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Optimized Selection of Training Samples for One-Class Neural Network Classifier

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***Abstract*— One-Class Classification (OCC) based on the Auto-Associative Neural Networks (AANN) has been widely used in various recognition applications for its effective robustness. Its main advantage lies in the description of samples more accurately to other OCCs. However, it is considerably sensitive to the presence of outliers or noisy data contained into the training set, which may affect badly the representative model. Hence, we propose in this paper an algorithm that uses the AANN for selecting the most representative training samples. The same AANN is retrained to reproduce the selected samples for generating an optimal representative model. The experimental evaluation conducted on several real-world benchmarks confirms the effective use of the Selected Training Samples for Associative Neural Network (STS-AANN) versus the training on the entire set.**

Keywords—One-Class; Auto-Associative Neural Networks; Noisy data.

I. INTRODUCTION

One-Class Classification (OCC) has been designed for training only patterns belonging to the target class distribution. Originally termed by Moya et al. [1], the OCC has been also termed as Outlier Detection [2], Novelty Detection [3] or Concept Learning [4]. Its main goal is to detect anomaly or a state for the target class [5, 6]. The assumed hypothesis is that only information of the target class is available. Therefore, no information about the potential nature of other classes is needed to derive the decision boundary. Thus, OCCs are applied when the data from other classes is extremely hard or impossible to collect.

Various types of OCC have been designed [7] according the envisaged application. In this context, a taxonomy has been done where the OCC are divided into three main categories based on the way OCC has been envisaged, implemented and applied by various researchers in different application fields [8].

Neural network is one among the most useful OCCs, which is usually referred to as auto-encoder and also as auto-associative neural networks (AANN). The AANN has been used for different applications. For instance, Gupta et al. [9] and Kishore et al. [10] used the AANN for on-line text-independent speaker verification. Leena et al. [11] trained AANN for language identification for distinguishing four Indian languages. Palanivel et al. [12] used AANN for real time face authentication. Manevitz and Yousef [13] used the AANN for automated document retrieval and classification.

In their application, the AANN is trained for filtering documents under different conditions. The used AANN classifier proved its effectiveness to achieve better results than the Nearest Neighbor, Naive-Bayes, Distance-based Probability and one-class support vector machine algorithms.

Recently, the AANN has been extended to the multi-class classification problem for classifying cognitive states of brain activity [14]. A genetic algorithm has been used for feature selection in order to enhance the recognition performance.

The most used AANN architecture is based on three layers (input, hidden and output layer). Usually, the AANN is used to compress the input data to less dimensions (for feature extraction), and subsequently to decompress these data back to original dimension in order to test the reconstruction ability. This classifier relies on training to reproduce the training dataset from the inputs to its outputs through adjusting parameters till minimizing the reconstruction error.

However, the main difficulty of using the AANN is its considerable sensitivity to the presence of outliers or noisy data contained into the training set [7]. Subsequently, the model induced by AANN may suffer from poor consistency when the training set includes abnormal data samples. Therefore, training the AANN to reproduce the entire data may achieve a bad representation model which affects considerably the performance.

Hence, we propose in this paper an algorithm that uses the AANN for selecting the most representative training samples. Selected samples are used for training appropriately the AANN through the reproduction process. The proposed approach allows an optimal selection of the training samples leading to achieve a better representative model of the AANN classifier.

This paper is organized as follows. Section 2 reviews the usual neural network based one-class classification. Section 3 presents the algorithm used for selecting the most representative samples from the entire training set. Experimental results conducted on several real-world benchmarks are presented in section 4. Finally, the conclusion is provided in the last section.

II. Overview of Neural Networks Based One-Class Classification

Neural networks are composed of interconnected processing units arranged in one or several layers that can be used to implement a complex functional mapping between input and output variables. The weights of the neural network are adjusted using training samples so that an error function would be minimized over the training set.

The basic design of the AANN is termed ''bottleneck''. This design assumes that a sample represented in an m-dimensional space is mapped to fewer dimensions and then reproduced for testing the reproduction ability of the model. Usually, an AANN is composed of three layers having m inputs, m outputs and k neurons on the hidden layer, where $k < m$. The AANN is then trained using the standard back-propagation algorithm to learn the identity function over the training set. This design has been used successively by Cottrell and Zipser [15] to produce a compression algorithm and Japkowicz et al. [16] for novelty detection.

Let N training samples of the target class defined as a set $S = \{x_1, \dots, x_N\}$, the AANN is trained on each sample in order to produce an identity function f that assigns for each input $x_i \in \mathbb{R}^p$ an output $f(x_i) \in \mathbb{R}^p$, $i = 1, \dots, N$ taking ideally the following form:

$$f(x_i) = x_i \quad (1)$$

The principle of the AANN is to adjust its weights according to the reconstruction error, which is defined as the absolute distance between output and its corresponding input. Formally, the reconstruction error is defined as:

$$Er(x) = |f(x) - x| \quad (2)$$

Such that $x \in S$

A test sample x may either be rejected or accepted according to the threshold value defined in the training step.

Fig. 1 shows an example of AANN composed of inputs and outputs having the same nodes, and two nodes in the hidden layer.

The extension of the AANN to the multi-class classification is based on training each class on its respective AANN for a defined set of classes $C = \{c_1, \dots, c_L\}$, where L defines the number of classes. A test sample is assigned to the corresponding AANN when the best reconstruction is correctly achieved, (i.e. having the least reconstruction

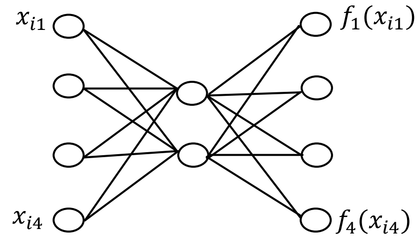


Fig. 1. The auto-associative neural network classifier

error Er). The class label $y(x)$ of a test sample x is determined as follows:

$$y(x) = \arg min\left(Er_j(x)\right), \text{with } j = 1, \dots, L \quad (3)$$

III. Selected Training Samples for Auto-Associative Neural Network

Several ways are possible for selecting the pertinent samples in order to reduce the outliers or noisy data. The most known method is based on support vectors developed by Schölkopf [17]. We propose in this work to investigate the AANN for detecting the outliers or noisy samples, then omitting them from the training set. This may lead to construct a robust representative model. The assumption relies on two main observations. First, when the AANN learns from the entire training samples, it learns the internal structure of the consistence training samples. Secondly, the outliers or noisy samples are defined as samples that have unlike structure than the consistence ones. Therefore, the reconstruction error of these samples is higher than that for the consistence ones. For instance, if the training set contains 10% of outliers, according to our assumption, those represent 10% of the highest reconstructed error among the entire training samples. This is can be explained mathematically through the following equations.

Denote S_{pr} and S_{out} the respective pertinent training sample set and the outlier set, which satisfies:

$$S = S_{pr} \cup S_{out} \quad (4)$$

The set fraction S_{out} containing N_{out} outliers is defined as a portion ν selected from the entire set S containing N samples.

$$S_{out} \subset S, N_{out} = \nu N \quad (5)$$

Such that, $$0 < \nu < 1 \quad (6)$$

Consequently, the set fraction S_{pr} of the pertinent samples that contains N_{pr} samples is defined as:

$$S_{pr} \subset S, N_{pr} = (1 - \nu)N \quad (7)$$

Denoting f_{ent} the representative model of AANN which is trained on the entire training set, the reconstruction error of each training sample x_i is then defined as:

$$Er(x_i) = \ |f_{ent}(x_i) - x_i| \quad (8)$$

We define an ordered set S_{ord} that contains the training samples which are ordered according to their reconstruction error from the minimum to the maximum value:

$$S_{ord} = \{\hat{x}_1, \dots, \hat{x}_N\} \quad (9)$$

Consequently, training samples are ordered according to their consistence values, such that $\hat{x}_1$ and $\hat{x}_N$ represent the most and the least consistence samples, respectively. Hence, the set of the most pertinent sample S_{pr} represents the first $(1-\nu)$ elements from the ordered set S_{ord} as:

$$S_{pr} = \{\hat{x}_1, \dots, \hat{x}_{(1-\nu)N}\} \quad (10)$$

Therefore, the optimal representation model is obtained through the following steps:

- **Step 1**: Train the AANN on the entire training samples S to find the initial model f_{ent}.
- **Step 2**: Order the training samples according to the reconstruction error from the minimum to the maximum value.
- **Step 3**: Select the pertinent training sample set S_{pr} according to equation 10.
- **Step 4**: Retrain the AANN on the pertinent training sample set S_{pr} to generate the optimal representative model f_{pr}.

IV. EXPERIMENTAL RESULTS

The proposed STS-AANN is evaluated against the AANN on several real-world benchmarks for solving the bi-class and multi-class classification problem. Hence, five different datasets from UCI datasets [18] are used, which are reported in table I. Each dataset is randomly divided into two subsets for training the classifier and testing its performance.

For training the classifier, different parameters should be tuned. Firstly, the number of epochs is fixed at 200, which seems widely enough for the used datasets. Another parameter that should be carefully tuned to produce a correct representative model is the number of nodes in the hidden layer. Hence, each classifier is trained on the target class by varying the number of nodes. The optimal number is selected according to the best reproduction of the training dataset and consequently the least reconstruction error. In order to select the best samples, the parameter ν is tuned between zero and one. This parameter is used for controlling the fraction or percentage of the outlier set. In this study, it is fixed as 10% from the entire training set. Consequently, ν is fixed at 0.1.

Performances of the classification are evaluated using Mean Recognition Rate (MRR). Table II reports MRR and the number of samples used for training AANN and STS-AANN.

As it can be seen from the Table II, training the AANN on the entire training set affects considerably the results on all the used datasets. Indeed, for a reduced number of samples, the MRR of the STS-AANN is higher comparatively to the AANN, which is trained on the entire set. For instance, the MRR for Breast cancer dataset is improved by more than 23% through selecting 418 samples from 465 ones.

Therefore, the most important for generating an effective representative model is not requiring a high number of training samples, but checking the consistence of the training set.

In order to prove the effective use of the proposed approach, we present an example of Banana dataset. Figure 2 shows the training samples of Banana dataset, which are mapped in their reconstruction error space generated by the initial model f_{ent}. The red stars and dots represent the first and the second classes, respectively. REF 1 and REF 2 denote the reconstruction errors of feature 1 and 2, respectively.

In order to select the most representative samples, the proposed selection algorithm is applied separately on each class. The selected samples are showed by the blue circles for the first and second classes, respectively.

We clearly note that, the consistence training samples are near to the center and thus, they are well reproduced by the model, which learnt the internal structure of target class samples. On the other hand, the outliers, which are not selected, are distributed far from the center. Therefore, the reconstruction error of these samples is higher than that for the consistence ones, which means that they have unlike structure than the consistence ones. As a result, the model that learns the internal structure from the training samples offers an easy way for detecting the outliers or noisy samples.

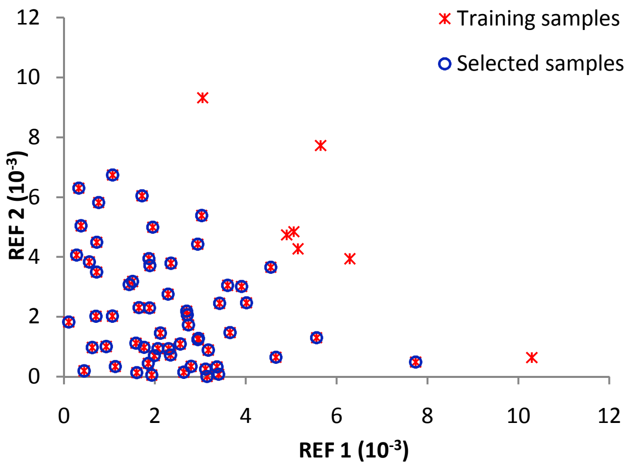
Fig. 3 shows the distribution of the training samples in their original space. As it can be seen, samples which are not similar to the majority are not selected by the algorithm. As it can be seen, the outliers are located in the borders of the training sample distribution.

TABLE I. DATASETS USED FOR EVALUATING THE PROPOSED APPROACH

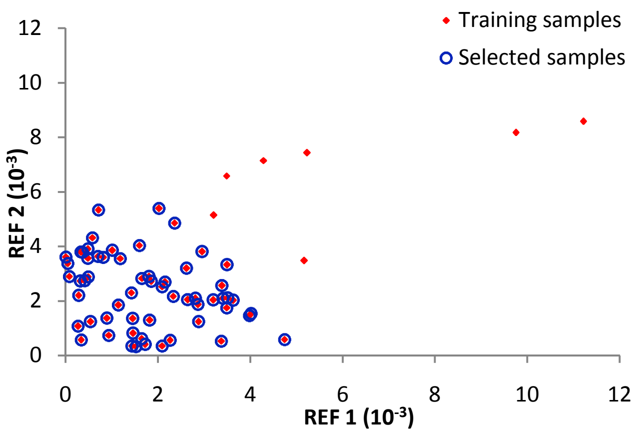
Dataset	# Classes	#Features	#Training samples	#Testing samples
Iris	3	4	99	51
Breast cancer	2	10	465	234
Glass	2	10	142	72
Pima Indian-diabetes	2	8	511	257
Banana	2	2	132	68

TABLE II. CLASSIFICATION RESULTS AND TRAINING SAMPLES NUMBER FOR BOTH CLASSIFIERS

Dataset	# Training samples		MRR (%)	
	Unselected	Selected	AANN	STS-AANN
Iris	99	**87**	90.12	**96.08**
Breast cancer	465	**418**	71.37	**94.87**
Glass	142	**127**	72.22	**93.06**
Pima Indian-diabetes	511	**459**	63.81	**70.04**
Banana	132	**118**	89.71	**92.65**

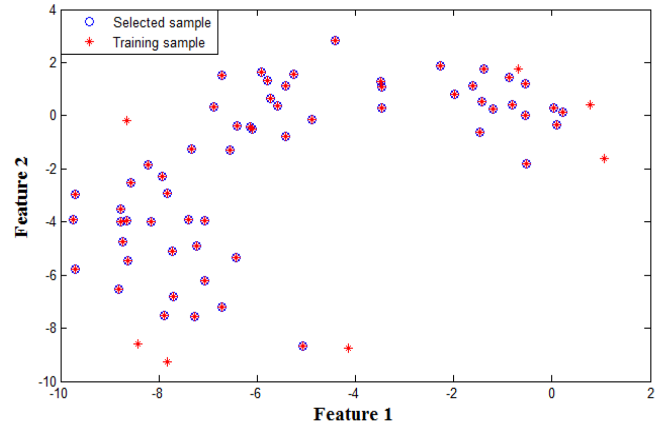


(a)

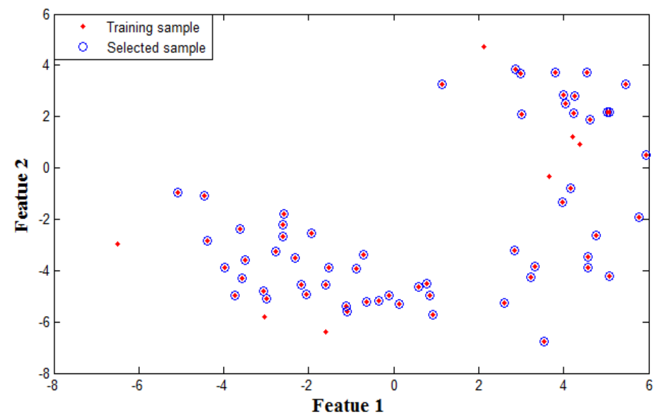


(b)

Fig. 2. Mapping the selected and unselected training samples in the reconstruction error space
(a) Class 1 (b) Class 2



(a)



(b)

Fig. 3. Mapping the selected and unselected training samples in the original space
(a) Class 1 (b) Class 2

Fig. 4 shows the effect of training sample selection through mapping test samples on both AANN and STS-AANN models (i.e. f_{pr} and f_{ent}, respectively). We can note that for the first class, there are 6 samples are missed during classification by the AANN model. In contrast, there are 5 samples missed by the STS-AANN.

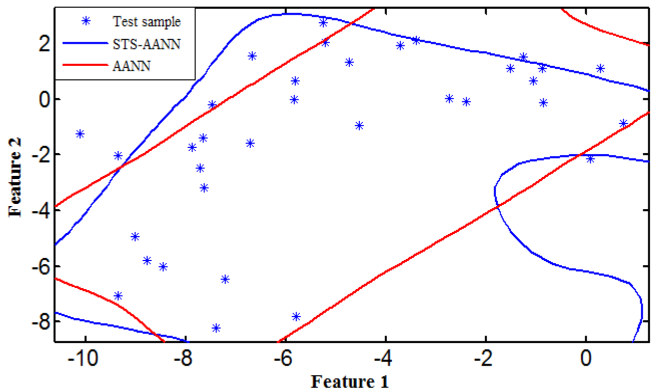
For the second class, 3 samples are outside of the AANN model, which are missed during the classification. In contrast, 2 samples are outside of the STS-AANN model.

V. CONCLUSION

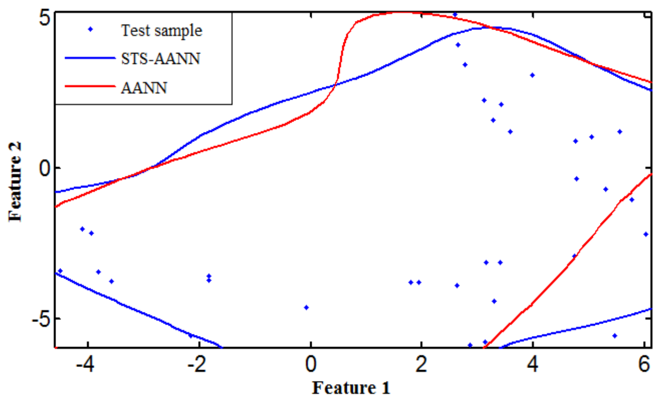
The objective of this paper aims to propose an effective selection of training samples for generating an optimal AANN model. The pertinent samples are selected according to their reconstruction error calculated between the input and its corresponding output generated by an initial model.

The proposed selection algorithm is very easy to implement and allows improving effectively the classification accuracy.

For future work, we plan to propose an algorithm that is able to tune automatically the percentage of outliers.



(a)



(b)

Fig. 4. Effect of training samples selection on the test samples (a) Class 1 (b) Class 2

REFERENCES

[1] M. Moya, M. Koch, and L. Hostetler, "One-class classifier networks for target recognition applications". In: *Proceedings World Congress on Neural Networks*, pp. 797–801 (1993)

[2] G. Ritter, and M. Gallegos, "Outliers in statistical pattern recognition and an application to automatic chromosome classification". Pattern Recognition Letters 18, 525–539 (1997)

[3] C. Bishop, "Novelty detection and neural network validation". IEEE Proceedings on Vision, Image and Signal Processing, Special Issue on Applications of Neural Networks 141(4), pp. 217–222, (1994)

[4] N. Japkowicz, "Concept-Learning in the absence of counterexamples: An autoassociation-based approach to classification". PhD thesis, New Brunswick Rutgers, The State University of New Jersey (1999)

[5] D.M.J. Tax, and R. P.W. Duin, "Characterizing one-class datasets". In Proceedings of the Sixteenth Annual Symposium of the Pattern Recognition Association of South Africa. (2005) 21–26.

[6] B. Krawczyk, and M. Wo´zniak. 2012. "Experiments on distance measures for combining one-class classifiers". in 2012 Federated Conference on Computer Science and Information Systems, pp.89–92. FedCSIS, 2012

[7] D.M.J. Tax, 2001. "One-class classification". PhD Thesis, Delft University of Technology. ISBN: 90-75691-05-x, 2001.

[8] Khan, S.S., Madden, M.G. "A survey of recent trends in one class classication". In: Articial Intelligence and Cognitive Science - 20th Irish Conference. Lecture Notes in Computer Science, vol. 6206, pp. 188-197. Springer (2010)

[9] Cheedella S. Gupta, S. R. Mahadeva Prasanna, and B. Yegnanarayana, "Autoassociative neural network models for online speaker verification using source features from vowels", INNS-IEEE International Joint Conference on Neural Networks, Hawaii, USA, May 12-17, 2002.

[10] Leena Mary and B. Yegnanarayana. "Autoassociative neural network models for language Identification". In 2004. Proceedings of International Conference, Intelligent Sensing and Information Processing, pp. 317-320, 2004.

[11] S. Palanivel, B. S. Venkatesh and B. Yegnanarayana, "Real time face authentication system using autoassocaitive neural network models". IEEE International Conference on Multimedia and Expo., pp. 257-260, Baltimore, July 2003.

[12] S. P. Kishore, B. Yegnanarayana and Suryakanth V. Gangas hetty, "Online text-independent speaker verification system using autoassociative neural network models". Proc. INNS-IEEE International Joint Conference on Neural Networks, Washington DC,USA, vol.2(4), pp. 1548-1553, July 14-19, 2001

[13] L. Manevitz, and M. Yousef, "One-class document classification via Neural Networks", Neurocomputing, vol. 70, pp. 1466–1481, 2007.

[14] O. Boehm, D. R. Hardoon, and L. M. Manevitz." Classifying cognitive states of brain activity via one-class neural networks with feature selection by genetic algorithms". *Int. J. Mach. Learn. & Cyber,* vol. 2, pp. 125–134, 2011.

[15] G.W. Cottrell, P.W. Munro, D. Zipser, "Image compression by back propagation: a demonstration of extensional programming". In: Sharkey NE (ed) Advances in cognitive science, vol 2. Abbex, Norwood, (N J) (1988).

[16] Japkowicz, N., Myers, C., and Gluck M. A.: 1995, 'A Novelty Detection Approach to Classification'. In: Proceedings of the 14th International Conference on Artificial Intelligence (IJCAI-95). pp. 518–523.

[17] B. Schölkopf, J.C. Platt, J. Shawe-Taylor, A.J. Smola, and R.C. Williamson. 2001. "Estimating the support of a high-dimensional distribution". Neural Computation, Vol. 13, no.7, pp.1443-14472.

[18] A. Frank, A. Asuncion, UCI machine learning repository (2012), http://archive.ics.uci.edu/ml