# Knowledge Transfer with a Multiresolution Ensemble of Classifiers

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## Abstract

We demonstrate transfer via an ensemble of classifiers, where each member focuses on one data resolution. Lower-resolution ensemble members are shared between tasks, providing a medium for the knowledge transfer.[1]

## 1. Introduction

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 between them.

Inspired by this idea, we explore the use of *multiresolution learning* for *knowledge transfer* between tasks. We claim that by exploiting the similarities between objects at low levels of detail, learning at multiple resolutions can facilitate transfer between related tasks.

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 of what can be learned from them, 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 often transfer to other related objects. This knowledge provides both a foundation for learning from the higher-resolution data, and a base of general knowledge applicable to a class of objects.

Learning at multiple resolutions has been shown to significantly improve generalization and classification time in single-task problems (Liang & Page, 1997; He et al., 2005; Blayvas & Kimmel, 2003). Multiresolution representations have also been used successfully in image retrieval systems (Li & Wang, 2003) and image classification systems (Zhang & Hebert, 1997).

We provide an ensemble framework for providing the transfer between learning tasks, with each member focusing on one resolution level. The low-resolution classifiers are shared between tasks, allowing knowledge transfer between these tasks.

## 2. Multiresolution Representations

Our experiments use input in the form of feature vectors, so we represent the instance space at multiple resolutions. To do this, we use two methods: (1) chopping the space into hypercubes and repeatedly merging them, and (2) repeatedly merging correlated attributes.

Both methods take as input labeled instance vectors $\{x_i, y_i\}_1^N$, where each $x_i$ belongs to the instance space $X \in \mathbb{R}^d$, and each $y_i$ belongs to the set of binary classes $Y = \{-1, 1\}$.

**The Hypercubes Representation** breaks the instance space $X$ into hypercubes at the highest resolution, then repeatedly combines these hypercubes to generate successively lower resolutions. This representation was previously used for multiresolution learning by He et al. (2005); we use their notation.

Let $\Omega$ be a hypercube in $\mathbb{R}^d$ that contains the instance space $X$.[2] For each dimension of $\Omega$, we slice that dimension into $l$ equal-size segments. By this method, $\Omega$ is broken into $l^d$ hypercubes. For $\Omega_k$, the $k^{th}$ resolution, we set $l = 2^k$. Therefore, $\Omega_k = \bigcup_{i=1}^{2^{k^d}} o_k^i$, where $o_k^i$ denotes the $i^{th}$ hypercube in $\Omega_k$. The multiresolution representation of the instance space $X$ with $r$

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[2]We define $\Omega$ to be six standard deviations larger than $X$ in each dimension.

resolution levels is given by $\{\Omega_k\}_{k=1}^r$.

For each level of resolution, $k = 1 \dots r$, we can map instance $x \in X$ to the hypercube $o_k^i$ containing $x$ via the function $g_k : X \rightarrow \Omega_k$. Each hypercube $o_k^i$ is represented by the coordinates of its center. Therefore, each $x \in X$ has a multiresolution representation $R(x) = \{center(g_k(x))\}_{k=1}^r$.

We estimate the label for each hypercube $o_k^i$ as the majority class label of all instances mapped to it by $g_k()$; ties are broken by uniform random selection. The label for each $x \in X$ has the multiresolution representation $S(x) = \{label(g_k(x))\}_{k=1}^r$. These labels are used solely for training purposes; the actual class labels $\{y_i\}_{i=1}^N$ are used for testing the classifiers.

**The Dimension-Merge Representation** repeatedly merges correlated dimensions of the instance space $X$. It determines the most correlated distinct dimensions of $X$ and then merges those dimensions by mapping them onto a linear regression fit of the correlation. This method is similar to the Hierarchical Dimensionality Reduction algorithm (Duda et al., 2001), which takes a set of data clusters and repeatedly merges the most correlated distinct clusters.

The Dimension-Merge algorithm is given in Figure 1. Each successive lower resolution contains one less dimension than the previous resolution, and the precision of the values along the merged dimension is reduced naturally by the merging process. The Dimension-Merge algorithm determines the sequence of attribute merges from the set of training instances $\{x_i\}_{i=1}^N$; during the testing phase, the resolutions of the test instances are computed using the sequence of attribute merges determined during training.

**Standard Feature Selection Methods** (e.g., principal components analysis, information gain) can be used to repeatedly reduce the dimension of the instance space; however, they typically produce successive resolutions with significant overlap. Consequently, using them in our ensemble architecture (Section 3) produces an ensemble of members with highly correlated errors. The ensemble members are not diverse; therefore, the ensemble will not be more accurate than any of its member classifiers (Dietterich, 2000), yielding poor results in our experiments (which we omit for space reasons).

## 3. The Multiresolution Ensemble

Given a set of multiresolution data $R$ with $r$ resolutions and associated class labels $S$, we create an ensemble of classifiers $\{c_k\}_{k=1}^r$ where each member focuses

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Given: $X = \{x_i\}_{i=1}^N$, $x_i \in \mathbb{R}^d$
  Set the array of resolutions $R = \{\}$.
  Set $R[d] = X$.
  for $k$ from $d-1$ downto 1 do
    Set $R[k] = R[k+1]$.
    Compute the correlation matrix for all pairs of
      distinct dimensions of $R[k]$.
    Determine the most correlated distinct attributes
      of $R[k]$, say $d_1$ and $d_2$.
    Determine the linear regression line $l$ for dimen-
      sions $d_1$ and $d_2$ of $R[k]$.
    for $i = 1 \dots N$ do
      Let $r_i$ be the $i^{th}$ element of $R[k]$.
      Project the point $(r_i[d_1], r_i[d_2])$ onto $l$.
      Let $v$ be the Euclidean distance between $(0,0)$
        and the projection of $(r_i[d_1], r_i[d_2])$ onto $l$.
      Set $r_i[d_1] = v$.
    end for
    Delete the dimension $d_2$ of $R[k]$.
  end for
  return $R$
```

*Figure 1.* The Dimension-Merge algorithm.

on one resolution of the data. Let $R_k(X)$ represent the instance space $X$ viewed at resolution $k$, for $k = 1 \dots r$.

The $k^{th}$ ensemble member, $c_k$, is trained on and outputs class predictions based on instances from $R_k(X)$.

The ensemble's prediction is a weighted majority vote of the member classifiers' predictions. We use the Adaboost weighting scheme (Schapire, 1999) to determine the weight of each member classifier. The weight $\alpha_k$ of classifier $c_k$ is inversely proportional to its error $\epsilon_k$ on the training data at resolution $k$:

$$\alpha_k = \frac{1}{2} \ln \left( \frac{1 - \epsilon_k}{\epsilon_k} \right) \quad . \tag{1}$$

### 3.1. Knowledge Transfer with the Ensemble

In this paper, we assume that transfer occurs between two tasks. To allow knowledge transfer between the tasks, we combine two ensembles into a tree. Each task has a unique multiresolution ensemble, but the lower-resolution ensemble members are shared between the tasks and trained on both tasks.

In this paper, the join point of the two ensembles is manually specified. Also, the weights ($\alpha$'s) of the shared ensemble members are determined based on both tasks and shared between ensembles. We are currently exploring methods for determining the join point computationally, and for using unshared weights for the shared members.

## 4. Experiments

### 4.1. Experimental Setup

We conducted experiments using the letter dataset from the UCI Machine Learning Repository (Blake & Merz, 1998). The letter dataset consists of various fonts of the twenty-six capital letters in the English alphabet characterized by 16 features. We use a subset of the letter dataset consisting of 1,000 instances. We examine several tasks involving transfer in the recognition of pairs of similar letters: "C" to "G," "O" to "Q," and "M" to "W." We also tested several pairs of dissimilar letters, and show results for one pair of letters that are similar in terms of construction, but differ when viewed at a low resolution: "F" to "E."

For example, consider transfer from the task of recognizing "C" to recognizing "G." We select out all instances of the target concept ("C" and "G") from the data set $D$. We create the following sets:

- $C$: all "C" instances in $D$, labeled as *positive*
- $G$: all "G" instances in $D$, labeled as *positive*
- $G_{update}$: subsets of $G$, of various sizes
- $Neg$: $D - (C \bigcup G)$, labeled as *negative*.

The sets $C$, $G$, and $Neg$ are divided into equal-sized training and testing portions ($C_{train}$, $C_{test}$, etc.). The sizes of $Neg_{train}$ and $Neg_{test}$ are trimmed to $\max(|C|, |G|)$, so the ratio of positive to negative instances in the training and test sets is roughly two-thirds, with the exception of the training set for the shared ensemble members.

Suppose that the ensemble tree splits at member $i$. Then $c_1, \ldots, c_i$ are shared between the "C" and "G" portions of the ensemble tree. These shared classifiers are trained on $C_{train} \bigcup G_{update} \bigcup Neg_{train}$; the other "C" classifiers ($c_{i+1}, \ldots, c_r$) are trained on $C_{train} \bigcup Neg_{train}$; and the other "G" classifiers ($c_{i+1}, \ldots, c_r$) are trained on $G_{update} \bigcup Neg_{train}$. We evaluate the "C" portion of the ensemble using $C_{test} \bigcup Neg_{test}$ and the "G" portion using $G_{test} \bigcup Neg_{test}$.

As the baseline for transfer, we train a single multiresolution "G" ensemble using $G_{update} \bigcup Neg_{train}$. We compare the learning curves for the "G" ensemble to the tree ensemble across varying sizes of $G_{update}$.

We experimented using both the Hypercubes representation (with $r = 7$ resolutions, specified manually as used by He et al. (2005)) and the Dimension-Merge representation ($r = 16$, since the letter data set has 16 dimensions). Our experiments used the J48 implementation of C4.5 provided in the Weka toolkit (Witten & Frank, 2005) as the base classifier.

### 4.2. Results and Discussion

Figure 2 shows the results of our experiments. Consider the learning task "C" to "G," depicted in Figures 2(a) and 2(d). The figures show the "C to G Tree" for learning with transfer against the "G Ensemble" for learning without transfer.

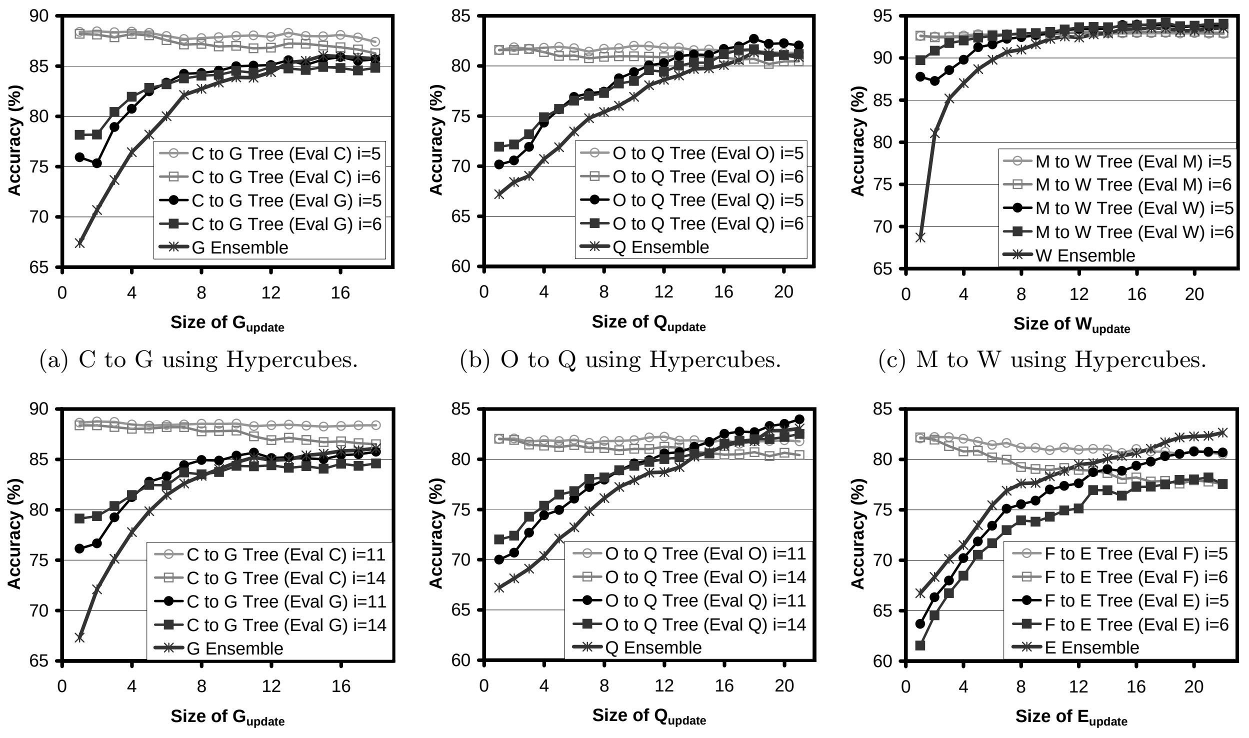
The black lines with round and square markers show the multiresolution tree ensemble's performance on the transfer task (recognizing "G"). The light gray lines show the multiresolution tree ensemble evaluated on the background task (recognizing "C"), demonstrating how the performance on the background task varies as the shared ensemble members learn the transfer task.

We explored using every possible split point ($i$) for the tree, and plot the two that show the greatest transfer in most cases. In every case, as $i$ decreases to 1, the learning curve approaches learning in isolation using the single ensemble. When all ensemble members are shared ($i = 7$ on Hypercubes and $i = 16$ on Dimension-Merge), the tree ensembles show excellent transfer with small transfer task (update) set sizes (in some cases, more than shown on the plots). However, with larger numbers of transfer task instances, the performance may drop below that of the single ensemble, due to interference between the tasks.

Figures 2(a)–2(e) show that learning using the multiresolution tree ensemble can outperform learning the transfer task in isolation. These figures also show that the optimal number of shared ensemble members may vary depending on the size of the transfer task set, and that the tree ensemble's performance on the background task may decrease as $i$ increases. These observations support our future work of making the ensemble tree dynamic in response to the training data. We have observed cases where the performance on the background task *increased* slightly with additional transfer task instances – an ideal case for transfer.

From the results on the "C" to "G" and the "O" to "Q" tasks, it appears that both the Hypercubes and Dimension-Merge representations are sufficient for allowing task transfer.

Figure 2(f) depicts a situation where the background task and transfer task are similar from a standpoint of letter construction ("F" and "E" differ by one stroke); however, the letters differ from a low-resolution viewpoint. Using transfer inhibits learning in this task: the best results are obtained by sharing only one ensemble member in the ensemble tree and are identical to that of learning the transfer task in isolation. We have tested the transfer between several other pairs of dissimilar letters and obtained similar results.



(a) C to G using Hypercubes. (b) O to Q using Hypercubes. (c) M to W using Hypercubes.

(d) C to G using Dimension-Merge. (e) O to Q using Dimension-Merge. (f) F to E using Hypercubes.

*Figure 2.* Learning curves for the letter recognition transfer over 200 trials using multiresolution ensembles.

## 5. Conclusion and Future Work

Our results show that the multiresolution ensemble can successfully transfer knowledge between learning tasks. Currently, we are exploring methods for computationally selecting the ensemble tree split point $i$, adapting the split point dynamically in response to the training data, and creating ensemble trees for multi-class problems. Our future work also includes adapting the multiresolution transfer framework to work with image data and alternate resolution methods.

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