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A Data Visualization Method for Investigating the Reliability of a High-Dimensional Low-back-pain MLP Network

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This study uses a new data visualization method, developed by the first author, to investigate the reliability of a real world low-back-pain Multi-layer Perceptron (MLP) network from a hidden layer decision region perspective. Using decision region identification information from an explanation facility, the MLP training examples are discovered to occupy decision regions in contiguous class threads across the 48-dimensional input space. MLP testing cases show a similar distribution and consistency within the contiguous threads but with a reduced reliability. Three test regions outside the network's knowledge bounds are situated between training regions with a consistent classification.

1. Introduction

A new data visualization method [1] has been developed by the first author for discovering the position of MLP input data from a hidden layer decision region perspective in *n*-dimensional input space. The decision region identification is part of an explanation facility developed by the first author [1-4] for directly interpreting the output on a case-by-case basis from any standard multi-layer perceptron (MLP) network that classifies binary input data in *n*-dimensional input space.

The explanation facility interprets the classifications of low-back-pain patients by a MLP with 48 input neurons [4]. For novelty detection, a new direct approach is taken, whereby the explanation facility warns the surgeons that the classification is potentially unreliable when a new low-back-pain input case is beyond the MLP network's knowledge bounds. The knowledge bounds are defined [1] by the first author as the set of hidden layer decision regions in the *n*-dimensional input space which contain the training examples.

The aim of this study is to present the results of using the hidden decision region data visualization method to investigate the reliability of the *48*-dimensional MLP.

2. Determining the MLP Knowledge Bounds

The role of the hidden layer neurons in a MLP network that performs a classification task is to separate the training examples into the classes specified during supervised training [1]. The hidden neurons H_j , j=1,m, create a number of separate decision regions in n-dimensional input space from the intersection of m (n−1)-dimensional hyper-planes given by:

$$w_{1j}\, x_1 + w_{2j}\, x_2 + \ldots\ldots + w_{ij}\, x_i + \ldots\ldots + w_{nj}\, x_n = T_j\,,$$

for threshold T_j at H_j [1,5] and input point x_i, i=1,n. For sigmoidal activations, each decision region has a unique combination of hidden layer activations $h_j \geq 0.5$ or $h_j < 0.5$, for j=1,m for input points within its boundaries and can be assigned a corresponding unique binary label, where 1 represents $h_j \geq 0.5$ and 0 represents $h_j < 0.5$ [1]. The MLP knowledge bounds are the set of unique decision regions, identified by binary labels, as determined from h_j, j=1,m, for all *correctly classified* training cases, after training is completed.

3. Low-back-pain MLP Training Data Reliability

Demographic and symptomatic information, results of outcome measures, physical examination and clinical assessments were collected from over two hundred low-back-pain patients and converted into binary input data. The surgeons provided a presumptive diagnosis for each patient according to one of the following three broad clinical categories: simple low-back-pain (SLBP), nerve root pain (ROOTP) and abnormal illness behavior (AIB).

An optimal MLP network was developed with 48 input neurons and 5 hidden neurons which had a 99% training performance for 97 randomly selected training cases and a 77% best generalized test for 99 randomly selected test cases [4]. The clinical value of the network is its enhanced performance in classifying AIB patients compared with the orthopedic surgeons [4].

3.1 Low-back-pain MLP Knowledge Bounds

Using the data visualization method, the decision regions containing the training examples are found by presenting each training case in turn to the 48-5-3 low-back-pain MLP and recording the corresponding hidden layer activations, which are then converted into 5 bit binary codes, as described in Section 2. The set of decision regions with training examples – the knowledge bounds of the network – are found to consist of 5 hidden layer decision regions for each of the SLBP and ROOTP classes and 2 decision regions for the AIB class, as shown in Table 1.

The ROOTP region 11110(30) is not considered part of the knowledge bounds since the classification of the single training example is incorrect (it was diagnosed as SLBP by the clinicians). The classification strength by decision region is also shown in Table 1, where a strong classification is an activation >0.85 at the class output neuron and <0.10 at all others, a medium classification is ≥0.5 and <0.25 respectively and a weak classification is <0.5 at all output neurons.

In several decision regions there is some activation for another class, as indicated in Table 1, and in some regions the classification is mixed, when the correct class has only a *marginally* higher activation. This was an unexpected result.

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Table 1. Knowledge bounds (training decision regions) of the 48-5-3 low-back-pain MLP

decision region	**class**	**correct training cases**	**classification strength**
01011 (11)	SLBP	20|20	strong
00011 (3)	SLBP	6|6	medium (some ROOTP)
11011 (27)	SLBP	4|4	medium (some AIB)
01010 (10)	SLBP	3|3	weak (some ROOTP)
11010 (26)	SLBP	1|1	mixed AIB
00110 (6)	ROOTP	37|37	very strong
10110 (22)	ROOTP	6|6	strong (some AIB)
10100 (20)	ROOTP	1|1	mixed AIB
00010 (2)	ROOTP	1|1	mixed SLBP
11110 (30)	**ROOTP**	**0 | 1**	medium (some AIB)
11000 (24)	AIB	11|11	strong (some SLBP)
11100 (28)	AIB	6|6	medium (some ROOTP)

3.2 Low-back-pain Training Data Reliability Within the Knowledge Bounds

As can be seen from Table 1, for each class, the decision region with the most training cases is significantly more reliable. These are ROOTP region(6), SLBP region(11) and AIB region(24).

From a hamming distance analysis of the decision region labels, the position of the training examples in adjacent regions with respect to hidden neuron boundaries can be visualized. It is found that the MLP preserves the continuity of the three types of low-back-pain classification in separate contiguous threads of decision regions across the *48*-dimensional input space. Examples of the main threads are shown in Figs.1-3.

	$\mathbf{H_3}$		$\mathbf{H_1}$		$\mathbf{H_4}$		$\mathbf{H_2}$	
00010(2)	|	00110(6)	|	10110(22)	|	10100(20)	|	11100(28)
SLBP /ROOTP		**ROOTP**		**ROOTP**		**ROOTP /AIB**		**AIB**
[1/1]		[37/37]		[(6/6]		[1/1]		[6/6]
				(some **AIB**)				(some **ROOTP**)

Figure 1. Training ROOTP thread 1 – illustrating which training examples are in adjacent regions with respect to the indicated H_j boundaries.

The contiguous threads also explain the mixed classifications in some training decision regions. For example, in the ROOTP thread shown in Fig.1 the strongest ROOTP(6) is a neighbor to the next strongest ROOTP(22) which adjoins the mixed ROOTP/AIB(20). The classification in region(20) is consistent with its position between a ROOTP thread and AIB(28) which has some ROOTP activation. In another view, as shown in Fig. 2, the incorrect classification in ROOTP(30) is consistent with its position between ROOTP(22) and AIB(28).

$\mathbf{H_3}$ $\mathbf{H_1}$ $\mathbf{H_2}$ $\mathbf{H_4}$

00010(2)	00110(6)	10110(22)	11110(30)	11100 (28)
SLBP /ROOTP	**ROOTP**	**ROOTP**	**ROOTP/AIB**	**AIB**
[1/1]	[37/37]	[6/6]	[0/1]	[6/6]
		(some **AIB**)	**(wrong)**	(some **ROOTP**)

Figure 2. Training ROOTP thread 2 – illustrating which training examples are in adjacent regions with respect to the indicated H_j boundaries.

In another view across the 48-dimensional decision space, as shown in Fig. 3, it can be seen that the AIB thread is contiguous to mixed SLBP/AIB(26) which is the last region in a SLBP thread.

$\mathbf{H_2}$ $\mathbf{H_1}$ $\mathbf{H_5}$ $\mathbf{H_4}$ $\mathbf{H_3}$

00011(3)	01011(11)	11011(27)	11010(26)	11000 (24)	11100 (28)
SLBP	**SLBP**	**SLBP**	**SLBP /AIB**	**AIB**	**AIB**
[6/6]	[20/20]	[4/4]	[1/1]	[11/11]	[6/6]
				(some **SLBP**)	(some **ROOTP**)

Figure 3. Training SLBP thread and AIB thread – illustrating which training examples are in adjacent regions with respect to the indicated H_j boundaries.

The relative position of each training example with respect to its hidden layer decision region boundaries can also be determined, from the actual hidden layer activations of the training example. For example, a training example with h_2=0.4 is much closer to the H_2 boundary (where h_2=0.5) than a training example with h_2=0.1.

4. Low-back-pain MLP Test Data Reliability

4.1 Distribution of low-back-pain test data within the MLP knowledge bounds

Using the same method, it was found that 96 of the 99 test cases lie within the knowledge bounds with a similar distribution to the training cases, as shown in Table 2. This confirms that the test cases have a similar distribution to the training cases in the *48*-dimensional input space, as recommended in network training [6].

As shown in Table 2, there are three novel test data decision regions outside the low-back-pain MLP knowledge bounds, regions (7), (14) and (25), each containing a single test case. Region (30), which contains the incorrectly classified training case, is represented with two correctly classified test cases, although one case very weakly. For this reason, region(30) could be considered as part of the knowledge bounds.

4.2 Test Data Reliability Within the Knowledge Bounds

From Table 2, it can be seen that the 23 miss-classified test cases are distributed uniformly throughout the test decision regions. However, the results

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Table 2. Testing decision regions of the 48-5-3 low-back-pain MLP

decision region	knowledge bounds	class	correct test cases	Classification strength
01011(11)	YES	SLBP	12|15	mostly strong
00011(3)	YES	SLBP	3|4	mixed ROOTP
11011(27)	YES	SLBP	5|7	medium (some AIB)
01010(10)	YES	SLBP	2|2	medium (some ROOTP)
11010(26)	YES	SLBP	2|4	weak (mixed AIB)
00110(6)	YES	ROOTP	28|34	mostly strong
10110(22)	YES	ROOTP	1|3	medium (some AIB)
10100(20)	YES	ROOTP	1|2	mixed AIB
00010(2)	YES	ROOTP	1|2	mixed SLBP
11110(30)	maybe	ROOTP	2|2	very weak to medium (some AIB and SLBP)
00111(7)	**NO**	ROOTP	0|1	medium (some SLBP)
01110(14)	**NO**	ROOTP	1|1	medium (some SLBP)
11000(24)	YES	AIB	11|13	medium (some SLBP)
11100(28)	YES	AIB	6|8	some to mixed ROOTP
11001(25)	**NO**	AIB	1|1	mixed SLBP

indicate that the classification is better than the average test classification rate in the most populated decision regions within the knowledge bounds.

The classification of the test cases also shows a similar pattern of consistency within the contiguous threads of training decision regions but with a reduced reliability compared to the training cases, as already discussed.

4.3 Test Data Reliability Beyond the Knowledge Bounds

From a hamming distance analysis it was discovered that the three new test decision regions are each situated between training decision regions inside the knowledge bounds, as shown in Fig. 4 for test region(14). Since the diagnosis is correct in two

H_4 **H_1** **H_2** **H_3** **H_5**

kb	kb	kb	**TEST**	kb	kb
10100(20)	10110(22)	00110(6)	**01110(14)**	01010(10)	01011(11)
ROOTP	**ROOTP**	**ROOTP**	**ROOTP**	**SLBP**	**SLBP**
[1/1]	[1/1]	[37/37]	[1/1]	[3/3]	[20/20]

Figure 4. Position of novel test region (14) within the low-back-pain MLP knowledge bounds

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out of three of these regions, this result indicates that the classification of new low-back-pain patients is partly reliable in regions *between* neighboring regions in the knowledge bounds.

5 Summary and Conclusions

In summary, the new method of data visualization from a hidden decision region perspective illustrates the position of the training examples of the 48-5-3 MLP in separate contiguous threads of decision regions for each class across the entire *48*-dimensional input space. The reliability of the training data classification is found to depend on the position of the decision region within the class threads where the region with the most training cases is significantly more reliable.

The method illustrates that the test cases are positioned mostly in the same contiguous threads as the training examples, which define the low-back-pain network knowledge bounds, but with a reduced reliability compared to the training cases. The three novel test decision regions outside the knowledge bounds are situated between decision regions inside the knowledge bounds, with a partly reliable classification. It is concluded that the MLP is *constrained* to have a continuous classification distribution in contiguous threads of hidden decision regions, thereby limiting the classification strength in parts of the threads. Possible reasons for this will be investigated.

References

1. M.L. Vaughn, "Derivation of the Weight Constraints for Direct Knowledge Discovery from the Multilayer Perceptron Network", *Neural Networks Journal*, Volume 12, 1999, pp.1259-1271.
2. M.L Vaughn, S.J Cavill, S.J.Taylor, M.A. Foy and A.J.B. Fogg, "Direct Explanations and Knowledge Extraction from a Multilayer Perceptron Network that Performs Low-Back-Pain Classification". In S.Wermter and R.Sun (eds.), *Hybrid Neural Systems*. Springer, pp. 270-285, 2000.
3. M.L.Vaughn, "Interpretation and Knowledge Discovery from the Multi Layer Perceptron Network: Opening the Black Box". *Neural Computing & Applications Journal*, 4(2), 1996, pp. 72-82.
4. M.L Vaughn, S.J Cavill, S.J.Taylor, M.A. Foy and A.J.B. Fogg, "Direct Explanations for the Development and Use of a Multi-Layer Perceptron Network that Classifies Low-Back-Pain Patients", *International Journal of Neural Systems*, Vol 11, No 4, 2001.
5. Looney, C.G., *"Pattern Recognition Using Neural Networks".* Oxford University Press, New York, 1997.
6. J. Denker, D. Schwarz, B. Wittner, S. Solla, R. Howard, L Jackel and J. Hopfield, "Large Automatic Learning, Rule Extraction, and Generalisation". *Journal of Complex Systems*, 1, 1987, pp. 877-922.