Matching Convolutional Neural Networks without Priors about Data

Carlos E. Rosar Kos Lassance[1,3], Jean-Charles Vialatte[1,2], Vincent Gripon[1] and Nicolas Farrugia[1]
[1] IMT Atlantique, Electronics Department, Brest, France [2] Cityzen Data, Brest, France [3] Contact email: carlos.rosarkoslassance@imt-atlantique.fr

1. Context

- Convolutional Neural Networks(**CNNs**) are the **state of the art in** various **image recognition** tasks [1]
- They do so because **they exploit the intrisic structure of the data**
- We aim to **generalize CNNs to signals** defined **on graphs**

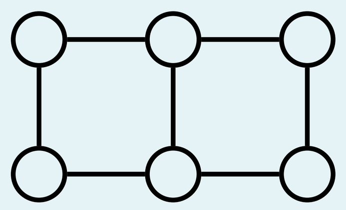
2. Related Work

Works in this area can be divided in:

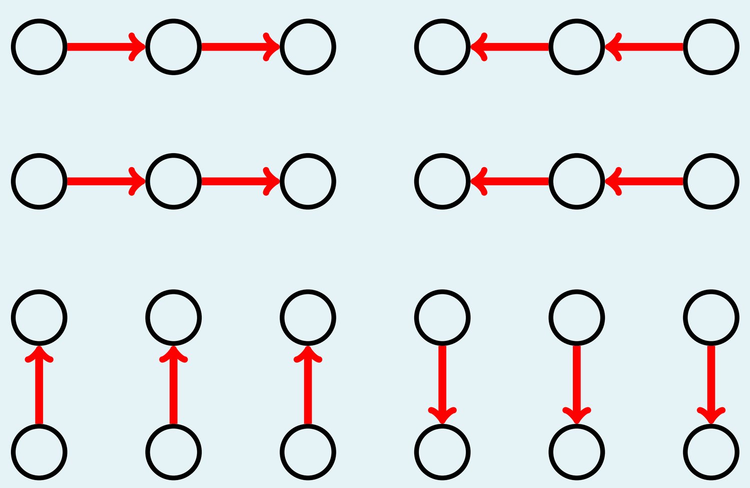
- Graph or node classification e.g [3, 6]
- Signal over graph classification e.g [2, 5]

We build upon [5]:

- Find translations in the graph
- Use these translations to create a weight sharing scheme
- For example consider a 3x2 Grid Graph:



- One way to generate the translations is:



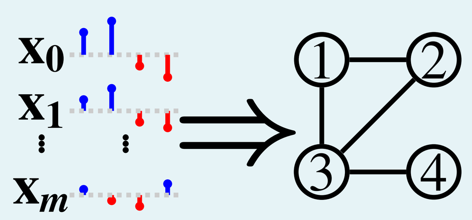
3. Ingredients

CNN have three key aspects for their success:

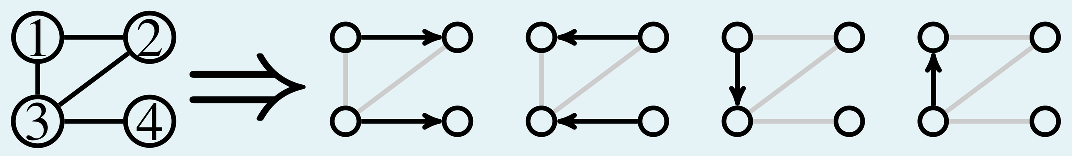
- Intrisic structure/Weight sharing scheme (introduced in [5], refined here)
- Subsampling (introduced here)
- Data augmentation (introduced here)

4. Global methodology

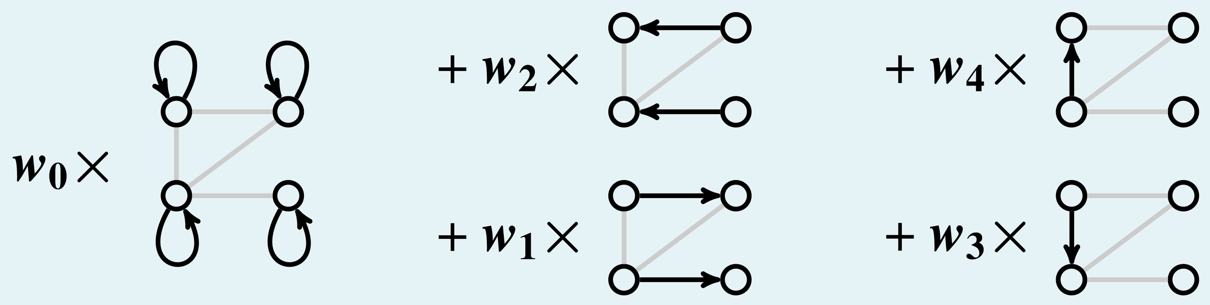
Step 0 (optional): infer a graph [5]



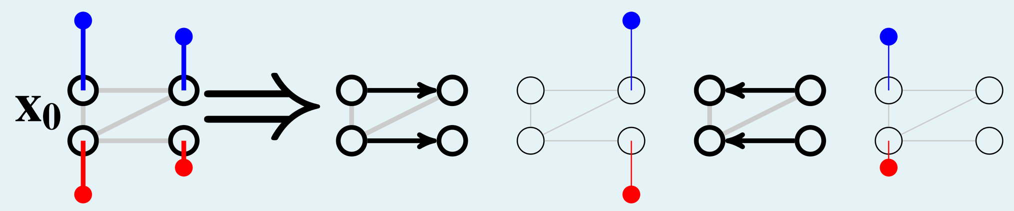
Step 1: infer translations [5]



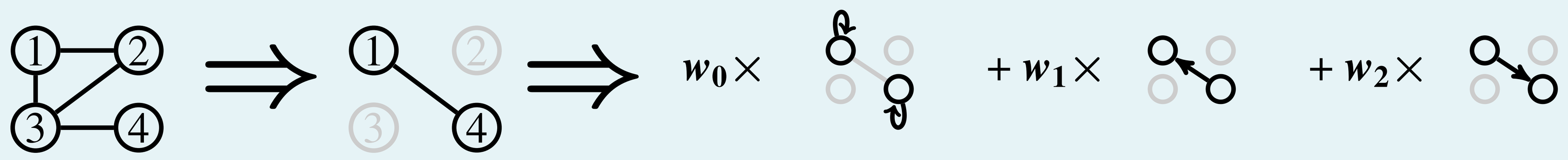
Step 2: design convolution weight-sharing [5]



Step 3: design data-augmentation



Step 4: design graph subsampling and convolution weight-sharing



5. Graph construction

- Oracle: based on a grid
- Geometrical distance: based on vertices coordinates if available
- Statistical properties of the signal: here we use a thresholded covariance matrix

6. Data augmentation

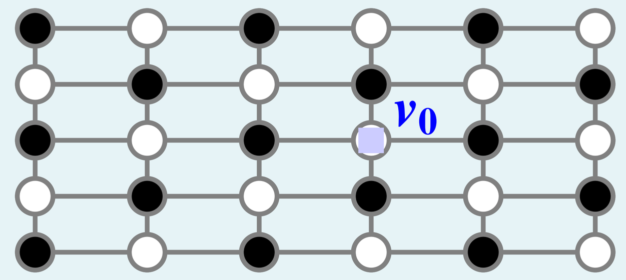
We use the translations of [5] as a proxy for random crop.

Original	Random Crop	Grid Translation	Covariance Translation
			

7. Subsampling

- Given an arbitrary initial vertex $v_0 \in V$, the set of kept vertices $V_{\downarrow r}$ is defined inductively:
  1) $V^0_{\downarrow r} = \{v_0\}$,
  2) $\forall t \in \mathbb{N}, V^{t+1}_{\downarrow r} = V^t_{\downarrow r} \cup \{v \in V, \forall v' \in V^t_{\downarrow}, v \notin N_{r-1}(v') \wedge \exists v' \in V^t_{\downarrow r}, v \in N_r(v')\}$.

Figure: Downscaling of the grid graph. Disregarded vertices in black.



8. Experiments

Two datasets are used for the tests reported bellow.

1. CIFAR-10 dataset, which is an image classification dataset
2. PINES a dataset that consists of fMRI scans, taken during an emotional picture rating task. Collected from `https://neurovault.org/collections/1964/`

Table: CIFAR-10 result comparison table.

Support	MLP [4]	CNN	Grid		Covariance	
			[2]	Proposed	Proposed	[5]
Full Data Augmentation	78.62%	**93.80%**	85.13%	93.94%	92.57%	—–
Data Augmentation - Flip	—–	92.73%	84.41%	92.94%	91.29%	—–
Graph Data Augmentation	—–	—–	—–	92.81%	**91.07%**	—–
None	69.62%	87.78%	—–	88.83%	85.88%	82.52%

Results for [4, 5] are obtained from the respective papers.

Table: PINES fMRI dataset accuracy comparison table.

Graph	None		Neighborhood Graph	
Method	MLP	CNN (kernel 1x1)	[2]	Proposed
Accuracy	82.62%	84.30%	82.80%	**85.08%**

Our shallow architecture is equivalent to [5].

9. Conclusion

- We proposed a new methodology that extends classical convolutional neural networks to irregular domains represented by a graph.
- We performed experiments and showed that
  - The method is able to match performance of classical convolutional neural networks on images without explicit knowledge about the underlying regular 2D structure.
  - The method is able to increase performance on a neuroimaging dataset with irregular structure.

10. References

[1] M. M. Bronstein, J. Bruna, Y. LeCun, A. Szlam, and P. Vandergheynst. Geometric deep learning: going beyond euclidean data. *IEEE Signal Processing Magazine*, 34(4):18–42, 2017.

[2] M. Defferrard, X. Bresson, and P. Vandergheynst. Convolutional neural networks on graphs with fast localized spectral filtering. In *Advances in Neural Information Processing Systems*, pages 3837–3845, 2016.

[3] T. N. Kipf and M. Welling. Semi-supervised classification with graph convolutional networks. *arXiv preprint arXiv:1609.02907*, 2016.

[4] Z. Lin, R. Memisevic, and K. Konda. How far can we go without convolution: Improving fully-connected networks. *arXiv preprint arXiv:1511.02580*, 2015.

[5] B. Pasdeloup, V. Gripon, J.-C. Vialatte, and D. Pastor. Convolutional neural networks on irregular domains through approximate translations on inferred graphs. *arXiv preprint arXiv:1710.10035*, 2017.

[6] P. Veličković, G. Cucurull, A. Casanova, A. Romero, P. Liò, and Y. Bengio. Graph attention networks. *arXiv preprint arXiv:1710.10903*, 2017.