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One-Class SVMs for Document Classification

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Abstract

We implemented versions of the SVM appropriate for *one-class* classification in the context of information retrieval. The experiments were conducted on the standard *Reuters* data set.

For the SVM implementation we used both a version of Schölkopf et al. and a somewhat different version of one-class SVM based on identifying "outlier" data as representative of the second-class. We report on experiments with different kernels for both of these implementations and with different representations of the data, including binary vectors, tf-idf representation and a modification called "Hadamard" representation. Then we compared it with one-class versions of the algorithms prototype (Rocchio), nearest neighbor, naive Bayes, and finally a natural one-class neural network classification method based on "bottleneck" compression generated filters.

The SVM approach as represented by Schölkopf was superior to all the methods except the neural network one, where it was, although occasionally worse, essentially comparable. However, the SVM methods turned out to be quite sensitive to the choice of representation and kernel in ways which are not well understood; therefore, for the time being leaving the neural network approach as the most robust.

Keywords: Support Vector Machine, SVM, Neural Network, Compression Neural Network, Text Retrieval, Positive Information

1. Introduction

Recently, mechanisms related to the Support Vector Machine (SVM) paradigm have produced the dramatically best results for information retrieval, e.g. in experiments as measured over the standard *Reuters* dataset (Dumais et al., 1998).

However, these studies are based on training using both positive and negative examples, as the basic SVM paradigm suggests. We have been interested, however, in information retrieval using *only* positive examples for training. This is important in many applications (see Manevitz and Yousef, 2001). Consider, for example, trying to classify sites of "interest" to a web surfer where the only information available is the history of the user's activities. One can envisage identifying typical positive examples by such tracking, but it would be hard to identify representative negative examples. Of course, the absence of negative information entails a price, and one should not expect as good results as when they are available (Dumais et al., 1998, Joachims, 1998).

Since Schölkopf et al. (1999) recently extended the SVM methodology to handle training using only positive information (what they call "one-class" classification), we decided to apply their method to documentation classification and compare it with other one-class methods, including a method we recently developed and studied based on a compression neural network as a filter.

There are many parameters in these methods, including the representation of the data, and the decisions involved in modifying basically two-class methods to one class ones. Our studies are fairly broad although not completely comprehensive; below we describe each of the choices we made.

In the end, it turns out that the suggestion of Schölkopf is quite excellent, substantially better than all other methods except the neural network based one with which it is comparable. Moreover, it is somewhat simpler to implement than the neural network method.

However, it turns out to be surprisingly sensitive to specific choices of representation and kernel in ways which are not very transparent. For example, the method works best with binary representation as opposed to tf-idf or "Hadamard" representations which are known to be superior in other methods. In addition, the proper choice of a kernel is dependent on the number of features in the binary vector. Since the difference in performance is very dramatic based on these choices, this means that the method is not robust without a deeper understanding of these representation issues.

This means that, for the moment, we would prefer the neural network method for reasons of robustness.

2. Document Representations, Data Set and Measurements

2.1 Document Representations

We used the following different representations in these experiments:

1. binary representation
2. frequency representation
3. *tf-idf* representation
4. *Hadamard* representation

These are defined as follows. List all the words (after "stemming"; i.e. removing suffixes and prefixes to avoid duplicate entries and removing basic "stop" words) in all the training documents sorted by the *document*-frequency (i.e. the number of documents it appears in). Choose the top m such words according to this "dictionary" frequency (called "keywords"). (See in the sequel for experiments with different values of m.)

For *binary* representation of a specific document, choose the m dimensional binary vector where the i^{th} entry is 1 if the i^{th} keyword appears in the document and 0 if it does not.

For the *frequency* representation, choose the m dimensional real valued vector, where the i^{th} entry is the normalized frequency of appearance of the i^{th} keyword in the specific document.

Table 1: **Number of Training/Test Items**

Category Name	Num Train	Num Test
Earn	966	2902
Acquisitions	590	1773
Money-fx	187	563
Grain	151	456
Crude	155	465
Trade	133	401
Interest	123	370
Ship	65	195
Wheat	62	186
Corn	62	184

For the *tf-idf* representation ("term frequency inverse document frequency"), choose the m dimensional real valued vector, where the i^{th} entry is given by the formula

$$tf - idf(keyword) = frequency(keyword) \cdot [log \frac{n}{N(keyword)} + 1].$$

where n is the total number of words in the dictionary and N is a function giving the total number of documents the keyword appears in.

The *Hadamard product* representation was discovered experimentally; it consists of the m dimensional vector where the i^{th} entry is the product of the frequency of the i^{th} keyword in the document and its frequency over all documents (in the training set). See Manevitz and Yousef (2001) for further discussion of this representation. In any case, it is clear that this transformation emphasizes differences between large and small feature entries.

2.2 Data Set and Measurements

To test the above ideas, we applied these filters to the standard *Reuters* dataset (Lewis, 1997), a preclassified collection of short articles. This is one of the standard test-beds used to test information retrieval algorithms (Dumais et al., 1998).

For each choice of category, we used 25% of the positive data from the training set to train; and then tested the filters on the remaining 75% of the data set. Table 1 shows the ten most frequent categories along with the number of training and test examples in each.

We treated each of the 10 categories as a binary classification task and evaluated the classifiers for each category separately.

For reporting the results, we used the F_1 measure, the recall and the precision values.

For text categorization, the effectiveness measure of recall and precision are defined as follows:

$$recall = \frac{Number\ of\ items\ of\ category\ identified}{Number\ of\ category\ members\ in\ test\ set}$$

$$precision = \frac{Number\ of\ items\ of\ category\ identified}{Total\ items\ assigned\ to\ category}$$

Van Rijsbergen (1979) defined the F_1-measure as a combination of recall (R) and Precision (P) with an equal weight in the following form: F_1(R,P)= $\frac{2RP}{R+P}$ (This implies that F_1, like R and P, is bounded by 1 and the best results under this measure are the higher values.)

3. SVM for One Class Classification: Separating Data from Origin

The SVM algorithm as it is usually construed is essentially a two-class algorithm (i.e. one needs negative as well as positive examples). Below we present two modifications, one due to Schölkopf and one we proposed, to allow its use for only positive data. Both mechanisms identify "outliers" amongst the positive examples and use them as negative examples. Below we refer to the Schölkopf method as "one-class" and to the other as "outlier".

We investigated both algorithms under a variety of choices of parameters. Our experiments were more extensive for the one-class SVM which seems to be the superior of the two.

3.1 Schölkopf Methodology

Schölkopf et al. (1999) suggested a method of adapting the SVM methodology to the one-class classification problem. Essentially, after transforming the feature via a kernel, they treat the origin as the only member of the second class. Then using "relaxation parameters" they separate the image of the one class from the origin. Then the standard two-class SVM techniques are employed.

They framed the problem in the following way:

Suppose that a dataset has a probability distribution P in the feature space. Find a "simple" subset S of the feature space such that the probability that a test point from P lies outside S is bounded by some a priori specified value.

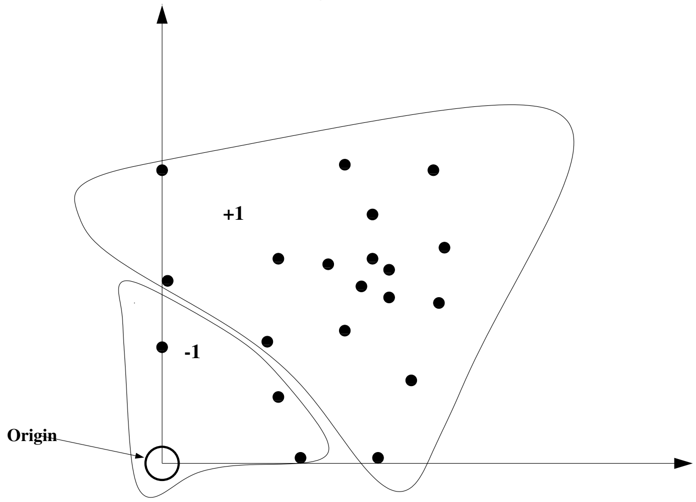
Supposing that there is a dataset drawn from an underlying probability distribution P, one needs to estimate a "simple" subset S of the input space such that the probability that a test point from P lies outside of S is bounded by some a prior specified $v \in (0, 1)$. The solution for this problem is obtained by estimating a function f which is positive on S and negative on the complement $\overline{S}$. In other words, Schölkopf et al., developed an algorithm which returns a function f that takes the value +1 in a "small" region capturing most of the data vectors, and -1 elsewhere.

The algorithm can be summarized as mapping the data into a feature space H using an appropriate kernel function, and then trying to separate the mapped vectors from the origin with maximum margin (see Figure 1).

$$f(x) = \begin{cases} +1 & \text{if } x \in S \\ -1 & \text{if } x \in \overline{S} \end{cases}$$

In our context, let $x_1, x_2, \ldots, x_l$ be training examples belonging to one class X, where X is a compact subset of R^N. Let $\Phi : X \longrightarrow H$ be a kernel map which transforms the training examples to another space. Then, to separate the data set from the origin, one needs to solve the following quadratic programming problem:

Figure 1: One-class SVM



One-Class SVM Classifier. The origin is the only original member of the second class.

$$min\frac{1}{2}\|w\|^2 + \frac{1}{vl}\sum_{i=1}^{l}\xi_i - \rho$$

subject to

$$(w \cdot \Phi(x_i)) \geq \rho - \xi_i \quad i = 1, 2, ..., l \quad \xi_i \geq 0$$

If w and ρ solve this problem, then the decision function

$$f(x) = sign((w \cdot \Phi(x)) - \rho)$$

will be positive for most examples x_i contained in the training set.

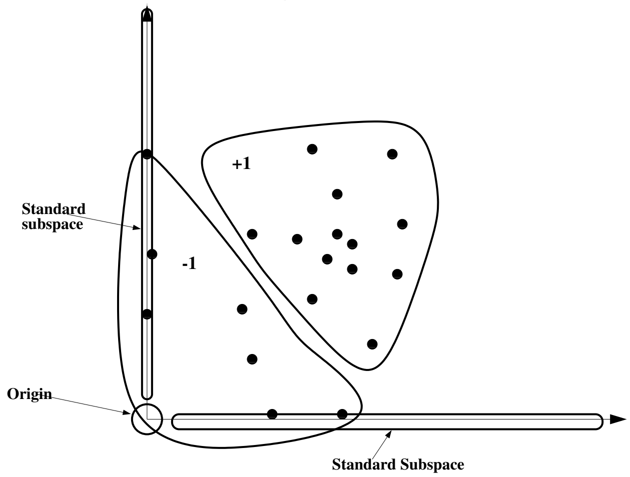
In our research we used the LIBSVM (version 2.0). This is an integrated tool for support vector classification and regression which can handle one-class SVM using the Sholkopf etc algorithms. The LIBSVM 2.0 is available at *http://www.csie.ntu.edu.tw/˜cjlin/libsvm*. We used the standard parameters of the algorithm.

For this "one-class SVM", one has to choose the original frequency representation, (e.g. the number of features), the appropriate kernel, and for each kernel the appropriate parameters. We allowed, linear, sigmoid, polynomial and radial basis kernels; each chosen with the standard parameters. For the original feature representation, we used binary, tf-idf and Hadamard representations. For the number of features we tried 10, 20, 40, 60 and 100 features for the one-class SVM.

3.2 Outlier Methodology

The basic idea is to work first in the feature space, and assume that not only is the origin in the second class (as in the previous section), but also that all data points "close enough" to the origin are to be considered as noise or outliers.

Figure 2: Outlier SVM



Outlier SVM Classifier. The origin and small subspaces are the original members of the second class. The diagram is conceptual only.

If a vector has few non-zero entries, then this indicates that this document shares very few items with the chosen feature subset of the dictionary. So, intuitively, this item will not serve well as a representative of the class. In this way, it is reasonable to treat such a vector as an outlier. (Note that while the idea of choosing the outliers as data points close to the origin is a general one, the intuitive justification of this procedure is specific to this application.)

Geometrically, using the Hamming distance means that all vectors lying on standard sub-spaces of small dimension (i.e. axes, faces, etc.) are treated as outliers (see Figure 2).

Hence, we decided to identify these outliers by counting the features of an example with non-zero value; and if this is less than a threshold, then the feature is labeled as a negative example.

This raises the problem as to how to choose the appropriate values for the threshold. We investigated this in two ways: (1) by experimentally trying different global values of the threshold and (2) by determining individual thresholds for the different categories. One should note that, in principle, this determination of threshold can be done automatically, e.g. by comparing results on a test set. After having determined the threshold one then continues with the standard two-class SVM.

For this "outlier-SVM", one also has to choose the original frequency representation, and how far from the origin a point can be (in our case, in Hamming distance) before being classified as an outlier.

For the outlier-SVM we tried 10 and 20 features for binary representations. Note that the features are individual category-specific, i.e. different features for each category. (We did sample runs with other representations (e.g. Hadamard, tf-idf) and larger numbers of features, but since the results were clearly poor, we did not complete the experiments.)

In addition, we experimented with varying the Hamming distance in order to define the outlier threshold. Note that this decision can also be chosen automatically (by comparing results on a test set after training) so we also did some statistics over the data set wherein each category had its own such threshold. Table 6 lists the number of documents designated as outliers for each choice of Hamming distance.

We allowed, linear, sigmoid, polynomial and radial basis kernels; each chosen with the "standard" parameters for the two class SVM.

4. Other Methods

In recent research (Manevitz and Yousef, 2001) we proposed a one-class neural network classification scheme and compared it over the standard *Reuters* data set with variants appropriate to the positive example case of several algorithms, using various choices of parameters and various methods of representing the details. For extensive details, see Manevitz and Yousef (2001).

Here we will compare the two SVM one-class algorithms with the following ones from that study:

1. Prototype (Rocchio's) algorithm

   The Prototype algorithm is widely used in information retrieval (Pazzani and Billsus, 1997, Balabanovic and Shoham, 1995, Pazzani et al., 1996, Lang, 1995, and others) . This algorithm is used frequently because it is considered as a baseline algorithm and it is simple to implement. For more details see Joachims (1996).

   The basic idea of the algorithm is to represent each document, $\mathbf{e}$, as a vector in a vector space so that documents with similar content have similar vectors. The value e_i of the i^{th} key-word is represented as the *tf-idf* weight.

   The Prototype algorithm learns the class model by combining document vectors into a prototype vector . This vector is generated by adding the document vectors of all documents in the class. Classification is done by judging the angular distance from the prototype vector. In our experiments, we used the F_1 measure to optimize the threshold.

2. Nearest Neighbor

   This is a modification of the standard Nearest Neighbor algorithm (Yang and Liu, 1999) appropriate for one-class learning. This algorithm was original presented in detail by Datta (1997); and the method of optimizing the parameters is explained by Manevitz and Yousef (2001).

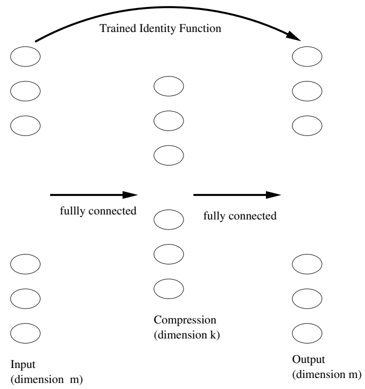
3. Naive Bayes

   Traditional Naive Bayes calculates the probability of being in a class given an example, which has specific values for the different attributes. One calculates this by assuming the different attributes are independent, applying Bayes' theorem and using the a priori probability of the different classes.

   P. Datta (1997) showed how to modify the algorithm for positive data only and we follow his presentation.

   E is the class of training documents in a category. We calculate $p(d|E)$ as the product of $p(w|E)$ for all keywords that appear in the document d. Each of the $p(w|E)$ is

Figure 3: A Neural Network with Bottleneck



estimated independently using the formula: $p(w|E) = \frac{n_w+1}{n+m}$ where n_w is the number of times word w occurs in E, n is the total number of words in E, and m is the number of keywords.

The threshold is calculated as a fraction (optimized using the F_1 measure) of the minimum over all examples in E of the value $p(d|E)$

4. Compression Neural Network

   The algorithm is based on a feed-forward three layer neural network with a "bottleneck". That is, under the assumption that the documents are represented in an m-dimensional space; we choose a three level network with m inputs, m outputs and k neurons on the hidden level, where $k < m$. Then the network is trained, under standard back-propagation, to learn the identity function on the sample examples (see Figure 3). This design was first used by G.W. Cottrell and Zipser (1988) to produce a compression algorithm. See also Japkowicz et al. (1995) for another use as a novelty detector.

   The idea is that while the bottleneck prevents learning the full identity function on m-space; the identity on the small set of examples is in fact learnable. Then the set of vectors for which the network acts as the identity function is a sort of sub-space which is similar to the trained set. This avoids the "saturation" problem of learning from only positive examples. Thus the filter is defined by applying the network to a given vector; if the result is the identity, then the vector is "interesting".

By running the same experiments using the two SVM-one class algorithms, we are in a position to make a comparative study.

The reader is referred to Manevitz and Yousef (2001) for detailed descriptions of each of the above algorithms and the various choices of parameters investigated.

5. Results

We present our results in a series of tables listing the F_1, recall and precision values over different parameters. The main summary table is Table 8 where results from all the tables are gathered for comparison.

5.1 One-class SVM (Schölkopf algorithm) Results

The results for this algorithm were very sensitive to the parameters. However, under proper choices it can give the best results.

In particular:

- This algorithm worked much better with the binary representation; in fact the results under all kernels were extremely poor under the other three representations we tested (frequency, tf-idf, and Hadamard). Table 5 presents the Hadamard results with 20 features; results with tf-idf and frequency were equally poor.
- 10 features were best in general, but this depended on the choice of kernel. For polynomial kernel the 20 features were dramatically better. On the other hand, for radial basis kernel 10 features were dramatically better than 20 features (see Table 3).
- Increasing the number of features further caused large decreases in performance (see Table 4).

  Aside: Note that the features are category-specific in our approach; unlike other studies such as performed by Joachims (1998), for example. This makes direct dimension comparison difficult. Roughly, the total number of features over all categories in our experiments is about 100 (for twenty features per category).
- We investigated the effect of removing the near-Hamming distance examples from the data set before running this algorithm. We did this for vectors with 10 features. Since the results are worse in all cases in comparison with the original algorithm, we do not reproduce the data tables here.

In summary, the best choice of parameters for this algorithm were 10 features, binary representation with radial basis kernel. However, the sensitivity to changes in any of these parameters makes it difficult to generalize to other applications. The linear kernel, however, while giving somewhat worse results did not seem to be as sensitive.

5.2 Outlier-SVM Results

The results were generally somewhat worse than the one-class SVM results reported above, especially when looked over the array of categories. Occasionally, (e.g. for polynomial kernel with 10 features) this method was superior. Compare Table 3 with Table 2.

For larger categories, one-class SVM obtained somewhat better results. Using macro averaging (i.e. taking into account the differing number of items in each category), this algorithm reports somewhat better results than the one-class SVM (see Table 8).

- We only tested this algorithm for binary representation.
- 10 features were preferable to 20 features. Compare Table 7 and the subtables in Table 2.
- For 10 features, the best choice of Hamming distance for outlier threshold was 4 or 5. Looking at Table 6 this means that roughly a third of the data were specified

Table 2: F_1 Values for the Outlier-SVM with different kernels. All with binary representation and vector dimension 10. The number in the first row indicates the number of non-zero feature entries which is required to consider an object an outlier.

Linear kernel

	3 F_1	4 F_1	5 F_1	6 F_1	7 F_1	Optimal F_1
Earn	0.689	0.750	0.712	0.586	0.446	0.750
Acq	0.488	0.504	0.450	0.323	0.195	0.504
Money	0.492	0.563	0.508	0.425	0.292	0.563
Grain	0.444	0.523	0.481	0.283	0.133	0.523
Crude	0.199	0.359	0.474	0.371	0.275	0.474
Trade	0.352	0.423	0.348	0.346	0.313	0.423
Int	0.308	0.455	0.465	0.422	0.298	0.465
Ship	0.402	0.287	0.265	0.142	0.040	0.402
Wheat	0.271	0.389	0.265	0.188	0.162	0.389
Corn	0.228	0.332	0.306	0.356	0.185	0.356
Average	0.387	0.458	0.427	0.344	0.233	0.484

Polynomial kernel

	3 F_1	4 F_1	5 F_1	6 F_1	7 F_1	Optimal F_1
Earn	0.718	0.784	0.705	0.584	0.445	0.784
Acq	0.319	0.484	0.414	0.283	0.088	0.484
Money	0.111	0.522	0.448	0.397	0.221	0.522
Grain	0.093	0.468	0.270	0.152	0.042	0.468
Crude	0.091	0.540	0.540	0.338	0.271	0.540
Trade	0.078	0.078	0.451	0.327	0.273	0.451
Int	0.073	0.346	0.480	0.354	0.096	0.480
Ship	0.115	0.078	0.020	0.000	0.000	0.115
Wheat	0.036	0.036	0.192	0.168	0.125	0.192
Corn	0.037	0.037	0.325	0.294	0.157	0.325
Average	0.167	0.337	0.384	0.289	0.171	0.436

Radial kernel

	3 F_1	4 F_1	5 F_1	6 F_1	7 F_1	Optimal F_1
Earn	0.688	0.751	0.712	0.586	0.440	0.751
Acq	0.488	0.503	0.449	0.304	0.117	0.503
Money	0.462	0.578	0.538	0.437	0.269	0.578
Grain	0.502	0.574	0.460	0.228	0.025	0.574
Crude	0.128	0.357	0.541	0.376	0.237	0.541
Trade	0.352	0.429	0.380	0.275	0.278	0.429
Int	0.253	0.441	0.457	0.365	0.092	0.457
Ship	0.327	0.333	0.142	0.040	0.000	0.333
Wheat	0.036	0.271	0.253	0.230	0.218	0.271
Corn	0.142	0.315	0.351	0.357	0.215	0.357
Average	0.337	0.455	0.428	0.319	0.189	0.479

Sigmoid kernel

	3 F_1	4 F_1	5 F_1	6 F_1	7 F_1	Optimal F_1
Earn	0.668	0.756	0.723	0.581	0.431	0.756
Acq	0.439	0.475	0.443	0.298	0.071	0.475
Money	0.468	0.535	0.525	0.431	0.038	0.535
Grain	0.429	0.547	0.448	0.155	0.000	0.547
Crude	0.124	0.382	0.494	0.372	0.257	0.494
Trade	0.362	0.449	0.377	0.268	0.292	0.449
Int	0.190	0.397	0.472	0.291	0.000	0.472
Ship	0.333	0.327	0.050	0.000	0.000	0.333
Wheat	0.036	0.261	0.221	0.213	0.129	0.261
Corn	0.037	0.337	0.344	0.313	0.177	0.344
Average	0.308	0.446	0.409	0.292	0.139	0.466

Table 3: One-class SVM using the binary representation.

Vector Dimension 10

	Linear			Sigmoid			Polynomial			Radial basis		
	F_1	R	P	F_1	R	P	F_1	R	P	F_1	R	P
Earn	0.676	0.534	0.912	0.702	0.566	0.924	0.409	0.547	0.326	0.676	0.534	0.921
Acq	0.483	0.489	0.477	0.481	0.483	0.478	0.185	0.391	0.121	0.482	0.491	0.474
Money	0.541	0.504	0.585	0.516	0.451	0.604	0.074	0.481	0.040	0.514	0.481	0.552
Grain	0.585	0.447	0.846	0.533	0.388	0.850	0.084	0.491	0.046	0.585	0.447	0.846
Crude	0.545	0.490	0.614	0.532	0.470	0.611	0.441	0.462	0.423	0.544	0.490	0.613
Trade	0.445	0.376	0.545	0.476	0.396	0.597	0.363	0.463	0.299	0.597	0.492	0.433
Int	0.473	0.410	0.558	0.454	0.367	0.593	0.145	0.483	0.085	0.485	0.440	0.541
Ship	0.563	0.600	0.531	0.518	0.471	0.575	0.025	0.471	0.013	0.539	0.564	0.516
Wheat	0.474	0.376	0.642	0.450	0.365	0.586	0.619	0.516	0.774	0.474	0.376	0.642
Corn	0.293	0.380	0.238	0.339	0.380	0.307	0.036	0.440	0.019	0.298	0.391	0.240
Avg	0.507	0.460	0.594	0.500	0.433	0.612	0.238	0.474	0.214	0.519	0.470	0.577

Vector Dimension 20

	Linear			Sigmoid			Polynomial			Radial basis		
	F_1	R	P	F_1	R	P	F_1	R	P	F_1	R	P
Earn	0.652	0.521	0.873	0.686	0.562	0.880	0.678	0.555	0.871	0.321	0.479	0.241
Acq	0.488	0.495	0.481	0.489	0.497	0.482	0.491	0.482	0.501	0.194	0.465	0.122
Money	0.487	0.470	0.504	0.494	0.479	0.509	0.503	0.428	0.611	0.084	0.541	0.045
Grain	0.504	0.467	0.548	0.504	0.467	0.548	0.487	0.412	0.596	0.071	0.480	0.038
Crude	0.496	0.430	0.586	0.496	0.430	0.588	0.485	0.408	0.599	0.111	0.589	0.062
Trade	0.441	0.359	0.571	0.441	0.361	0.566	0.453	0.366	0.592	0.239	0.496	0.157
Int	0.440	0.456	0.424	0.425	0.429	0.420	0.425	0.356	0.528	0.092	0.518	0.050
Ship	0.220	0.517	0.139	0.219	0.517	0.139	0.310	0.410	0.250	0.025	0.405	0.013
Wheat	0.449	0.392	0.525	0.449	0.392	0.525	0.420	0.338	0.552	0.097	0.548	0.053
Corn	0.376	0.356	0.395	0.376	0.358	0.395	0.352	0.282	0.468	0.029	0.673	0.015
Avg	0.455	0.446	0.504	0.458	0.449	0.505	0.460	0.403	0.557	0.126	0.519	0.079

Table 4: One-class SVM using the binary representation, with different vector dimensions. Some sample categories.

	Linear			Sigmoid			Polynomial			Radial basis		
	F_1	R	P	F_1	R	P	F_1	R	P	F_1	R	P
	dimension 40											
Grain	0.479	0.453	0.707	0.425	0.331	0.594	0.059	0.524	0.031	0.478	0.453	0.506
Ship	0.135	0.482	0.078	0.203	0.205	0.202	0.027	0.589	0.014	0.135	0.482	0.078
Wheat	0.416	0.392	0.442	0.307	0.226	0.482	0.030	0.548	0.015	0.414	0.392	0.439
Corn	0.340	0.380	0.308	0.325	0.250	0.464	0.029	0.625	0.015	0.339	0.380	0.307
	dimension 60											
Grain	0.436	0.434	0.438	0.398	0.300	0.593	0.056	0.486	0.029	0.434	0.434	0.435
Ship	0.177	0.400	0.114	0.229	0.169	0.358	0.029	0.671	0.014	0.178	0.405	0.014
Wheat	0.383	0.381	0.385	0.254	0.182	0.419	0.028	0.591	0.014	0.388	0.387	0.389
Corn	0.326	0.347	0.307	0.272	0.195	0.450	0.027	0.592	0.013	0.324	0.347	0.303
	dimension 100											
Grain	0.412	0.425	0.400	0.259	0.157	0.727	0.031	0.232	0.017	0.412	0.425	0.400
Ship	0.164	0.446	0.100	0.150	0.092	0.400	0.028	0.625	0.014	0.164	0.446	0.100
Wheat	0.530	0.376	0.897	0.258	0.150	0.903	0.039	0.634	0.020	0.530	0.376	0.897
Corn	0.273	0.320	0.237	0.186	0.125	0.370	0.028	0.619	0.014	0.272	0.320	0.236

Table 5: One-class SVM using the Hadamard representation, with vector dimension 20 (m=20).

	Linear			Sigmoid			Polynomial			Radial basis		
	F_1	R	P	F_1	R	P	F_1	R	P	F_1	R	P
Earn	0.592	0.440	0.905	0.285	0.172	0.824	0.000	0.000	0.000	0.523	0.369	0.896
Acq	0.253	0.368	0.192	0.007	0.005	0.014	0.000	0.000	0.000	0.039	0.321	0.049
Money	0.266	0.278	0.255	0.168	0.312	0.114	0.000	0.000	0.000	0.266	0.278	0.255
Grain	0.067	0.035	0.888	0.066	0.035	0.615	0.098	0.910	0.051	0.067	0.035	0.888
Crude	0.139	0.101	0.227	0.068	0.116	0.048	0.000	0.000	0.000	0.139	0.101	0.227
Trade	0.523	0.755	0.400	0.273	0.795	0.165	0.000	0.000	0.000	0.523	0.755	0.400
Int	0.149	0.083	0.704	0.169	0.102	0.487	0.000	0.000	0.000	0.162	0.094	0.583
Ship	0.150	0.707	0.084	0.105	0.641	0.057	0.000	0.000	0.000	0.150	0.707	0.084
Wheat	0.054	0.225	0.031	0.014	0.059	0.008	0.051	0.962	0.026	0.057	0.236	0.032
Corn	0.079	0.304	0.046	0.019	0.043	0.012	0.040	0.989	0.020	0.079	0.304	0.046
Avg	0.227	0.329	0.373	0.117	0.228	0.234	0.018	0.286	0.009	0.200	0.320	0.346

as outliers. This indicates that it would be useful to find a better criteria for the original specification of keywords. This is somewhat difficult because in our context only positive information is available.

In summary, the best parameters for this algorithm were binary representation, feature length 10, and linear kernel function (there was not much difference from the radial basis kernel).

6. Comparisons and Conclusions

In Table 8, we list the best F_1 results from one-class SVM, outlier-SVM and the four other algorithms from the work by Manevitz and Yousef (2001). The results from ten Reuters categories are presented. We also list, in this table, the "macro" averages which take into account the different number of items in each category.

Looking over this table, and focusing on the unweighted average, we see that the one-class SVM as proposed by Schölkopf et al., gives the best overall performance. This is quite clear with respect to all the other algorithms except the compression NN algorithm which is comparable. Schölkopf's proposal has the usual advantages of SVM; in particular it is less computationally intensive than neural networks.

Under the "macro" averaging, the NN and outlier-SVM were somewhat superior. This means that while the one-class SVM was more robust with regards to smaller categories, the NN and outlier-SVM showed good results by emphasizing success in the larger categories.

On the other hand, the one-class SVM was very sensitive to the parameters and choice of kernel. The neural network method, in comparison, seemed relatively stable over these parameters. (In our experiments, the linear kernel was, however, fairly stable although its results were slightly worse than the neural network algorithm.) Thus, under current knowledge, i.e. until understanding of the parameter choice is clearer, it would seem that the neural network method is the preferred one.

Table 6: Cumulative number of negative examples (outliers) used from the training set to train the outlier-SVM classifier.

Vector Dimension 10

Category Name	Original	1	2	3	4	5	6	7
Earn	966	35	144	231	318	451	630	765
Acquisitions	590	33	78	157	254	371	467	532
Money-fx	187	7	26	43	67	101	123	157
Grain	151	2	21	37	61	100	122	139
Crude	155	1	16	30	55	72	92	110
Trade	133	2	9	17	27	50	73	91
Interest	123	3	8	19	38	51	84	107
Ship	65	8	20	33	46	53	58	63
Wheat	62	1	5	8	23	39	46	49
Corn	62	2	7	8	20	30	35	44

Vector Dimension 20

Category Name	Original	3	4	5	6	7	8
Earn	966	41	120	235	410	538	650
Acquisitions	590	98	148	235	311	368	422
Money-fx	187	18	30	48	74	97	118
Grain	151	13	29	45	68	96	110
Crude	155	14	23	37	49	65	82
Trade	133	8	14	18	27	39	51
Interest	123	11	14	35	45	62	78
Ship	65	20	31	35	40	47	52
Wheat	62	1	7	15	23	32	45
Corn	62	2	7	9	11	26	32

Table 7: Outlier-SVM using binary representation with different kernel functions, outliers with Hamming distance 7, vector dimension 20.

	Linear			Sigmoid			Polynomial			Radial basis		
	F_1	R	P	F_1	R	P	F_1	R	P	F_1	R	P
Earn	0.605	0.490	0.791	0.593	0.451	0.864	0.391	0.249	0.909	0.592	0.477	0.779
Acq	0.449	0.376	0.556	0.452	0.366	0.591	0.329	0.214	0.706	0.449	0.371	0.567
Money	0.480	0.463	0.498	0.474	0.415	0.551	0.315	0.202	0.716	0.484	0.431	0.551
Grain	0.350	0.364	0.337	0.369	0.271	0.574	0.091	0.048	0.849	0.384	0.289	0.573
Crude	0.455	0.501	0.416	0.522	0.541	0.504	0.458	0.354	0.647	0.493	0.511	0.476
Trade	0.419	0.618	0.317	0.432	0.735	0.306	0.078	1.000	0.041	0.441	0.685	0.325
Int	0.390	0.391	0.388	0.378	0.321	0.461	0.137	0.075	0.736	0.379	0.332	0.440
Ship	0.280	0.189	0.536	0.221	0.128	0.806	0.000	0.000	0.000	0.236	0.143	0.666
Wheat	0.225	0.413	0.154	0.197	0.268	0.155	0.031	0.016	0.428	0.183	0.376	0.121
Corn	0.217	0.391	0.150	0.352	0.467	0.282	0.037	1.000	0.019	0.353	0.472	0.282
Avg	0.378	0.419	0.414	0.399	0.396	0.509	0.186	0.315	0.505	0.399	0.408	0.478

Table 8: Comparison of One-class SVM (binary representation), Outlier-SVM (binary representation), Neural Networks (Hadamard representation), Naive Bayes, Nearest Neighbor (Hadamard representation), and Prototype Algorithms (*tf-idf* representation). (Each method with the best representation tested.)

	One-class SVM Radial Basis F_1	Outlier-SVM Linear F_1	Neural Networks F_1	Naive Bayes F_1	Nearest Neighbor F_1	Prototype F_1
Earn	0.676	0.750	0.714	0.708	0.703	0.637
Acq	0.482	0.504	0.621	0.503	0.476	0.468
Money	0.514	0.563	0.642	0.493	0.468	0.484
Grain	0.585	0.523	0.473	0.382	0.333	0.402
Crude	0.544	0.474	0.534	0.457	0.392	0.398
Trade	0.597	0.423	0.569	0.483	0.441	0.557
Int	0.485	0.465	0.487	0.394	0.295	0.454
Ship	0.539	0.402	0.361	0.288	0.389	0.370
Wheat	0.474	0.389	0.404	0.288	0.566	0.262
Corn	0.298	0.356	0.324	0.254	0.168	0.230
Avg	0.519	0.484	0.513	0.425	0.423	0.426
Macro	0.572	0.587	0.615	0.547	0.530	0.516

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