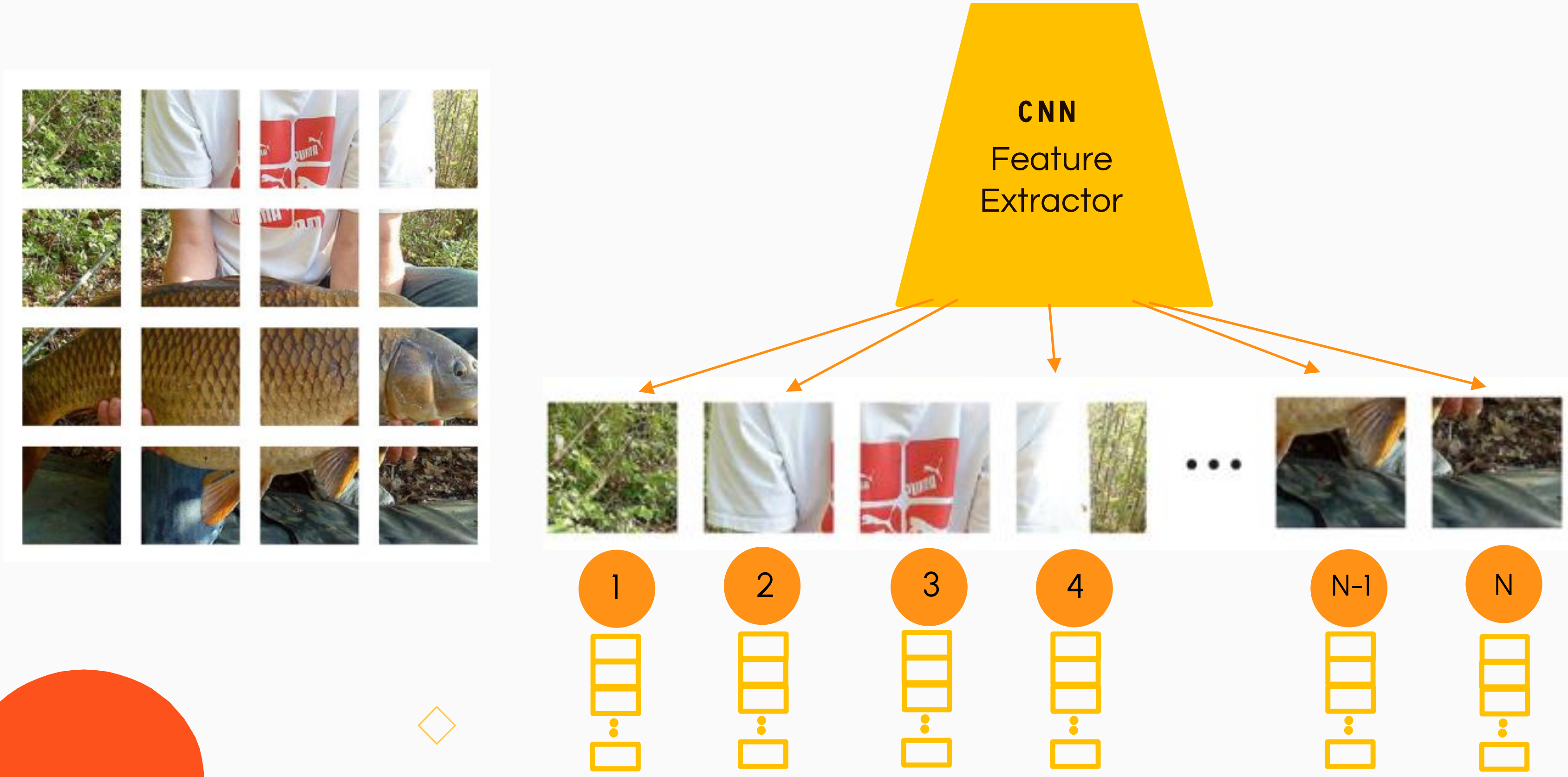


RetinaNet ~~ResNet~~ + FPN + Focal Loss
Vision GNN

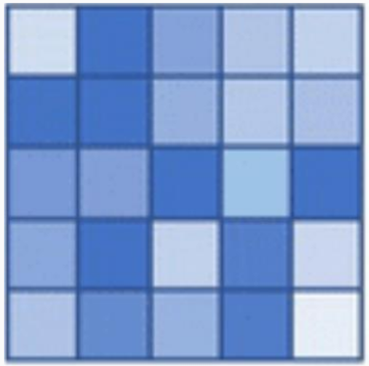
Dataset(s) – COCO Dataset, PubTables 1M Dataset, FinTab Dataset

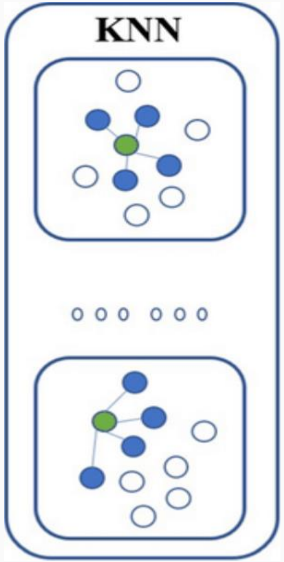
Wang, X., Liu, Z., Zhang, S., Li, B., Wang, T., & Zhang, J. (2022). Vision GNN: An Image is Worth Graph of Nodes. *Advances in Neural Information Processing Systems, 35*. Retrieved from https://arxiv.org/abs/2206.00272

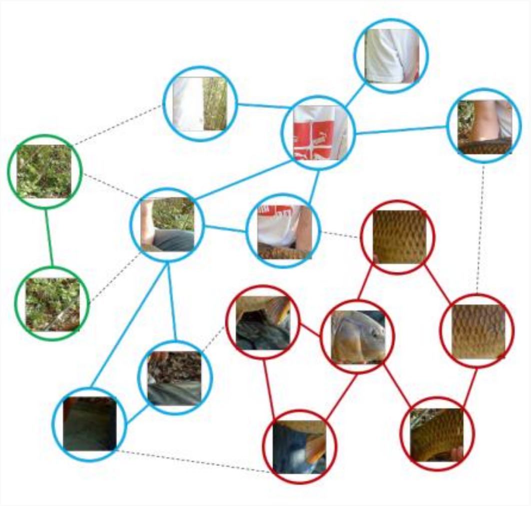
Vision GNN Works by...



Graph Represnation





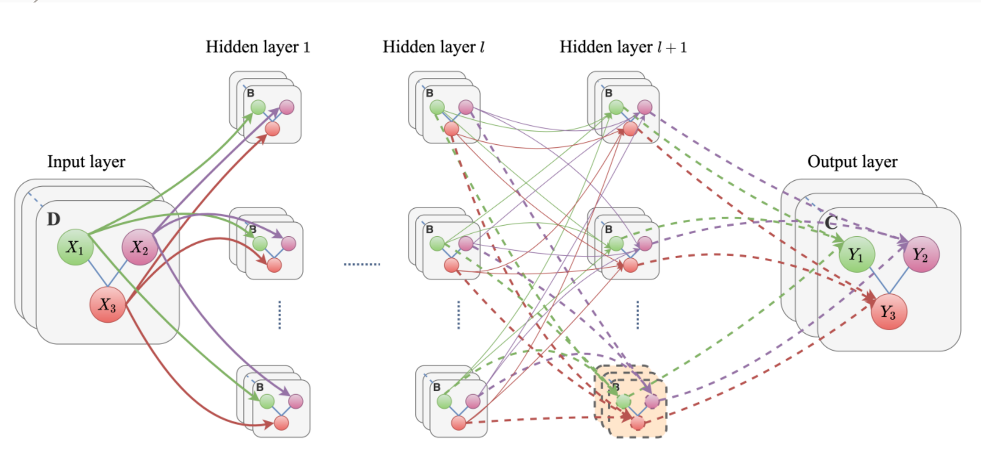


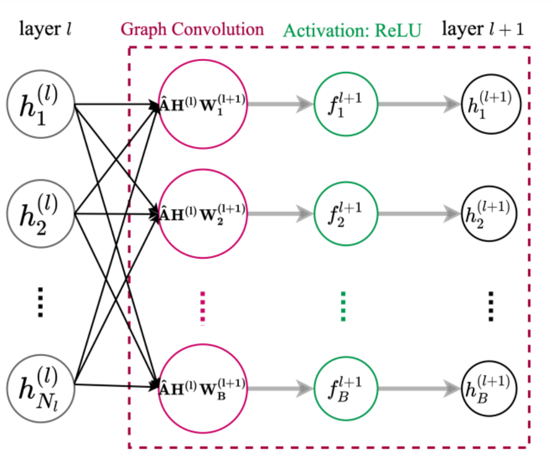
Directed Graph

Benefits

1. Generalized Data Structure
2. Flexibility for Complex Objects
3. Part-Object Relationships

Graph Convolution





Heidari, N. (2020, March 27). Progressive Graph Convolutional networks for Semi-Supervised Node Classification. arXiv.org. https://arxiv.org/abs/2003.12277

$$\mathbf{h}_{\mathcal{N}_v}^t = \text{AGGREGATE}_t\left(\{\mathbf{h}_u^{t-1}, \forall u \in \mathcal{N}_v\}\right)$$

$$\mathbf{h}_v^t = \sigma\left(\mathbf{W}^t \cdot [\mathbf{h}_v^{t-1} \| \mathbf{h}_{\mathcal{N}_v}^t]\right)$$

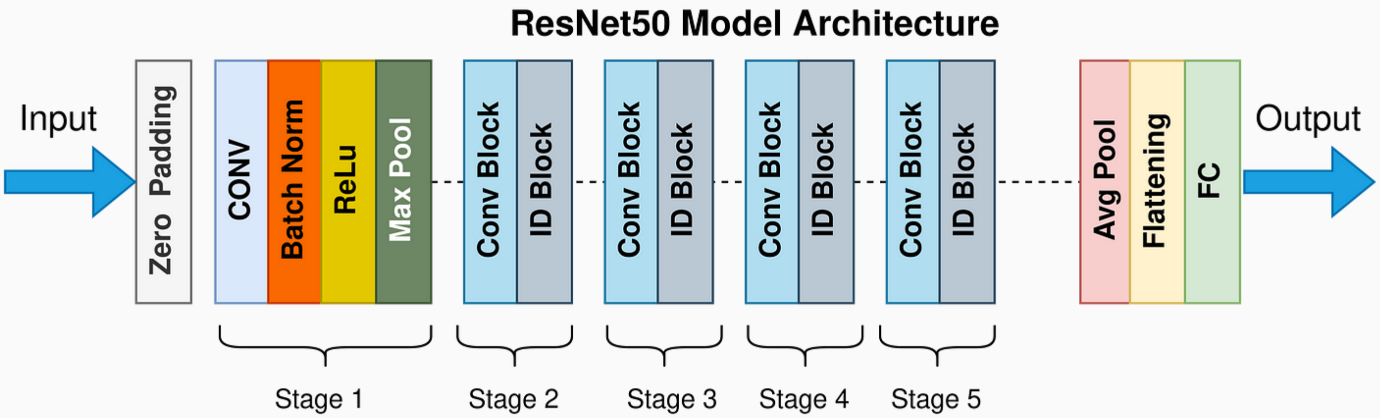
$$\mathbf{h}_{\mathcal{N}_v}^t = \max(\{\sigma\left(\mathbf{W}_{\text{pool}}\mathbf{h}_u^{t-1} + \mathbf{b}\right), \forall u \in \mathcal{N}_v\})$$

like mean, sum or max function

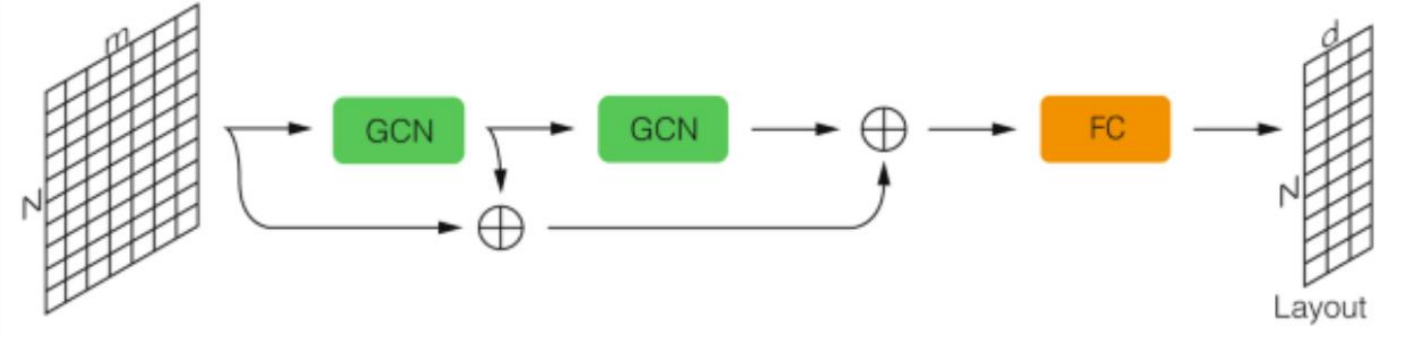
$$\mathbf{h}_v^{(k)} = \sigma(\mathbf{W}^{(k)} \cdot f_k(\mathbf{h}_v^{(k-1)}, \{\mathbf{h}_u^{(k-1)}, \forall u \in S_{\mathcal{N}(v)}\}))$$

where $\mathbf{h}_v^{(0)} = \mathbf{x}_v$, $f_k(\cdot)$ is an aggregation function, $S_{\mathcal{N}(v)}$ is a random sample of the node v's neighbors.

Comparision with CNNS



Sapireddy, S. R. (2023, July 1). ReSNEt-50: Introduction - Srinivas Rahul Sapireddy - Medium. Medium. https://srsapireddy.medium.com/resnet-50-introduction-b5435fdba66f



Both, C., Dehmamy, N., Yu, R. et al. Accelerating network layouts using graph neural networks. Nat Commun 14, 1560 (2023). https://doi.org/10.1038/s41467-023-37189-2

ViG Models

ViG-Ti

Flops(B): 1.3
Params(M): 7.1

ViG-S

Flops(B): 4.5
Params(M): 22.7

ViG-B

Flops(B): 17.7
Params(M): 86.8

ResNet -18

Flops(B): 1.82
Params(M): 11.7

ResNet -50

Flops(B): 3.86
Params(M): 25.6

ResNet -101

Flops(B): 7.1
Params(M): 44.6

Model	Depth	Dimension D
ViG-Ti	12	192
ViG-S	16	320
ViG-B	16	640

Results on CIFAR

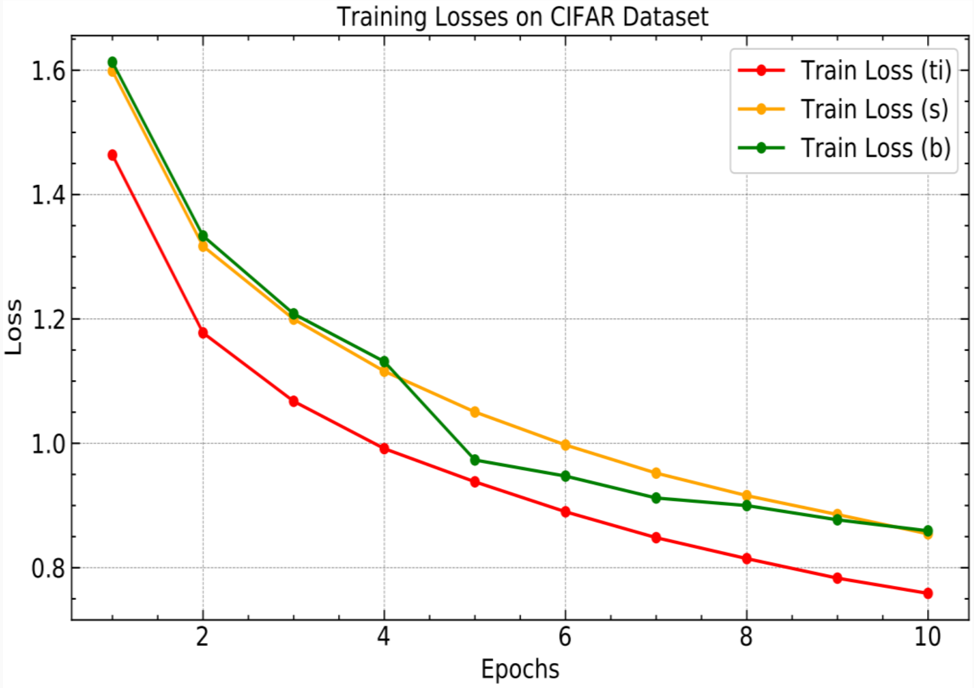


Table 3. ViG models on CIFAR Dataset

Model	Top-1	Top-5
ViG-Ti	66.1	97.67
ViG-S	65.64	97.95
ViG-B	67.71	98.78

Results on ImageNet-1k

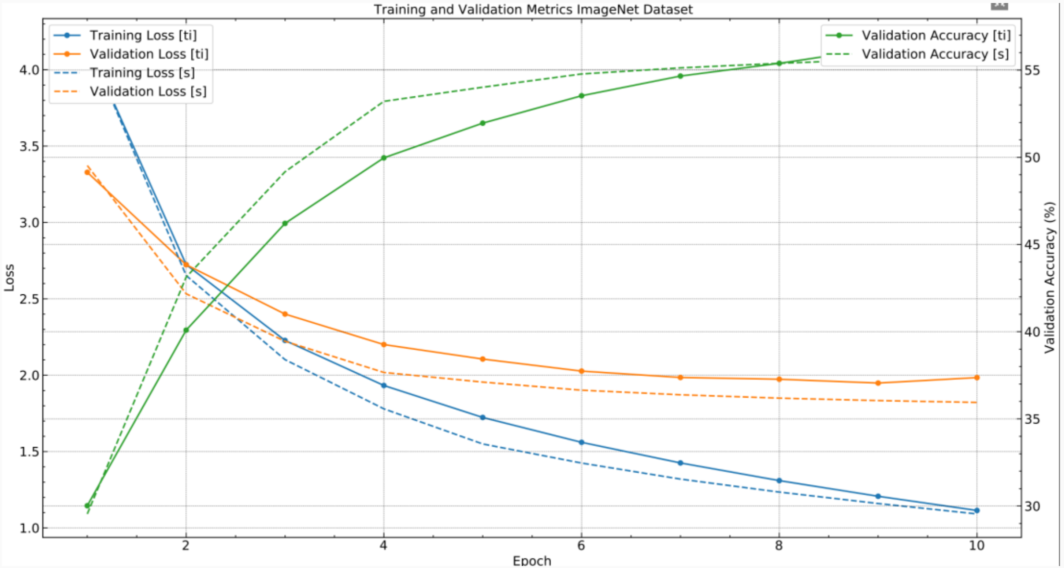


Table 4. ViG models on ImageNet Dataset

Model	Top-1	Top-5
ViG-Ti	69.49	98.32
ViG-S	66.77	98.95

Conclsuion

1. ViG models (ViG-Ti, ViG-S, ViG-B) show promise in our training, with potential for comparable or superior performance to ResNet variants (ResNet-18, ResNet-50, ResNet-101) as we increase training epochs.

2. ViG models match ResNet models in size (FLOPs and parameters) but outperform them in image classification.

3. Future plans include training on coco, FinTab and Pubtables dataset. Also, implementing LT GNN for better transfer learning.