Graph Convolutional Neural Networks

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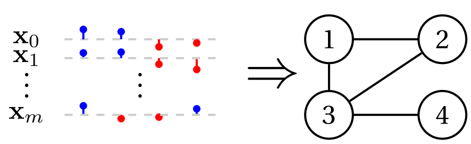
1 Overview

Convolutional Neural Networks (CNNs) have been able to surpass traditional machine learning methods in various image based tasks. This is possible as they exploit the learning capabilities of deep neural networks while also taking advantage of the intrinsic regular 2D structure of the data. But when data lacks regular structure, there is no natural notion of convolutions, stride/pooling or data augmentation. Such irregularities occur in various domains covering social networks to neuroscience, internet of things, citation graphs, point cloud manifolds... The question of developing solutions that are counterparts of CNNs in irregular domains has recently been a very active field of research.

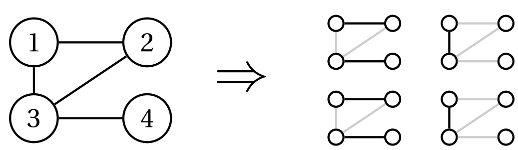
We proposed a new methodology that extends classical convolutional neural networks to irregular domains represented by a graph. The methodology scales linearly well with the order of the graph. Moreover, training can be performed using existing libraries for deep learning. We performed experiments and showed that our method is able to match performance of classical convolutional neural networks on images without explicit knowledge about the underlying regular 2D structure. It also significantly outperforms existing extended convolutional neural networks alternatives based on graphs. We also demonstrated the ability of the proposed methods to adapt to slightly irregular domains by performing experiments on a neuroimage dataset.

Keywords: Deep Learning, Graph Signal Processing

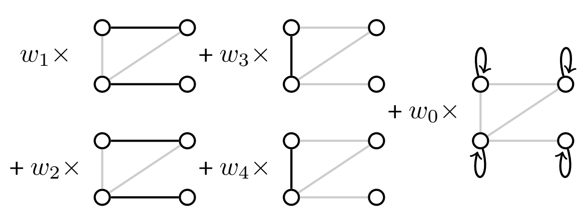
Step 0 (optional): infer a graph



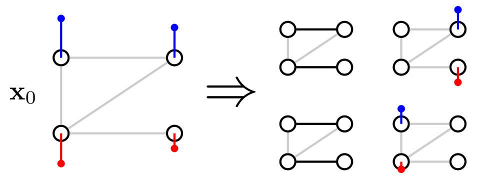
Step 1: infer translations (Subsection B)



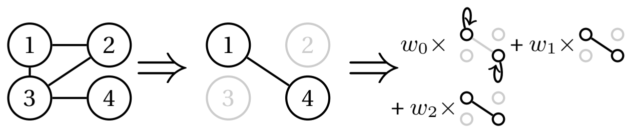
Step 2: design convolution weight-sharing (Subsection C)



Step 3: design data-augmentation (Subsection D)



Step 4: design graph subsampling and convolution weight-sharing (Subsection E)



2 Professors involved

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References

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