Stacked Sequential Learning

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Abstract

We describe a new sequential learning scheme called “stacked sequential learning”. Stacked sequential learning is a meta-learning algorithm, in which an arbitrary base learner is augmented so as make it aware of the labels of nearby examples. We evaluate the method on several “sequential partitioning problems”, which are characterized by long runs of identical labels. We demonstrate that on these problems, sequential stacking consistently improves the performance of non-sequential base learners; that sequential stacking often improves performance of learners (such as CRFs) that are designed specifically for sequential tasks; and that a sequentially stacked maximum-entropy learner generally outperforms CRFs.

1 Introduction

In this paper, we will consider the application of sequential probabilistic learners to sequential partitioning tasks. Sequential partitioning tasks are sequential classification tasks characterized by long runs of identical labels: examples of these tasks include document analysis, video segmentation, and gene finding.

Motivated by some anomalous behavior observed for one sequential learning method on a particular partitioning task, we will derive a new learning scheme called stacked sequential learning. Like boosting, stacked sequential learning is a meta-learning method, in which an arbitrary base learner is augmented—in this case, by making the learner aware of the labels of nearby examples. Sequential stacking is simple to implement, can be applied to virtually any base learner, and imposes only a constant overhead in training time: in our implementation, the sequentially stacked version of the base learner $A$ trains about seven times more slowly than $A$.

In experiments on several partitioning tasks, sequential stacking consistently improves the performance of non-sequential base learners. More surprisingly, sequential stacking also often improves performance of learners specifically designed for sequential tasks, such as conditional random fields and discriminatively trained HMMs. Finally, on our set of benchmark problems, a sequentially stacked maximum-entropy learner generally outperforms conditional random fields.

2 Motivation

2.1 A Task for Which MEMMs Fail

To motivate the novel learning method that we will describe below, we will first analyze the behavior of one well-known sequential learner on a particular real-world problem. In a recent paper [2], we evaluated a number of sequential learning methods on the problem of recognizing the “signature” section of an email message. Each line of an email message was represented with a set of hand-crafted features, such as “line contains a possible phone number”, “line is blank”, etc. Each email message was represented as a vector $x_1, \ldots, x_n$, where $x_i$ is the feature-vector representation of the $i$-th line of the message. A line was labeled as positive if it was part of a signature section, and negative otherwise. The labels for a message were represented as another vector $y$, where $y_i$ is the label for line $i$.

The dataset contains about 33,013 labeled lines from 617 email messages. About 10% of the lines are labeled “positive”. Signature sections always fall at the end of a message, usually in the last 10 lines. In the experiments below, the data was split into a training set (of 438 sequences/emails), and a test set with the remaining sequences, and we used the “basic” feature set from Carvalho & Cohen.
We describe a new sequential learning scheme called stacked sequential learning. Stacked sequential learning is a meta-learning algorithm, in which an arbitrary base learner is augmented so as to make it aware of the labels of nearby examples. We evaluate the method on several sequential partitioning problems, which are characterized by long runs of identical labels. We demonstrate that on these problems, sequential stacking consistently improves the performance of non-sequential base learners; that sequential stacking often improves performance of learners (such as CRFs) that are designed specifically for sequential tasks; and that a sequentially stacked maximum-entropy learner generally outperforms CRFs.
The complete dataset is represented as a set $S$ of examples $S = \{(x_1, y_1), \ldots, (x_t, y_t), \ldots, (x_m, y_m)\}$. Sequential learning is the problem of learning, from such a dataset, a sequential classifier—i.e., a function $f$ such that $f(x)$ produces a vector of class labels $y$. Clearly, any ordinary non-sequential learning algorithm can be used for sequential learning, by ignoring the sequential nature of the data\footnote{Specifically, one could build a dataset of non-sequential examples $(x_i, y_i)$ from $S$, and use it to train a classifier $g$ that maps a single feature-vector $x$ to a label $y$. One can then use $g$ to classify each instance $x_i$ in the vector $x = (x_1, \ldots, x_n)$ separately, ignoring its sequential position, and append the resulting predictions $y_i$ into an output vector $y$.}.

In the previous paper \cite{2}, we reported results for several non-sequential and sequential learners on the signature-detection problem, including a non-sequential maximum entropy learner \cite{1} (henceforth ME) and conditional random fields \cite{8} (henceforth CRFs). Another plausible sequential learning method to apply to this task are maximum-entropy Markov models (MEMMs) \cite{9}, also called maximum-entropy taggers \cite{11}, conditional Markov models \cite{7}, and recurrent sliding windows \cite{4}. In this model, the conditional probability of a label sequence $y$ given an instance sequence $x$ is defined to be

$$
\Pr(y|x) = \prod_i \Pr(y_i|y_{i-1}, x_i) \tag{1}
$$

The local model $\Pr(y_i|y_{i-1}, x_i)$ is learned as follows. First one constructs an extended dataset, which is a collection of non-sequential examples of the form $((x_i, y_i), (y_i, y_a))$, where $x_i, y_{i-1}$ denotes an instance in which the original feature vector for $x_i$ is augmented by adding a feature for $y_{i-1}$. We will call $(x_i, y_{i-1})$ an extended instance, and call $y_{i-1}$ a history feature. Note that $y_i$ is the class label for the extended example $((x_i, y_i), y_a)$.

After constructing extended instances, one trains a maximum-entropy conditional model from the extended dataset. Inference is done by using a Viterbi search to find the best label sequence $y$ according to Equation (1)\footnote{We used the implementations of ME, MEMMs, and CRFs provided by Minorthird \cite{10}, which uses Gaussian priors and a limited-memory quasi-Newton method for optimization. A limit of 50 optimization iterations was also used, although this limit does not substantially change the result of this section.}

MEMMs have a number of nice properties. Relative the more recently-proposed CRF model, MEMMs are easy to implement, and (since no inference is done at learning time) relatively quick to train. MEMMs can also be easily generalized by replacing the local model with one that uses a longer “history” of $k$ previous labels—i.e., a model of the form $\Pr(y_i|y_{i-1}, \ldots, y_{i-k}, x_i)$—and replacing the Viterbi search with a beam search. Such a learner scales well with the history size and number of possible classes $y$.

Unfortunately, as Table 1 shows, MEMMs perform extremely badly on the signature-detection problem, with an error rate many times the error rate of CRFs. In fact, on this problem, MEMMs perform much worse than the non-sequential maximum-entropy learner ME, or even the default error rate\footnote{We used the implementations of ME, MEMMs, and CRFs provided by Minorthird \cite{10}, which uses Gaussian priors and a limited-memory quasi-Newton method for optimization. A limit of 50 optimization iterations was also used, although this limit does not substantially change the result of this section.}.

The MEMM’s performance is better if one is allowed to change the threshold used to classify examples. Letting $\tilde{p}_i$ be the probability $\Pr(y_i = +|x_i, y_{i-1})$ computed by the local model in the Viterbi classification of $x$, we computed, for each learner, the threshold $\theta$ such the rule $[(y_i = +) \Leftrightarrow (\tilde{p}_i > \theta)]$ gives the lowest test error rate. The column labeled “Min Error” in Table 1 gives this result. (Of course, since the computation of $\theta$ was done using the test data, this is only a lower bound on attainable error rate.) The “Min Error” for MEMMs is much lower than the error for MEMMs with the default threshold, but still higher than either non-sequential ME or CRFs.

### 2.2 Analysis

The literature suggests several possible explanations for these results. For instance, Lafferty et al \cite{8} show that MEMMs can represent only a proper subset of the distributions that can be represented by CRFs (the “label bias problem”). However, “label bias” does not explain why MEMMs perform worse than non-sequential ME, since MEMMs clearly can represent a proper superset of the distributions that ME can represent. Klein and Manning \cite{7} describe an “observation bias problem”, in which MEMMs give too little weight to the history features. Error analysis on the signature-detection task suggests that the opposite is happening here: relative to the weights assigned by a CRF, MEMM is actually giving too much weight to the history features, and too little to the features from $x_i$. The conjecture that the history features are
being overweighted is also consistent with the empirical observation that on many test email messages, the learned MEMM makes a false positive classification somewhere before the signature starts, and then “gets stuck” and marks every subsequent line as part of a signature.

To test this theory, we encouraged the MEMM to downweight the history features by adding noise to the training (not test) data, as follows. For each training email/sequence $x$, we consider each feature-vector $x_i \in x$ in turn, and toss a coin with a 10% chance of landing “heads”. If the coin flip comes up “heads”, we swap $x_i$ with some other feature-vector $x_j$ chosen uniformly from $x$. Adding this “sequence noise” almost doubles the error rate for CRFs, but greatly reduces the error rate for MEMMs. (Of course, this type of noise does not affect non-sequential ME.) This experiment further supports the hypothesis that MEMM is overweighting history features.

3 Stacked Sequential Learning

3.1 Description

The poor results for MEMM described above can be intuitively explained as a mismatch between the data used to train the local models of the MEMM, and the data used to test the model. With noise-free training data, it is always the case that a signature line is followed by more signature lines, so it is not especially surprising that the MEMM’s local model tends to weight this feature heavily. However, this regularity need not always hold for the test data, which is drawn from predictions made by the local model on different examples.

In theory, of course, this training/test mismatch is compensated for by the Viterbi search, which is in turn driven by the confidence estimates produced by the local model. However, if the assumptions of the theory are violated (for instance, if there are high-order interactions not accounted for by the maximum-entropy model), the local model’s confidence estimates may be incorrect, leading to poor performance.

To correct the training/test mismatch, it is sufficient to modify the extended dataset so that the true previous class $y_{i-1}$ in an extended instance $(x_i, y_{i-1})$ is replaced by a predicted previous class $\hat{y}_{i-1}$. Below we will outline one way to do this.

Assume that one is given a sample $S = \{(x_i, y_i)\}$ of size $m$, and a sequential learning algorithm $A$. Previous work on a meta-learning method called stacking [13] suggests the following scheme for constructing a sample of $(x, \hat{y})$ pairs in which $\hat{y}$ is a vector of “predicted” class-labels for $x$. First, partition $S$ into $K$ equal-sized disjoint subsets $S_1, \ldots, S_K$, and learn $K$ functions $f_1, \ldots, f_K$, where $f_j = A(S - S_j)$. Then, construct the set

$$\hat{S} = \{(x_i, \hat{y}_i) : \hat{y}_i = f_j(x_i) \text{ and } x_i \in S_j\}$$

In other words, $\hat{S}$ pairs each $x_i$ with the $\hat{y}_i$ associated with performing a $K$-fold cross-validation on $S$. The intent of this method is that $\hat{y}$ is similar to the prediction produced by an $f$ learned by $A$ on a size-$m$ sample that does not include $x$.

This procedure is the basis of the meta-learning algorithm of Table 2. This method begins with a sample $S$ and a sequential learning method $A$. In the discussion below we will assume that $A$ is ME, used for sequential data.

Using $S$, $A$, and cross-validation techniques, one first pairs each $x_i \in S$ with the $\hat{y}_i$ associated with performing cross-validation with ME. These predictions are then used to create a dataset $S'$ of extended instances $x'$, which in the simplest case, are simply vectors composed of instances of the form $(x_i, \hat{y}_{i-1})$, where $\hat{y}_{i-1}$ is the $(i-1)$-th label in $\hat{y}$.

The extended examples $S'$ are then used to train
Figure 1: Stacked sequential learning, varying history size \((W_h)\) and window size \((W = W_h = W_f)\). The base learning algorithm \(A\) is maximum-entropy (ME), unless otherwise stated.

a model \(f' = A(S')\). If \(A\) is the non-sequential maximum-entropy learner, this step is similar to the process of building a “local model” for an MEMM: the difference is that the history features added to \(x_i\) are derived not from the true history of \(x_i\), but are approximations of the off-sample predictions of an ME classifier.

At inference time, \(f'\) must be run on examples that have been extended by adding prediction features \(\hat{y}\). To keep the “test” distribution similar to the “training” distribution, \(f\) will not be used as the inner loop of a Viterbi or beam-search process; instead, the predictions \(\hat{y}\) are produced using a non-sequential maximum-entropy model \(f\) that is learned from \(S\). The algorithm of Table 2 simply generalizes this idea from ME to an arbitrary sequential learner, and from a specific history feature to a parameterized set of features.

In our experiments, we introduced one small but important refinement: each “history feature” \(\hat{y}\) added to an extended example is not simply a predicted class, but a numeric value indicating the log-odds of that class. This makes accessible to \(f'\) the confidences previously used by the Viterbi search.

3.2 Initial results

We applied stacked sequential learning with ME as the base learner (henceforth s-ME) to the signature-detection dataset. We used \(K = 5\), \(W_h = 1\), and \(W_f = 0\). (Notice that with these parameters the extended instance constructed from \(x_i\) includes \(\hat{y}_i\) as well as \(\hat{y}_{i-1}\).) The s-ME method obtains an error rate of 2.63% on the signature-detection task. This is less than the baseline ME method (3.20%) but still higher than CRFs (1.17%). However, three extensions to s-ME are straightforward to implement, and dramatically improve performance.

More past labels. Like MEMMs, s-ME can efficiently handle a large “history” of previous predicted classes. In fact, s-ME can handle large histories more easily than MEMMs, as it does not need to resort to beam search for inference—the only impact of more history features is to add new features to the extended instances. On the signature-detection task, increasing the history size reduces error to 2.38% (with a history size of 11) as is shown in Figure 1.

Past and future labels. Unlike MEMMs, the extended instance for \(x_i\) can include predicted classes not only of previous instances, but also of “future” instances—instances that follow \(x_i\) in the sequence \(x\). We explored different “window sizes” for s-ME, where a “window size” of \(W\) means that \(W_h = W_f = W\), i.e., the \(W\) previous and \(W\) following predicted labels are added to each extended instance. This reduces error rates substantially, to only 0.71%. This is a 46% reduction from CRF’s error rate of 1.17%. The improvement is also statistically significant.

Used in this way, s-ME is a sort of bidirectional model, broadly similar to the model proposed by Toutanova et al for part of speech tagging [12]. We note that here, as in Toutanova’s results, it is more valuable to use information about both the previous and future labels than to consider only previous labels.

Different base learners. Stacked sequential learning can be applied to any learner; in particular, since the extended examples are sequential, it can be applied any sequential learner. We evaluated stacked sequential CRFs (henceforth s-CRFs) with varying window sizes on this problem. As shown in Figure 1 s-CRFs also outperform CRFs, and again, the difference is both substantial and statistically significant. However, with large window sizes, there is little difference in performance between s-CRF and s-ME.

3.3 Discussion

A graphical view of a MEMMs is shown in Part(a) of Figure 2. We use the usual convention in which nodes for known values are shaded. Each node is associated with a maximum-entropy conditional model which defines a probability distribution given its input values.

Part (b) of the figure presents a similar graphical view of the classifier learned by sequential stacking. (The specifically, a two-tailed paired t-test rejects with > 95% confidence the null hypothesis that the difference in error rate between s-ME and CRF on a randomly selected sequence \(x\) has a mean of zero.)
(a) Maximum-entropy Markov model (MEMM)  
(b) Sequential stacking  
(c) Sequential stacking with width $W = 2$  
(d) Two-level sequential stacking  

Figure 2: Graphical views of alternative sequential-stacking schemes.

One way to interpret the hybrid layer is as a means of making the inference more robust. If the middle-layer nodes were treated as ordinary unobserved variables, the top-layer conditional model ($f'$) would rely heavily on the confidence assessments of the lower-layer model ($f$). Forcing $f'$ to treat these variables as observed quantities allows $f'$ to develop its own model of how the $\hat{y}$ predictions made by $f$ correlate with the actual outputs $y$. This allows $f'$ to accept or downweight $f$’s predictions, as appropriate. As suggested by the dotted line in the figure, stacking conceptually creates a “firewall” between $f$ and $f'$, insulating $f'$ from possible errors in confidence made by $f$.

Part (c) of the figure shows a sequential stacking model with a window of $W_h = W_f = 2$. To simplify the figure, only the edges that eventually lead to the node $Y_i$ are shown.

Part (d) of the figure shows another plausible extension of sequential stacking, in which each $\hat{y}$ is replaced with a better approximation of $y$—namely, the output of sequential stacking itself. (Again to simplify the figure, a minimal set of arcs are shown, in this case for stacking with $W_h = 1$ and $W_f = -1$.) This “deeper” stacking scheme can be implemented quite easily, for instance by applying the sequential stacking scheme to the base learner s-ME. However, our initial experiments were discouraging: for instance, the depth-two learner s-(s-ME) has a slightly higher error rate than s-ME (3.04%). The limited amount of training data available for the lowest-level models may be an issue:
Table 3: Comparison of different sequential algorithms on a set of nine benchmark tasks.

<table>
<thead>
<tr>
<th>Task</th>
<th>MEMM</th>
<th>ME</th>
<th>CRF</th>
<th>s-ME</th>
<th>s-CRF</th>
</tr>
</thead>
<tbody>
<tr>
<td>A/aigen</td>
<td>53.61</td>
<td>8.02</td>
<td>20.35</td>
<td>6.91</td>
<td>5.78</td>
</tr>
<tr>
<td>A/ainn</td>
<td>70.09</td>
<td>6.61</td>
<td>2.14</td>
<td>3.65</td>
<td>1.67</td>
</tr>
<tr>
<td>A/aix</td>
<td>13.86</td>
<td>5.02</td>
<td>6.83</td>
<td>4.59</td>
<td>11.79</td>
</tr>
<tr>
<td>T/aigen</td>
<td>0.30</td>
<td>2.60</td>
<td>2.39</td>
<td>1.92</td>
<td>0.00</td>
</tr>
<tr>
<td>T/ainn</td>
<td>1.36</td>
<td>1.39</td>
<td>0.28</td>
<td>0.00</td>
<td>0.28</td>
</tr>
<tr>
<td>T/aix</td>
<td>3.51</td>
<td>1.25</td>
<td>5.26</td>
<td>0.05</td>
<td>4.44</td>
</tr>
<tr>
<td>2/video</td>
<td>8.86</td>
<td>8.86</td>
<td>7.59</td>
<td>3.80</td>
<td>7.59</td>
</tr>
<tr>
<td>mailsig</td>
<td>31.83</td>
<td>3.47</td>
<td>1.17</td>
<td>1.08</td>
<td>0.77</td>
</tr>
</tbody>
</table>

Figure 3: Comparison of the error rates for s-ME with the error rates of ME, MEMM, and CRFs.

4 Experimental Results

4.1 Additional Problems

We also evaluated non-sequential ME, MEMMs, CRFs, s-ME, and s-CRFs on several other sequential partitioning tasks. For stacking, we used $K = 5$ and a window size of $W_h = W_f = 5$ on all problems. These were the only parameters used in this section, and no changes were made to the sequential stacking algorithm, which was developed based on observations made from the signature-detection task only.

One set of tasks involved classifying lines from FAQ documents with labels like “header”, “question”, “answer”, and “trailer”. We used the features adopted by McCallum et al. [9] and the three tasks (ai-general, ai-neural-nets, and aix) adopted by Dietterich et al. [5]. The data consists of 5-7 long sequences, each sequence corresponding to a single FAQ document; in total, each task contains between 8,965 and 12,757 labeled lines. Our current implementation of sequential stacking only supports binary labels, so we considered the two labels “trailer” (T) and “answer” (A) as separate tasks for each FAQ, leading to a total of six new benchmarks.

Another set of tasks were video segmentation tasks, in which the goal is to take a sequence of video “shots” (a sequence of adjacent frames taken from one camera) and classify them into categories such as “anchor”, “news” and “weather”. This dataset contains 12 sequences, each corresponding to a single video clip. There are a total of 418 shots, and about 700 features, which are produced by applying LDA to a 5x5, 125-bin RGB color histogram of the central frame of the shot. (This data was provided by Yik-Cheung Tam and Ming-yu Chen.) We constructed two separate video partitioning tasks, corresponding to the two most common labels.

All eight of these additional tasks are similar to the signature-detection task in that they contain long runs of identical labels, leading to strong regularities in constructed history features. Error rates for the learning methods on these eight tasks, in addition to the previous signature-detection task, are shown in Table 3. In each case a single train/test split was used to evaluate error rates. The bold-faced entries are the lowest error rate on a row.

We observe that MEMMs suffer extremely high error rates on two of the new tasks (finding “answer” lines for ai-general and ai-neural-nets), suggesting that the “anomalous” behavior shown in signature-detection may not be uncommon, at least in sequential partitioning tasks.

Also, comparing s-ME to ME, we see that s-ME improves the error rate in 8 of 9 tasks, and leaves it unchanged once. Furthermore, s-ME has a lower error
Table 4: Comparison of different sequential algorithms on a set of nine benchmark tasks.

<table>
<thead>
<tr>
<th>Task</th>
<th>VP</th>
<th>VPHMM</th>
<th>s-VP</th>
<th>s-VPHMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>aigen</td>
<td>7.87</td>
<td>12.09</td>
<td><strong>7.33</strong></td>
<td>12.09</td>
</tr>
<tr>
<td>ainn</td>
<td>6.59</td>
<td>10.26</td>
<td><strong>3.76</strong></td>
<td>10.26</td>
</tr>
<tr>
<td>aix</td>
<td>5.50</td>
<td>4.86</td>
<td><strong>3.61</strong></td>
<td>5.95</td>
</tr>
<tr>
<td>aigen</td>
<td>1.68</td>
<td>2.16</td>
<td><strong>0.18</strong></td>
<td>2.16</td>
</tr>
<tr>
<td>ainn</td>
<td>1.44</td>
<td>1.93</td>
<td><strong>0.19</strong></td>
<td>1.93</td>
</tr>
<tr>
<td>aix</td>
<td>3.40</td>
<td>1.95</td>
<td>1.16</td>
<td><strong>1.01</strong></td>
</tr>
<tr>
<td>video</td>
<td>11.39</td>
<td>13.92</td>
<td><strong>11.39</strong></td>
<td>11.39</td>
</tr>
<tr>
<td>video</td>
<td>6.33</td>
<td>25.32</td>
<td>3.80</td>
<td>6.33</td>
</tr>
<tr>
<td>mailsig</td>
<td>3.40</td>
<td>1.95</td>
<td>1.16</td>
<td><strong>1.01</strong></td>
</tr>
</tbody>
</table>

Overall, s-ME seems to be preferable to either of three older approaches (ME, MEMMs, and CRFS). This is made somewhat more apparent by the scatter plot of Figure 3. On this plot, each point is placed so the $y$-axis position is the error of s-ME, and the $x$-axis position is the error of an earlier learner; thus points below the line $y = x$ are cases where s-ME outperforms another learner. (For readability, the range of the $x$ axis is truncated—it does not include the highest error rates of MEMM.)

Stacking also improves CRF on some problems, but the effect is not as consistent: s-CRF improves the error rate on 5 of 9 tasks, leaves it unchanged twice, and increases the error rate twice. In the table, one of the two stacked learners has the lowest error rate on 8 of the 9 tasks.

4.2 Additional Base Learners

We conducted the same experiments with two margin-based base learners: the non-sequential voted perceptron algorithm (VP) [6] and a voted-perceptron based training scheme for HMMs proposed by Collins (VPHMMs) [3]. Table 4 shows the results for these methods, and their sequentially-stacked versions. Both the sequential and non-sequential voted perceptrons were run for 20 epochs.

In this case, s-VP outperforms or ties both VP and VPHMM on all nine problems. The s-VPHMM has lower error rate than the VPHMM 4 times, a higher error rate once, and the same error rate 4 times.

There does not seem to be any clear pattern in the relative performance between s-ME and s-VP—neither method consistently outperforms the other. Nor does any clear pattern appear in the relative performance of s-CRF and s-VPHMM. This is not unexpected, since in practice, it is often the case that probabilistic methods work best on some problems, and margin-based methods work best on others.

4.3 Overview of results

An overview of the improvements obtained by sequential stacking on these problems is shown in Figure 4 and Table 5. The scatter plot shows the error rate of ME plotted against the error rate of ME, the error rate of s-VP plotted against VP, and similarly for s-VPHMM vs VPHMM and CRFs vs s-CRFs.

The plot shows a plausible pattern: sequential stacking nearly always improves the performance on the non-sequential learners (ME and VP) but improves performance of the sequential learners (CRFs and VPHMMs) less consistently. This pattern is confirmed by a series of one-tailed sign tests performed on pairs of learners, which are summarized in Table 5.

The sign test does not consider the amounts by which error rates are changed. From the figures and tables, it is clear that when error rates are lowered, they are often lowered substantially. However, even for CRFs,

Figure 4: Comparison of the error rates various algorithms with and without sequential stacking.

<table>
<thead>
<tr>
<th>Method</th>
<th>W-L-T</th>
<th>null</th>
<th>confidence</th>
</tr>
</thead>
<tbody>
<tr>
<td>ME</td>
<td>8-0-1</td>
<td>E[Δ(A)]≥0</td>
<td>&gt;0.98</td>
</tr>
<tr>
<td>VP</td>
<td>8-0-1</td>
<td>E[Δ(A)]≥0</td>
<td>&gt;0.98</td>
</tr>
<tr>
<td>VPHMM</td>
<td>4-1-4</td>
<td>E[Δ(A)]&gt;0</td>
<td>&gt;0.98</td>
</tr>
<tr>
<td>CRF</td>
<td>5-2-2</td>
<td>E[Δ(A)]&gt;0</td>
<td>&gt;0.92</td>
</tr>
</tbody>
</table>

Table 5: Comparison of stacked vs unstacked learners, using a one-tailed sign test on error rates obtained on the nine benchmark problems. Here $Δ(A)$=error(s-A)-error(A), i.e., the difference in errors between s-A and A on a randomly selected task.
the error rate is only once raised by more than a very small proportion (for the “A/aix” benchmark).

5 Conclusions

Sequential partitioning tasks are sequential classification tasks characterized by long runs of identical labels: examples of these tasks include document analysis, video segmentation, and gene finding. In this paper, we have evaluated the performance of certain well-studied sequential probabilistic learners to sequential partitioning tasks. It was observed that MEMMs sometimes obtain extremely high error rates. Error analysis suggests that this problem is neither due to “label bias” [8] nor “observation bias” [7], but to a mismatch between the data used to train the MEMM’s local model, and the data on which the MEMM’s local model is tested. In particular, since MEMMs are trained on “true” labels and tested on “predicted” labels, the strong correlations between adjacent labels associated sequential partitioning tasks can be misleading to the MEMM’s learning method.

Motivated by these issues, we derived a novel method in which cross-validation is used correct this mismatch. The end result is a meta-learning scheme called stacked sequential learning. Sequential stacking is simple to implement, can be applied to virtually any base learner, and imposes an constant overhead in learning time (the constant being the number of cross-validation folds plus two). In experiments on several partitioning tasks, sequential stacking consistently improves the performance of two non-sequential base learners, often dramatically. On our set of benchmark problems, sequential stacking with a maximum-entropy learner as the base learner outperforms CRFs 7 of 9 times, and ties once. Perhaps more surprisingly, sequential stacking also often improves performance of learners specifically designed for sequential tasks, such as conditional random fields and discriminately trained HMMs.

Some initial experiments on a named entity recognition problem suggest that sequential stacking does not improve performance on non-partitioning problems; however, in future work, we plan to explore this issue with more detailed experimentation. We also plan to extend our implementation to handle non-binary label sets.

Acknowledgements

The author wishes to thank many friends and colleagues for input, in particular Vitor Carvalho and David McAllister. He is also grateful to Yik-Cheung Tam and Ming-yu Chen for providing the video-segmentation data. This work was supported by grants from the Information Processing Technology Office (IPTO) of the Defense Advanced Research Projects Agency (DARPA).

References


