Quantitative Model Selection for Heterogeneous Time Series Learning

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Abstract

A key benefit of modular learning is the ability to apply different algorithms to suit the characteristics of each subtask. This approach requires methods for task decomposition, classifier fusion, and matching of subproblems to learning techniques. In this paper, we present a new method for technique selection from a "repertoire" of statistical learning architectures (specifically, artificial neural networks and Bayesian networks) and methods (Bayesian learning, mixture models, and gradient learning). We first discuss the problem of learning *heterogeneous* time series, such as sensor data from multiple modalities. We then explain how to construct *composite learning* systems by selecting model components. Finally, we outline the design of a composite learning system for geospatial monitoring problems and present an application (precision agriculture) that demonstrates its potential benefits.

Keywords: **metric-based technique selection, time series learning, probabilistic networks, modular task decomposition, data fusion**

Introduction

Decomposition of statistical machine learning tasks can reduce both complexity and variance [JJ94]. The *mixture-of-experts model*, or mixture model, is a divide-and-conquer approach that integrates multiple sources of knowledge (including committees of experts or agents) [JJB91, JJ94, Bi95]. *Aggregation* mixtures reduce variance by replicating training data across the mixture components [Wo92, Br96]; *partitioning* mixtures use interaction among these components (at the level of *data fusion*) to force specialization among them [JJ94, FS96].

In this paper, we discuss a third function of mixture models in concept learning: to combine classifiers specialized to different projections or partitions of the training data. Such multistrategy learning approaches, where the "right tool" is analytically identified for each subtask, are useful in problems that exhibit *heterogeneity*. An example is spatiotemporal sequence learning for *time series classification*. We develop a collection of probabilistic (artificial neural and Bayesian) network architectures with complementary learning methods for inductive supervised learning, a new metric-based model selection system, and an algorithm for selecting the learning components indicated by the data set characteristics.

The key novel contributions of our system are:

1. Recombinable and reusable learning components for time series
2. Metrics for *temporal* characteristics that prescribe learning techniques
3. A framework for task decomposition and fusion of classifiers learned by different techniques

Heterogeneous Time Series Learning

In *heterogeneous* time series, the embedded temporal patterns belong to different categories of statistical models, such as moving averages (MA) and autoregressive (AR or exponential trace) models [MMR97]. A multichannel time series learning problem can be decomposed into homogeneous subtasks by aggregation or synthesis of attributes. *Aggregation* occurs in multimodal sensor fusion (e.g., for medical, industrial, and military monitoring), where each group of input attributes represents the bands of information available to a sensor [SM93]. In geospatial data mining, these groupings may be topographic [Hs97]. Complex attributes may be *synthesized* explicitly by constructive induction, as in causal discovery of latent (hidden) variables [Pe88, He96]; or implicitly by preprocessing transforms [HR98].

In this section, we draw an analogy between concept learning in heterogeneous time series and compression of heterogeneous files. We briefly present a successful heterogeneous compressor that employs metric-based file analysis and extend our analogy to the design of a modular, probabilistic network-based learning system.

Compression of Heterogeneous Files

Heterogeneous files are those that contain multiple types of data such as text, image, or audio. We have developed an experimental data compressor for that outperforms commercial, general-purpose compressors on heterogeneous files [HZ95]. It divides a file into fixed-length segments and empirically analyzes each (cf. [Sa89, HM91]) for its *file type* and dominant *redundancy type*.

Network Type	Architectural Metric
Simple recurrent network (SRN)	Exponential trace (AR) autocorrelation
Time delay neural network (TDNN)	Moving average (MA) autocorrelation
Gamma network	Autoregressive integrated moving average (ARIMA) autocorrelation
Temporal naïve Bayesian network	Knowledge map score (relevant attribute count)
Hidden Markov model (HMM)	Perplexity

Table 1. Network types and their prescriptive metrics

Learning Method	Distributional Metric
HME, gradient	Modular cross entropy
HME, EM	Modular cross entropy + missing data noise
HME, MCMC	Modular cross entropy + sample complexity
Specialist-moderator, gradient	Dichotomization ratio
Specialist-moderator, EM	Dichotomization ratio + missing data noise
Specialist-moderator, MCMC	Dichotomization ratio + sample complexity

Table 2. Learning methods and their prescriptive metrics

For example, *dictionary* algorithms such as Lempel-Ziv coding are most effective with frequent repetition of strings; *run length encoding*, on long runs of bits; and *statistical* algorithms such as *Huffman coding* and *arithmetic coding*, when there is nonuniform distribution among characters. These correspond to our *redundancy metrics*: string repetition ratio, average run length, and population standard deviation of ordinal character value. The normalization function over these metrics is calibrated on a corpus of homogeneous files. Using the metrics and file type, our system predicts, and applies, the most effective algorithm and update (e.g., paging) heuristic for the segment. In experiments on a second corpus of heterogeneous files, the system selected the best of the three available algorithms on about 98% of the segments, yielding significant performance wins on 95% of the test files [HZ95].

Adapting Statistical File Analysis to Heterogeneous Learning

The analogy between compression and learning [Wa72] is especially strong for technique selection from a database of components. Compression algorithms correspond to network architectures in our framework; heuristics, to applicable methods (mixture models, learning algorithms, and hyperparameters for Bayesian learning). Metric-based file analysis for compression can be adapted to technique selection for heterogeneous time series learning. To select among network architectures, we use indicators of temporal patterns typical of each; similarly, to select among learning algorithms, we use predictors of their effectiveness. The analogy is completed by the process of segmenting the file (corresponding to problem decomposition by aggregation and synthesis of attributes) and concatenation of the compressed segments (corresponding to fusion of test predictions).

Composite Learning

Database of Learning Components

Table 1 lists the network types (the rows of a "lookup table" of learning components) and the indicator metrics corresponding to their strengths [Hs97]. SRNs, TDNNs, and gamma networks are all temporal varieties of artificial neural networks (ANNs) [MMR97]. A *temporal Bayesian multinet* is a *global knowledge map* as defined by Heckerman [He91], such that some random variables may be temporal (e.g., the duration or rate of change of an original variable). A hidden Markov model (HMM) is a stochastic state transition diagram whose transitions are also annotated with probability distributions (over output symbols) [Le89].

Table 2 lists the learning methods (the columns of the "lookup table"). A *hierarchical mixture of experts* (HME) is a mixture model composed of generalized linear elements (as used in feedforward ANNs) [JJB91, JJ94]. It can be trained by gradient learning, expectation-maximization [JJ94], or Markov chain Monte Carlo (MCMC) methods (i.e., random sampling as in the Metropolis algorithm for simulated annealing) [MMR97]. A *specialist-moderator network*, which also admits different learning algorithms, is a mixture model whose components have different input and output attributes [HR98].

Metric-Based Model Selection

In Table 1, our prototype *architectural metrics* for temporal ANNs are average autocorrelation values for the preprocessed data. For example, to compute autocorrelation for an AR model, we first apply convolution of an exponential decay window (an AR *kernel function*) [MMR97]. This estimates the predictive power of the model *if chosen as the learning architecture*. The K-map score for a Bayesian multinet is the average number of variables *relevant* to each pair of diagnosable causes) in an associative knowledge map [He91]. This knowledge map is computed by thresholding on the correlations between causes and observable effects. Finally, the indicator metric for HMMs is the empirical *perplexity* (arithmetic mean of the branch factor) for a constructed HMM [Le89].

In Table 2, the prototype *distributional* metrics for HME networks are based on modular cross entropy (i.e., the Kullback-Leibler distance between conditional distributions in each branch of the tree-structured mixture model) [JJ94]. The metrics for specialist-moderator networks are proportional to dichotomization ratio (the number of distinguishable equivalence classes of the overall mixture divided by the product of its components') [HR98]. To select a learning algorithm, we use gradient learning as a baseline and add a term for the gain from estimation of missing data (by EM) [JJ94] or global optimization (by MCMC) [Ne96], adjusted for the conditional sample complexity.

Definition. A *composite* is a set of tuples $\mathbf{L} = \left(\left(A_1, B_1, \theta_1, \gamma_1, S_1 \right), \ldots, \left(A_k, B_k, \theta_k, \gamma_k, S_k \right) \right)$, where A_i and B_i are constructed input and output attributes, θ_i and γ_1 are network parameters, and hyperparameters cf. [Ne96], and S_i is a learning algorithm.

The general algorithm for composite time series learning is:

Given:

1. A (multichannel) time series data set $D = ((\mathbf{x}^{(1)}, \mathbf{y}^{(1)}), \ldots, (\mathbf{x}^{(n)}, \mathbf{y}^{(n)}))$ with input attributes $\mathbf{A} = (a_1, \ldots, a_I)$ such that $\mathbf{x}^{(i)} = (x_1^{(i)}, \ldots, x_I^{(i)})$ and output attributes $\mathbf{B} = (b_1, \ldots, b_O)$ such that $\mathbf{y}^{(i)} = (y_1^{(i)}, \ldots, y_O^{(i)})$
2. A constructive induction algorithm F such that $F(A, B, D) = \{(A', B')\}$

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Algorithm Select-Net
  repeat
    Generate a candidate representation $(A', B') \in F(A, B, D)$.
    Compute architectural metrics that prescribe the network type.
    Compute distributional metrics that prescribe the learning method.
    Normalize these metrics using a precalibrated model (see Figure 1).
    Select the most strongly prescribed network type $(\theta, \gamma)$ and learning method $S$ for $(A', B')$, i.e., the table entry (row and column) with the highest metrics.
    if the fitness (strength of prescription) of the selected model meets a predetermined threshold
    then accept the proposed representation and learning technique $(A', B', \theta, \gamma, S)$
  until the set of plausible representations is exhausted
Compile and train a composite, L, from the selected complex attributes and techniques.
Compose the classifiers learned by each component of L using data fusion.
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Figure 1. Normalization of metrics x_τ

t_τ: shape parameter
λ_τ: scale parameter

$$G_\tau(x_\tau) = \int_0^{x_\tau} f_\tau(x)\,\mathrm{d}\,x$$

$$f_\tau(x) = \frac{\lambda_\tau\,\mathrm{e}^{-\lambda_\tau x}(\lambda_\tau x)^{t_\tau - 1}}{\Gamma(t_\tau)}$$

$$\Gamma(t_\tau) = \int_0^\infty \mathrm{e}^{-y}\,y^{t_\tau - 1}\,\mathrm{d}\,y$$

Preliminary Experimental Results

Figure 2. A Geospatial Diagnosis Problem

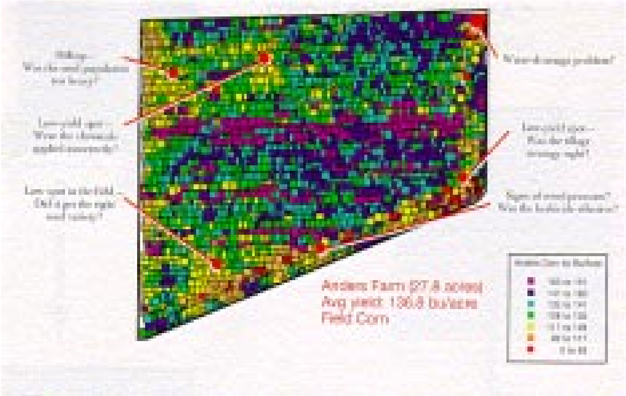

Figure 2 depicts an (atemporal) spatially referenced data set for diagnosis in *precision agriculture*. The inputs are: yield monitor data, crop type, elevation data and crop management records; the learning target, *cause of observed yield* (e.g., drought) [Hs98]. Such classifiers may be used in normative expert systems [He91] to provide decision support for crop production planning in subsequent years. We use biweekly remote sensing images and meteorological, hydrological, and crop-specific data to learn to classify influents of *expected crop quality* (per farm) as *climatic* (drought, frost, etc.) or *non-climatic* (due to crop management decisions) [Hs98].

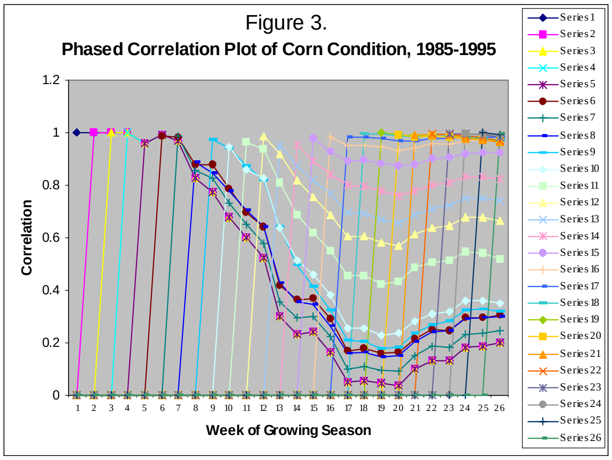
Figure 3.

Phased Correlation Plot of Corn Condition, 1985-1995

Figure 3 visualizes a heterogeneous time series. The lines shown are autocorrelation plots of (subjective) weekly *crop condition* estimates, averaged from 1985-1995 for the state of Illinois. Each point represents the correlation between one week's mean estimate and those for subsequent weeks. The data is heterogeneous because it contains both a moving average pattern (the linear increments in autocorrelation for the first 10 weeks) and an exponential trace pattern (the larger, unevenly spaced increments from 0.4 to about 0.95 in the rightmost column). The MA pattern expresses weather “memory” (correlating early and late drought); the AR pattern, physiological damage from drought. Task decomposition can improve performance here, by isolating the MA and AR components for identification and application of the correct specialized architecture (a TDNN or SRN, respectively).

Figure 4.

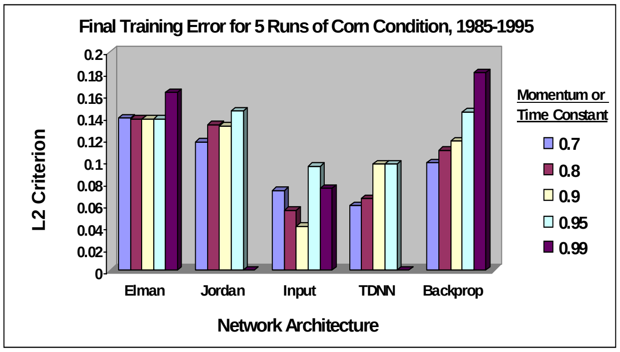

Figure 4 shows bar charts of the mean squared error from 125 training runs using ANNs of different configurations (5 architectures, 5 momentum or delay constant values for gradient learning, and 5 averaged runs per combination). On all runs, Jordan recurrent networks with a delay constant of 0.99 and TDNN with a momentum of 0.99 failed to converge, so the corresponding bars are omitted. Cross validation results indicate that overtraining on this data set is minimal. As a preliminary study, we used a gamma network to select the correct classifier (if any) for each exemplar from among the two best overall networks (input recurrent with momentum of 0.9 and TDNN with momentum of 0.7). The error rate was reduced by almost half, indicating that even with identical inputs and targets, a simple mixture model could reduce variance [Hs98].

Conclusions and Future Work

We have presented the design of a heterogeneous time series learning system with metric-based model selection, which evolved from a successful heterogeneous data compressor [HZ95, Hs98]. Our current research applies this system to a heterogeneous time series concept learning problem: monitoring and diagnosis for precision agriculture [Hs97, Hs98]. We are addressing the related problems of task decomposition by constructive induction (aggregation and transformation of ground attributes) and fusion of test predictions from probabilistic network classifiers [HR98, RH98].

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