Learning with Data Streams – An NNTree Based Approach

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Abstract. The plasticity-stability dilemma is a key problem for learning with data streams. On the one hand, the learner must be plastic enough to adapt to the new data. On the other hand, it must be stable enough to integrate information. In this paper, we try to resolve this problem using neural network trees (NNTrees). An NNTree is a decision tree (DT) with each non-terminal node containing an expert neural network (ENN). The NNTrees are plastic because they can adapt to the new data through retraining of the ENNs and/or through generation of new nodes. The NNTrees are also stable because retraining is performed partially and locally. In this paper, we propose an algorithm that can grow NNTrees effectively and efficiently. Experiments with several public databases show that the NNTrees obtained by the proposed methods are comparable with the NNTrees or DTs obtained with all data provided all-at-once.

Keywords: Machine learning, neural networks, decision trees, on-line learning, neural network trees, plasticity-stability dilemma.

1 Introduction

The plasticity-stability dilemma is a key problem for learning with data streams. On the one hand, the learner must be plastic enough to adapt to the new data. On the other hand, it must be stable enough to integrate information. Usually, fully connected neural networks are plastic but not stable. To make the system stable, some kind of localization is necessary. In this paper, we try to resolve this problem using neural network trees (NNTrees). An NNTree is a decision tree (DT) with each non-terminal node containing an expert neural network (ENN). The basic structure of an NNTree is shown in Fig. 1. The NNTrees are plastic because they can adapt to the new data through retraining of the ENNs and/or through generation of new nodes. The NNTrees are also stable because retraining of the ENNs is performed partially and locally. Partial retraining means that the weights of the ENNs are updated only for a limited number of epochs. Local retraining means that, for each new datum, only the ENNs on the “search path” are modified.

Note that traditional DTs can also be induced using a data stream through restructuring of the tree [1]. The problem in this approach is that all information

Fig. 1. Structure of an neural network tree

for restructuring the tree must be preserved. This is not possible if the duration of the data stream is very long. Using the NNTrees, however, we do not have to keep all information. As shown in this paper, a sliding window might be good enough to keep information for retraining the ENNs or for generating new nodes.

The main contribution of this paper is to propose an NNTree based algorithm for learning with data streams. The basic idea of this algorithm is to retrain the ENNs to adapt to new data. Retraining is performed partially in two senses. First, only a limited number of epochs are used in retraining. Second, only a smaller number of data kept in a sliding window are used in retraining. New nodes can be generated when retraining alone is not enough. This paper is organized as follows. In Section 2, we provide a brief review of some basic concepts related to DT. Section 3 proposes the new learning algorithm in detail. The efficiency and efficacy of the new algorithm is verified through experiments with several public databases in Section 4. Section 5 is the conclusion.

2 Review of Decision Trees

2.1 The Definition

A decision tree (DT) is a directed graph with no cycles. There is one special node called root. We usually draw a DT with the root at the top (see Fig. 1). Each node (except the root) has exactly one node above it, which is called its *parent*. The nodes directly below a node are called its *children*. A node is called a *terminal node* if it does not have any child. A node is *non-terminal* if it has at least one child. The node of a DT can be defined as a 5-tuple as follows:

$$node = \{I, F, Y, N, L\} \quad (1)$$

where I is a unique number assigned to each node, F is a test function that assigns a given input pattern to one of the children, Y is a set of pointers to the children, $N = |Y|$ is the number of children or the size of Y , and L is the class label of the node if it is a terminal node. For terminal nodes, F is not defined and Y is empty ($N=0$). Usually, L is not defined for non-terminal nodes.

The process for recognizing an unknown pattern x is as follows:

- Step 1: Set the root as the current node.
- Step 2: If the current node is a terminal node, assign x with the class label of this node, and return; otherwise, find $i = F(x)$.
- Step 3: Set the i -th child as the current node, and return to Step 2.

2.2 Induction of the DTs

To induce a DT, it is assumed that a training set is available. Usually, the DT is induced by partitioning the training set recursively. This procedure involves three steps: 1) splitting nodes, 2) determining which nodes are terminal nodes, and 3) assigning class labels to terminal nodes.

To see a node is a terminal node or not, the simplest way is to check if all or most examples assigned to this node belong to the same class. If all or most examples are from the same class, the node is terminal, and its label is usually defined as the class label of the majority examples.

The purpose of splitting a node is to find a good test function F for that node, so that the training examples assigned to this node can be partitioned into N groups according to the test results. Here we need a measure to quantify the “goodness” of the test function. Many criteria have been proposed in the literature [2]-[6]. For example, the criterion used in the well known induction algorithm C4.5 is the information gain ratio [6]. It is known that the performance of a DT dose not appear to vary significantly over a wide range of criteria [2].

2.3 Definition of the NNTrees

An NNTree is a DT with each non-terminal node containing an ENN (see Fig. 1). To use an NNTree for learning with data streams, we define a node of an NNTree as follows:

$$node = \{I, F, Y, N, L, W\} \quad (2)$$

where W is a sliding window to keep examples for retraining. The sliding window is nothing but a queue (or a first-in-first-out memory). The test function F is now defined by an ENN. As the ENNs, we use three layer multilayer perceptrons (MLPs). There are M inputs, K hidden neurons and N output neurons.

Using an NNTree, an example x can be recognized as follows:

- Step 1: Set the root as the current node.
- Step 2: If the current node is a terminal node, assign x with the class label of this node, and return; otherwise, find

$$F(x) = i = \arg \max_{1 \leq k \leq N} o_k \quad (3)$$

where o_k is the k -th output of the ENN.

- Step 3: Set the i -th child as the current node, and return to Step 2.

3 Learning with Data Streams Using the NNTrees

A direct method for learning with data streams is to fix the structure of the NNTree, and retrain the ENNs only. This method, however, cannot get good results because retraining the ENNs alone is not powerful enough to integrate new information effectively [10]. To improve the learnability of an NNTree, we proposed a new algorithm in this paper. Fig. 2 shows the flow-chart of this algorithm. The learning process is described as follows:

- Step 0: Initialize the tree by putting the first training example into the sliding window W of the root node, and define the class label of the root node s that of the first example. The tree now contains only one terminal node.
- Step 1: Set the current node as the root node and receive a training example x with the class label $label(x)$ from the data stream.

Fig. 2. Flow chart of the algorithm for learning with a data stream

- Step 2: Insert x into the sliding window W of the current node.
- Step 3: If the current node is terminal, goto Step 5; otherwise, continue.
- Step 4: Define the group label of x (see the definition given below), retrain the ENN using the back propagation (BP) algorithm for a limited number of epochs with data in W . After retraining, if the j -th output of the ENN is the maximum for x , set the current node as the j -th child of the current node, and return to Step 2.
- Step 5: If the L value of the current node is $label(x)$, return to Step 1; otherwise, continue (do nothing if x can be recognized correctly).
- Step 6: If the splitting condition (see the definition given below) is not satisfied, return to Step 1; otherwise, continue.
- Step 7: Create N child nodes and one ENN for the current node, and return to Step 1. The ENN is designed using BP algorithm with data in W . Based on the outputs of the ENN so designed, data in W are split into N parts. Data of the i -th part are put into the sliding window of the i -th child.

The group label of a example x , denoted by $g(x)$, is i ($i = 1, 2, \dots, N$) if this example is assigned to the i -th child node of the current node. Note that $g(x)$ is different from the class label of x . The class label $label(x)$ is given before learning (for supervised learning), while $g(x)$ must be determined during learning. In the proposed algorithm, the $g(x)$ is found as follows

1. Find $k = F(x)$, where $F(x)$ is the function realized by the ENN of the current node.
2. If $\exists y \in W_k$, where W_k is the sliding window of the k -th child, such that $label(y) = label(x)$, then $g(x) = k$.
3. Else, if $\exists y \in W_j$ ($j \neq k$), such that $label(y) = label(x)$, then $g(x) = j$.
4. Else, $g(x) = k$.

Once the group label of x is defined, we can retrain the ENN in the current node for a limited number of epochs. Note that the number of epochs is one when the ENN can assign x to the correct child (in the sense defined by $g(x)$). Note also that if x is a completely new example, i.e., we have not observed any example of the class $label(x)$ before, it will be assigned to the k -th child, where $k = F(x)$.

To prevent the tree from growing too fast, we use a splitting condition to determine when to split the node (in Step 6 of the learning algorithm). The condition used in our study is defined as follows:

$$|S| > T \text{ and } n_{wrong} > |S| \times s \quad (4)$$

where S is the set of examples assigned to the current node so far, $|S|$ is the size of S , n_{wrong} is the number of mis-classified examples, T is a threshold and s is the splitting-rate. Generally speaking, T and s depend on the training set size and the number of classes. In this study, we just set T to 30 and s to 0.1. With these values, the above condition can be read as “the current node will not be split if $|S|$ is less than 30, or if the mis-classified examples are less than 10% of S ”. Note that S is not preserved during learning. Only $|S|$ is used.

Table 1. Parameters of the Databases

	Number of examples	Number of features	Number of classes
cancer	683	9	2
crx	690	15	2
dermatology	358	34	6
ionosphere	351	34	2
iris	150	4	3
vehicle	846	18	4
optdigits	5620	64	10
pen-based	10992	16	10

When a terminal node is going to be split, we must design a new ENN for this node, and partition the data in the sliding window into N groups based on this ENN. In this paper, the data are grouped as follows. Suppose that we want to partition the data in W into N sub-sets $S_1, S_2, \dots, S_N$, which are initially empty sets. For any given example x ,

1. If there is a $y \in S_i$, such that $label(y) = label(x)$, assign x to S_i ;
2. Else, if there is a S_i , such that $S_i = \Phi$, assign x to S_i , where Φ is the empty set;
3. Else, find y , which is the nearest neighbor of x in $\cup S_i$, and assign x to the same sub-set as y , where $\cup$ represents the union of sets.

With the group labels so defined, we can design an ENN using the BP algorithm.

4 Experimental Results

To verify the efficiency of the proposed algorithm, we conducted several experiments using eight databases taken from the machine learning repository of the University of California at Irvine. The databases used include: cancer, crx, dermatology, ionosphere, iris, vehicle, optdigits and pen-based. These databases are actually real-life applications related to medical diagnosis, character recognition and so on. Parameters related to the databases are given in Table 1. 10-fold cross validation was used in the experiments. For learning with data streams, we select the training examples one-by-one without replacement, and provide it to the NNTree for retraining. The learning process will stop when all training examples are used.

The results of C4.5 [6] and ITI [1] are used for comparison. In the experiments, all parameters for C4.5 and ITI were default values. The main parameters related to the proposed method include: 1) the number of inputs M for each ENN is the number of features; 2) the number of hidden neurons K is 4; 3) the number of outputs N is 2/ 4) the maximum number of epochs for retraining the ENNs is 100; 5) the number of epochs for creating a new ENN is 1,000; and 6) the learning rate is 0.5.

The computer used in the experiments is a Unix workstation with the following specifications: 1) the system model is Sun Java Workstation W1100z; 2) the

main memory is 1 GB; 3) the CPU is 1.8GHz AMD Opteron 144 (1MB cache); and 4) the OS is Solaris 9. All algorithms were run on the same computer.

Note that C4.5 is an off-line learning algorithm. It assumes that all data are available before learning, and thus the results should be better in terms of accuracy when compared with the results obtained by ITI or the proposed algorithm. However, if we consider the computational cost for learning with data streams, C4.5 will be the worst if the duration of the data stream is long. This is because a new tree must be induced for each new example. Compare ITI with the algorithm proposed here, ITI must preserve all information for restructuring the tree during learning. Thus, for long data streams, the computational cost of ITI will be higher than that of the proposed algorithm.

Tables 2-5 are the results obtained by C4.5, ITI and the proposed method with different sliding window sizes. In the tables, “Tree size” is the number of all nodes, “Error rate (%)” is the rate for the test set, and “Computing time” is the time in seconds used for one run. For C4.5, only the results after pruning are provided here. For each result, there are two values. One is the average value over 10 runs, and another is the 95% confident interval.

4.1 Discussion About the Accuracy

As expected, the accuracy of the DTs (decision trees) induced by C4.5 are the best for 4 cases out of 8. This is because that all data are available before learning. Although the authors of [1] claimed that ITI can obtain the same results as C4.5, the results given here do not support their claim. People may expect that NNTrees should outperform the DTs because they are more complex. This may be true for off-line learning. In this paper, however, we are talking about learning with data streams. That is, data are available only one by one. Results given here actually show that the NNTree based approach can resolve the plasticity-stability dilemma to some extent because the NNTrees are comparable with the DTs induced by C4.5 or ITI. In 3 of the cases they are the best.

4.2 Discussion About the Size

In all cases, the number of nodes required by the NNTrees are smaller or much smaller than that of the DTs obtained by C4.5 or ITI. This is because an ENN is much more powerful than an axis-parallel hyperplane. Usually, one ENN can replace many hyperplanes for making the same decision. However, the tree size alone cannot be used to measure the complexity of the system. If we count the number of free parameters, the NNTrees are actually more complex. This increase in complexity is the main reason why NNTrees are able to learning with data streams.

4.3 Discussion About the Computational Cost

The main computational costs of the proposed algorithm include: 1) cost for computing the output of the network for each example, 2) cost for updating the

Table 2. Results of C4.5

Database	Tree size	Error rate (%)	Computing Time
cancer	23.2±10.8	4.8±4.3	0.021±0.002
crx	30.3±24.3	14.6±7.2	0.035±0.003
dermatology	32.6±6.9	6.4±6.8	0.020±0.003
ionosphere	27.2±6.5	10.8±8.7	0.090±0.011
iris	8.2±2.0	4.0±6.8	0.016±0.002
vehicle	136.0±45.5	28.5±8.5	0.078±0.010
optdigits	410.0±29.4	9.4±2.1	0.966±0.061
pen-based	380.4±23.8	3.5±1.0	0.687±0.011

Table 3. Results of ITI

Database	Tree size	Error rate (%)	Computing Time
cancer	18.4±2.2	4.6±2.5	0.115±0.017
crx	28.6±4.4	13.5±3.46	0.618±0.039
dermatology	37.0±3.0	6.7±3.75	0.582±0.092
ionosphere	19.2±2.6	12.8±6.17	1.194±0.096
iris	5.8±0.6	3.8±4.4	0.012±0.004
vehicle	118.8±12.2	28.59±5.14	4.933±0.445
optdigits	919.2±53.8	22.3±1.6	510.639±65.885
pen-based	648.2±28.6	5.8±0.9	480.042±11.180

Table 4. Results of proposed method, window size=50

Database	Tree size	Error rate (%)	Computing Time
cancer	3.20±0.63	4.1±1.8	0.383±0.273
crx	17.40±3.86	17.4±4.1	5.604±2.190
dermatology	11.80±1.03	3.6±3.2	0.321±0.108
ionosphere	9.00±2.31	13.6±4.9	1.789±1.040
iris	6.00±1.05	5.0±5.7	0.352±0.237
vehicle	59.40±9.18	31.3±4.6	16.699±3.113
optdigits	41.00±5.25	7.8±1.9	24.052±5.316
pen-based	68.00±11.78	7.1±1.9	29.361±3.532

Table 5. Results of proposed method, window size=100

Database	Tree size	Error rate (%)	Computing Time
cancer	3.20±0.63	4.5±3.1	2.385±1.485
crx	14.20±2.53	16.7±3.6	14.614±2.474
dermatology	11.60±0.97	2.2±2.9	0.564±0.257
ionosphere	8.40±2.32	11.9±6.7	6.415±2.763
iris	5.60±0.97	4.4±5.2	0.803±0.477
vehicle	59.20±9.11	30.0±3.5	41.468±8.224
optdigits	39.80±7.07	6.9±1.6	82.543±22.161
pen-based	54.00±9.30	5.9±1.3	88.233±15.901

weights, 3) cost for all epochs, 4) cost for all nodes on the *search path*, and 5) cost for all training examples. Put all these costs together, we have the total cost:

$$Cost(Proposed) = O(M \times K \times N_w \times N_e \times \log T \times N_t)$$

where M is the dimensionality of the feature space, K is the number of hidden neurons, N_w is the number of examples in the sliding window, T is the size of the current tree, and N_t is the length of the data stream.

On the other hand, the computational cost of C4.5 is

$$\begin{aligned} Cost(C4.5) &= O[M \times m \times \log T \times (1 + 2 + \dots + N_t)] \\ &= O(M \times m \times \log T \times N_t^2) \end{aligned} \quad (5)$$

where m is the possible number of values of a feature and T is the size of the current tree. Note that the computational costs in all levels (not node) should be almost the same. Therefore, instead of using $(T - 1)/2$, which is the number of non-terminal nodes, we use $\log T$ here. Note also that in the worst case, $m = N_t$, and thus

$$Cost(C4.5) = O(M \times \log T \times N_t^3)$$

Based on the above considerations, we can get the ratio between the cost of the proposed method and that of C4.5:

$$\begin{aligned} R &= \frac{O(M \times K \times N_w \times N_e \times \log T \times N_t)}{O(M \times \log T \times N_t^3)} \\ &= \frac{O(K \times N_w \times N_e)}{O(N_t^2)} \end{aligned} \quad (6)$$

In the experiments, $N_e = 100$, $K = 4$, and $N_w = 50$, or 100. Thus, for long data streams, C4.5 will be much more time-consuming than the proposed method. Note that in Table 2, the computing time is only for the case $n_t = N_t$. If the data are provided one by one, the computing time should times the factor $N_t(N_t + 1)/2$.

As for the algorithm ITI, we do not know exactly the computational cost. In fact, even the authors of [1] did not provide an analysis of the computational cost. However, from the results given in Tables 3-5 we can see that for long data streams, ITI is more time consuming than the proposed method. This is also what we have expected.

5 Conclusion

In this paper, we have studied learning with data streams using the NNTrees, and proposed a new algorithm. The efficiency and efficacy of the algorithm have been verified through experiments with eight public databases. Note that all databases used in the experiments are not “endless data streams”. We will do

more experiments in the future using longer data streams to verify the usefulness of the proposed algorithm. In fact, we are trying to apply the proposed algorithm to stock prediction. More results will be reported later.

Acknowledgments

This research is supported in part by the Grants-in-Aid for Scientific Research of Japan Society for the Promotion of Science (JSPS), No. 17500148.

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