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Denoising Autoencoder Self-Organizing Map (DASOM)

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ABSTRACT: In this report, we address the question of combining nonlinearities of neurons into networks for modelling increasingly varying and progressively more complex functions. A fundamental approach is the use of higher-level representations devised by restricted Boltzmann machines and (denoising) autoencoders. We present the Denoising Autoencoder Self-Organizing Map (DASOM) that integrates the latter into a hierarchically organized hybrid model where the front-end component is a grid of topologically ordered neurons. The approach is to interpose a layer of hidden representations between the input space and the neural lattice of the self-organizing map. In so doing the parameters are adjusted by the proposed unsupervised learning algorithm. The model therefore maintains the clustering properties of its predecessor, whereas by extending and enhancing its visualization capacity enables an inclusion and an analysis of the intermediate representation space. A comprehensive series of experiments comprising optical recognition of text and images, and cancer type clustering and categorization is used to demonstrate DASOM's efficiency, performance and projection capabilities.

KEYWORDS: unsupervised learning, denoising autoencoder, self-organizing map, clustering, visualization

1. Introduction

The structural and functional nature of biological neural systems provides a developmental template for artificial neural network algorithms. Structurally networks of topographically ordered neurons mimic nerve nets of the visual cortex (Von der Malsburg, 1973) and deep models (H. Lee, Ekanadham, & Ng, 2008) capture and store higher representations extracted from inherent regularities and structure in data (Ito & Komatsu, 2004). Functionally layered hierarchical architectures imitate sensory signal propagation and preprocessing/processing in regions of the brain (T. S. Lee & Mumford, 2003; T. S. Lee, Mumford, Romero, & Lamme, 1998). Such findings and advances in neuroscience have fueled numerous aspects of machine learning research, and have paved the way for designing distributed information representation-processing models based on complex layered architectures.

The extensively studied and widely applied clustering paradigm (Jain, 2010; Jain, Murty, & Flynn, 1999; Xu & Wunsch, 2005) forms a substantial part of the unsupervised learning backbone. Cluster analysis lends itself to varying approaches where principally the theme of grouping (separating) data elements based on their similarity/closeness (difference/distance) is common to much of these unsupervised classification algorithms. In a clustering method, partitioning the data into subsets subject to the criteria that the intra-cluster's internal homogeneity is greater than the inter-cluster's external heterogeneity, is the norm. Despite these fundamental commonalities there remains a diverse range of clustering approaches, for addressing generic problems that are enriched by a comprehensive array of problem-specific clustering algorithms.

The Self-Organizing Map (SOM) (Kohonen, 2001, 2013) is a specific type of unsupervised learning algorithm that represents the distribution-characteristics of input samples on planes of topographically ordered nodes and in doing so achieves clustering through dimensionality reduction. The intrinsic nonlinear mapping capabilities of the SOM on its low-dimensional neural surface distinguish it from most of the techniques that fall within the wider class of clustering algorithms. This advantage over more typical clustering approaches has led to the SOM methodology being as a means of visualizing nonlinear relations of data, topology-based cluster analysis, vector quantization and projection of multi-dimensional data. Because of the versatility of the SOM the scope of applications to which it has been applied is vast ranging from pattern recognition, image-text processing, mining, genomics, medical diagnostics, robotics and economics.

A difficulty that arises during pattern recognition from unlabeled data is the presence of large numbers of elements that make no contribution, or contribute marginally, to the data representation (features) of the dataset. The performance of machine learning methods therefore depends on the choice of

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