Multi-Label Text Categorization with a Data Correlated VG-RAM Weightless Neural Network

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Abstract: In multi-label text categorization, one or more labels (or categories) can be assigned to a single document. In many such categorization tasks, there can be correlation on the assignment of subsets of the set of categories. This can be exploited to improve machine learning techniques devoted to multi-label text categorization. In this paper, we examine a Virtual Generalizing Random Access Memory Weightless Neural Network (VG-RAM WNN) architecture that takes advantage of the correlation between categories to improve text categorization performance. We compare the performance of this architecture, that we named Data Correlated VG-RAM WNN (VG-RAM WNN-COR), with that of standard VG-RAM WNN and ML-KNN categorizers using ten multi-label text categorization performance metrics. Our experimental results show that VG-RAM WNN-COR has an overall better performance than VG-RAM WNN and ML-KNN for the set of metrics considered.

Keywords: VG-RAM Weightless Neural Networks, machine learning, multi-label text categorization, label correlation, categorization of economic activities, multi-label text categorization performance metrics

I. Introduction

Most works on text categorization in the literature are focused on single-label text categorization problems, where each document may only have a single label [16]. However, in real-world problems, multi-label categorization is frequently necessary [15, 5, 4, 17, 3, 6, 13, 20, 21]. From a theoretical point of view, single-label categorization is more general than multi-label, since an algorithm for single-label categorization can also be used for multi-label categorization: one needs only to transform the multi-label categorization problem into \( n \) independent single-label problems, where \( n \) is the number of possible labels (or categories) [16]. However, this equivalence only holds if the \( n \) categories are stochastically independent, that is, the association of a category \( c_i \) to a document is independent of the association of another category, \( c_j \), to the same document, which is frequently not the case. Fortunately, several techniques for multi-label categorization have been proposed, such as multi-label decision trees [4], kernel methods [5, 3] or neural networks [13, 20], and many of them specifically for multi-label text categorization [15, 17, 6, 13, 20]. Multi-label categorization systems can take advantage of the correlation between categories in order to improve their performance.
ology, and Section VI our experimental results. Our conclusions follow in Section VII.

II. Multi-Label Text Categorization

Text categorization may be defined as the task of assigning categories (or labels), from a predefined set of categories, to documents [16]. In multi-label text categorization, one or more categories may be assigned to a document.

Let $D$ be the domain of documents, $\mathcal{C} = \{c_1, \ldots, c_{|C|}\}$ a set of pre-defined categories, and $\Omega = \{d_1, \ldots, d_{|\Omega|}\}$ an initial corpus of documents previously categorized manually by a domain expert into subsets of categories of $\mathcal{C}$. In multi-label learning, the training-(and-validation) set $TV = \{d_1, \ldots, d_{|TV|}\}$ is composed of a number of documents, each associated with a subset of categories of $\mathcal{C}$. $TV$ 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 $Te = \{d_{|TV|+1}, \ldots, d_{|\Omega|}\}$, on the other hand, consists of documents for which the categories are unknown to the categorization system. After being trained and tuned on $TV$, the categorization system is 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 $f : D \times C \mapsto \mathbb{R}$ that returns a degree of belief for each pair $(d, c) \in D \times C$, that is, a number between 0 and 1 that, roughly speaking, represents the confidence with which the test document $d_j$ should be categorized under the category $c_i$. The real-valued function $f(\cdot)$ can be transformed into a ranking function $r(\cdot)$, such that, if $f(d_j, c_i) > f(d_j, c_k)$, then $r(d_j, c_i) < r(d_j, c_k)$, and if $f(d_j, c_i) < f(d_j, c_k)$, then $r(d_j, c_i) > r(d_j, c_k)$. If $f(d_j, c_i) = f(d_j, c_k)$ we have a tie.

When there are no ties, i.e., $f(d_j, c_i) \neq f(d_j, c_k)$ for all $i \neq k$, $f(\cdot)$ can be transformed into a ranking function $r(\cdot)$ that is an one-to-one mapping onto $\{1, 2, \ldots, |C|\}$. However, if there are ties ($f(d_j, c_i) = f(d_j, c_k)$ for some $i \neq k$), the categories can be ranked in many different ways.

In this paper, we adopted the ranking method called ordinal ranking [18], that assigns distinct ordinal ranking positions to all categories, including those tied. In this method, the assignment of distinct ordinal ranking positions to tied categories is done at random.

Let $C_j$ be the set of pertinent categories of the test document $d_j$, and $\hat{C}_j$ the set of categories predicted for $d_j$. A successful categorization system will tend to rank categories in $C_j$ higher than those not in $\hat{C}_j$. Those categories $c_i$ ranked above a threshold $\tau_i$ are then predicted to the test document $d_j$, i.e., $\hat{C}_j' = \{c_i | f(d_j, c_i) \geq \tau_i\}$.

III. VG-RAM WNN and VG-RAM WNN-COR

RAM-based neural networks [1], also known as weightless neural networks (WNN), do not store knowledge in their connections but in Random Access Memories (RAM) inside the network’s nodes, or neurons. In spite of their remarkable simplicity, WNN are very effective as pattern recognition tools, offering fast training and test, and easy implementation [2]. However, if the network input is too large, the memory size of the neurons of WNN becomes prohibitive, since it must be equal to $2^n$, where $n$ is the input size. Virtual Generalizing RAM (VG-RAM) networks are RAM-based neural networks that only require memory capacity to store the data related to the training set [9].

A. VG-RAM WNN Neurons

VG-RAM WNN neurons store the input-output pairs seen during training, instead of only the output. In the test phase, the memory of VG-RAM neurons is searched associatively by comparing the input presented to the network with all inputs in the input-output pairs learned. The output of each VG-RAM neuron is taken from the pair whose input is nearest to the input presented—the distance function employed by VG-RAM neurons is the Hamming distance. If there is more than one pair at the same minimum distance from the input presented, the neuron’s output is chosen randomly among these pairs.

<table>
<thead>
<tr>
<th>lookup table</th>
<th>X1</th>
<th>X2</th>
<th>X3</th>
<th>Y</th>
</tr>
</thead>
<tbody>
<tr>
<td>entry #1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>category 1</td>
</tr>
<tr>
<td>entry #2</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>category 2</td>
</tr>
<tr>
<td>entry #3</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>category 3</td>
</tr>
<tr>
<td>input</td>
<td>↑</td>
<td>↑</td>
<td>↓</td>
<td></td>
</tr>
</tbody>
</table>

Figure 1: VG-RAM WNN lookup table.

Figure 1 shows the lookup table of a VG-RAM neuron with three synapses ($X_1$, $X_2$, and $X_3$). This lookup table contains three entries (input-output pairs), which were stored during the training phase (entry #1, entry #2 and entry #3). During the test phase, when an input vector (input) is presented to the network, the VG-RAM test algorithm computes the distance between this input vector and each input of the input-output pairs stored in the lookup table. In the example of Figure 1, the Hamming distance from the input to entry #1 is two, because both $X_2$ and $X_3$ bits do not match the input vector. The distance to entry #2 is one, because $X_1$ is the only non-matching bit. The distance to entry #3 is three, as the reader may easily verify. Hence, for this input vector, the algorithm evaluates the neuron’s output, $Y$, as category 2, since it is the output value stored in entry #2.

B. VG-RAM WNN-COR Neurons

While in VG-RAM WNN each neuron is trained to output a single category for each input vector, in VG-RAM WNN-COR each neuron may be trained to output a set of categories for each input vector.

Figure 2 illustrates the lookup table of a VG-RAM WNN-COR neuron with three synapses ($X_1$, $X_2$, and $X_3$) and three entries (input-output pairs) stored during the training phase (entry #1, entry #2 and entry #3). Similar to VG-RAM WNN, when an input vector is presented to the network in the test phase, the VG-RAM WNN COR test algorithm computes the distance between this input vector and each input of the input-output pairs in the lookup table. In the example of Figure 1, the Hamming distance from the input to entry #1 is two, because both $X_2$ and $X_3$ bits do not match the input vector. The distance to entry #2 is one, because $X_1$ is the only non-matching bit. The distance to entry #3 is three, as the reader may easily verify. Hence, for this input vector, the algorithm evaluates the neuron’s output, $Y$, as category 2, since it is the output value stored in entry #2.
and 3, i.e. the value of $Y$ represents both categories, 1 and 3.

<table>
<thead>
<tr>
<th>lookup table</th>
<th>$X_1$</th>
<th>$X_2$</th>
<th>$X_3$</th>
<th>$Y$</th>
</tr>
</thead>
<tbody>
<tr>
<td>entry #1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>category 2</td>
</tr>
<tr>
<td>entry #2</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>category 1, 3</td>
</tr>
<tr>
<td>entry #3</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>category 1, 2, 3</td>
</tr>
<tr>
<td>input</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>category 1, 3</td>
</tr>
</tbody>
</table>

**Figure. 2**: VG-RAM WNN-COR lookup table.

### C. Text Categorization with VG-RAM WNN and VG-RAM WNN-COR

To categorize text documents using VG-RAM WNN, we represent a document as a multidimensional vector $V = \{v_1, \ldots, v_{|V|}\}$, where each element $v_i$ corresponds to a weight associated to a specific term in the vocabulary of interest (see Section V-B). We use single layer VG-RAM WNN (Figure 3) whose neurons’ synapses $X = \{x_1, \ldots, x_{|X|}\}$ are randomly connected to the network’s input $N = \{n_1, \ldots, n_{|N|}\}$, which has the same size of the vectors representing the documents, i.e., $|N| = |V|$. Note that $|X| < |V|$ (our experiments have shown that $|X| < |V|$ provides better performance). Each neuron’s synapse $x_i$ forms a minchinton cell with the next, $x_{i+1}$ ($x_{i|X|}$ forms a minchinton cell with $x_1$) [11]. The type of the minchinton cell we have used returns 1 if the synapse $x_i$ of the cell is connected to an input neuron $n_j$ whose value is larger than that of the element $n_k$ to which the synapse $x_{i+1}$ is connected (i.e, $n_j > n_k$); otherwise, it returns zero.

During training, for each document in the training set, the corresponding vector $V$ is connected to the VG-RAM WNN’s input $N$ and the neurons’ outputs $O = \{o_1, \ldots, o_{|O|}\}$ to one of the categories of the document. All neurons of the VG-RAM WNN are then trained to output this category with this input vector. The training for this input vector is repeated for each category associated with the corresponding document. During test, for each test document, the inputs are connected to the corresponding vector and the number of neurons outputting each category is counted. The network’s output is computed by dividing the count of each category by the number of neurons of the network. This output is organized as a vector whose size is equal to the number of categories. The value of each vector element varies from 0 to 1 and represents the percentage of neurons which presented the corresponding category as output (the sum of the values of all elements of this vector is always equal to 1). In this way, the output of the network implements the function $f(\cdot)$, defined in Section II.

To categorize text documents using VG-RAM WNN-COR we use the same setup of the VG-RAM WNN illustrated in Figure 3. In the training phase, for each document in the training set, the corresponding vector $V$ is connected to the input of the VG-RAM WNN COR, $N$, and the output of its neurons, $O$, to the set of categories assigned to the document. Each neuron of the VG-RAM WNN-COR is trained to output this set with this input vector. During the test phase, for each test document, the corresponding vector $V$ is connected to the input of the network, $N$. The function $f(\cdot)$ is computed by dividing the number of votes for each category by the total number of categories outputted by the network. The number of votes for each category is obtained by counting their occurrences in all sets outputted by the network.

### IV. ML-kNN

The Multi-Label k-Nearest Neighbors (ML-KNN) [21] categorizer is a version of the k-Nearest Neighbors (KNN) [16] especially designed for multi-label categorization. In this categorizer, the $k$ nearest neighbors of $d_j$ are identified in $TV$. The Euclidean distance is used to find the nearest neighbors of $d_j$. Then, for the given $k$, the maximum a posteriori (MAP) principle is employed for determining the belief for each pair $\{d_j, c_i\} \in D \times C$ using statistical information obtained from the category sets of the neighbors of $d_j$, i.e., the number of neighboring documents belonging to each possible category. Zhang and Zhou [21] evaluated the performance of ML-KNN on several multi-label learning problems. In their experiments, ML-KNN achieved higher performance than well-established algorithms, such as Boostexter [15], the multi-label kernel method Rank-SVM [5], and the multi-label decision tree ADTBoost.MH [4]. This has motivated us to use ML-KNN as a baseline in the VG-RAM WNN-COR evaluation.

### V. Experimental Methodology

We employed a series of experiments to compare VG-RAM WNN-COR with VG-RAM WNN and ML-KNN. For that, we (i) used two data sets composed of textual descriptions of economic activities of companies categorized manually according lawful Brazilian economic activities. We (ii) preprocessed these data sets using standard IR techniques, and used the resulting data to (iii) tune VG-RAM WNN-COR, VG-RAM WNN, and ML-KNN categorizers and (iv) perform experiments for comparing VG-RAM WNN-COR with VG-RAM WNN and ML-KNN using multi-label text categorization performance metrics. The following subsections present the details of the parts (i), (ii), and (iii) of our experimental evaluation of VG-RAM WNN-COR. The experimental results, or part (iv), are presented in the next section.
A. Data Sets

The categorization of companies according to their economic activities is an important step of the process of obtaining information for statistical analysis of the economy within a city, state or country. In Brazil, all economic activities recognized by law are cataloged in a table called “Classificação Nacional de Atividades Econômicas (CNAE)” (National Classification of Economic Activities) [7]. Government officials must find the semantic correspondence between textual descriptions of economic activities of companies and one or more entries of the CNAE table for each new company or any that changes its set of economic activities.

To compare the performance of VG-RAM WNN-COR with that of VG-RAM WNN and ML-KNN on the categorization of economic activities, we employed two data sets, each of which composed of textual descriptions of economic activities of companies categorized into a subset of CNAE categories by Brazilian government officials trained in this task. The first data set, called EX100, consists of 6911 documents (textual descriptions) categorized into 105 different economic activities (categories). Each one of these categories occurs in exactly 100 different documents of this data set, i.e., there are 100 instances of documents of each category; the average number of categories per document is roughly 1.52 (standard deviation 0.79). The characteristics of EX100 allows examining the performance of categorizers in the case where the categories (or labels) are evenly distributed across the documents. This data set also contains the official brief description of each one of the 105 CNAE categories and their corresponding code.

The second data set, called AT100, consists of 10495 documents categorized into 762 categories. Each category appears in up to 100 different documents, i.e., there are between 1 and 100 instances of documents of each category; the average number of categories per document is roughly 1.49 (standard deviation 0.86). The characteristics of AT100 allows examining the performance of categorizers in the case where there are rare categories. This data set also contains the official brief description of each one of the 762 CNAE categories and their corresponding code.

We partitioned EX100 into 10 subsets of 691 documents (the last one had 692) and AT100 into 10 subsets of 1049 documents (the last one had 1054) in order to perform 10-fold cross-validation experiments.

B. Data Preprocessing

We transformed all words in our data sets into their uninflected form (term), i.e., the dictionary form of the word (known as lemma [10]), and then removed all prepositions using the Diadómer electronic dictionary of the Brazilian Portuguese language [12]. After that, we identified all distinct terms in each training set, TV, i.e., the vocabulary of interest.

Note that, as we are using 10-fold cross-validation, we have 10 training sets for EX100 and 10 for AT100 and, therefore, 20 vocabularies of interest. Using the vocabulary of interest associated with each training set, we transformed all documents of the 20 training set/test set pairs into their corresponding multidimensional vector of weights, \( V = \{v_1, \ldots, v_{|V|}\} \), where \(|V|\) is the number of terms that occurs at least once in the current training set. Each element \(v_i\) corresponds to the weight associated to each word \(i\) of the vocabulary of interest present in the document. This weight was computed according to the standard normalized tf/idf weighting function [16].

The average size of the vocabulary of interest is roughly 3609.8 terms (standard deviation 21.17) for EX100, and roughly 5377.6 terms (standard deviation 19.45) for AT100. Table V-B shows the sizes of the vocabularies of interest of EX100 and AT100 for the 20 training set/test set pairs.

<table>
<thead>
<tr>
<th>Fold</th>
<th>EX100</th>
<th>AT100</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3605</td>
<td>5392</td>
</tr>
<tr>
<td>2</td>
<td>3614</td>
<td>5404</td>
</tr>
<tr>
<td>3</td>
<td>3634</td>
<td>5406</td>
</tr>
<tr>
<td>4</td>
<td>3594</td>
<td>5386</td>
</tr>
<tr>
<td>5</td>
<td>3600</td>
<td>5363</td>
</tr>
<tr>
<td>6</td>
<td>3654</td>
<td>5360</td>
</tr>
<tr>
<td>7</td>
<td>3578</td>
<td>5363</td>
</tr>
<tr>
<td>8</td>
<td>3612</td>
<td>5386</td>
</tr>
<tr>
<td>9</td>
<td>3601</td>
<td>5363</td>
</tr>
<tr>
<td>10</td>
<td>3606</td>
<td>5353</td>
</tr>
</tbody>
</table>

Table 1: The size of the vocabulary of interest of each one of the 20 training set/test set pairs.

C. Categorizers Validation

The VG-RAM WNN-COR, VG-RAM WNN and ML-KNN categorizers possess parameters that can be optimized for achieving best performance in a given data set. To tune (or to validate) these categorizers, we used a single training(-and-validation) set, TV, for each data set detailed above. We divided each of these two TV sets into 10 subsets, and used the first nine to train and the last one to tune the parameters of the categorizers for each data set according to the ranking loss [14] metric (see Section VI-A). This metric evaluates the fraction of category pairs \((c_i, c_j)\), \(c_i \in C_j\) and \(c_j \in C_j\), that are or may be reversely ordered \((f(d_j, c_i) \leq f(d_j, c_k))\) in the ranking of categories for the test document \(d_j\) of a given data set. We chose the metric ranking loss for validation because it is not affected by ties, can be used for evaluating the whole ranking produced by the categorizers, and is commonly used for evaluating rank-based text categorization systems [14, 15, 5, 21].

Figure 4 and Figure 5 present the results of the validation experiments employed for tuning the number of neurons and synapses per neuron of the VG-RAM WNN-COR and VG-RAM WNN, and the parameter \(k\) of ML-KNN, for the EX100 and AT100 data sets, respectively. As Figure 4(a) shows, for the EX100 data set, the performance of VG-RAM WNN-COR increases (ranking loss decreases) with the number of neurons in the x-axis and with the number of synapses per neuron represented by each curve, but levels off when the network have about \(32 \times 32\) (1024) neurons and 512 synapses per neuron; while, for the AT100 data set (Figure 5(a)), the performance levels off when the network have about \(32 \times 32\) (1024) neurons and 1024 synapses per neuron. Therefore, in the experimental evaluation of VG-RAM WNN-COR with EX100 we used \(32 \times 32\) (1024) neurons and 512 synapses per neuron, while with AT100 we used \(32 \times 32\) (1024) neurons.
and 1024 synapses per neuron. Applying the same reasoning and using the results shown in Figure 4(b) and Figure 5(b), for VG-RAM WNN we chose $|O| = 32 \times 32 (1024)$ and $|X| = 1024$ for EX100, and $|O| = 32 \times 32 (1024)$ and $|X| = 512$ for AT100. Finally, we found that, in the case of ML-KNN, $k$ equal to 100 nearest neighbors produces the best performance results for both the EX100 and AT100 data sets (see Figure 4(c) and Figure 5(c)).

VI. Experimental Results

The metrics used in the literature to evaluate text categorization performance can roughly be divided into two groups:

(i) **Evaluation metrics for ranked sets**, which evaluate the whole ranking of categories derived from the real-valued function $f(\ldots)$; these include one-error [14], coverage [15], ranking loss [14], average precision [10], and R-precision [10];

(ii) **Evaluation metrics for unranked sets**, which evaluate the set of categories predicted for the test document $d_j$, $\hat{C}_j$ (see Section II), among which the most frequent are Hamming loss [14], exact match [8], precision [10, 16], recall [10, 16], and $F_\beta$ [10, 16].

In the following two subsections, we present the experiments we have used to compare the VG-RAM WNN-COR performance against that of VG-RAM WNN and ML-KNN.

A. Results with Metrics for Ranked Sets

One-error ($one-error_j$) evaluates if the top ranked category is present in the set of pertinent categories $C_j$ of the test document $d_j$:

$$one-error_j = \begin{cases} 0 & \text{if } [\arg \max_{c_i \in C} f(d_j, c_i)] \in C_j \\ 1 & \text{otherwise} \end{cases}$$

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

The overall performance is obtained by:

$$one-error = \frac{1}{|T_e|} \sum_{j=1}^{|T_e|} one-error_j$$

The smaller the value of one-error, the better the performance of the categorization system. The performance is perfect when $one-error = 0$.

Figure 6 shows the VG-RAM WNN-COR, VG-RAM WNN and ML-KNN performance in terms of one-error for EX100 and AT100 (the smaller the better). As the figure shows,
VG-RAM WNN-COR has about the same performance of VG-RAM WNN for EX100, but outperforms it for AT100 (two-tailed paired t-test at 5% significance level). This is to be expected since, when we have enough examples of each category (EX100), the benefits of data correlation may diminish; while, when certain categories are not well represented in the data set (AT100), data correlation between those and others in the data set, when captured, may allow better categorization performance. Both VG-RAM WNN-COR and VG-RAM WNN outperform ML-KNN for EX100 and AT100 (two-tailed paired t-test at 5% significance level). The performance is perfect when of the categorization system. The performance is perfect when 

where \( \bar{C}_j \) is the complementary set of \( C_j \) in \( C \). The overall performance is computed as:

\[
\text{ranking-loss} = \frac{1}{|T_e|} \sum_{j=1}^{|T_e|} \text{ranking-loss}_j.
\]

The smaller the value of \( \text{ranking loss} \), the better the performance of the categorizer. The performance is perfect when \( \text{ranking-loss} = 0 \).

Figure 7 shows the VG-RAM WNN-COR, VG-RAM WNN and ML-KNN performance in terms of \( \text{ranking loss} \) for EX100 and AT100 (the smaller the better). As the figure shows, VG-RAM WNN-COR outperforms VG-RAM WNN for EX100 and AT100 (two-tailed paired t-test at 5% significance level). This happens because data correlation allows VG-RAM WNN-COR to move pertinent categories up in the ranking, reducing the coverage. Although Figure 7 may suggests that VG-RAM WNN-COR outperforms ML-KNN for EX100 and AT100, the performance advantage is only significant for AT100 (two-tailed paired t-test at 5% significance level). However, it is important to note that, exploring data correlation, VG-RAM WNN may outperform ML-KNN.
are in line with those of |nations (see above).

WNN outperform ML-KNN for EX100 and AT100 (two-
nificance level). Both VG-RAM WNN-COR and VG-RAM

c
where

\hat{c} j

is the set of pertinent categories of the test
document d_j, and \hat{C}_j is the set of predicted
categories that goes from the top of the ranking until
the ranking position k. If there is a category c_i ∈ C_j at
position k and f(d_j, c_i) = 0, then the precision value
obtained for \hat{C}_j in Equation (7) is
taken to be 0.

The overall performance is calculated as:

\text{avg-precision}_j = \frac{1}{|C_j|} \sum_{k=1}^{|C_j|} \frac{|\hat{C}_j \cap C_j|}{|\hat{C}_j|},

(7)

where |C_j| is the number of pertinent categories of the
test document d_j, and \hat{C}_j is the set of predicted
categories that goes from the top of the ranking until
the ranking position k.

The larger the value of \text{average precision}, the better the
performance of the categorization system. The performance is
perfect when avg-precision = 1.

Figure 9 shows the categorizers’ performance in terms of
\text{average precision} for EX100 and AT100 (the larger the better).

The metrics examined in this section evaluate the set of cate-
gories predicted for a given d_j, C_j, instead of a ranking,
as the metrics described in the previous section. Because of
that, we need a means of thresholding the ranking of cate-
gories derived from f(.,.). There are various techniques for
determining the threshold \tau_j for each category c_i [19, 16].
We evaluate the performance of all categorizers examined
under a perfect thresholding policy; i.e., we choose the car-
dinality of the predicted set of categories for d_j, |\hat{C}_j|, to be
equal to |C_j| (or approximately equal to |C_j|). Thus, as we
have done for the metric \text{R-precision} (see above), we
derive \hat{C}_j from the |C_j| top ranked categories for d_j and call
it \hat{C}_j |C_j|.

\text{R-precision} \text{ (R-precision)} evaluates the precision computed
with the |C_j| top ranked categories for d_j:

\text{R-precision}_j = \frac{|\hat{C}_j \cap C_j|}{|C_j|},

(9)

where \hat{C}_j |C_j| is the set of |C_j| top ranked categories. Note
that categories c_i in the set of |C_j| top ranked categories for
which f(d_j, c_i) = 0 should not be inserted into \hat{C}_j |C_j|.

The overall performance is obtained by:

\text{R-precision} = \frac{1}{|T_e|} \sum_{j=1}^{|T_e|} \text{R-precision}_j,

(10)

The larger the value of \text{R-precision}, the better the performance
of the categorizer. The performance is perfect when
\text{R-precision} = 1.

Figure 10 shows the categorizers’ performance in terms of
\text{R-precision} for EX100 and AT100 (the larger the better).

Similarly to the case of \text{average precision}, VG-RAM WNN-
COR presents the same performance of VG-RAM WNN for
EX100, but outperforms it for AT100 (two-tailed paired t-
test at 5% significance level). Both VG-RAM WNN-COR and
VG-RAM WNN outperform ML-KNN for EX100 and AT100 (two-
tailed paired t-test at 5% significance level).

\text{B. Results with Metrics for Unranked Sets}

The metrics examined in this section evaluate the set of cate-
gories predicted for a given d_j, C_j, instead of a ranking,
as the metrics described in the previous section. Because of
that, we need a means of thresholding the ranking of cate-
gories derived from f(.,.). There are various techniques for
determining the threshold \tau_j for each category c_i [19, 16].
We evaluate the performance of all categorizers examined
under a perfect thresholding policy; i.e., we choose the car-
dinality of the predicted set of categories for d_j, |\hat{C}_j|, to be
equal to |C_j| (or approximately equal to |C_j|). Thus, as we
have done for the metric \text{R-precision} (see above), we
derive \hat{C}_j from the |C_j| top ranked categories for d_j and call
it \hat{C}_j |C_j|.

\text{Hamming loss} \text{ (Hamming-loss)} evaluates how many times
the test document d_j is misclassified (i.e., a category not be-
longing to the document is predicted or a category belonging
to the document is not predicted), normalized by the total

Average precision \text{ (avg-precision)} evaluates the average of
precisions computed truncating the ranking of categories
for the test document d_j after each category c_i ∈ C_j in turn:

\text{avg-precision}_j = \frac{1}{|C_j|} \sum_{k=1}^{|C_j|} \frac{|\hat{C}_j \cap C_j|}{|\hat{C}_j|},

(7)

\text{R-precision} = \frac{1}{|T_e|} \sum_{j=1}^{|T_e|} \text{R-precision}_j,

(10)
number of categories:

\[
\text{Hamming-loss}_j = \frac{|\hat{C}_j \cap C_j|}{|C_j|}, \tag{11}
\]

where \(\cap\) indicates the symmetric difference between the set of predicted categories, \(\hat{C}_j\), and the set of pertinent categories of \(d_j, C_j\).

The overall performance is calculated as:

\[
\text{Hamming-loss} = \frac{1}{|Te|} \sum_{j=1}^{|T|} \text{Hamming-loss}_j. \tag{12}
\]

The smaller the value of Hamming loss, the better the performance of the categorizer. The performance is perfect when \(\text{Hamming-loss} = 0\).

Figure 11 shows the categorizers’ performance in terms of Hamming loss for EX100 and AT100 (the smaller the better). As before, VG-RAM WNN-COR presents the same performance of VG-RAM WNN for EX100, but outperforms it for AT100 (two-tailed paired t-test at 5% significance level). Both VG-RAM WNN-COR and VG-RAM WNN outperform ML-KNN for EX100 and AT100 (two-tailed paired t-test at 5% significance level).

**Exact match** (exact-match\(_j\)) evaluates how frequently all and only all pertinent categories are present in the set of predicted categories for \(d_j\):

\[
\text{exact-match}_j = \begin{cases} 
1 & \text{if } C_j \subseteq \hat{C}_j; \\
0 & \text{otherwise}.
\end{cases} \tag{13}
\]

The overall performance is obtained by:

\[
\text{exact-match} = \frac{1}{|Te|} \sum_{j=1}^{|T|} \text{exact-match}_j. \tag{14}
\]

The larger the value of exact match, the better the performance of the categorizer. The performance is perfect when \(\text{exact-match} = 1\).

Figure 12 shows the categorizers’ performance in terms of exact match for EX100 and AT100 (the larger the better). As before, VG-RAM WNN-COR presents the same performance of VG-RAM WNN for EX100, but outperforms it for AT100 (two-tailed paired t-test at 5% significance level). Both VG-RAM WNN-COR and VG-RAM WNN outperform ML-KNN for EX100 and AT100 (two-tailed paired t-test at 5% significance level).

**Precision on a per-category basis** (precision\(_c\)) evaluates the fraction of test documents categorized under the category \(c_i\) that are truly associated with \(c_i\), and can be estimated using the contingency table for the category \(c_i\), shown in Table VI-B, as:

\[
\text{precision}_i = \frac{TP_i}{TP_i + FP_i}, \tag{15}
\]

where \(FP_i\) (false positives for \(c_i\)) is the number of test doc-
uments that have been incorrectly categorized under $c_i$, TN$_i$ (true negatives) is the number of test documents that have been correctly not categorized under $c_i$, TP$_i$ (true positives) is the number of test documents that have been correctly categorized under $c_i$, and FN$_i$ (false negatives) is the number of test documents that have been incorrectly not categorized under $c_i$.

<table>
<thead>
<tr>
<th>Category $c_i$</th>
<th>Expert judgments</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>YES</td>
</tr>
<tr>
<td></td>
<td>TP$_i$</td>
</tr>
<tr>
<td></td>
<td>FN$_i$</td>
</tr>
</tbody>
</table>

Table 2: The contingency table for the category $c_i$.

The average of precision$^c_i$ can be computed in two different ways:

(i) Macroaveraging evaluates the average over the results for different categories:

$$\text{macro-precision}^c = \frac{\sum_{i=1}^{C} \text{precision}_i^c}{|C|}.$$  \hfill (16)

(ii) Microaveraging evaluates the sum over all individual decisions in terms of the contingency table for the category $c_i$:

$$\text{micro-precision}^c = \frac{\sum_{i=1}^{C} TP_i}{\sum_{i=1}^{C} (TP_i + FP_i)}.$$  \hfill (17)

The larger the value of macro-precision$^c$ and micro-precision$^c$, the better the performance of the categorizer. The performance is perfect when macro-precision$^c = 1$ and micro-precision$^c = 1$.

Figure 13 and Figure 14 show the categorizers’ performance in terms of macro-precision$^c$ and micro-precision$^c$, respectively, for EX100 and AT100 (the larger the better). Again, VG-RAM WNN-COR presents the same performance of VG-RAM WNN for EX100, but outperforms it for AT100 (two-tailed paired t-test at 5% significance level). Both VG-RAM WNN-COR and VG-RAM WNN outperform ML-KNN for EX100 and AT100 (two-tailed paired t-test at 5% significance level).

Recall on a per-category basis (recall$^c_i$) evaluates the fraction of test documents truly associated with the category $c_i$ that are categorized under $c_i$, and can also be estimated using the contingency table for the category $c_i$ shown in Table VI-B, as:

$$\text{recall}^c_i = \frac{TP_i}{TP_i + FN_i}.$$  \hfill (18)

Estimates of macro-recall$^c$ and micro-recall$^c$ are calculated as:

$$\text{macro-recall}^c = \frac{\sum_{i=1}^{C} \text{recall}^c_i}{|C|};$$  \hfill (19)

$$\text{micro-recall}^c = \frac{\sum_{i=1}^{C} TP_i}{\sum_{i=1}^{C} (TP_i + FN_i)}.$$  \hfill (20)

The larger the value of macro-recall$^c$ and micro-recall$^c$, the better the performance of the categorizer. The performance is perfect when macro-recall$^c = 1$ and micro-recall$^c = 1$.

Figure 15 and Figure 16 show the categorizers’ performance in terms of macro-recall$^c$ and micro-recall$^c$, respectively, for EX100 and AT100 (the larger the better). VG-RAM WNN-COR presents the same performance of VG-RAM WNN for EX100, but outperforms it for AT100 (two-tailed paired t-test at 5% significance level). Both VG-RAM WNN-COR and VG-RAM WNN outperform ML-KNN for EX100 and AT100 (two-tailed paired t-test at 5% significance level).

$F_\beta$ on a per-category basis ($F_{\beta}^c_i$) evaluates the weighted harmonic mean of precision$^c_i$ and recall$^c_i$:

$$F_{\beta}^c_i = \frac{(\beta^2 + 1) \text{precision}_i^c \times \text{recall}_i^c}{\beta^2 \text{precision}_i^c + \text{recall}_i^c}.$$  \hfill (21)

In this formula, $\beta$ may be seen as the relative degree of importance attributed to precision$^c_i$ and recall$^c_i$ [16]. If $\beta = 0$ then $F_{\beta}^c_i$ coincides with precision$^c_i$, whereas if $\beta = +\infty$ then...
**Figure 15**: Macro-recall $c$ (the larger the better)

**Figure 16**: Micro-recall $c$ (the larger the better)

$F_{\beta}^c$ coincides with recall$^c_i$. Usually, a value $\beta = 1$ is used, which attributes equal importance to precision$^c_i$ and recall$^c_i$. Estimates of macro-$F_{\beta}^c$ and micro-$F_{\beta}^c$ are given by:

$$macro-F_{\beta}^c = \frac{1}{|C|} \sum_{i=1}^{C} F_{\beta}^c_i;$$

$$micro-F_{\beta}^c = \frac{(\beta^2 + 1)\text{micro-precision}^c \times \text{micro-recall}^c}{\beta^2\text{micro-precision}^c + \text{micro-recall}^c}.$$  

The larger the value of macro-$F_{\beta}^c$ and micro-$F_{\beta}^c$, the better the performance of the categorizer. The performance is perfect when macro-$F_{\beta}^c = 1$ and micro-$F_{\beta}^c = 1$.

Figure 17 and Figure 18 show the categorizers’ performance in terms of macro-$F_1^c$ and micro-$F_1^c$, respectively, for EX100 and AT100 (the larger the better). VG-RAM WNN-COR presents the same performance of VG-RAM WNN for EX100, but outperforms it for AT100 (two-tailed paired t-test at 5% significance level). VG-RAM WNN-COR outperforms ML-KNN for EX100 and AT100 (two-tailed paired t-test at 5% significance level).

**Figure 17**: Macro-$F_1^c$ (the larger the better)

**Figure 18**: Micro-$F_1^c$ (the larger the better)

**Precision on a per-document basis** (precision$^d_j$) evaluates the fraction of predicted categories that are pertinent for the test document $d_j$, and can be estimated in terms of the contingency table for $d_j$ shown in Table VI-B as:

$$precision^d_j = \frac{TP_j}{TP_j + FP_j},$$

where $FP_j$ (false positives for $d_j$) is the number of categories that have been incorrectly predicted for $d_j$; and $TN_j$ (true negatives), $TP_j$ (true positives), and $FN_j$ (false negatives) are defined accordingly.
The average of \(\text{precision}_d^j\) can be computed in two different ways:

\[
\text{macro-precision}_d^j = \frac{\sum_{j=1}^{|Te|} \text{precision}_d^j}{|Te|}; \quad (25)
\]

\[
\text{micro-precision}_d^j = \frac{\sum_{j=1}^{|Te|} TP_j}{\sum_{j=1}^{|Te|} (TP_j + FP_j)}. \quad (26)
\]

The larger the value of \(\text{macro-precision}_d^j\) and \(\text{micro-precision}_d^j\), the better the performance of the categorizer. The performance is perfect when \(\text{macro-precision}_d^j = 1\) and \(\text{micro-precision}_d^j = 1\).

Figure 19 and Figure 20 show the categorizers’ performance in terms of \(\text{macro-precision}_d^j\) and \(\text{micro-precision}_d^j\), respectively, for EX100 and AT100 (the larger the better). VG-RAM WNN-COR presents the same performance of VG-RAM WNN for EX100, but outperforms it for AT100. VGRAM WNN-COR outperforms ML-KNN for EX100 and AT100.

Recall on a per-document basis (\(\text{recall}_d^j\)) evaluates the fraction of pertinent categories that are predicted for the test document \(d_j\), and can also be estimated in terms of the contingency table for \(d_j\) shown in Table VI-B as:

\[
\text{recall}_d^j = \frac{TP_j}{TP_j + FN_j}. \quad (27)
\]

Estimates of \(\text{macro-recall}_d^j\) and \(\text{micro-recall}_d^j\) are calculated as:

\[
\text{macro-recall}_d^j = \frac{\sum_{j=1}^{|Te|} \text{recall}_d^j}{|Te|}; \quad (28)
\]

\[
\text{micro-recall}_d^j = \frac{\sum_{j=1}^{|Te|} TP_j}{\sum_{j=1}^{|Te|} (TP_j + FN_j)}. \quad (29)
\]

The larger the value of \(\text{macro-recall}_d^j\) and \(\text{micro-recall}_d^j\), the better the performance of the categorizer. The performance is perfect when \(\text{macro-recall}_d^j = 1\) and \(\text{micro-recall}_d^j = 1\).

Figure 21 and Figure 22 show the categorizers’ performance in terms of \(\text{macro-recall}_d^j\) and \(\text{micro-recall}_d^j\), respectively, for EX100 and AT100 (the larger the better). VG-RAM WNN-COR presents the same performance of VG-RAM WNN for EX100, but outperforms it for AT100. VGRAM WNN-COR outperforms ML-KNN for EX100 and AT100.

\[F_\beta\] on a per-document basis (\(F_{\beta_j}^d\)) evaluates the weighted...
The harmonic mean of precision$_d^j$ and recall$_d^j$:

$$ F_{\beta_d^j} = \frac{(\beta_d^j)^2 \text{precision}_d^j \times \text{recall}_d^j}{\beta_d^j \text{precision}_d^j + \text{recall}_d^j}. \quad (30) $$

Estimates of macro-F$_\beta^d$ and micro-F$_\beta^d$ are given by:

$$ \text{macro-F}_{\beta^d} = \frac{1}{|C|} \sum_{j=1}^{|C|} F_{\beta_d^j}, \quad (31) $$

$$ \text{micro-F}_{\beta^d} = \frac{(\beta^d)^2 \text{micro-precision}_d \times \text{micro-recall}_d}{\beta^d \text{micro-precision}_d + \text{micro-recall}_d}. \quad (32) $$

The larger the value of macro-F$_\beta^d$ and micro-F$_\beta^d$, the better the performance of the categorizer. The performance is perfect when macro-F$_\beta^d = 1$ and micro-F$_\beta^d = 1$.

Figure 23 and Figure 24 show the categorizers’ performance in terms of macro-$F_1^d$ and micro-$F_1^d$, respectively, for EX100 and AT100 (the larger the better). VG-RAM WNN-COR presents the same performance of VG-RAM WNN for EX100, but outperforms it for AT100. VG-RAM WNN-COR outperforms ML-KNN for EX100 and AT100.

Note that the microaveraged metrics give an equal result, independently of being defined on a per-category basis or on a per-document basis. To understand why this is so, let $FP_{ij} = 1$ if the category $c_i$ has been incorrectly predicted for the test document $d_j$, $FP_{ij} = 0$ otherwise; and $TP_{ij} = 1$ if $c_i$ has been correctly predicted for $d_j$, $TP_{ij} = 0$ otherwise. Estimates of microaveraged precision on a per-document basis (micro-precision$^d$) and on a per-document basis (micro-precision$^C$) can be obtained, respectively, as:

$$ \text{micro-precision}^d = \frac{\sum_{i=1}^{|C|} TP_{ij}}{\sum_{i=1}^{|C|} (TP_{ij} + FP_{ij})} \quad (33) $$

$$ \text{micro-precision}^C = \frac{\sum_{i=1}^{|C|} \sum_{j=1}^{|T_e|} TP_{ij}}{\sum_{i=1}^{|C|} (\sum_{j=1}^{|T_e|} TP_{ij} + \sum_{j=1}^{|T_e|} FP_{ij})} \quad (34) $$

As one can observe in Equations (33) and (34), micro-precision$^C$ is equal to micro-precision$^d$. Analogously, one can show that micro-recall$^d$ and micro-F$_\beta^C$ are equal to micro-recall$^d$ and micro-F$_\beta^d$, respectively.

C. Statistical T-Test

To present a clearer view of the relative performance of the algorithms, a partial order $\succ$ is defined on the set of all comparing algorithms for each evaluation metric, where $A1 \succ A2$.
means that the performance of algorithm A1 is significantly better than that of algorithm A2 on the specific metric (two-tailed paired t-test at 5% significance level). If the performance is not significantly better, we say A1 ≡ A2. The partial order on all comparing algorithms in terms of each evaluation metric for the EX100 and AT100 data sets is shown in Table 4 and Table 5, respectively.

It is important to note that it is possible that A1 performs better than A2 in terms of some metrics but equivalent or worse in others. In this case, it is hard to judge which algorithm is superior. So, in order to give an overall performance assessment of an algorithm, we employed a score that takes into account its performance against that of the other algorithms on all metrics. Concretely, for each evaluation metric, if A1 > A2 holds, then A1 is rewarded with a positive score +1 and A2 is penalized with a negative score −1. Based on the accumulated score of each algorithm on all evaluation metrics, a total order > is defined on the set of all comparing algorithms, as shown in the last line of Table 4 and Table 5, where A1 > A2 means that A1 performs better than A2 on the EX100 and AT100 data sets, respectively. The accumulated score of each algorithm is also shown in the parentheses. As shown in Table 4 and Table 5, VG-RAM WNN-COR has an overall better performance than VG-RAM WNN and ML-KNN on both the EX100 and AT100 databases for the set of metrics considered.

### VII. Conclusions

In this paper, we presented an experimental evaluation of Data Correlated VG-RAM WNN (VG-RAM WNN-COR) on multi-label text categorization and compared its performance with that of standard VG-RAM WNN and ML-KNN categorizers. In order to do that, we used two data sets composed of textual descriptions of economic activities of companies categorized manually according to lawful Brazilian economic activities. Our experimental results showed that VG-RAM WNN-COR has an overall better performance than VG-RAM WNN and ML-KNN on the two databases for the set of metrics considered.

### VIII. Acknowledgments

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### References


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Alberto Ferreira De Souza is Comendador of the order of Rubem Braga.

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