An Enhanced Probabilistic Neural Network Approach Applied to Text Classification

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Abstract. Text classification is still a quite difficult problem to be dealt with both by the academia and by the industrial areas. On the top of that, the importance of aggregating a set of related amount of text documents is steadily growing in importance these days. The presence of multi-labeled texts and great quantity of classes turn this problem even more challenging. In this article we present an enhanced version of Probabilistic Neural Network using centroids to tackle the multi-label classification problem. We carried out some experiments comparing our proposed classifier against the other well known classifiers in the literature which were specially designed to treat this type of problem. By the achieved results, we observed that our novel approach were superior to the other classifiers and faster than the Probabilistic Neural Network without the use of centroids.

Keywords: Information Retrieval, Probabilistic Neural Network, Multi-label Problem.

1 Introduction

Automatic text classification is an activity that is becoming more and more important nowadays. This might be due to the huge amount of information available and the great challenge for the information retrieval. In addition, many of real databases are multi-labeled and have a great amount of categories, which make the text classification task even more difficult [1]. Such problems are tackled by the information retrieval (IR) communities, both in academic and industrial contexts.

To treat such issues, in this paper we used a slightly modified version of the standard structure of the Probabilistic Neural Network (PNN) presented in [3]. In this modified version, we used centroids for the training of the PNN. In order to evaluate these PNN's versions, the classical one and that proposed by us in this paper, we used a set of multi-labeled Yahoo's databases, initially used in [6]. Furthermore, we compared their results against the other specialized classifiers in multi-labeled classification. Both versions of the PNN achieved better results, in our evaluation, than that performed by the other classifiers. The enhanced PNN with centroids was the best in our evaluation.

This work is organized as follows. In Section 2, we detail our algorithms. We describe the metrics used to evaluate in Section 3. In Section 4, the experiments and results are discussed. Finally, we present our conclusions in Section 5.

2 The Algorithms

The Probabilistic Neural Network is an artificial neural network for nonlinear computing which approaches the Bayes optimal decision boundaries. The original PNN algorithm [2] was designed for single-label problems. Thus, its standard architecture was slightly modified, so that it is now capable of solving multi-labeled problems.

In this modified version, instead of four, the PNN is composed of only three layers: the *input* layer, the *pattern* layer and the *summation* layer, as it is showed in Figure 1. Thus, like in the original structure, this version of PNN needs only one training step, therefore, its training is faster than other well known feed-forward neural networks [4].

The training consists in assigning each training sample w_j of category C_j to a neuron of pattern layer of category C_j . Thus, the weight vector of this neuron is the characteristics vector of the sample.

For each d_j test instance passed by the input layer to a neuron in the pattern layer, it computes the output for the d_j . The computation is showed in Equation 1.

$$F_{k,i}(d_j) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{d_j^t w_{k,i} - 1}{\sigma^2}\right), \quad (1)$$

where the d_j is the pattern characteristics input vector, and the $w_{k,i}$ is the k^{th} sample for a neuron of category C_i , $k \in N_i$, whereas N_i is the number of neurons of C_i . In addition, d_j and $w_{k,i}$ were normalized so that $d_j^t d_j = 1$ and $w_{k,i}^t w_{k,i} = 1$. The σ is the Gaussian standard deviation, which determines the receptive field of the Gaussian curve.

The next step is the summation layer. In this layer, all outputs of the previous layer are summed, Equation 2, in each cluster C_i producing $p_i(d_j)$ values, where $|C|$ is the total number of categories and h_i is the priori probability of the class C_i . Whether we consider the priori probability from database of training, so we can inconsiderate the fraction $\frac{h_i}{N_i}$.

Fig. 1. The modified Probabilistic Neural Network architecture

$$p_i(d_j) = \frac{h_i}{N_i} \sum_{k=1}^{N_i} F_{k,i}(d_j) \quad i = 1, 2, \dots, |C|. \quad (2)$$

Finally, for the selection of the categories which will be assigned by the neural network to each sample, we consider the most likely categories pointed out by the summation layer based on a chosen threshold.

Differently from other types of networks, such as those feed forward based, the proposed PNN needs few parameters to be configured: the σ , (see in Equation 1) and the determination of threshold value. Another advantage of the probabilistic neural networks is that it is easy to add new categories, or new training inputs, into the already running structure, which is good for the on-line applications [4]. On the other hand, one of its drawbacks is the great number of neurons in the pattern layer that, as a consequence, may produce a high consumption of memory and slow rate of classification. Moreover, the presence of repeated samples may harm the performance of the classifier.

2.1 Probabilistic Neural Network with Centroids

To minimize the drawbacks of the PNN, we propose a technique of centroids, such that is used only one neuron for class in the pattern layer. Equation 3 shows a mathematical procedure to obtain the centroid for each class C_i , where $w_{k,i}$ is the k^{th} sample of training of class C_i , N_i is the number of samples of C_i and W_i is the obtained centroid. To reduce the loss of information, we also obtain from database the priori probability h_i of each class. Thus, the fraction $\frac{h_i}{N_i}$ of Equation 2 will be reduced to h_i , because N_i will be equal to 1, and the centroid W_i is associated to the neuron of pattern layer of class C_i . Hence, with this procedure, the PNN will have only one neuron per category in the pattern layer.

$$W_i = \frac{1}{N_i} \sum_{k=1}^{N_i} w_{k,i} \quad h_i = N_i \quad i = 1, \dots, |C|. \quad (3)$$

3 Metrics

Formalizing the problem we have at hand, text categorization may be defined as the task of assigning documents to a predefined set of categories, or classes [1]. In multi-label text categorization a document may be assigned to one or more categories. Let $\mathcal{D}$ be the domain of documents, $\mathcal{C} = \{c_1, c_2, \dots, c_{|C|}\}$ a set of pre-defined categories, and $\Omega = \{d_1, d_2, \dots, d_{|\Omega|}\}$ an initial corpus of documents previously categorized by some human specialists into subsets of categories of $\mathcal{C}$.

In multi-label learning, the training(-and-validation) set $TV = \{d_1, d_2, \dots, d_{|TV|}\}$ is composed of a number documents, each associated with a subset of categories in $\mathcal{C}$. TV is used to train and validate (actually, to tune eventual parameters of) a categorization system that associates the appropriate combination of categories to the characteristics of each document in the TV . The test set $Te = \{d_{|TV|+1}, d_{|TV|+2}, \dots, d_{|\Omega|}\}$, on the other hand, consists of documents for which the categories are unknown to the automatic categorization systems. TV has $|TV|$ samples and Te has $|\Omega| - |TV| = p$ samples. After

being trained, as well as tuned, by the *TV*, the categorization systems are used to predict the set of categories of each document in *Te*.

A multi-label categorization system typically implements a real-valued function of the form $f: \mathcal{D} \times \mathcal{C} \rightarrow \mathbb{R}$ that returns a value for each pair $\langle d_j, c_j \rangle \in \mathcal{D} \times \mathcal{C}$ that, roughly speaking, represents the evidence for the fact that the test document d_j should be categorized under the category $c_j \in C_j$, where $C_j \subset \mathcal{C}$. The real-valued function $f(.,.)$ can be transformed into a ranking function $r(.,.)$, which is an one-to-one mapping onto $\{1, 2, \dots, |\mathcal{C}|\}$ such that, if $f(d_j, c_1) > f(d_j, c_2)$, then $r(d_j, c_1) < r(d_j, c_2)$. If C_j is the set of proper categories for the test document d_j , then a successful categorization system tends to rank categories in C_j higher than those not in C_j . Additionally, we also use a threshold parameter so that those categories that are ranked above the threshold τ (i.e., $c_k | f(d_j, c_k) \geq \tau$) are the only ones to be assigned to the test document.

We have used five multi-label metrics discussed in [6] to evaluate the performance of classifiers. We now present each one of these metrics:

Hamming Loss (hloss) evaluates how many times the test document d_j is misclassified, i.e., a category not belonging to the document is predicted or a category belonging to the document is not predicted.

$$\text{hloss} = \frac{1}{p} \sum_{j=1}^p \frac{1}{|C|} |P_j \Delta C_j|, \quad (4)$$

where $|C|$ is the number of categories and Δ is the symmetric difference between the set of predicted categories P_j and the set of appropriate categories C_j of the test document d_j . The predicted categories are those which rank higher than the threshold τ .

One-error (one-error) evaluates if the top ranked category is present in the set of appropriate categories C_j of the test document d_j .

$$\text{one-error} = \frac{1}{p} \sum_{j=1}^p \text{error}_j, \quad \text{error}_j = \begin{cases} 0 & \text{if } [\arg \max_{c \in \mathcal{C}} f(d_j, c)] \in C_j \\ 1 & \text{otherwise.} \end{cases} \quad (5)$$

where $[\arg \max_{c \in \mathcal{C}} f(d_j, c)]$ returns the top ranked category for the test document d_j .

Coverage (coverage) measures how far we need to go down the rank of categories in order to cover all the possible categories assigned to a test document.

$$\text{coverage} = \frac{1}{p} \sum_{j=1}^p (\max_{c \in C_j} r(d_j, c) - 1), \quad (6)$$

where $\max_{c \in C_j} r(d_j, c)$ returns the maximum rank for the set of appropriate categories of the test document d_j .

Ranking Loss (rloss) evaluates the fraction of category pairs $\langle c_k, c_l \rangle$, for which $c_k \in C_j$ and $c_l \in \bar{C}_j$, that are reversely ordered for the test document d_j :

$$\text{rloss} = \frac{1}{p} \sum_{j=1}^p \frac{|\{(c_k, c_l) | f(d_j, c_k) \leq f(d_j, c_l)\}|}{|C_j| |\bar{C}_j|}, \quad (7)$$

where $(c_k, c_l) \in C_j \times \bar{C}_j$, and $\bar{C}_j$ is the complementary set of C_j in $\mathcal{C}$.

Average Precision (avgprec) evaluates the average of precision computed after truncating the ranking of categories after each category $c_i \in C_j$ in turn:

$$\text{avgprec} = \frac{1}{p} \sum_{j=1}^p \frac{1}{|C_j|} \sum_{k=1}^{|C_j|} \text{precision}_j(R_{jk}), \quad (8)$$

where R_{jk} is the set of ranked categories that goes from the top ranked category until a ranking position k , where there is a category $c_i \in C_j$ for d_j , and $\text{precision}_j(R_{jk})$ is the number of pertinent categories in R_{jk} divided by $|R_{jk}|$.

The smaller the value of *hamming loss*, *one-error*, *coverage* and *ranking loss*, and the larger the value of *average precision*, the better the performance of the categorization system. The performance is optimal when $\text{hloss} = \text{one-error} = \text{rloss} = 0$ and $\text{avgprec} = 1$.

4 Experiments

We carry out a series of experiments to compare the versions of PNN against the classifiers: ML-kNN, that is based on the kNN [6], Rank-SVM [9], a modified version of SVM, ADTBoost.MH [7] and BoosTexter [8], that both are techniques based on decision trees. We have used 11 text databases from Yahoo domain in our experiments¹, where each database has 2000 samples to training and 3000 to test, the average number of classes is 30 and there is a mean of 1.48 classes assigned by sample. To evaluate the performance of the algorithms we used the metrics presented in Section 3², and the results were obtained directly from the [6], with exception of the PNNs' results.

In [6] is not mentioned any use of a search strategy for the optimization of the classifiers' parameters. To turn it in a fair comparison with the other techniques, we will test our approaches of PNNs considering only the order of magnitude of the variance's value. For this, we used part of training set of Arts database from Yahoo and we tested the variance's values 10, 1 and 0.1 on a cross-validation experiment. The chosen value was 0.1. The threshold's value used to the Hamming Loss metric was 0.5, the same value used by ML-kNN, therefore, this parameter was also not optimized to the PNNs.

The results yielded with the use of the Yahoo's database are presented in Tables from 1 to 5. Each one of the tables represents a metric, where each row is a data set and each column is a classifier. The term "Average" in the last row means the average value of the metric obtained by each classifier to all databases.

To accomplish a clearer evaluation of the classifiers, we adopted two criteria derived from [6]. The first criterion creates one partial order " $\succ$ " that evaluates the performance between two classifiers for each metric. In that way, if the classifier A1 has a better performance than A2 to a given metric, so we have $A1 \succ A2$. In order to perform this task, we used two-tailed paired t-test at 5% significance level.

However, the presented criterion is insufficient to obtain the performance of classifiers as a whole, therefore, we used a second criterion. In this one is applied a system

¹ Databases and codes of the versions of PNN are available at <http://www.inf.ufes.br/~elias/ciarp2009.zip>

² Ranking Loss to ADTBoost.MH was not reported because, according to [6], the algorithm of this classifier did not supply such information.

Table 1. Hamming Loss obtained by the classifiers

Data Set	ML-kNN	BoosTexter	ADTBoost.MH	Rank-SVM	PNN	PNN-centroid
Arts&Humanities	0.0612	0.0652	0.0585	0.0615	0.0630	0.0626
Business&Economy	0.0269	0.0293	0.0279	0.0275	0.0307	0.0289
Computers&Internet	0.0412	0.0408	0.0396	0.0392	0.0447	0.0412
Education	0.0387	0.0457	0.0423	0.0398	0.0437	0.0437
Entertainment	0.0604	0.0626	0.0578	0.0630	0.0640	0.0635
Health	0.0458	0.0397	0.0397	0.0423	0.0514	0.0481
Recreation&Sports	0.0620	0.0657	0.0584	0.0605	0.0634	0.0631
Reference	0.0314	0.0304	0.0293	0.0300	0.0307	0.0289
Science	0.0325	0.0379	0.0344	0.0340	0.0353	0.0353
Social&Science	0.0218	0.0243	0.0234	0.0242	0.0281	0.0245
Society&Culture	0.0537	0.0628	0.0575	0.0555	0.0596	0.0599
Average	0.0432	0.0459	0.0426	0.0434	0.0468	0.0454

Table 2. One-Error obtained by the classifiers

Data Set	ML-kNN	BoosTexter	ADTBoost.MH	Rank-SVM	PNN	PNN-centroid
Arts&Humanities	0.6330	0.5550	0.5617	0.6653	0.5597	0.5293
Business&Economy	0.1213	0.1307	0.1337	0.1237	0.1317	0.1313
Computers&Internet	0.4357	0.4287	0.4613	0.4037	0.4457	0.4557
Education	0.5207	0.5587	0.5753	0.4937	0.5463	0.5420
Entertainment	0.5300	0.4750	0.4940	0.4933	0.5530	0.4960
Health	0.4190	0.3210	0.3470	0.3323	0.4080	0.3807
Recreation&Sports	0.7057	0.5557	0.5547	0.5627	0.6037	0.5670
Reference	0.4730	0.4427	0.4840	0.4323	0.4780	0.4727
Science	0.5810	0.6100	0.6170	0.5523	0.6123	0.5930
Social&Science	0.3270	0.3437	0.3600	0.3550	0.3753	0.3703
Society&Culture	0.4357	0.4877	0.4845	0.4270	0.4647	0.4637
Average	0.4711	0.4463	0.4612	0.4401	0.4708	0.4547

Table 3. Coverage obtained by the classifiers

Data Set	ML-kNN	BoosTexter	ADTBoost.MH	Rank-SVM	PNN	PNN-centroid
Arts&Humanities	5.4313	5.2973	5.1900	9.2723	4.8503	4.6250
Business&Economy	2.1840	2.4123	2.4730	3.3637	2.1087	2.0527
Computers&Internet	4.4117	4.4887	4.4747	8.7910	4.0380	3.8963
Education	3.4973	4.0673	3.9663	8.9560	3.4980	3.4067
Entertainment	3.1467	3.0883	3.0877	6.5210	3.0663	2.8883
Health	3.3043	3.0780	3.0843	5.5400	3.0093	2.8730
Recreation&Sports	5.1010	4.4737	4.3380	5.6680	4.2773	4.0573
Reference	3.5420	3.2100	3.2643	6.9683	2.9097	2.7560
Science	6.0470	6.6907	6.6027	12.401	5.9930	5.6180
Social&Science	3.0340	3.6870	3.4820	8.2177	3.1357	2.9430
Society&Culture	5.3653	5.8463	4.9545	6.8837	5.3350	5.2323
Average	4.0968	4.2127	4.0834	7.5075	3.8383	3.6681

Table 4. Ranking Loss obtained by the classifiers

Data Set	ML-kNN	BoosTexter	ADTBoost.MH	Rank-SVM	PNN	PNN-centroid
Arts&Humanities	0.1514	0.1458	N/A	0.2826	0.1306	0.1223
Business&Economy	0.0373	0.0416	N/A	0.0662	0.0367	0.0349
Computers&Internet	0.0921	0.0950	N/A	0.2091	0.0826	0.0787
Education	0.0800	0.0938	N/A	0.2080	0.0803	0.0773
Entertainment	0.1151	0.1132	N/A	0.2617	0.1103	0.1025
Health	0.0605	0.0521	N/A	0.1096	0.0526	0.0491
Recreation&Sports	0.1913	0.1599	N/A	0.2094	0.1556	0.1432
Reference	0.0919	0.0811	N/A	0.1818	0.0732	0.0685
Science	0.1167	0.1312	N/A	0.2570	0.1166	0.1073
Social&Science	0.0561	0.0684	N/A	0.1661	0.0601	0.0546
Society&Culture	0.1338	0.1483	N/A	0.1716	0.1315	0.1286
Average	0.1024	0.1028	N/A	0.1930	0.0936	0.0879

Table 5. Average Precision obtained by the classifiers

Data Set	ML-kNN	BoosTexter	ADTBoost.MH	Rank-SVM	PNN	PNN-centroid
Arts&Humanities	0.5097	0.5448	0.5526	0.4170	0.5645	0.5851
Business&Economy	0.8798	0.8697	0.8702	0.8694	0.8763	0.8779
Computers&Internet	0.6338	0.6449	0.6235	0.6123	0.6398	0.6420
Education	0.5993	0.5654	0.5619	0.5702	0.5889	0.5980
Entertainment	0.6013	0.6368	0.6221	0.5637	0.5991	0.6295
Health	0.6817	0.7408	0.7257	0.6839	0.7047	0.7207
Recreation&Sports	0.4552	0.5572	0.5639	0.5315	0.5396	0.5672
Reference	0.6194	0.6578	0.6264	0.6176	0.6441	0.6512
Science	0.5324	0.5006	0.4940	0.5007	0.5073	0.5278
Social&Science	0.7481	0.7262	0.7217	0.6788	0.7113	0.7272
Society&Culture	0.6128	0.5717	0.5881	0.5717	0.5993	0.6018
Average	0.6249	0.6378	0.6318	0.6015	0.6341	0.6480

Table 6. Relative performance of the classifiers by the two criteria

HL-Hamming Loss; OE-One-error; C-Coverage; RL-Ranking Loss; AP-Average Precision A1-ML-kNN; A2-BoosTexter; A3-ADTBoost.MH; A4-Rank-SVM; A5-PNN; A6-PNN-centroid	
Metrics	Criterion 1
HL	A1 > A5, A1 > A6, A3 > A2, A4 > A2, A3 > A5, A3 > A6, A4 > A5, A4 > A6, A6 > A5
OE	A2 > A3, A2 > A5, A6 > A5
C	A1 > A4, A5 > A1, A6 > A1, A2 > A4, A5 > A2, A6 > A2, A3 > A4, A5 > A3, A6 > A3, A5 > A4, A6 > A4, A6 > A5
RL	A1 > A4, A5 > A1, A6 > A1, A2 > A4, A5 > A2, A6 > A2, A5 > A4, A6 > A4, A6 > A5
AP	A2 > A4, A3 > A4, A6 > A3, A5 > A4, A6 > A4, A6 > A5
Techniques	Criterion 2
ML-kNN	{PNN, PNN-centroid} > ML-kNN > Rank-SVM
BoosTexter	{PNN,PNN-centroid} > BoosTexter > Rank-SVM
ADTBoost.MH	PNN-centroid > ADTBoost.MH > Rank-SVM
Rank-SVM	{ML-kNN, BoosTexter, ADTBoost.MH,PNN, PNN-centroid} > Rank-SVM
PNN	PNN-centroid > PNN > {ML-kNN, BoosTexter, Rank-SVM}
PNN-centroid	PNN-centroid > {ML-kNN, BoosTexter, Rank-SVM, ADTBoost.MH, PNN}

based on rewards and punishes. For example, for the case of $A1 \succ A2$ the classifier A1 is rewarded with +1 and the classifier A2 is punished with -1. Then, we compare the classifiers two a two through of the sum of their rewarded and punished between them. In this case, if A1 have a positive value in relation to A2, so A1 is superior to A2, *i. e.*, $A1 > A2$. Thus, the results obtained by the two criteria are shown in Table 6.

Table 6 shows that PNN-centroid is superior over to every algorithm, while the Rank-SVM is the worst. Moreover, the PNN shows to be the second better, being inferior just to the PNN-centroid and it had similar performance to ADTBoost.MH, whereas the other classifiers (ML-kNN, ADTBoost.MH and BoosTexter) were superior just to Rank-SVM. In addition, the PNN-centroid had a low time for classification (more than 10 times faster) and a small consumption of memory, when we compared with the PNN. Finally, the training phase of both PNNs was faster than the other algorithms.

5 Conclusions

The problem of text classification is still greatly challenging, due to the huge amount of information available. Other issues are the great quantity of classes and the presence of multi-labeled databases, which together increase the difficult of this task.

In this work, we presented an experimental evaluation on multi-label text classification of the performance of Probabilistic Neural Network and another version of it

with centroids. Therefore, we conducted a comparative study of these PNNs and other four classifiers specially designed to solve this problem. The results showed that both versions of PNN devised by us presented good results, specially the PNN with centroids, that was superior to all the other classifiers. In addition, our approach is faster and consumed less memory than PNN without centroids.

A direction for future works is to study methods that can improve the results found in this article even more. Moreover, we are planning to tackle the problem of on-line learning using the proposed neural network in this paper.

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