1 Topic

Description of the CVM (Core Vector Machine) and BVM (Ball Vector Machine) methods from the LIBCVM library (http://c2inet.sce.ntu.edu.sg/ivor/cvm.html).

The Support Vector Machines algorithms are well-known in the supervised learning domain. They are especially appropriate when we handle a dataset with a large number "p" of descriptors[1]. But they are much less efficient when the number of instances "n" is very high. Indeed, a naive implementation is of complexity $O(n^3)$ for the calculation time and $O(n^2)$ for the storing of the values. In consequence, instead of the optimal solution, the learning algorithms often highlight the near-optimal solutions with a tractable computation time[2].

I recently discovered the CVM and BVM approaches. The idea of the authors is really clever: since only approximate best solutions can be highlighted, their approaches try to resolve an equivalent problem which is easier to handle - the minimum enclosing ball problem in computational geometry - to detect the support vectors. So, we have a classifier which is as efficient as those obtained by the other SVM learning algorithms, but with an enhanced ability to process datasets with a large number of instances.

I found the papers really interesting. They are all the more interesting that all the tools enabling to reproduce the experiments are provided: the program and the datasets. So, all the results shown in the paper can be verified. It contrasts to too numerous papers where some authors flaunt tremendous results but we can never reproduce them.

The CVM and BVM methods are incorporated into the **LIBCVM** library. This is an extension of the LIBSVM (version 2.85), which is already included into Tanagra. The source code for LIBCVM being available, I compiled it as a DLL (Dynamic-link Library) and I included it also into **Tanagra 1.4.44**.

In this tutorial, we describe the behavior of the CVM and BVM supervised learning methods on the "Web" dataset available on the website of the authors. We compare the results and the computation time to those of the C-SVC algorithm based on the LIBSVM library.

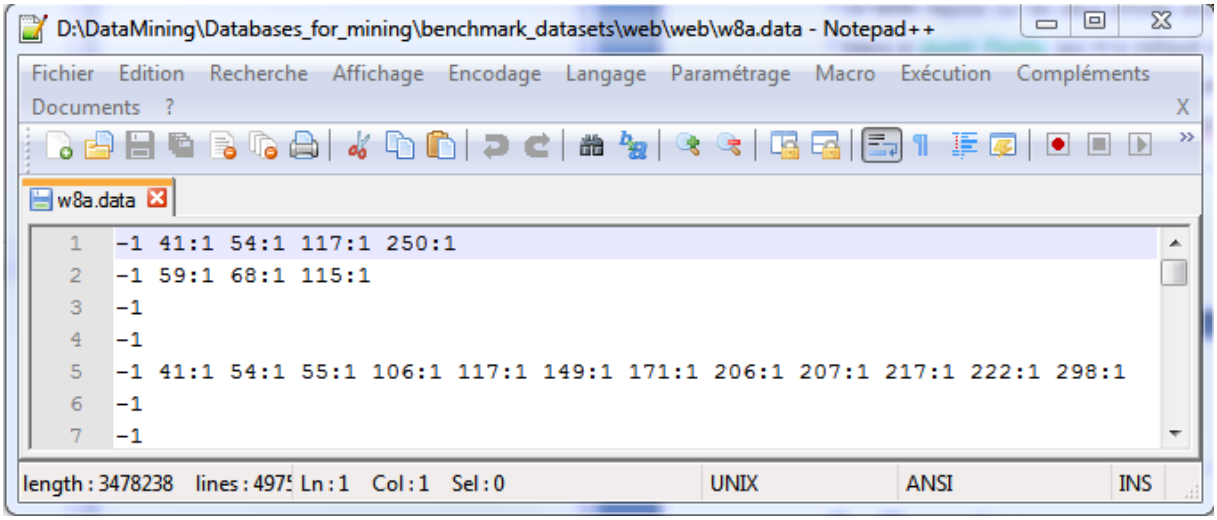
2 "Web" dataset in the sparse format

The "web » database is initially subdivided in 2 files: "w8a.data" corresponds to the learning sample (49,749 instances); "w8a.test" is the test sample (14,951 instances). They are both in the sparse format, handled – among others – by the SVMLIGHT and the LIBSVM libraries.

Each row represents an instance of the dataset. The first value is the class membership. Then, we have a list of couples of values divided by the character ":". The first one is the variable number; the second one is the value associated to this variable. Thus, the value for the not referenced variables in a row is implicitly 0. This kind of representation enables to dramatically reduce the size of the data file without loss of information. Below, we observe the firsts instances of "w8a.data" data file.

[1] E.g. http://data-mining-tutorials.blogspot.fr/2009/07/implementing-svm-on-large-dataset.html (n=135, p=31,809).

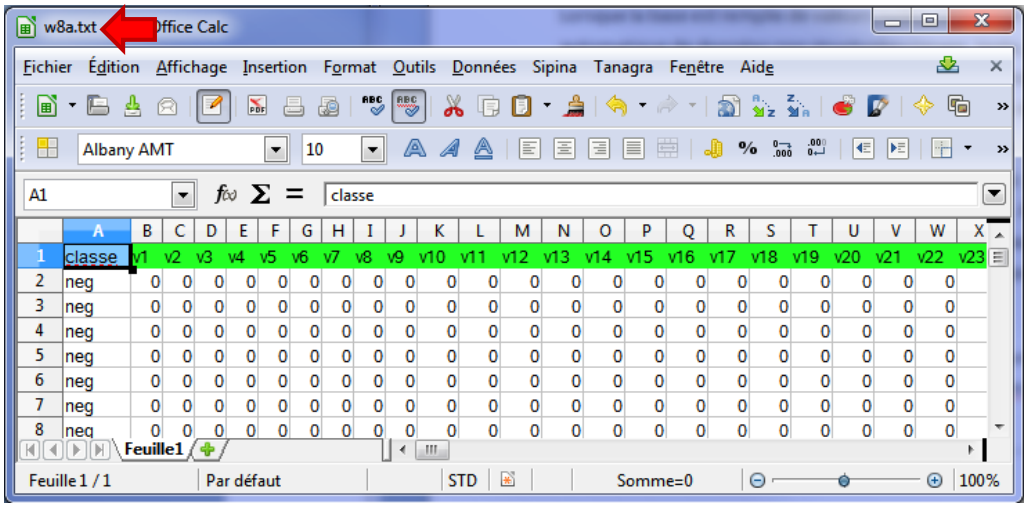
[2] Paragraph based on the papers available on the LIBCVM website - http://c2inet.sce.ntu.edu.sg/ivor/cvm.html



The first observation belongs to the class "-1". Then, we have V1 = 0 since this variable is not referenced; V2 = 0; ...; V41 = 1 because we observe "41:1"; V42 = 0; ...; V54 = 1; etc.

A data file with a large number of null values is common when it is obtained from the pretreatment of an unstructured document (e.g. text, image). This is a kind of compression. Except that the resulting file is readable with a simple text editor.

For convenience, we have concatenated the two data files and we used a small program to transform the file in the dense format (standard tab separated attribute value description, "**w8a.txt**"). Thus, we have a data file with 64,700 rows and 301 columns (including the class attribute). We show here the firsts rows of the new data file.

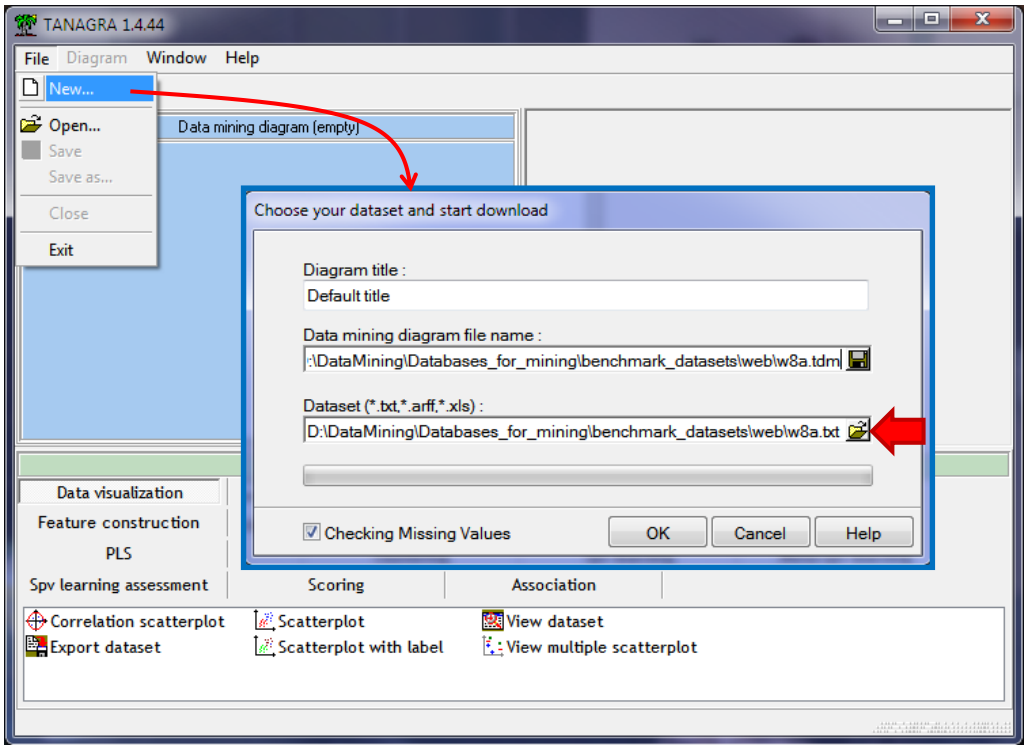


3 Core Vector Machine (CVM)

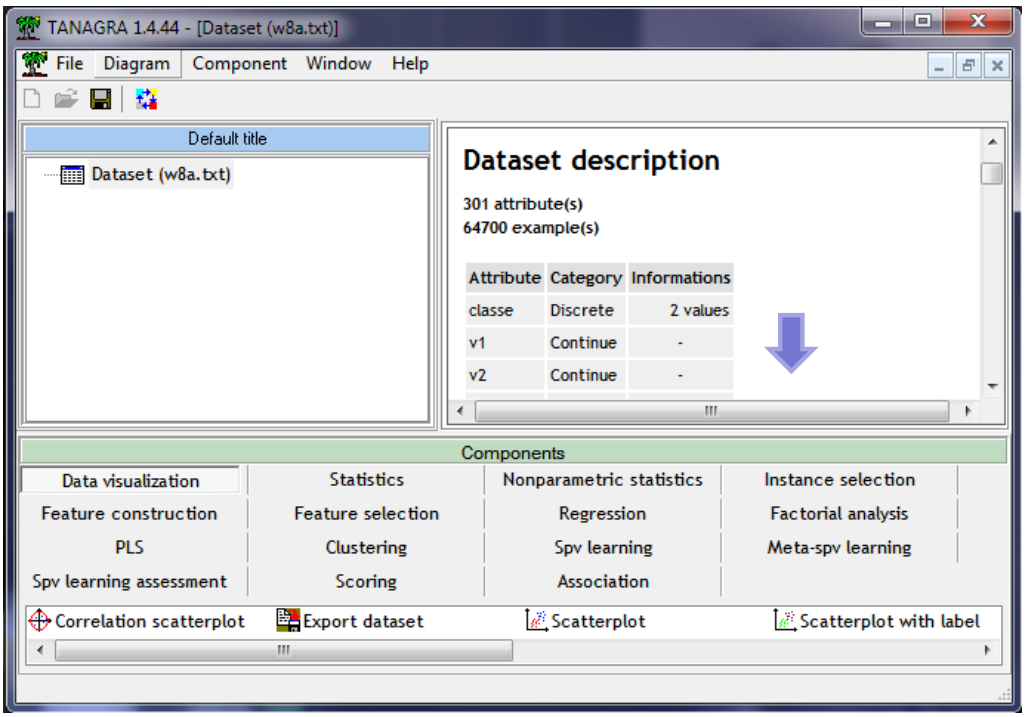
We do not describe the CVM approach in this section. This has been done in the Tsang and al. paper available online: Ivor W. Tsang, James T. Kwok, Pak-Ming Cheung. **Core vector machines: Fast SVM training on very large data sets.** *Journal of Machine Learning Research*, 6:363-392, 2005. According to the authors, the main consequence is that we can handle large datasets with similar results to the standard implementation of the SVM algorithms. To check this, we will compare the results with those of C-SVC from the LIBSVM library (section 5).

3.1 Importing the data file

Into Tanagra, we click on the FILE / NEW menu to create a new diagram. We select the "w8a.txt" data file and we start the data importation.

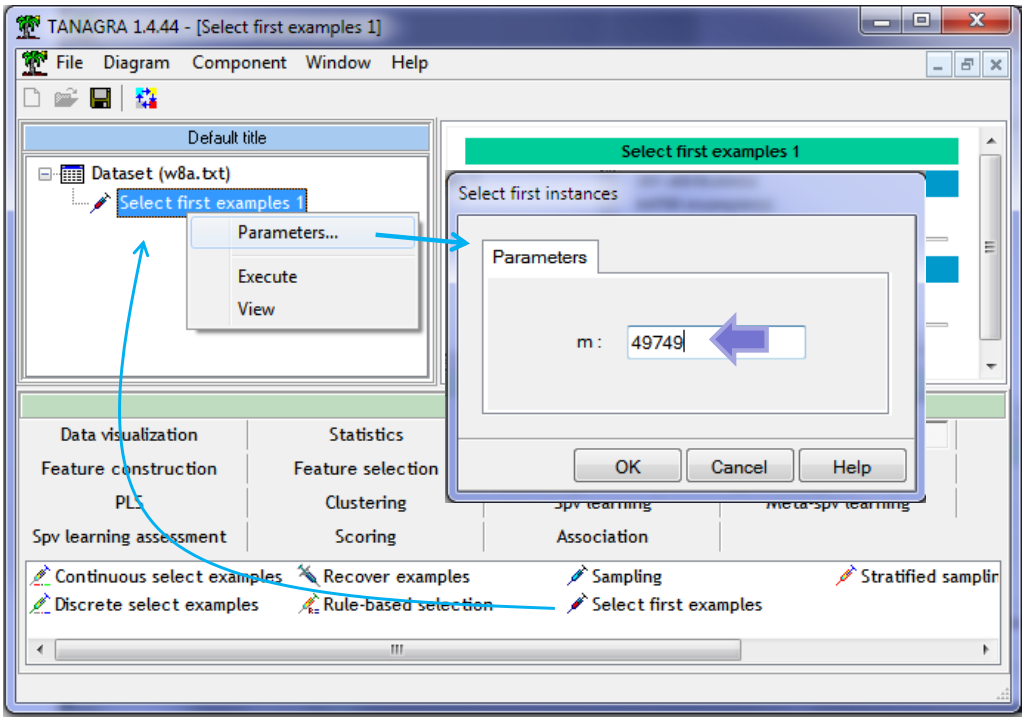


301 variables and 64,700 instances are imported. The class attribute is discrete; all the others are viewed as continuous even if they are binary. This last remark is not insignificant. This will determine the data transformation mode for the learning process.

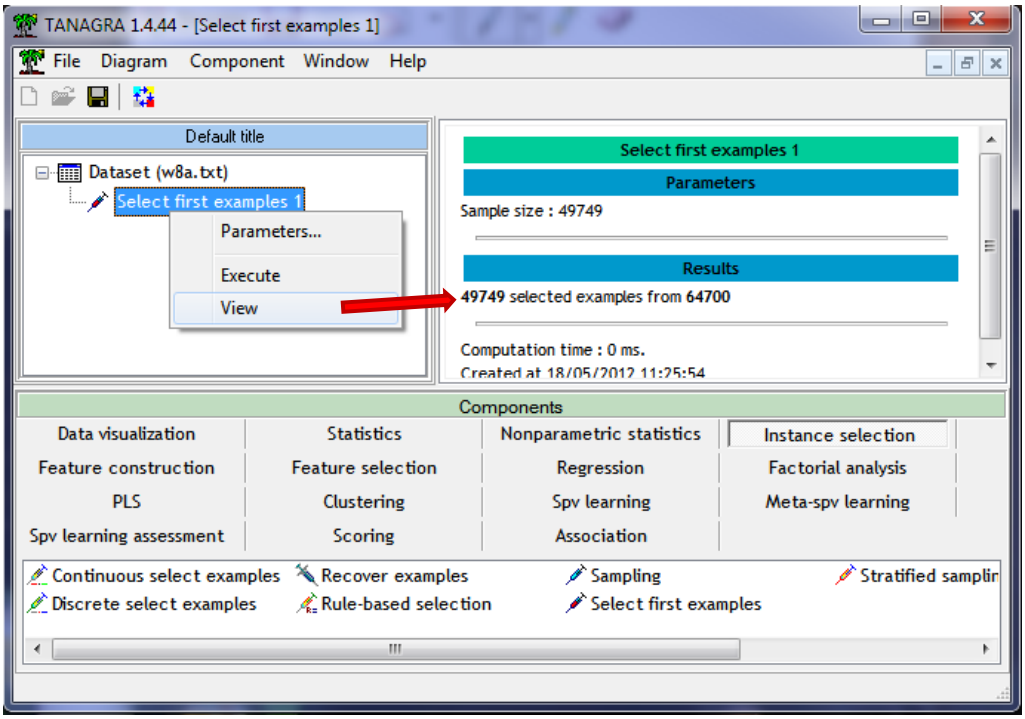


3.2 Partition into learning and test samples

The learning sample corresponds to the first 49,749 instances. We partition the dataset using the SELECT FIRST EXAMPLES component (INSTANCE SELECTION tab).



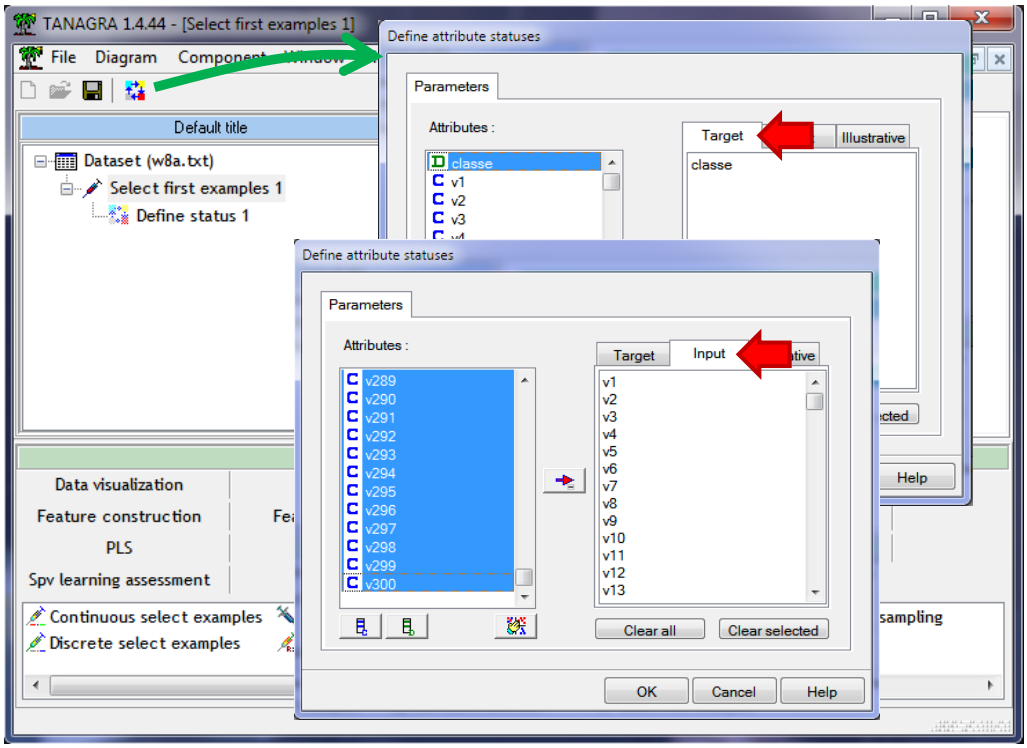
We add the component into the diagram. We activate the PARAMETERS contextual menu. We set "m = 49749". We validate the choice and we click on the VIEW menu.



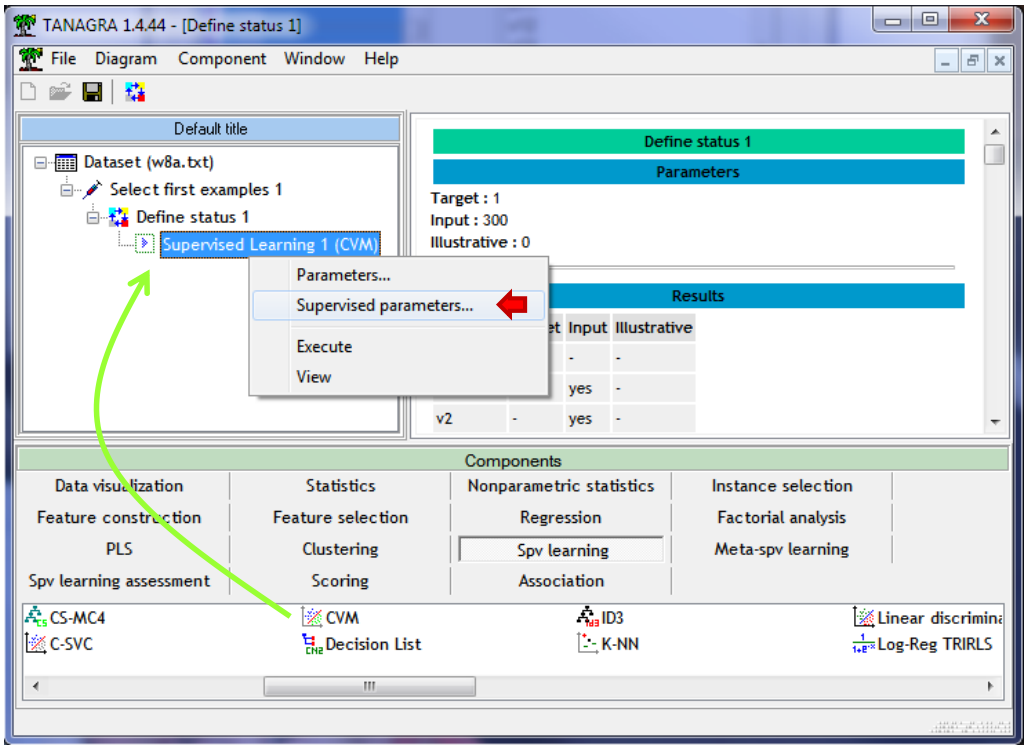
Tanagra confirms the selection of the first observations.

3.3 Set the parameters of learning process

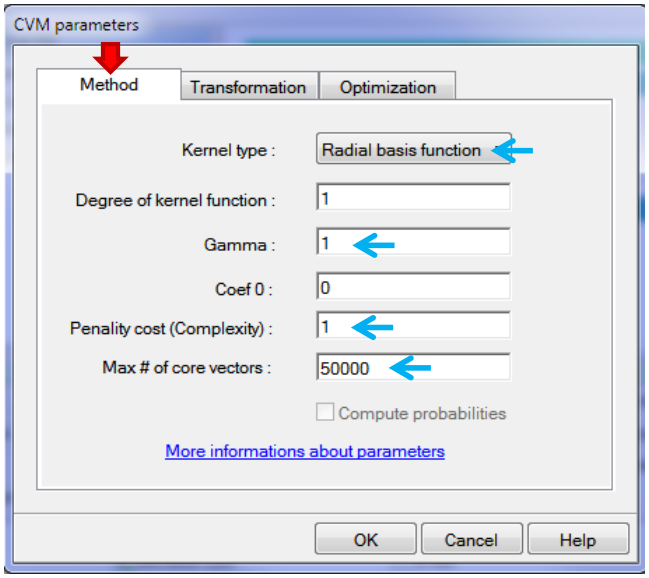
We insert the DEFINE STATUS component to indicate the role of the variables: CLASSE is the target attribute; the others are the input ones “V1…V300”.



Then, we add the CVM (SPV LEARNING tab). We set the parameters by clicking on the SUPERVISED PARAMETERS menu.



Into the **METHOD** tab, we specify the settings of the learning process[3]:

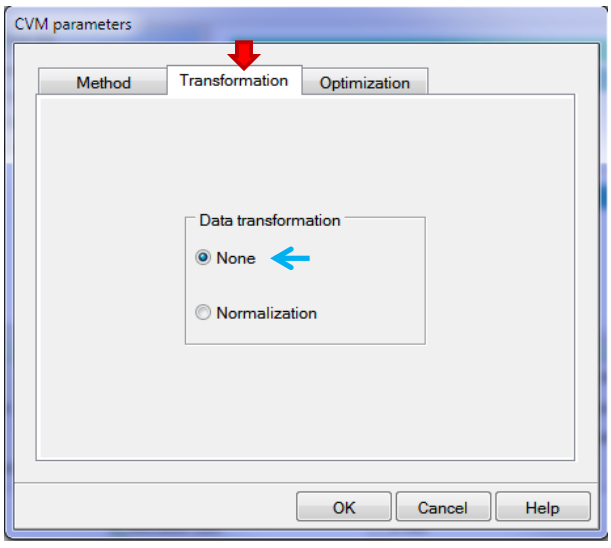


- Kernel Type: RBF (Radial Basis Function, option : –t 2)
- Gamma: 1 (-g 1)
- Cost: 1 (–c 1)
- Max number of core vectors: 50000 (-f 50000)

Into the **TRANSFORMATION** tab, we set the eventual data transformation used. **This option is specific to Tanagra**. By default, Tanagra uses the following NORMALIZATION for each input attribute:

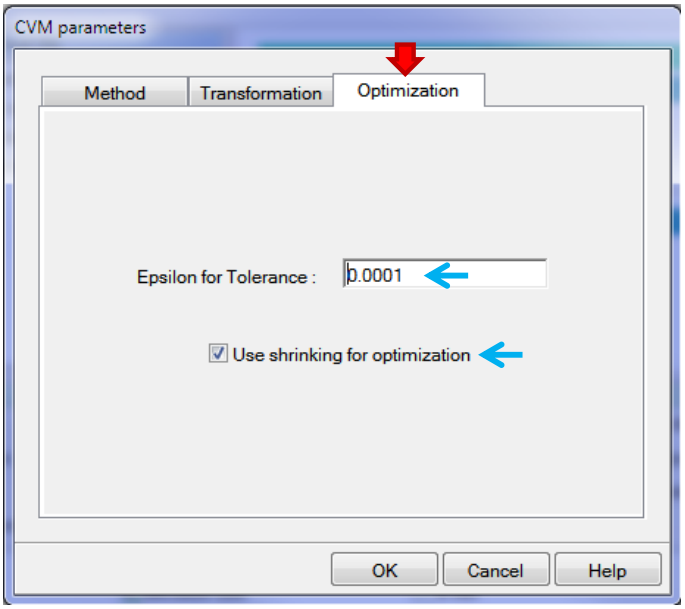
$$z = 2 \times \frac{x - x_{min}}{x_{max} - x_{min}} - 1$$

So, Z varies between [-1; +1]. This transformation is important when the variables are expressed in different units. The variances are not the same. The variables which have higher amplitude may influence excessively the calculations. For our dataset, we have only binary input attributes 0/1. This normalization is not really required. This is the reason for which we select the **NONE** option.



[3] See http://c2inet.sce.ntu.edu.sg/ivor/cvm.html to understand these settings (Section **How to Use**).

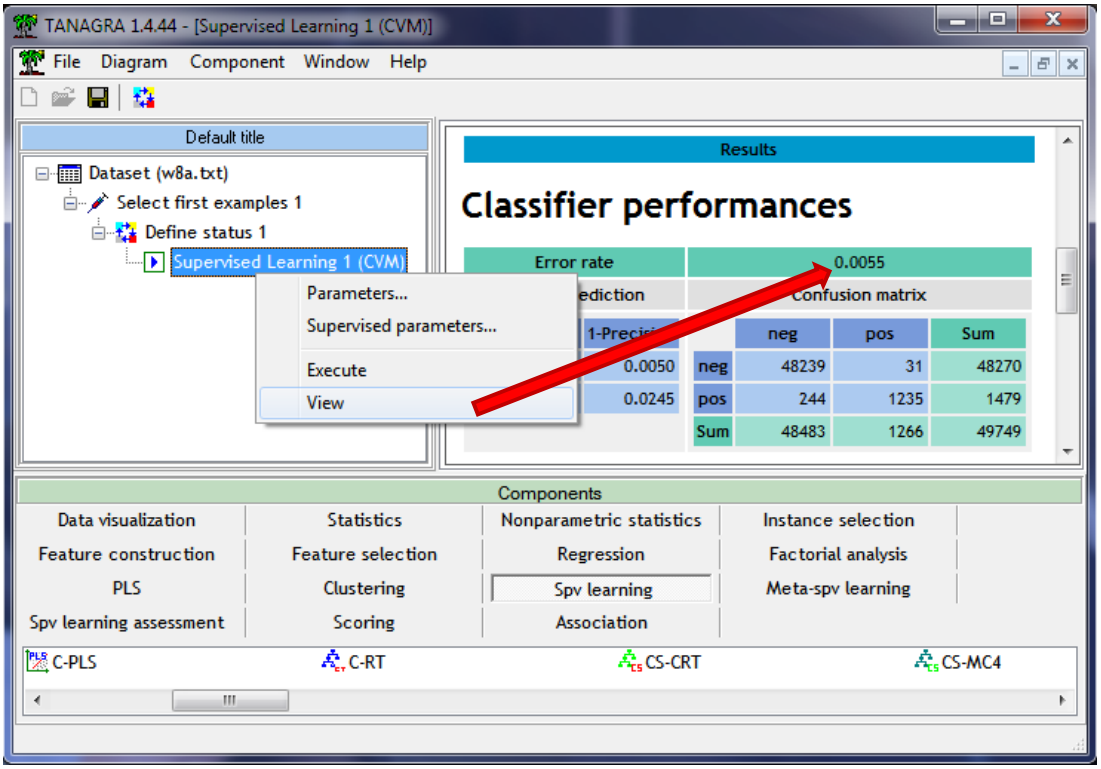
In the **OPTIMIZATION** tab, we set the options which influence the quality of the optimization (and which influence also the calculation times!):



- Epsilon: 0.0001 (-e 0.0001)
- Use shrinking for optimization (-h 1).

We validate and we click on the VIEW menu to run the learning phase.

3.4 Training phase and model evaluation



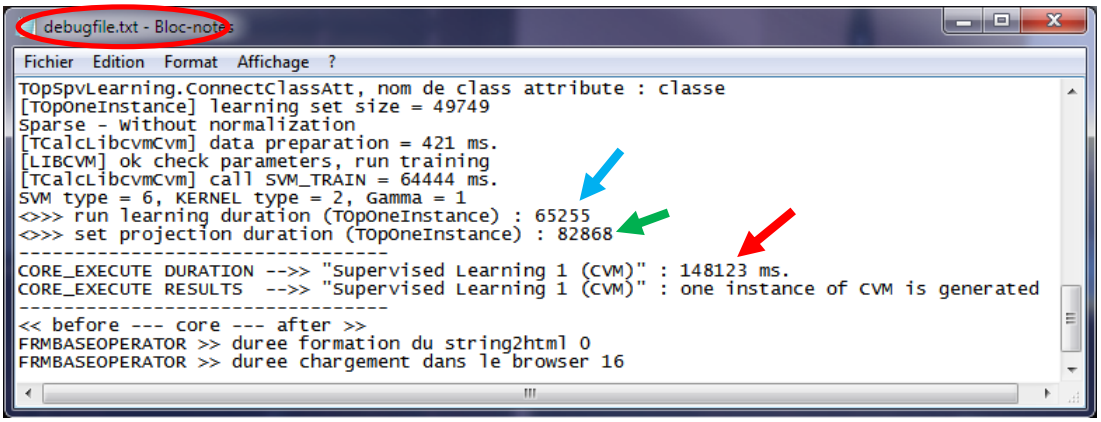
The resubstitution error rate is 0.55% (244 + 31 = 275 misclassified instances on 49,749). There are 3,843 support vectors.

SVM characteristics

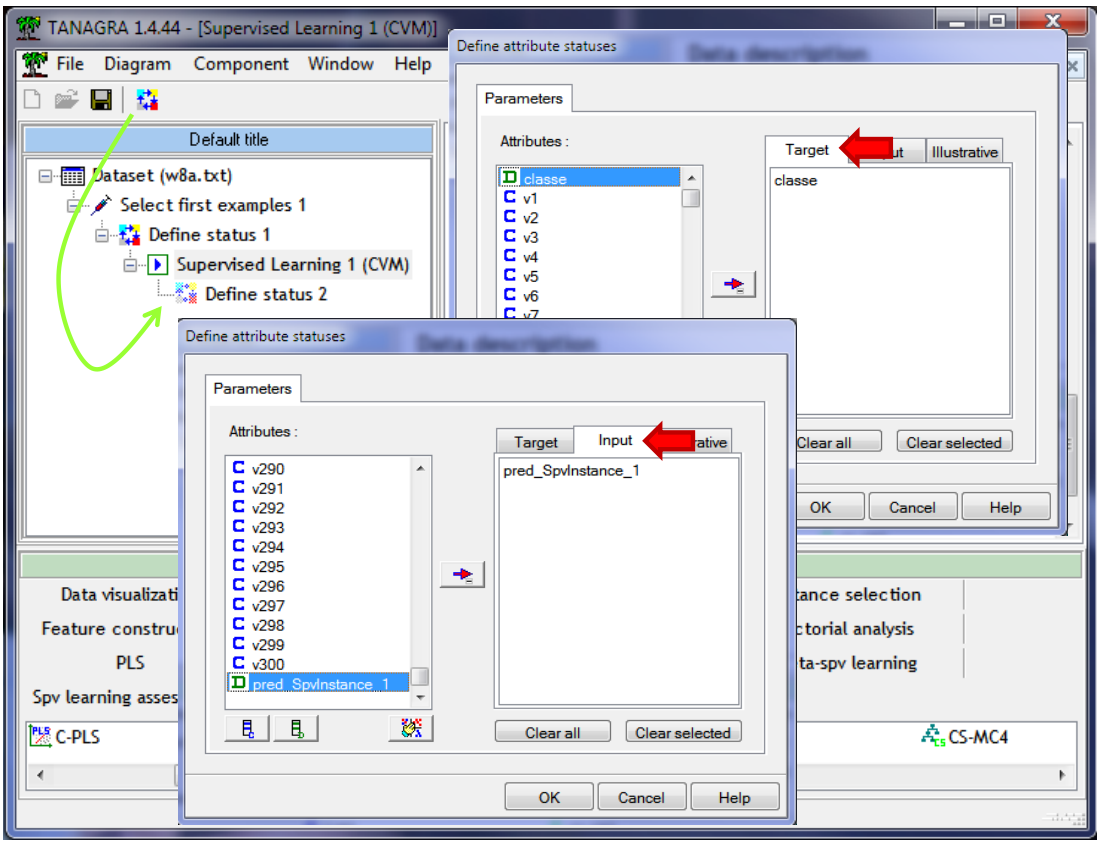
Characteristic	Value
# classes	2
# support vectors	3843
# support vectors for each class	
# sv. for neg	2592
# sv. for pos	1251

Computation time : 148123 ms.
Created at 18/05/2012 11:59:47

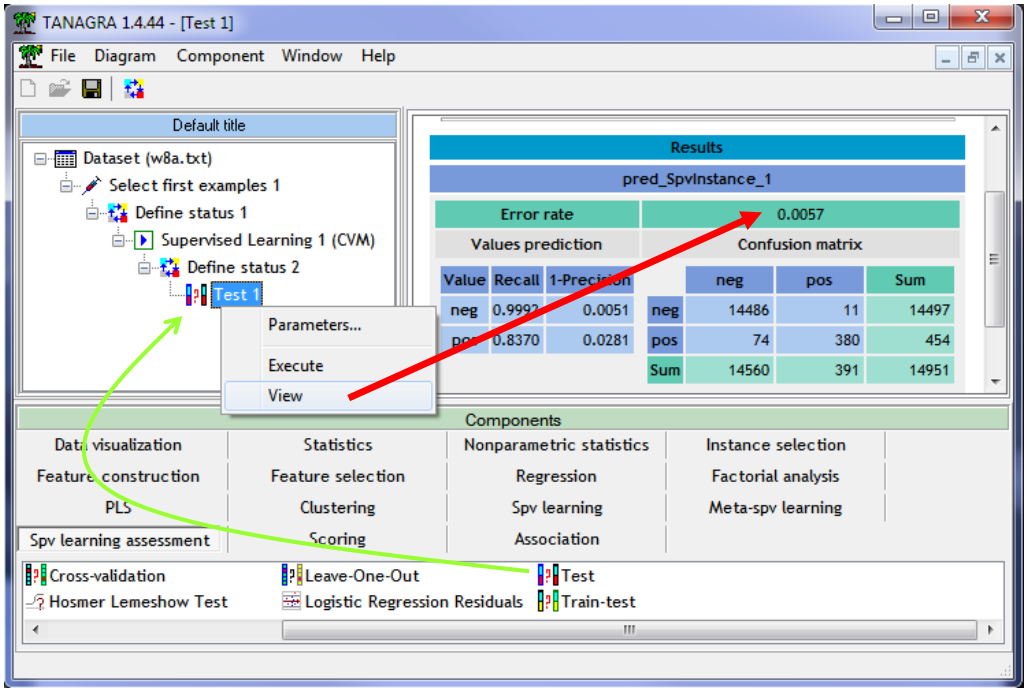
The calculation time of the learning phase is 148 seconds. But it can be divided in two parts, the detail for each step is provided into the log file (**debugfile.txt**): 65 seconds are dedicated to the creation of the model, this is really fast for a SVM like algorithm considering the size of our dataset; 83 seconds correspond to the classification of the instances into the learning sample *AND* the test sample. This second step is needed for the calculation of the error rate on the learning sample, but it is also need for the calculation of the test error rate. Its execution time is not negligible. It will be all the more important that the number of support vectors is high.



To obtain the test error rate, we add again the DEFINE STATUS component. We set CLASSE as TARGET, and the prediction column PRED_SPVINSTANCE_1 as INPUT.



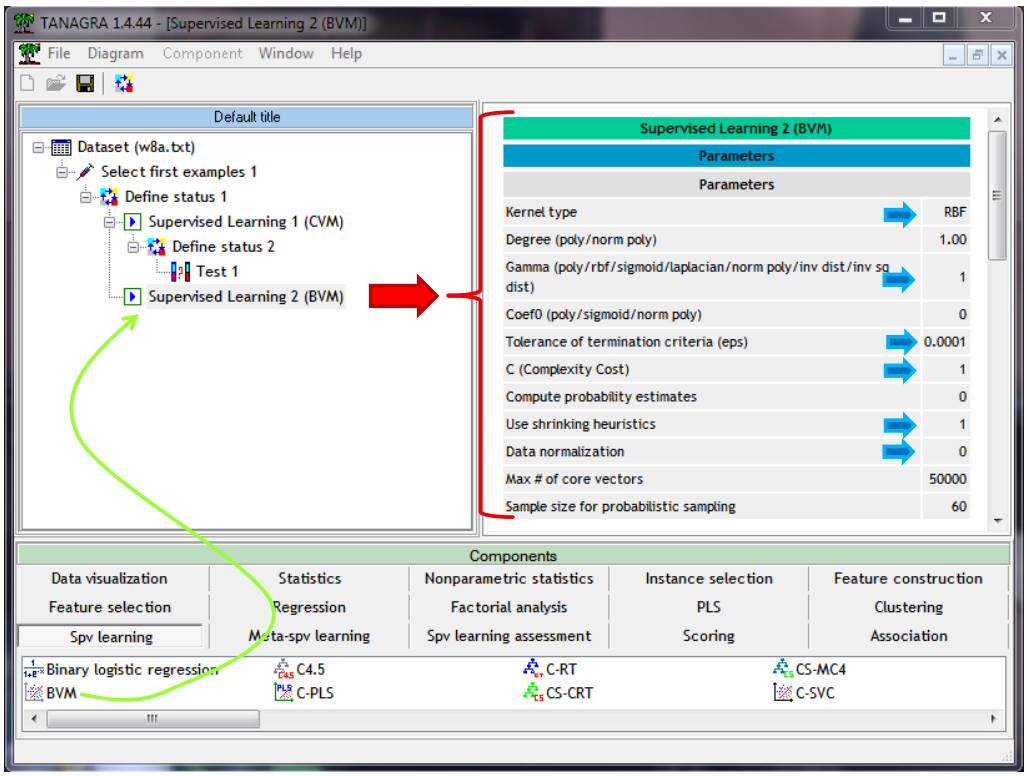
Then, we insert the TEST component (SPV LEARNING ASSESSMENT tab) into the diagram. By default, it computes the confusion matrix on the unselected instances into the branch i.e. the test sample.



The test error rate is 0.57%, with 85 (74 +11) misclassified among 14,951 instances.

4 Ball Vector Machine

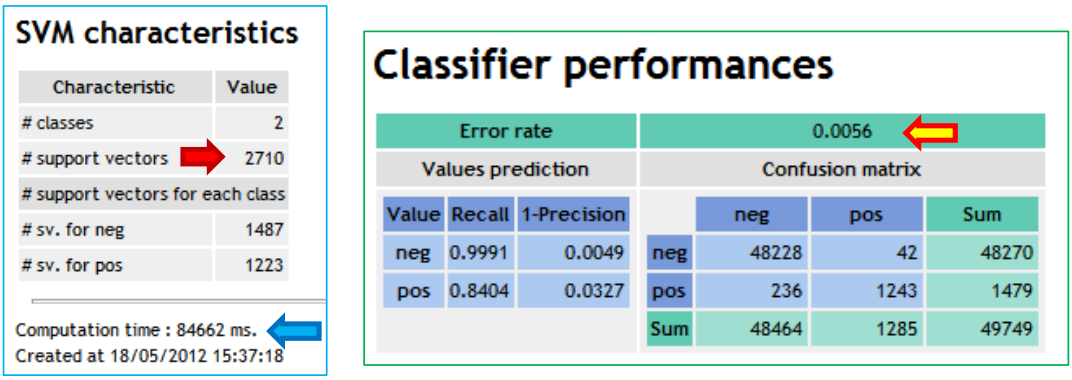
BVM is a variant of CVM. The reference article is: I. W. Tsang, A. Kocsor, J. T. Kwok. Simpler core vector machines with enclosing balls. *Proceedings of the Twenty-Fourth International Conference on Machine Learning (ICML)*, Corvallis, Oregon, USA, June 2007.



Roughly speaking, the minimization requirement during the search of the enclosing ball is relaxed. The calculation time should be reduced during the learning process. But the classification performance (accuracy) should not be affected.

We add the BVM component (SPV LEARNING tab) into the diagram. We set exactly the same settings as the CVM component above. We leave the default values for the additional parameters.

The calculation time is 84 seconds (27 for the model construction, 57 for the classification of all the instances). We obtain 2,710 support vectors. The resubstitution error rate is 0.56%.



SVM characteristics

Characteristic	Value
# classes	2
# support vectors	2710
# support vectors for each class	
# sv. for neg	1487
# sv. for pos	1223

Computation time : 84662 ms.
Created at 18/05/2012 15:37:18

Classifier performances

Error rate	0.0056

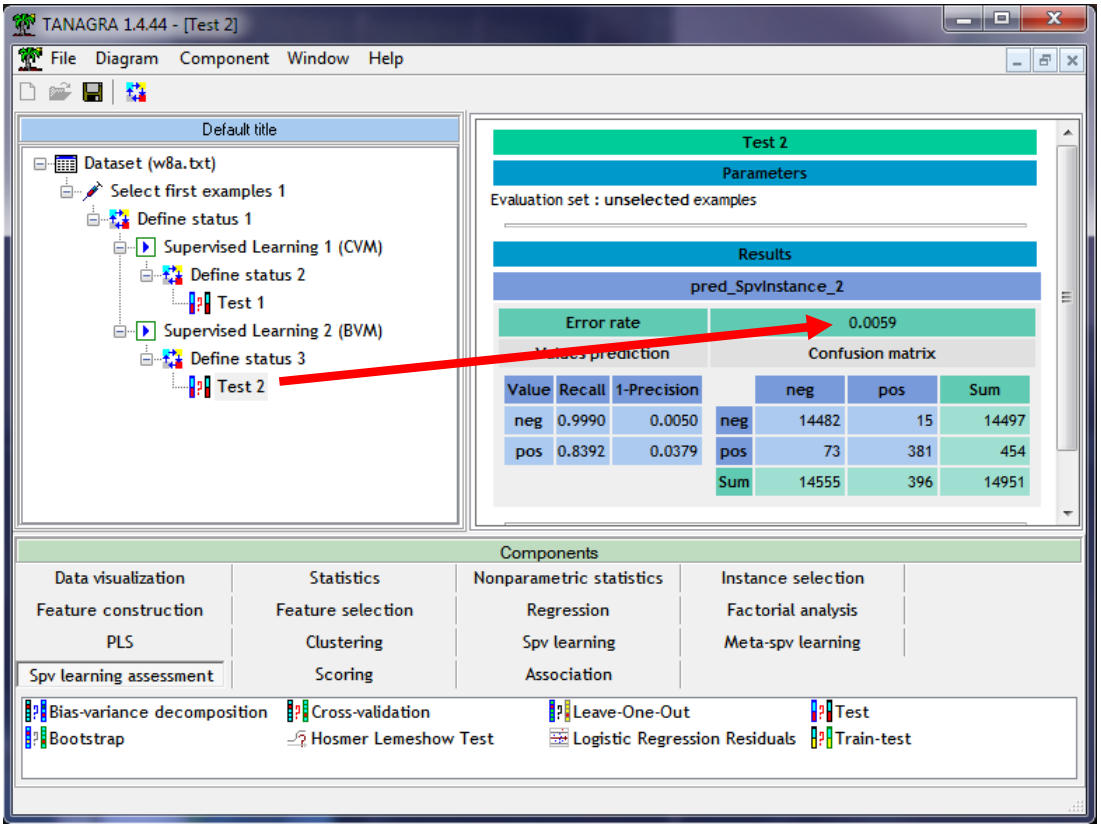
Values prediction

Value	Recall	1-Precision
neg	0.9991	0.0049
pos	0.8404	0.0327

Confusion matrix

	neg	pos	Sum
neg	48228	42	48270
pos	236	1243	1479
Sum	48464	1285	49749

The test error rate is 0.59% (88 misclassified among 14,951 instances).

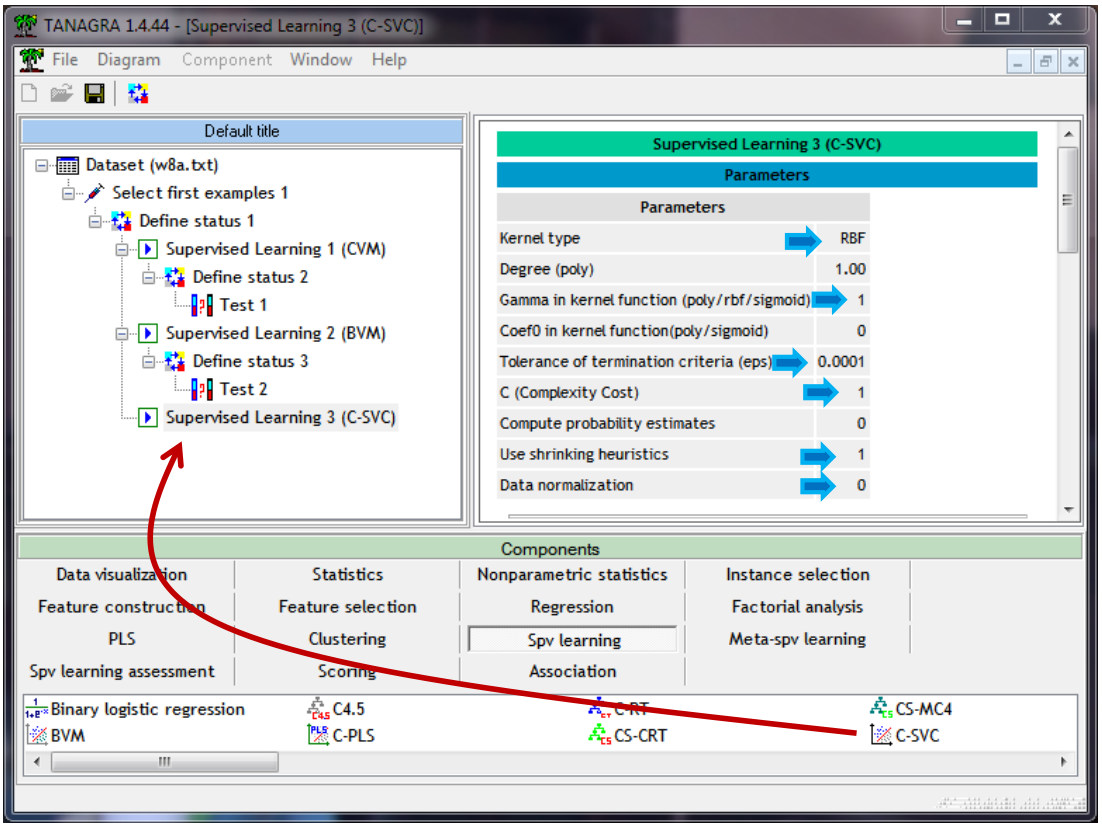


5 Comparison with C-SVC [LIBSVM]

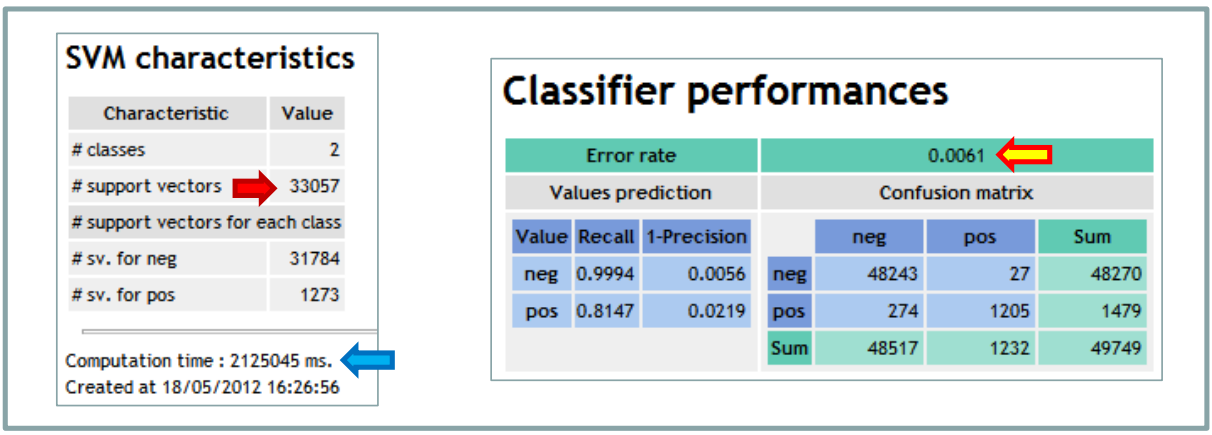
5.1 The C-SVC approach from the LIBSVM library

CVM and BVM are expected to provide results comparable to those of standard SVM implementation, while being able to handle large databases. To verify this, we apply the C-SVC from the state-of-the-art LIBSVM library on the same dataset.

We add the C-SVC component (SPV LEARNING tab) into the diagram. We set the same settings as for CVM and BVM.

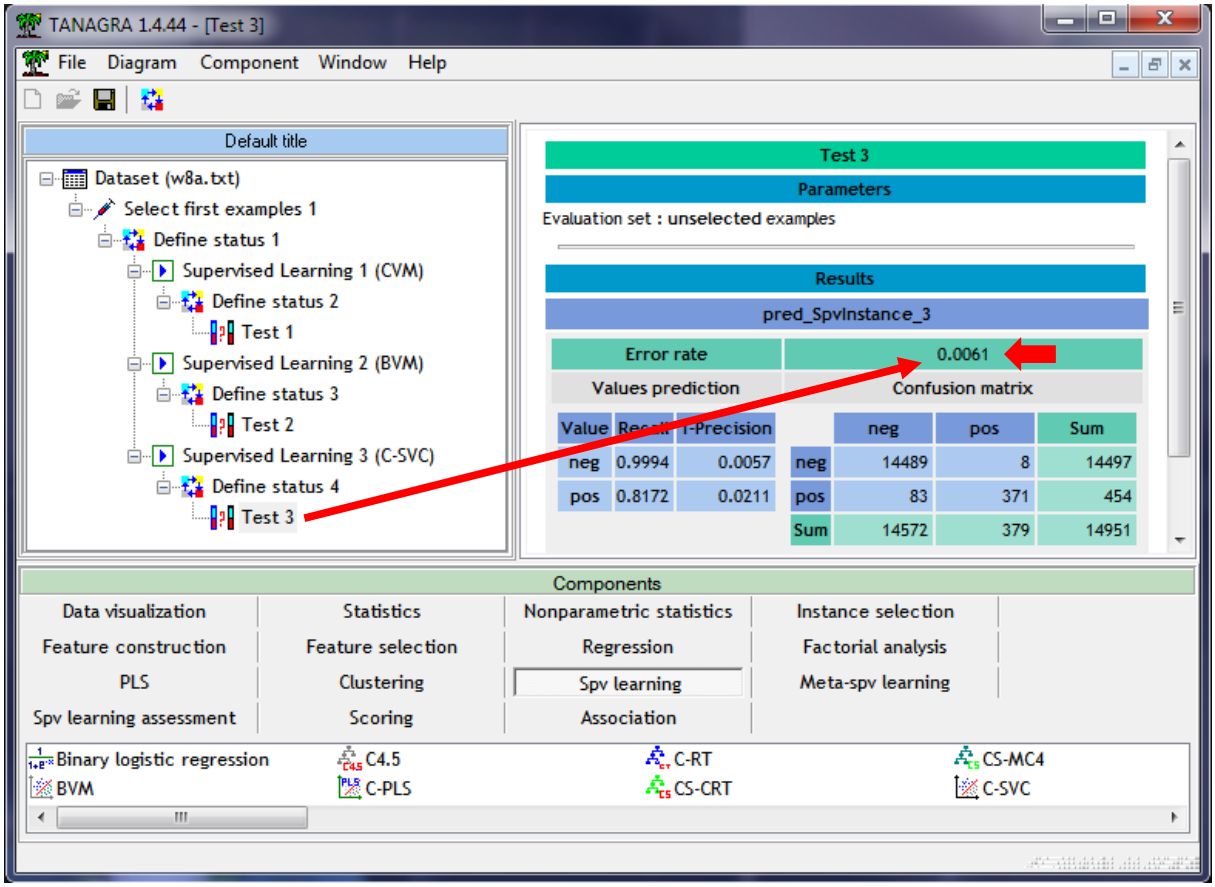


We launch the calculations.



We obtain 33,057 support vectors in 2,125 seconds (≈ 35 minutes!). More specifically, the time for the model construction is 1,560 seconds; it is 564 seconds for the classification of the instances. The resubstitution error rate is 0.61%.

The test error rate is 0.61%. This is similar to those of CVM and BVM.



5.2 Comparison

To compare the methods, we summarize the key results in the following table:

Method	Model characteristics		Calculation time (sec.)	
	# support vector	Test error rate	Model construction	Classification (64,700 cases)
CVM [LIBCVM]	3843	0.57 %	60	80
BVM [LIBCVM]	2710	0.59 %	**27**	57
C-SVC [LIBSVM]	33057	0.61 %	1560	564[4]

With the same settings, and the same accuracy than C-SVC, the calculation time is divided by 27 for CVM; and by 57 for BVM. It seems also that these approaches can handle very large datasets (e.g. the KDD-99 database with n = 4,898,431 instances in the authors' experiments).

Note: To be honest, the differences are not always as spectacular. By changing the settings (e.g. gamma = 0, which is equivalent to set gamma = 1 / number of descriptors), we can obtain slightly less accurate classifiers, but the calculations times become very similar.

[4] The calculation time is strongly penalized by the large number of support vectors. Speaking generally, fastness in classification phase depends on the number of supports vectors.

6 Conclusion

The CVM and BVM algorithms from the LIBCVM library seem particularly efficient. They are a very credible alternative to conventional implementations of the SVM algorithms in the treatment of large databases (with many instances). These methods are incorporated in Tanagra 1.4.44 (and later).