Using Multiresolution Learning for Transfer in Image Classification

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Abstract

Our work explores the transfer of knowledge at multiple levels of abstraction to improve learning. By exploiting the similarities between objects at various levels of detail, multiresolution learning can facilitate transfer between image classification tasks.

We extract features from images at multiple levels of resolution, then use these features to create models at different resolutions. Upon receiving a new task, the closest-matching stored model can be generalized (adapted to the appropriate resolution) and transferred to the new task.

Introduction

Learning complex models in the natural world depends on the ability to selectively transfer knowledge at multiple scales, or resolutions. The coarse scales of low resolutions show the general aspects of objects and, most importantly, allow us to group related objects together and treat them similarly. At the smaller scales revealed in higher resolutions, fine details begin to emerge, revealing differences between the objects.

Most related objects are similar when viewed at a low resolution. For example, low-resolution images of most four-legged farm animals have the same general shape. Knowledge learned at a low resolution may apply to all of these animals (e.g., has four legs, eats grass). At higher resolutions, details begin to emerge that differentiate them (e.g., horses have manes, cows have udders).

Low-resolution representations are simple and therefore easy to learn, but the value of what can be learned from them is limited. High-resolution representations have a much higher value for learning, but learning is more difficult due to the added complexity. Learning from low-resolution data may yield limited amounts of knowledge, but that knowledge will more often transfer to other related objects. This transferable knowledge provides both a foundation for learning from the higher-resolution data, and a base of general knowledge applicable to classes of objects.

Inspired by this idea, we explore learning at multiple resolutions for knowledge transfer. We claim that by exploiting the similarities between objects at various levels of detail, learning at multiple resolutions can facilitate transfer between related tasks. This work is a continuation of our previous work on knowledge transfer using feature-vector data (Eaton & desJardins 2006).

Multiresolution Learning

For images, the automatic generation of different resolutions can be accomplished using multiresolution analysis, providing a principled and formal mechanism for abstracting the information contained in the image.

Our method takes high-resolution images as input, then extracts features at multiple resolutions using one of two procedures. The first procedure, *multi-scale feature extraction*, uses scale-space processing (Lindeberg 1996) to generate successively lower resolution images, then extracts features from each resolution using a method proposed by Serre et al. (2005), yielding a set of feature vectors that represent each image at different resolutions. Serre et al.'s feature extraction method was inspired by a biological model of the first two layers of the primate visual cortex. Multiple image resolutions could also be generated using wavelet decomposition (Walker 1999).

The second procedure, *multi-band feature extraction*, uses a modified form of Serre et al.'s algorithm. Serre et al.'s original algorithm extracts the responses of Gabor filters at multiple bandwidths on various patches of the image, and then takes the maximum of each patch's responses (over all bands) to compose the final feature vector. We apply Serre et al.'s algorithm to each high-resolution image, but we omit the final $\max$ operation to yield a set of feature vectors that characterizes each image at different bandwidths. The different bands correspond to features of different sizes, so we treat each band as a "resolution." Both multi-scale and multi-band feature extraction have yielded promising results in our preliminary experiments.

We present three methods for classification using multiresolution data: the single-resolution classifier, the multiresolution classifier, and the multiresolution ensemble. Each method takes as input a set of multiresolution data, with each data point represented at multiple resolutions by a set of feature vectors.

The Single-Resolution Classifier focuses on data at a single predetermined resolution. Note that the typical ma-

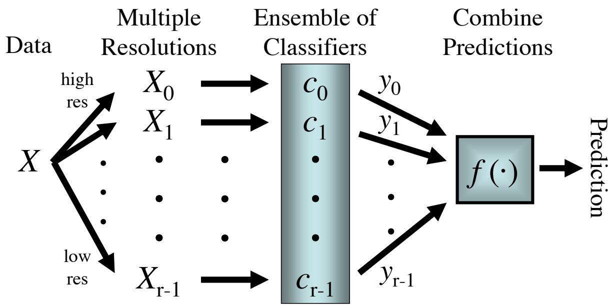

Figure 1: The Multiresolution Ensemble.

chine learning classifier is equivalent to a single-resolution classifier that only uses data at the highest resolution.

The Multiresolution Classifier focuses on multiple resolutions simultaneously. The multiresolution classifier learns to classify the data using features from a specific range of resolutions, excluding resolutions outside of that range.

The Multiresolution Ensemble (Eaton & desJardins 2006) combines many single-resolution classifiers, one for each resolution of input, into an ensemble classifier. A function $f(y_0, \ldots, y_{r-1})$ combines the individual members' predictions, $y_0, \ldots, y_{r-1}$, into the ensemble's prediction; the class of f determines the type of combination. For example, using a linear discriminant for f will result in a weighted majority vote of the members' predictions, and using a support vector machine with a polynomial or Gaussian kernel will result in a non-linear combination of the members' predictions. The function f is optimized during training.

Transfer using Multiresolution Classifiers

A task represents a target mapping from data to labels. We use a lifetime learning framework where the system is trained on a number of tasks in series. Our transfer architecture stores the best models learned for all previous tasks. Then, upon receiving a new task and associated labeled data, it selects a previously learned model for transfer to this new task based on *a priori* or *a posteriori* prediction accuracy on a held-out test set.

Multiresolution analysis has the property that higher resolutions of an object can be obtained from lower resolutions of that object by adding details. Therefore, higher-resolution classifiers are specializations of lower-resolution classifiers, so transferring knowledge learned from low-resolution classifiers transfers generalized knowledge. For this reason, the transfer method imposes the constraint that all lower-resolution knowledge learned by a particular classifier (up to some resolution, determined during the transfer process) must be transferred to the new task.

For single-resolution classifiers, this restriction does not apply, since they have only one level of knowledge. For the multiresolution classifier and multiresolution ensemble, knowledge from the lower-resolution portion (again, up to some point) is transferred to the new task. The transfer occurs by cloning the portion of the classifier to be transferred and then updating it with multiresolution data on the new task. This technique yields a multiresolution ensemble with lower-resolution classifiers trained on both the previous task and the new task, and higher-resolution classifiers trained solely on the new task. Currently, we limit our framework to transfer from only one model; techniques such as Bollacker et al.'s (2000) supra-classifier could be used for expanding our framework to transfer from multiple previously-trained classifiers.

Discussion and Future Work

Our preliminary results support our hypothesis that incorporating low-resolution knowledge can support knowledge transfer using the multiresolution classifiers described above. We are currently in the process of a more extensive evaluation of the transfer architecture and multiresolution learning methods. For this evaluation, we are using a variety of transfer scenarios with single-object image recognition tasks from the Caltech 101 and 256 data sets (Fei-Fei, Fergus, & Perona 2004; Griffin, Holub, & Perona 2006). Our preliminary results on these scenarios indicate that using multiresolution information, especially with the multiresolution classifier and multiresolution ensemble, can significantly improve transfer performance.

In the future, we plan to apply the multiresolution transfer approach to purely feature-vector data, and to explore the theoretical connections between the knowledge transfer problem and multiresolution analysis.

Acknowledgments

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