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ELM Embedded Discriminative Dictionary Learning for Image Classification

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Abstract

Dictionary learning is a widely adopted approach for image classification. Existing methods focus either on finding a dictionary that produces discriminative sparse representation, or on enforcing priors that best describe the dataset distribution. In many cases, the dataset size is often small with large intra-class variability and nondiscriminative feature space. In this work we propose a simple and effective framework called ELM-DDL to address these issues. Specifically, we represent input features with Extreme Learning Machine (ELM) with orthogonal output projection, which enables diverse representation on nonlinear hidden space and task specific feature learning on output space. The embeddings are further regularized via a maximum margin criterion (MMC) to maximize the inter-class variance and minimize intra-class variance. For dictionary learning, we design a novel weighted class specific $\ell_{1,2}$ norm to regularize the sparse coding vectors, which promotes uniformity of the sparse patterns of samples belonging to the same class and suppresses support overlaps of different classes. We show that such regularization is robust, discriminative and easy to optimize. The proposed method is combined with a sparse representation classifier (SRC) to evaluate on benchmark datasets. Results show that our approach achieves state-of-the-art performance compared to other dictionary learning methods.

Keywords: Discriminative dictionary learning, extreme learning machine, sparse representation, maximum margin criterion.

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1. Introduction

Feature representation [1] is a central topic for the task 25 2 of image classification. Natural images usually come with 26 3 large amounts of variability and noise because of varied 27 4 illuminations and viewpoints. Finding an efficient repre-28 5 sentation that is robust to such variations is important 29 6 for classification tasks. Typically, such representations include hand crafted features such as SIFT [2] or HOG [3], $_{31}$ 8 or features learned from a deep neural network and large $_{\scriptscriptstyle 32}$ 9 data [4]. They have been found successful for image classi- $_{33}$ 10 fication in the past twenty years. Although deep learning $_{\rm 34}$ 11 based approaches have been widely used in recent years, $_{35}$ 12 they still suffers from over-fitting when the underlying 36 13 dataset is small. 14 37

Sparse representation can be regarded as a type of fea- $_{38}$ 15 ture learning for natural signals, which is especially ef- $_{39}$ 16 fective when little or no prior knowledge is known about $_{40}$ 17 the underlying dataset. The sparse representation method $_{_{41}}$ 18 aims to find a set of filters that can approximate each sam- $_{\scriptscriptstyle 42}$ 19 ple linearly with only a portion of its elements. It has been $_{_{43}}$ 20 found to be particularly effective for image and vision pro- $_{\scriptscriptstyle 44}$ 21 cessing [5] for two reasons: 1) Sparse coding can be used $_{45}$ 22

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to model the receptive fields of simple cells in the mammalian primary visual cortex [6, 7]; 2) Image patches often reside near a low dimensional manifold, and a semantically rich representations will recover such subspace as a small sets of atoms (from a properly learned dictionary), leading naturally to sparse representations [8]. Therefore, in this paper we consider image classification as the underlying task to validate the proposed algorithm.

Among all the necessary components for a good sparse representation, dictionary learning is most important because the atoms represent examples of the target dataset. Technically, the objective of dictionary learning is to minimize a reconstruction objective with respect to the sparse codes and the dictionary jointly, where the sparse codes are representations of each input image, and the dictionary is shared among the image dataset. It is also possible to enforce additional regularizations apart from reconstructions to encode knowledge of underlying tasks in the objective. These regularizations are meant to be "discriminative" in the sense that they are designed for the specific task rather than general reconstructions and should improve task-related performance. This is particularly important for computer vision applications, where the coding vectors are responsible for a definitive high-level task (e.g. classification) other than reconstruction, and additional information (e.g. labels of images) is usually available and can be utilized.

Typically, one can enforce class-specific constraints on sparse codes from the same class to achieve discrimination

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