Diversity Analysis for Ensembles of Word Sequence Recognisers

Roman Bertolami and Horst Bunke

Institute of Computer Science and Applied Mathematics
University of Bern, Neubrückstrasse 10, CH-3012 Bern, Switzerland
{bertolam, bunke}@iam.unibe.ch

Abstract. In this paper we propose a general framework for analysing the diversity of ensembles of word sequence recognition systems. The goal of the framework is to enable the application of any diversity measure developed for standard multi-class classification problems to ensembles of word sequence recognisers. Experiments with several diversity measures are conducted on artificial as well as on real world data and show the effectiveness of the proposed approach.

1 Introduction

Ensemble methods have been applied to many different fields of pattern recognition [1]. In handwriting recognition, improvements have been reported in isolated character [2] as well as in single word recognition [3,4]. Only recently work has been published on ensemble methods for word sequence recognition [5,6,7], which is still a field with many challenges.

The goal of ensembles methods is to correct the errors of one ensemble member with the output of the other ensemble members. To achieve this goal we need a certain diversity among the ensemble members. Intuitively speaking, the members should make no coincident errors, i.e. the errors of one classifier should be independent of the errors of the other classifiers. A high diversity of a classifier ensemble is considered to be a strong hint to good performance. Hence, measuring diversity allows one to predict the performance of an ensemble without the need of conducting computationally expensive experiments. Several diversity measures have been proposed in the literature for multi-class problems. Surveys can be found in [8,9,10].

Two different groups of diversity measures for ensembles of classifiers can be distinguished: pairwise measures and nonpairwise measures. Pairwise measures derive the final diversity of an ensemble of N classifiers from the $N(N-1)$ pairwise diversity values. Usually the mean of these values is used as ensemble diversity. Popular members of this group of diversity measures are correlation, disagreement, and double fault. On the other hand, nonpairwise measures consider all the classifier of an ensemble together and calculate one diversity value directly. Popular nonpairwise diversity measures are entropy and Sharkey-Level based measures.

All diversity measures currently known have been developed for conventional multi-class classification problems. To the knowledge of the authors, no diversity measures for word sequence recognition have been proposed until now.

The aim of the current paper is to provide a generic framework to apply diversity measures, developed for conventional multi-class classification problems, to the task of word sequence recognition. Word sequence recognition is a difficult problem because not only a single class, but a sequence of word classes of unknown length has to be returned by the recogniser. Even though appropriate diversity measures for word sequence recognition are potentially useful in the ensemble generation process, no such measures have been published yet. The contribution of this paper is to make classical diversity measures available for word sequence recognisers.

The remaining part of the paper is organised as follows. Section 2 introduces the diversity analysis framework and provides an example in detail. Experiments conducted on artificial as well as on real world data are described in Sect. 3. Finally, conclusions are drawn in the last section of the paper.

2 Methodology

Assume we have an ensemble where each of the n recognisers outputs a word sequence $W_i = (w_{i_1}, \dots, w_{i_{m_i}})$; $i = 1, \dots, n$. The number of words m_i in these sequences may differ and therefore a synchronisation process is required first. The synchronised results of the ensemble members are stored in a Word Transition Network (WTN) [11]. Because the class labels are used to calculate the diversity measures, the segments of the WTN have to be labelled with the ground truth. Any diversity measure available for multi-class problems can then be applied to the segments and based on these measures the final ensemble diversity is derived. Next, we describe various aspects of the proposed diversity analysis framework in greater detail. An extensive example of the entire process is provided in Section 2.3.

2.1 Synchronisation of the Word Sequences

Let the n ensemble members have recognised their individual word sequences $(W_1, \dots, W_n)$. Each of these sequences might contain a different amount of words and therefore an alignment procedure is necessary to synchronise the n word sequences. Any possible string alignment procedure can be used for this purpose. However, because the optimal alignment of multiple strings is an *NP*-complete problem [12], we suggest to use a heuristic approach (e.g. incremental) for the alignment. For details see [11]. The result of the alignment is a WTN which consists of m segments. Each arc in the WTN is labelled with a word out of $(W_1, \dots, W_n)$. Null transition arcs ε occur when the number of words in $(W_1, \dots, W_n)$ is not equal for each W_i ($i = 1, \dots, n$).

Next, the ensemble result is derived applying some decision rule to each segment of the WTN. Any kind of decision strategy can be used, but for the sake

Table 1. Probabilities of coincident errors between classifier C_i and C_j

	C_i correct	C_i wrong
C_j correct	a	b
C_j wrong	c	d

of simplicity we just use a voting procedure. The resulting sequence of decision results constitute the combination result $\hat{W}$. Note that if the decision result of a segment is a null transition, this segment does not contribute any word to $\hat{W}$.

Once we have the combination result $\hat{W}$ and the ground truth, we can label the segments of the WTN. Therefore, we first align $\hat{W}$ with the ground truth. Using the alignment we can map the words in the ground truth to the WTN segments.

2.2 Application of Diversity Measures

Existing diversity measures can then be applied to the labelled segments of the WTN, similarly to conventional multi-class classification problems. The average of these measures gives the final ensemble diversity.

In the present work we apply pairwise as well as Sharkey-Level based diversity measures to word sequence recognition. Pairwise diversity measures consider only a pair of recognisers at a time. Any possible pair of ensemble members produces a diversity value. The average across all pairs gives the final diversity. Based on the probabilities of coincident errors between two recognisers C_i and C_j (Tab. 1) several measures have been proposed.

Correlation. Because the output of two recognisers can be considered as numerical values (1 for correct and 0 for wrong), we can calculate the correlation coefficients.

$$\rho_{i,j} = \frac{ad - bc}{\sqrt{(a+b)(c+d)(a+c)(b+d)}} \quad (1)$$

Disagreement. The disagreement measure is a very intuitive measure of diversity. It is the probability that the two considered recognisers will disagree on their decision.

$$D_{i,j} = b + c \quad (2)$$

Double Fault. Another quite intuitive measure is the double fault measure which is the probability that both recognisers make a wrong decision.

$$DF_{i,j} = d \quad (3)$$

The second kind of diversity measures are derived from the Sharkey-Levels introduced in [13]. Each segment of the WTN can be assigned to one of the following levels:

Level 1. No coincident errors. Each ensemble member produces the correct result.

Level 2. Some coincident errors, but the majority of the ensemble members provide the correct result.

Level 3. Majority is not correct but some of the members produce the correct result.

Level 4. The correct result is not output by any of ensemble members.

The frequencies of the different levels are then used as diversity measures. Thus, L_i is the frequency that a segment of the WTN belongs to Level i , where $i = 1, \dots, 4$.

2.3 Example

Next, we will provide an example of the entire process of calculating diversity measures for ensembles of handwritten text line recognisers. The input is the handwritten text line *They will be asked to comment* shown in Fig 1. Features are extracted and each ensemble member performs the recognition step. The recognised word sequences ($W_1, \dots, W_9$) are shown in Fig. 2.

Next, the word sequences ($W_1, \dots, W_9$) are synchronised. An iterative alignment is used for this purpose [11]. The result of this alignment step is shown in Fig. 3. Note that null transition arcs have to be inserted at the beginning of some text lines to align the additional word in W_1 and W_7 .

Once the alignment is performed, we can calculate the combination result for each alignment segment. We apply a majority voting and get the word sequence *they will be asked to council*. To label the alignment segments we first have to align the combination result ($\hat{W}$) with the ground truth (T) as shown in Fig. 4.

Based on this information we label the segments of the aligned word sequences of Fig. 3. The result of the labelling process is shown in Fig. 5.

Now we are able to apply any of the described diversity measures, originally developed for conventional multi-class classification problems, to our sequence recognition problem. E.g. the Level 1 diversity measure yields $4/7$, whereas the Level 3 diversity measure is equal to $1/7$.

3 Experiments and Results

One of the main motivations for computing ensemble diversity is to predict the performance of an ensemble of recognisers without the need to to run computationally expensive experiments. Hence, the aim of the experiments is to show relationships between the recognition accuracy and the different diversity measures. Experimental evaluation of the proposed framework is conducted on a synthetic and a real world data set.

3.1 Synthetic Word Sequences

To be able to test our framework, we generate artificial ensemble results. First the ground truth is created and then the ensemble results are generated.

Fig. 1. Handwritten input text

W_1 : if they will be asked to council
 W_2 : they will be asked to comment
 W_3 : it will be asked to comment
 W_4 : they will be asked to council
 W_5 : they will be asked to council
 W_6 : they will be asked to comment
 W_7 : if it will be asked to comment
 W_8 : they will be asked to council
 W_9 : they will be asked to council

Fig. 2. Results from the different ensemble members

W_1 :	if	they	will	be	asked	to	council
W_2 :	ε	they	will	be	asked	to	comment
W_3 :	ε	it	will	be	asked	to	comment
W_4 :	ε	they	will	be	asked	to	council
W_5 :	ε	they	will	be	asked	to	council
W_6 :	ε	they	will	be	asked	to	comment
W_7 :	if	it	will	be	asked	to	comment
W_8 :	ε	they	will	be	asked	to	council
W_9 :	ε	they	will	be	asked	to	council

Fig. 3. Alignment of the ensemble results in a WTN

$\hat{W}$:	they	will	be	asked	to	council
T:	They	will	be	asked	to	comment

Fig. 4. Alignment of the combination result and the ground truth

W_1 :	if	they	will	be	asked	to	council
W_2 :	ε	they	will	be	asked	to	comment
W_3 :	ε	it	will	be	asked	to	comment
W_4 :	ε	they	will	be	asked	to	council
W_5 :	ε	they	will	be	asked	to	council
W_6 :	ε	they	will	be	asked	to	comment
W_7 :	if	it	will	be	asked	to	comment
W_8 :	ε	they	will	be	asked	to	council
W_9 :	ε	they	will	be	asked	to	council
T:	ε	They	will	be	asked	to	comment

Fig. 5. Labelling the segments

To build the ground truth for a word sequence, the number of words n is first defined by a random number in a given range. Next, n words are randomly chosen from the underlying lexicon and then used as the ground truth word sequence.

Next, the ensemble results are generated iteratively. Given the ground truth word sequence, the first ensemble member's result sequence is created randomly with a given accuracy. The next member's result sequence is then generated with respect to a defined correlation to the previously generated word sequence. This process is continued until the desired number of results has been obtained.

We generated ensembles with five, ten, fifteen, and twenty members with a lexicon of 10,000 word classes. In our experiments we also varied the correlation between two successive members to obtain ensembles with different diversities.

The advantage of the artificial data is that we can control the correlation between the ensemble members. Also the number of classes can be chosen. Therefore, we are able to simulate different application domains, e.g. character sequences (~ 80 classes) or word sequences ($\sim 10,000$ classes). Furthermore, an arbitrarily large amount of data can be produced relatively fast. On the other hand, it may happen that the generated ensemble member results do not sufficiently well model the results produced by real word ensemble members.

3.2 Ensembles of Handwritten Text Line Recognisers

In the second part of the experimental evaluation we use real word data from offline handwritten text line recognition. The data originate from [14] where three different ensemble member selection strategies have been validated. For this purpose, many different ensembles of various sizes have been built and tested which we now use to evaluate the proposed diversity framework.

The ensemble members were derived from specific integration of a statistical language model in the hidden Markov model based recognition system. The handwritten text lines that were used originate from the IAM¹ database [15]. For further details about the experimental setup of the recognition and ensemble generation step we refer to [14].

3.3 Diversity Analysis Results

In the experiments described in this section we investigate which of the proposed diversity measures, applied in our framework, is a better indicator of the accuracy of the combined ensemble results. Furthermore, we analyse the differences between the artificial and the real world data results.

The results for the pairwise measures Correlation, Disagreement, and Double Fault are shown in Fig. 6. While clear tendencies can be seen in the outcomes of the artificial ensemble, only the Double Fault measure seems to be a useful indicator for the accuracy of the ensemble performance on the real world data. The four different lines that can be observed in the artificial data plots originate from the four different sizes of the analysed ensembles.

Figure 7 shows the results of the level based diversity measures. On the real world data set, the best indicator of a good performance is Level 4. This means

¹ The IAM database is publicly available for download at <http://www.iam.unibe.ch/~fki/iamDB>

Fig. 6. Evaluation of pairwise diversity measures. The x-axis shows the values of the diversity measure whereas the ensemble accuracy is displayed on the y-axis. The results with artificial data are shown in left column, whereas the outcome on the real world data is shown on the right.

that if we are able to decrease the number of segments where the target word does not even occur a single time, we can expect that the overall performance of the ensemble increases.

The correlation coefficients between the different diversity measures and the recognition accuracy are listed in Tab 2. These values support the optical impression of Fig. 6 and Fig. 7.

Fig. 7. Evaluation of level based diversity measures. The x-axis shows the values of the diversity measure whereas the ensemble accuracy is displayed on the y-axis. The results with artificial data are shown in left column, whereas the outcome on the real world data is shown on the right.

Table 2. Correlation coefficients of the different diversity measures

	Artificial Data	Real Data
Correlation	-0.8	-0.45
Disagreement	0.77	0.42
Double Fault	-0.45	-0.81
Level 1	-0.92	-0.66
Level 2	0.3	0.7
Level 3	0.9	-0.15
Level 4	-0.95	-0.83

4 Conclusions

We have proposed a framework for diversity analysis of ensembles of word sequence recognition systems. The framework allows one to apply any diversity measure available for conventional multi-class classification problems to ensembles of word sequence recognisers.

In the proposed framework, the word sequences of the individual ensemble members are synchronised in a sequence of segments first. Next, these segments are labelled with the ground truth. Once each segment is labelled, diversity measures for multi-class problems can be applied to the segments. The average of these values gives then the final diversity of the ensemble.

Experiments have been conducted with artificial as well as with real world data from offline handwritten text line recognition. Several pairwise and nonpairwise diversity measures have been applied to both tasks to show the effectiveness of the different measures within the proposed framework. Some of these diversity measures seem to be useful indicators of good ensemble performance.

In the current paper we have exclusively considered the task of word sequence recognition. However, the proposed framework is applicable to continuous speech recognition and other domains as well, where an individual classifier outputs a sequence of classes, rather than just a single class.

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