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CNN ARCHITECTURES FOR GRAPH DATA

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ABSTRACT

In this ongoing work, we describe several architectures that generalize convolutional neural networks (CNNs) to process signals supported on graphs. The general idea of the replace time invariant filters with graph filters to generate convolutional features and to replace pooling with sampling schemes for graph signals. The different architectures are compared and the key trade offs are identified. Numerical simulations with both synthetic and real-world data are used to illustrate the advantages of the proposed approaches.

Index Terms— Convolutional neural networks, deep learning, graph signal processing, geometric learning

1. INTRODUCTION

Convolutional neural networks (CNNs) have shown remarkable performance in a wide array of inference and reconstruction tasks [1], in fields as diverse as pattern recognition, computer vision and medicine [2–4]. The objective of CNNs is to find a computationally feasible architecture capable of reproducing the behavior of a certain unknown function. Typically, CNNs consist of a succession of layers, each of which performs three simple operations – usually on the output of the previous layer – and feed the result into the next layer. These three operations are: 1) convolution, 2) application of a nonlinearity, and 3) pooling or downsampling. Because the classical convolution and downsampling operations are defined for regular (grid-based) domains, CNNs have been applied to act on data modeled by such a regular structure, like time or images.

However, an accurate description of modern datasets such as those in social networks or genetics [5, 6] calls for more general irregular structures. A framework that has been gaining traction to tackle these problems is that of graph signal processing (GSP) [7–9]. GSP postulates that data can be modeled as a collection of values associated with the nodes of a graph, whose edges describe pairwise relationships between the data. By exploiting the interplay between the data and the graph, traditional signal processing concepts such as the Fourier transform, sampling and filtering have been generalized under the GSP framework to operate on a broader array of datasets [10–12].

Motivated by the success of CNNs and the need to deal with irregular domains, recent efforts have been made to extend CNNs to work with data (signals) defined on manifolds and graphs [13]. Since in the GSP literature the notion of convolution is generalized to that of node-invariant graph filters (GFs) –matrix polynomials of the graph Laplacian–, existing CNN works operating on graph signals have replaced classical convolutions with such node-invariant GFs [14]. Nonetheless, how to generalize pooling remains elusive. Attempts using hierarchical multilayer clustering algorithms have been made [15], but clustering is usually a computationally intensive operation [16].

This ongoing work presents several new architectures for CNNs operating on graph signals. To that end we replace: a) linear time invariant filters with (different types of) graph filters, and b) pooling (and possibly the subsequent nonlinearity) with sampling schemes tailored for graph data. The different architectures, which can be implemented using local exchanges, are compared and the key trade offs are identified. Numerical simulations with both synthetic and real-world data are used to illustrate the advantages of the proposed approaches.

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