

RSSalg software user manual

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The purpose of this document is to give an overview of RSSalg software. RSSalg software is a tool intended for experimenting with Semi-Supervised Learning (SSL) techniques. These methods aim to train a quality classification model in the case where unlabeled data is abundant but very little annotated training data is available. RSSalg software encompasses the implementation of co-training, a major SLL technique, and several of its single-view variants. It provides a fold cross-validation procedure and supports standard metrics for learning algorithm evaluation. It is free and open-source, available under the GNU General Public License. This document describes how to use RSSalg software for experimenting with SSL techniques and how to extend it for customized purposes.

Preface

The purpose of this document is to give an overview of *RSSalg software*. *RSSalg software* is a tool intended for training a classification model in the case where unlabeled data is abundant but very little annotated training data is available.

In sections 0-4 we give an overview of *RSSalg software* functionalities. Section 0 states the problem. In section 2 we review the classification algorithms implemented in *RSSalg software* and their (user-controllable) parameters. Section 3 explains the built-in cross-validation procedure used for classifier comparison. Finally, section 4 describes all software outputs.

In section 5 we show the empirical experiments which demonstrate *RSSalg software* functionalities. These ready-to-run reproducible experiments can be found in *RSSalg software* code repository¹. We discuss the obtained results and give guidelines on when to expect the best performance of each of the algorithms implemented in *RSSalg software*.

Section 6 explains how to install and run *RSSalg software*. This step -by-step tutorial with screenshots will explain how to use *RSSalg software* GUI (Graphical User Interface) to create and run new experiments.

Finally, in section 7 we give an overview of *RSSalg software* architecture. This section also includes a detailed explanation how to expand *RSSalg software* code with custom implementations.

¹ <https://github.com/slivkaje/RSSalg-software/tree/master/dist/data>

Contents

Preface	1
1 When to use <i>RSSalg software</i>	4
2 Algorithms implemented in <i>RSSalg software</i>	4
2.1 Co-training.....	4
2.1.1 Co-training parameters.....	5
2.2 RSSalg.....	5
2.2.1 Automatic determination of threshold values.....	6
2.2.2 RSSalg parameters	6
2.3 The list of implemented settings	6
3 Experimental design implemented in <i>RSSalg software</i>	7
4 <i>RSSalg software</i> outputs.....	7
5 Illustrative examples of <i>RSSalg software</i> usage.....	10
5.1 Comparing the performance of different semi-supervised algorithms.....	11
5.1.1 Choosing the datasets.....	11
5.1.2 Evaluation procedure.....	12
5.1.3 Choosing algorithm parameters	13
5.1.4 Summary of the parameter values used in the experiment	13
5.1.5 Results	14
5.2 Testing the influence of the number of random splits used in RSSalg	16
5.3 Testing the influence of different underlying classification models.....	17
6 Creating the property files and running the experiment: a tutorial on News 2x2 dataset	20
6.1 Problem setting.....	20
6.1.1 Experimental setting.....	20
6.1.2 Co-training parameters.....	21
6.2 Installing and starting <i>RSSalg software</i>	21
6.2.1 Building the project.....	21
6.2.2 Running the project by using the built executable	22
6.2.3 Running the project by using Apache Ant.....	22
6.3 Specifying parameter values in <i>RSSalg software</i>	23
6.3.1 Specifying dataset settings.....	23
6.3.2 Specifying cross-validation experiment settings.....	28

6.3.3	Specifying co-training settings	29
6.3.4	Specifying experiment settings	31
6.3.5	Specifying genetic algorithm settings	41
6.4	Running the experiment in <i>RSSalg software</i>	42
7	<i>RSSalg software</i> architecture	44
7.1	CoTraningData class.....	45
7.2	Algorithm class	46
7.3	Classifiers class.....	46
7.4	MeasureIF interface.....	47
7.5	SplitterIF interface	47
7.6	StartExperiment class	47
7.7	RSSalg implementation	49
7.8	<i>RSSalg software</i> implementation details	51
7.9	Extending <i>RSSalg software</i>	51
7.9.1	Adding a new algorithm	51
7.9.2	Adding a new feature-splitting method.....	52
7.9.3	Adding a new performance measure.....	53
7.9.4	Adding a new threshold optimization technique	53
8	References	54

1 When to use *RSSalg* software

RSSalg software is a free and open-source tool for experimenting with Semi-Supervised Learning (SSL) classification techniques. It is registered under GNU General Public License.

When training a prediction model we are often faced with a problem of lacking a sufficient amount of labeled training data. Data labeling may require manual human work which may be very expensive regarding both time and money. For example, unlabeled clinical notes are abundant; however, labeling them with a goal of training a medical diagnostic expert system requires a group of trained medical experts that must manually inspect and carefully label each sample. The predictive power of the obtained prediction model is largely dependent on the size and quality of the training sample [1].

SSL techniques strive to incorporate both labeled and unlabeled data in the training process, thus minimizing the human effort concerning hand-labeling data while keeping the desired level of quality of the prediction model [2]. *RSSalg* software can be used to train a classification model in a supervised fashion (using only available labeled data) or in the semi-supervised manner (using both labeled and unlabeled data), thus enabling the user to assess how much did the unlabeled data augment the learning process.

A major SSL technique is co-training [3]. Co-training is applicable on the datasets that have a natural separation of features in two views. *RSSalg* software enables the user to run co-training with user-defined feature split.

In practice, an adequate feature split for co-training might be unknown (these datasets are referred to as single-view datasets in the co-training literature). The lack of feature split may be addressed by creating an artificial feature split for co-training. In *RSSalg* software the user can choose to run co-training on a single-view dataset using the randomly generated feature split. Researchers can also easily extend *RSSalg* software by adding their feature-splitting implementations (section 7.9.2).

Another way to address the lack of adequate feature split is to combine co-training with ensemble methods. One such technique is *Random Split Statistic algorithm (RSSalg)* [4] which can be applied on single-view datasets). The RSSalg method is implemented in *RSSalg* software.

RSSalg software encompasses the cross-validation experimental design and a number of standard metrics for evaluating algorithm performance, such as accuracy, precision, recall and *f1*-measure (section 3).

RSSalg software is beneficial for the researchers who wish to experiment with their SSL solutions. Implemented algorithms are highly configurable regarding parameter values, allowing the researchers to test the parameter influence on algorithm performance empirically. Experiments are fully reproducible as one of the user-controlled parameter is the random number generator seed. It is easy to extend *RSSalg* software by adding new SSL algorithms, feature splitting techniques, and evaluation measures (section 7.9).

In summary, *RSSalg* software can be used to train and evaluate different classification algorithms built on the dataset that:

- may contain both labeled and unlabeled instances;
- may or may not have a feature split that can be utilized in the learning process.

2 Algorithms implemented in *RSSalg* software

This section will first give a high-level overview of two main algorithms implemented in *RSSalg* software: co-training and RSSalg and provide a list all their parameters which are tunable in *RSSalg* software (sections 2.1 and 2.2, respectively). Section 2.3 gives a full list of settings implemented in *RSSalg* software.

2.1 Co-training

A high-level overview of co-training is illustrated in figure 1. In co-training two different views are used to train two different classifiers using the same available labeled data (L). The trained classifiers are applied to the set of unlabeled data (U) with the goal of selecting and labeling the most confident instances. These instances are added to the initial labeled set, and both classifiers are retrained in the supervised fashion on the enlarged training set. This process is repeated for a predefined number of iterations.

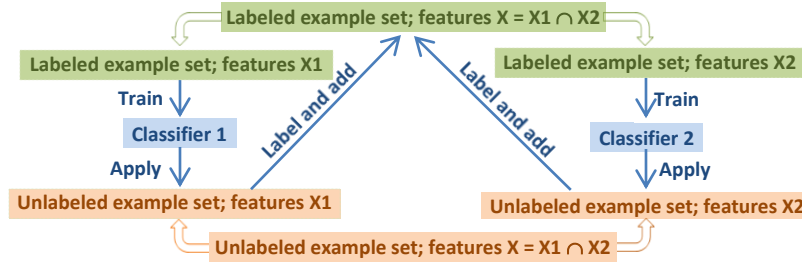


Figure 1. A high-level overview of co-training algorithm

2.1.1 Co-training parameters

The performance of co-training, as introduced in [3], depends on the following algorithm parameters which are all tunable in *RSSalg software*:

- **The number of co-training iterations k .** In *RSSalg software* user can:
 - (1) specify the desired number of iterations k after which co-training stops (regardless of how many unlabeled examples are left out of the training process) or
 - (2) specify to stop co-training when all unlabeled instances have been labeled.
- **The growth size (denoted p/n in [3]).** In *RSSalg software* user can specify $mcc_1, mcc_2, \dots, mcc_l$ where mcc_i denotes the number of instances most confidently classified as category i which will be added to L in each iteration of co-training, and l denotes the number of categories. Authors in [3] suggest that, for the best performance of co-training, p/n should be representative of the underlying label distribution.
- **The usage (and size) of a small unlabeled pool u' .** In [3] authors use the small unlabeled pool u' for the selection of most confidently labeled instances that will be added to L in each iteration of co-training (rather than selecting the most confidently labeled instances directly from U). After each iteration, u' is replenished by randomly selected examples from U to keep its size constant. Authors in [3] have found that using u' makes the underlying co-training classifiers choose the instances more representative of the underlying distribution that generated U . In *RSSalg software*:
 - (1) the user can opt to use a small unlabeled pool, in which case he needs to specify the size of u' , or
 - (2) he can choose to select examples directly from U (as some authors do [5]) by setting the size of u' to 0.
- **The classification model used for underlying view classifiers in co-training.** Underlying view classification models may significantly affect the algorithm performance [6]. In *RSSalg software* user can provide an arbitrary classifier from Weka libraries [7] to use for each view separately. User can also provide an implementation of a custom classifier, the only requirement being that it complies with Weka's *Classifier* interface². Section 5.3 explores the effect of using different underlying classification models.

2.2 RSSalg

The first step in *RSSalg* is to create an ensemble of diverse co-training classifiers. The ensemble is formed by generating a predefined number of random feature splits. Each split is used for running a separate co-training process on the same data. Since each split is different, each run of co-training produces a different enlarged training set, consisting of initially labeled data and data labeled during the co-training process. Examples from all acquired enlarged training sets are integrated into one unique training set. If the same instance was labeled in multiple enlarged training sets, its label is determined by majority vote. The integrated set is then filtered to keep only the most confidently labeled instances. The instance is considered confidently labeled if: (1) it appears in most of the produced enlarged training sets and (2) it was assigned the same label in the majority of those sets. Two thresholds are defined for these two conditions: each instance that does not meet the thresholds is omitted from the dataset. After filtering, the integrated training set is used to train a supervised classification model which can be used to predict the label for previously unseen examples. The high-level overview of *RSSalg* is shown in figure 2.

² <http://weka.sourceforge.net/doc.dev/weka/classifiers/Classifier.html>

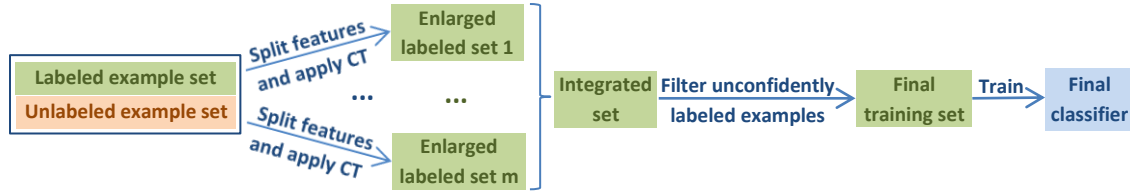


Figure 2. A High-level overview of RSSalg

2.2.1 Automatic determination of threshold values

For threshold optimization in RSSalg, a **Genetic Algorithm (GA)** is used: each threshold pair is considered a candidate (an individual in GA generation). A threshold pair defines the instances that will be utilized for training the final model in RSSalg. Thus, the fitness of the candidate should reflect the quality of the final model. In RSSalg, the quality of the model is assessed using the labeled instances that were left out (filtered) from the final training set and used as candidate fitness.

2.2.2 RSSalg parameters

In addition to parameters used in underlying co-training classifiers, RSSalg introduces some additional parameters:

- **The number of random splits m** (used for creating m different co-training classifiers). In *RSSalg software* user can specify any number of splits (larger than 0). The effect of the number of splits is explored in section 5.2 of this document.
- **Classification model used for training a final classifier in RSSalg.** In *RSSalg software* user can provide an arbitrary classifier from Weka libraries [7]. The user can also provide an implementation of a custom classifier, the only requirement being that it complies with Weka's *Classifier* interface².
- **Parameters of the genetic algorithm used for automatic determination of threshold values.** In *RSSalg software* user should provide standard GA parameters: number of individuals in one generation (i.e. the generation size), the maximal number of GA iterations, whether to stop if there was no improvement in a specified number of generations, crossover and mutation thresholds and elitism. There are two additional RSSalg-specific parameters used in GA: the performance measure for the final classifier in RSSalg which is being optimized (accuracy, precision, etc.) and the testing threshold [4] (minimal amount of left out instances needed for evaluating the model).

2.3 The list of implemented settings

This section gives a full list of the settings currently implemented in *RSSalg software*:

1. Supervised settings:
 - **L_{acc}**: Supervised learner trained on the labeled portion of the data
 - **All_{acc}**: Supervised learner trained on both labeled and unlabeled instances with correct label assigned
2. Semi-supervised settings:
 - **Natural**: co-training run with natural (user-defined) feature split.
 - **Random**: co-training run with random feature split obtained by randomly assigning each feature to one of the two views of roughly equal size. *RSSalg software* reports the average performance of m runs of co-training with different random feature splits.
 - **MajorityVote (MV)**: a majority vote of m co-training classifiers trained using m different random splits (the same classifiers created in **Random** setting)
 - **RSSalg**: RSSalg as introduced in [4]. RSSalg is an ensemble technique which uses m co-training classifiers obtained using m different random splits. As in **MV**, the user can choose to use the m co-training classifiers created by **Random** setting.
 - **RSSalg_{best}**: RSSalg with thresholds optimized on test data (RSSalg_{best} in [4]. RSSalg_{best} serves as the indication of the upper bound performance of RSSalg. It is used to evaluate the threshold optimization procedure in RSSalg.

It is important to note that the Natural setting is applicable only on the datasets for which the feature split is defined³. All other settings are applicable on both single-view and multi-view datasets (the feature split information is not used in the learning process).

3 Experimental design implemented in *RSSalg* software

RSSalg software encompasses the k -fold cross-validation procedure outlined in [6]: the dataset is divided in k stratified folds; in each iteration of the cross-validation procedure:

- A different fold f is used for random selection of the initial labeled set (L). The size of L is $|L|=c_1 + c_2 + \dots + c_l$, where c_i denotes the number of instances per category i and l denotes the number of categories;
- The remaining data from fold f as well as j ($j < k$) adjacent folds are used as unlabeled data U (the class label information for these instances is disregarded);
- The remaining $k-j-1$ folds are used as test data T .

With parameters k, j, c_1, \dots, c_l user can control the size and label distribution of the labeled set L and the size of the unlabeled set U . The cross validation procedure for $k=10$ and $j=5$ is illustrated in figure 3.

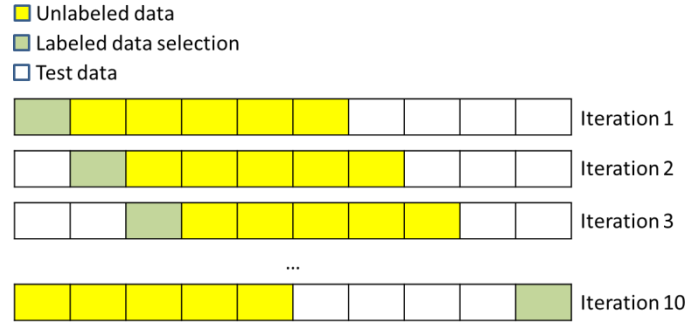


Figure 3. Illustration of the 10-fold cross-validation procedure in which five folds are used as unlabeled data

When running the software user is provided with two options (covered in details in section 6.3.1):

- 1) Load an existing experiment⁴ (previously generated by our tool or a custom one)
- 2) Let *RSSalg* software produce a new experiment using user-provided k, j, c_1, \dots, c_l .

4 *RSSalg* software outputs

In *RSSalg* software user can specify a folder to which all outputs will be recorded (section 6.3.1). We will refer to this folder as the ‘result folder.’ Each time an experiment is run *RSSalg* software will do the following:

- (Optional) Record the generated cross-validation experiment.** If the user has chosen for *RSSalg* software to produce a new cross-validation experiment, *RSSalg* software will record the resulting data partition to the result folder. Please refer to section 6.3.1.2 for the structure of the recorded cross-validation experiment.
- Display micro- and macro-averaged performance measures.** The user may specify one or more performance measures that will be displayed as shown in figure 5.
- Record the obtained performances on disk.** The collected performances will be registered in ‘Results.xml’ file located inside the result folder. An example of ‘Results.xml’ file is given in section 6.4.
- Display the results of all recorded experiments.** *RSSalg* software will list all of the results recorded in ‘Results.xml’ file (figure 5).

³ For example, WebKB course dataset in [3] is defined to have a feature split: the first view (i.e. feature set) contains the features extracted from the links pointing to the web page, while the second view contains the features extracted from the text of the web page

⁴ Experiment in this context denotes the dataset divided in folds (the number of folds may be one) where the data in each fold is divided among L , U , and T .

- e. **(Optional) Record the enlarged training set.** During the execution of each SSL algorithm, some of the instances from the unlabeled set will be labeled and transferred to the labeled set. An enlarged training set may be recorded to the disk as an ARFF file (section 6.3.4 on *Recording results*).
- f. **(Optional) Record the “training/test statistics.”** The “training statistics” of a single classifier refers to recording the details of training an SSL classifier: for each unlabeled instance that is labeled and transferred to L during the learning process, the prediction and classifier confidence is recorded. The “testing statistics” of a single classifier refers to recording the details of classifier evaluation: for each instance from the test data, the prediction and classifier confidence is recorded. In *RSSalg software* each algorithm creates an ensemble of classifiers⁵. Thus, the recorded “training/test statistics” holds the training/test details for each classifier from the ensemble (section 6.3.4 on *Recording results*).
- g. **(Optional) Log the performance of co-training.** As explained in section 6.3.3, we can log each iteration of co-training (the performance of individual views and the performance of their combination). If co-training is run multiple times (e.g. in **Random** setting), *RSSalg software* will log each co-training process individually.
- h. **(Optional) Log the threshold optimization process in RSSalg.** The threshold optimization properties will be recorded in the ‘ThresholdOptimiserlog.txt’ file (section 6.3.5).

Figure 4 provides an example of the result folder structure. Figure 5 presents an example of the output displayed in the console (or GUI).

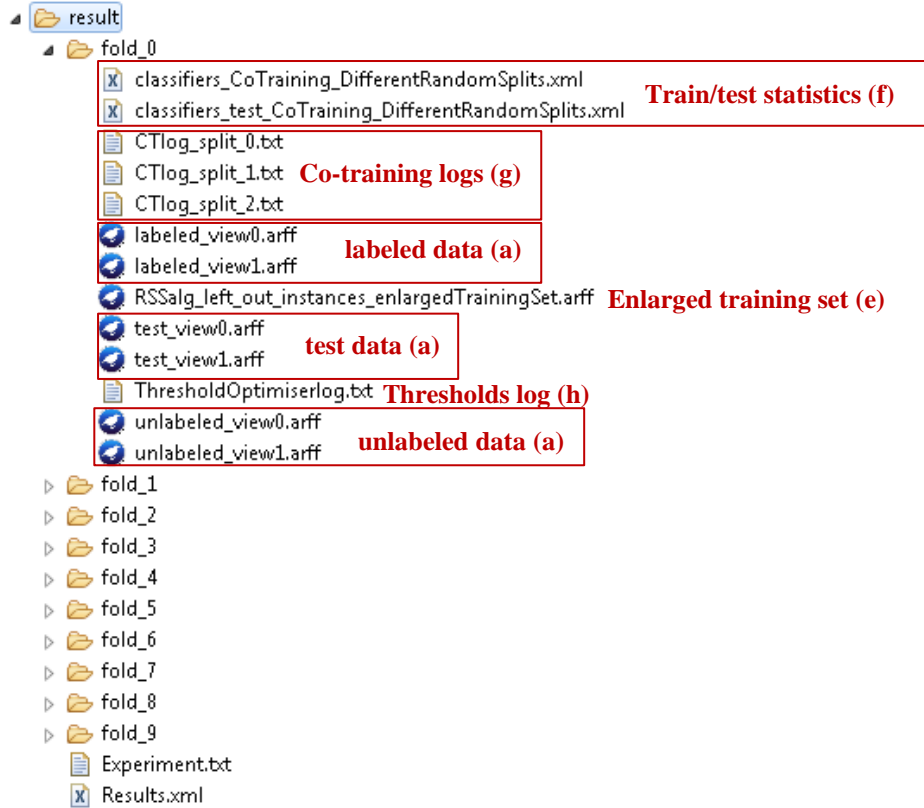


Figure 4. An example of the structure of result folder after running several experiments

⁵ Though an ensemble may contain only one classifier, e.g., in **Lacc** setting

Starting Fold 9
 Reading .\data\News2x2\resultfold_9
 Split 0:
 accuracy: 79.62
 f1-measure for class positiveClass: 75.27
 f1-measure for class negativeClass: 82.68

Experiment finished.

accuracy
 micro averaged: 76.84
 macro averaged: 76.84 +/- 5.1
 f1-measure for class positiveClass
 micro averaged: 74.83
 macro averaged: 74.58 +/- 6.06
 f1-measure for class negativeClass
 micro averaged: 78.55
 macro averaged: 78.43 +/- 5.12

Calculated performance measures for the current experiment

Results of all performed experiments (stored in Results.xml file)

Experimental results:
 Experiments [noSplits= 1, noIterations=20, growth size= 5(positiveClass) 5(negativeClass)]
 Supervised_experiment_L
 accuracy: microAveraged=76.84, macroAveraged=76.84+/-5.1
 f1-measure for class positiveClass: microAveraged=74.83, macroAveraged=74.58+/-6.06
 f1-measure for class negativeClass: microAveraged=78.55, macroAveraged=78.43+/-5.12

 Supervised_experiment_All
 accuracy: microAveraged=89.72, macroAveraged=89.72+/-1.66

 CoTraining
 accuracy: microAveraged=77.71, macroAveraged=77.71+/-10.75

 Experiments [noSplits= 100, noIterations=20, growth size= 5(positiveClass) 5(negativeClass)]
 CoTraining_DifferentRandomSplits
 accuracy: microAveraged=78.88, macroAveraged=78.35+/-7.98

 RSSalg_left_out_instances_DifferentRandomSplits_accuracy_optimized
 accuracy: microAveraged=87.4, macroAveraged=87.4+/-3.85

 RSSalg_best_DifferentRandomSplits_accuracy_optimized
 accuracy: microAveraged=89.16, macroAveraged=89.16+/-2.09

 Majority_vote_of_Co-training_classifiers_on_test_set_DifferentRandomSplits
 accuracy: microAveraged=84.05, macroAveraged=84.05+/-5.23

Figure 5. An example of the displayed output (L_{acc} experiment on News2x2 dataset)

5 Illustrative examples of *RSSalg* software usage

In this section, we will demonstrate how to use *RSSalg* software for experimenting with semi-supervised classification algorithms. To test an SSL algorithm, we will treat only the portion of a dataset as labeled data and treat the remainder of the dataset as unlabeled data (by disregarding the label information). *RSSalg* software allows for testing the following traits an SSL algorithm should have:

T1. Is the algorithm able to improve the performance of the supervised baseline by using (only) unlabeled data?

We will evaluate the performance of a supervised learner trained only on the labeled portion of the data L by running \mathbf{L}_{acc} setting implemented in *RSSalg* software. The goal of an SSL algorithm is to surpass this performance by incorporating (only) unlabeled data in the process of learning.

T2. Does the algorithm reduce the number of labeled instances needed for learning while maintaining model quality?

We will evaluate the performance of a supervised learner trained on both labeled examples and unlabeled examples with the correct label assigned (i.e. while training this supervised learner we do not disregard the label of the instances chosen to be unlabeled) by running \mathbf{All}_{acc} setting. We can look at this performance as our goal performance, i.e. we would like to minimize the number of labeled instances needed for learning while still holding the performance of the classifier on this level.

T3. When is the good performance of the algorithm guaranteed?

SSL techniques usually rely on imposing certain assumptions about the data and can yield poor performance if those assumptions are violated [2]. For example, co-training imposes assumptions about the properties of the used feature split [3] and violating these assumptions can cause it to degrade the performance of the initial learner instead of improving it [8]. Furthermore, in an SSL setting, we lack the sufficient amount of labeled test data to evaluate algorithms. Thus, it is important to characterize which traits should a dataset have so we can guarantee the good performance of our algorithm.

To test the robustness of the methods implemented in *RSSalg* software, we perform the experiments on multiple datasets of various properties that may affect the performance of different algorithms: size, dimensionality, and redundancy. Here we will explain how these dataset properties can affect the algorithms implemented in *RSSalg* software.

The size of the dataset might influence the performance of the algorithms. To comply with the original co-training settings where only a few labeled training examples are used [3], in our experiments we use only a few examples as our initial labeled data, regardless of the size of the dataset. Thus, the larger the dataset is, we dispose of more unlabeled data which might augment the training process.

Another factor that might influence the algorithm performance is the dimensionality of the dataset. For low-dimensional datasets, we only have a low number of different roughly equal random splits of features. Furthermore, in such case both views will have only a small number of features which might affect their discriminative power, thus violating the sufficiency condition in co-training⁶ [3]. However, co-training suffers little from the view insufficiency when the two views have a large enough diversity [9].

Based on the results presented in [5], we expect that the performance of the settings based on co-training ran with random split (**Random**, **MV**, and **RSSalg**) will be best when the dataset has a high feature redundancy.

T4. Is there a principal way of choosing optimal parameter values for the algorithm?

Selected parameter values might significantly affect algorithm performance. There is a lot of research that shows that co-training greatly depends on the chosen parameter values [5][8][10] and the lack of principal way of selecting co-training parameters is one of its greater disadvantages [10]. Selecting optimal parameter values for co-training is certainly an interesting open research question and, with that in mind,

⁶ For example, Diabetes dataset (section 5.1.1) has only eight features; thus there are 35 combinations of delimiting the features in two groups of 4. Thus, the maximal number of classifiers used in *RSSalg* is 35, and in each case underlying co-training classifiers use only four features which might make them feeble.

RSSalg software was designed to be maximally configurable regarding user-supplied parameters. Exploring the influence of all parameter combinations for co-training is an exhaustive task and out of the scope of this manual. However, in the experiments performed in this section, we will show that *RSSalg software* can be used to address this question empirically. In section 5.2 we test the influence of the number of random splits (m) on **MV**, **RSSalg**, and **RSSalg_{best}**. In section 5.3 we examine the impact of different classification models used for individual views in co-training on the performance of algorithms implemented in *RSSalg software*.

For an ensemble technique such as RSSalg it is important to test the following traits:

T5. Does an ensemble perform better than its individual classifiers on average?

In *RSSalg software* we can run **MV** and **RSSalg** on the same m classifiers generated in **Random** setting. We expect these configurations to perform better than **Random** which represents the average performance of the individual classifiers in the ensemble.

T6. Is aggregating the knowledge of individual classifiers better than simple majority vote?

To test this, we will apply **RSSalg** and **MV** on the same set of classifiers. We hypothesize that **RSSalg** will perform better than **MV**.

T7. Is the threshold procedure used in RSSalg optimal?

The vote aggregation method in RSSalg relies on thresholds which are automatically tuned using unlabeled data. We would like to test whether the obtained thresholds are indeed optimal, i.e. if we would get the same values if we had actual labels for optimization. If the threshold procedure is optimal, the performance of **RSSalg** should be close to the performance of **RSSalg_{best}**.

In section 5.1 we test whether the algorithms implemented in *RSSalg software* possess all listed traits except for T4. Trait T4 is partially explored in section 5.2 where we verify the sensitivity of the algorithms to the number of performed random splits m and in section 5.3 where we test the sensitivity of the algorithms to the classification models used for individual views in co-training.

5.1 Comparing the performance of different semi-supervised algorithms

In this section, we test whether the SSL algorithms implemented in *RSSalg software* possess all of the listed traits (except T4 which is explored independently in the next two sections).

5.1.1 Choosing the datasets

To test T3, we perform the experiments on multiple publicly available datasets of various size, dimensionality and feature redundancy: three natural language datasets (WebKB-Course [3], LingSpam [11] and News2x2 [5]) and 12 UCI datasets.

Table 1 lists the datasets and their underlying properties:

- Dim – the dimensionality (the number of features) of the dataset;
- Pos class – the class considered to be “positive” in the experiment⁷;
- $|L|$, $|All|$ – size of the labeled training set L and the total number of instances used in training (both labeled and unlabeled instances), respectively. The number of instances is given as number of positive instances/number of negative instances;
- Baseline – accuracy achieved by classifying all instances to the majority class;
- p/n – the dataset-specific growth size parameter used in co-training: the number of instances most confidently labeled as positive and negative, respectively, that will be added to labeled set L in each iteration of co-training

The first four rows of table 1 are grouped as they belong to the group of natural language datasets characterized by the high level of feature redundancy [12]. On the other hand, the rest of the UCI datasets are manually constructed by carefully selecting features. Thus, we expect little redundancy in these feature sets.

⁷ In *RSSalg software*, if all class probabilities of the instance are equal, the tie is broken by assigning the example to the class specified as “positive”

The natural language datasets are preprocessed as proposed in [6]: an English stopwords filter removes the 319 common words; stemming is performed using Porter’s stemmer [13]; for each of the views separately, 200 most frequent words are used. After preprocessing, the text is represented using the bag of words model in combination with *tfidf* measurement [14]. The used text preprocessing and text representation techniques do not depend on the class labels and therefore do not violate the co-training setting (in which the class labels are available for only a few labeled instances). The described preprocessed versions of WebKB-Course, LingSpam, and News2x2 datasets are available for download on the *RSSalg software* code repository⁸.

The UCI datasets marked with **I** in table 1 are part of the Weka distribution of 37 classification problems originally obtained from the UCI repository⁹, and the remaining UCI *Spambase* dataset can be downloaded from UCI machine learning repository¹⁰.

Table 1. A summary of the datasets used in experiments;

Dataset	Dim	Pos class	L	A	Baseline	p/n
WebKB *	400	non-course	5/5	492/138	78.1	1/3
LingSpam *	400	spam	5/5	288/1447	83.4	2/10
News2x2 *	400	positiveClass	5/5	600/600	50.0	5/5
Spambase	57	0	2/1	1672/1087	60.6	1/1
Hepatitis I	19	LIVE	1/1	73/19	79.4	11/3
Kr-vs-kp I	36	won	6/5	1001/916	52.2	1/1
Credit-g I	20	good	1/1	420/180	70.0	5/2
Heart-statlog I	13	present	2/3	72/90	55.6	5/6
Sonar I	60	Rock	1/1	58/66	53.4	6/7
Ionosphere I	34	g	5/3	135/75	64.1	2/1
Breast-cancer I	9	no-recurrence-events	1/1	120/51	70.3	5/2
Credit-a I	15	+	4/5	184/229	55.5	1/1
Breast-w I	9	malignant	1/2	144/274	65.5	1/2
Mushroom I	22	e	3/3	2524/2349	51.8	1/1
Diabetes I	8	tested_positive	1/2	160/300	65.1	1/2

5.1.2 Evaluation procedure

To compare the performance of the algorithms, we use the *k*-fold cross-validation procedure described in section 3. Here, we divide the data into ten folds ($k=10$), use five folds as unlabeled data ($j=5$) and the remaining four folds as test data. Authors in [6] also use $k=10$ and $j=5$ as illustrated in figure 3. If we examine the co-training algorithm, we can see that it uses only a small number of labeled and unlabeled instances for training. If we applied a standard 10-fold-cross validation procedure where 90% of the data is used for training and 10% for testing, many instances would be left unused. Using $k=10$ and $j=5$ enables us better utilization of the available data: each time 40% of the data is used for testing and the remaining 60% for training. In *RSSalg software*, the user can set j and k parameters through the file named ‘cv.properties,’ table 2.

When choosing the size and the distribution of the initial labeled set L two criteria govern us:

- (1) the distribution of labels in L is roughly the same as the distribution of labels in the original dataset as in [3]¹¹
- (2) When choosing the size of L , we derive the initial accuracy by applying \mathbf{L}_{acc} setting and the goal accuracy by using \mathbf{All}_{acc} setting. We choose L so that the difference $\mathbf{All}_{acc} - \mathbf{L}_{acc}$ is large enough in order to give space for possible improvement by SSL techniques (10-20 %).

The exact size and the distribution of the initial set L for each dataset are listed in table 1. The user can define the initial set L through `className` and `noLabeled` properties in ‘cv.properties.’ For example, to form an initial labeled set L from Spambase dataset consisting of two randomly chosen instances belonging to class 0 and one randomly selected instance belonging to the class 1, the following property values should be set: `className="0" "1"` and `noLabeled=2 1`.

⁸ The preprocessed versions of the WebKB-Course, News2x2, and LingSpam datasets are available at <https://github.com/slivkaje/RSSalg-software/tree/master/dist/data>

⁹ <http://www.cs.waikato.ac.nz/ml/weka/datasets.html>

¹⁰ <http://archive.ics.uci.edu/ml/>

¹¹ With the exception of LingSpam and WebKB datasets where we kept the settings recommended in [6]

As the measure of performance in this experiment, we will use accuracy (table 2, common experiment properties).

Since there is randomness involved in the creation of labeled/unlabeled/test splits, and co-training and RSSalg algorithms as well, for the exact replicability of these experiments it is important to maintain the same sequence of random numbers. In *RSSalg software* this is done by supplying the random number generator seed. In this experiment, we use 2016 as the seed (table 2, ‘data.properties’).

5.1.3 Choosing algorithm parameters

For better mutual comparison, all algorithms use the same underlying co-training parameters and the same number of random splits for multiple-split settings. In our experiments we use the following underlying co-training parameters (table 2, ‘co-training.properties’):

- the number of co-training iterations k is 20 as in [6];
- a small unlabeled pool u of size 50 is used for the selection of most confidently labeled examples in each iteration as in [6];
- the number of instances most confidently labeled as ‘positive’ (p) and the number of instances most confidently labeled as ‘negative’ (n) that are added to the initial labeled set L in each co-training iteration for each dataset are listed in table 1. The numbers p and n are chosen to reflect the original dataset distribution as recommended in [3];
- the classification model used for underlying view classifiers in co-training and for the final model in RSSalg is Naïve Bayes (table 2, ‘data.properties’). Naïve Bayes is the most common choice of an underlying classifier used in co-training studied. In section 5.3 we will perform the experiments using other classifiers.

The number of different random splits (m) used in **Random**, **MV**, **RSSalg** and **RSSalg_{best}** settings is 100 except of Diabetes dataset where the maximal number of balanced random feature splits is 35 (table 2, common experiment properties).

In **RSSalg** and **RSSalg_{best}** settings, GA is used for automatic threshold optimization. We have used the following GA configuration (table 2, ‘GA.properties’):

- the generation size was 50;
- the maximal number of iterations was 50, but the process was stopped if there was no improvement in 5 successive generations;
- the crossover threshold was 0.3;
- the probability of bit mutation was 0.02;
- elitism was used;
- the testing threshold in RSSalg was set to 20%;

All these parameters were empirically chosen.

5.1.4 Summary of the parameter values used in the experiment

Table 2 summarizes the parameter values common for all experiments performed in this section. All experiments presented here are entirely reproducible by using the same parameter values. These parameters are supplied to *RSSalg software* through several property files. Pre-created property files needed for running the experiments presented here are available on *RSSalg software* code repository¹². Detailed instructions on creating these property files are listed in section 6.

¹² <https://github.com/slivkaje/RSSalg-software/tree/master/dist/data>

Table 2. A summary of the property values common for all presented experiments

Property file	Property name in <i>RSSalg</i> software	Used value
data.properties	randomGeneratorSeed	2016
	classifiers	weka.classifiers.bayes.NaiveBayes
	combinedClassifier	weka.classifiers.bayes.NaiveBayes
cv.properties	noFolds	10
	noUnlabeled	6
	noTest	4
co-training.properties	labelAllUnlabeledData	false
	coTrainingIterations	20
	poolSize	50
GA.properties	generationSize	50
	Iterations	50
	noImprovalGenerations	5
	crossoverTS	0.3
	mutationTS	0.02
	elitism	true
	testingTS	0.2
	optimizationMeasure	classificationResult.measures.AccuracyMeasure
	optimizationMeasureClass	avg
Common experiment properties	measures	classificationResult.measures.AccuracyMeasure
	measuresForClass	avg
	noSplits	100 (except for of Diabetes dataset where the maximal number of different balanced random splits of 35 is used)
	(This property is used in all settings that require multiple random splits for co-training: Random , MV , RSSalg and RSSalg_best)	

5.1.5 Results

Table 3 presents the accuracy and standard deviation obtained by each tested method on all considered datasets. The performance of Natural setting is reported only for WebKB, LingSpam and News2x2 datasets where it was applicable. Note that the experiments presented here are the same set of experiments used in [4] to demonstrate the advantages of RSSalg over considered alternatives. However, the results shown here slightly differ from those presented in [4] (regarding reported accuracy) due to latter software refactoring which affected the sequence of numbers generated by Java random number generator and the usage of different random number generator seed.

Table 3. Algorithm performance (accuracy \pm standard deviation) of all considered algorithms

Datasets	L_{acc}	All_{acc}	Natural	Random	MV	RSSalg	RSSalg best
WebKB	76.1 \pm 8.2	96.3 \pm 1.1	87.7 \pm 4.7	83.9 \pm 5.6	88.1 \pm 5.1	87.7 \pm 3.7	90.2 \pm 4.0
LingSpam	78.2 \pm 9.4	89.3 \pm 3.1	71.1 \pm 14.7	77.0 \pm 9.1	79.6 \pm 7.2	86.7 \pm 3.5	88.1 \pm 3.8
News2x2	76.8 \pm 5.1	89.7 \pm 1.7	77.7 \pm 10.8	78.4 \pm 8.0	84.1 \pm 5.2	87.1 \pm 4.0	89.2 \pm 2.0
Spambase	67.4 \pm 3.8	79.6 \pm 1.2		75.0 \pm 4.4	79.6 \pm 6.0	76.6 \pm 7.1	78.0 \pm 5.7
Hepatitis	59.6 \pm 17.9	84.2 \pm 2.8		80.6 \pm 8.3	83.0 \pm 4.5	82.6 \pm 2.8	85.7 \pm 3.6
Kr-vs-kp	65.0 \pm 4.8	87.7 \pm 0.6		53.2 \pm 3.2	55.7 \pm 4.1	56.6 \pm 3.6	65.4 \pm 5.2
Credit-g	55.8 \pm 10.0	73.2 \pm 2.8		60.3 \pm 5.4	65.8 \pm 4.8	64.4 \pm 5.0	70.2 \pm 1.7
Heart-statlog	66.2 \pm 7.5	85.0 \pm 2.0		80.0 \pm 4.4	82.1 \pm 4.5	80.4 \pm 4.2	83.1 \pm 4.4
Sonar	54.9 \pm 6.3	67.9 \pm 4.7		51.1 \pm 5.2	54.9 \pm 4.6	54.7 \pm 4.2	58.4 \pm 3.2
Ionosphere	70.2 \pm 6.8	83.3 \pm 5.3		73.9 \pm 4.7	71.8 \pm 5.7	72.0 \pm 7.3	77.8 \pm 4.1
Breast-cancer	56.4 \pm 11.6	74.1 \pm 1.9		68.0 \pm 5.8	69.7 \pm 3.9	68.8 \pm 4.4	72.2 \pm 3.3
Credit-a	68.0 \pm 3.6	78.1 \pm 2.5		71.3 \pm 14.2	78.7 \pm 3.9	74.6 \pm 4.5	79.3 \pm 3.5
Breast-w	80.5 \pm 11.8	96.0 \pm 1.2		93.8 \pm 3.1	95.1 \pm 1.6	94.3 \pm 2.6	96.1 \pm 1.6
Mushroom	80.5 \pm 10.0	95.4 \pm 0.4		82.6 \pm 12.2	89.0 \pm 0.8	88.3 \pm 1.4	89.2 \pm 1.5
Diabetes	64.6 \pm 5.4	75.2 \pm 1.4		54.1 \pm 9.4	64.7 \pm 4.9	64.5 \pm 4.8	68.2 \pm 2.2

For easier analysis, we graphically summarize the results presented in table 3 in figure 6. The graphs presented in figure 6 show the percentage improvement of accuracy achieved by each of the algorithms. The percentage improvement of accuracy is calculated as

$$\frac{Alg_{acc} - L_{acc}}{All_{acc} - L_{acc}} \cdot 100\%,$$

where Alg_{acc} denotes the algorithm accuracy. A negative percentage improvement value shows the degradation of accuracy compared to initial classifier L_{acc} .

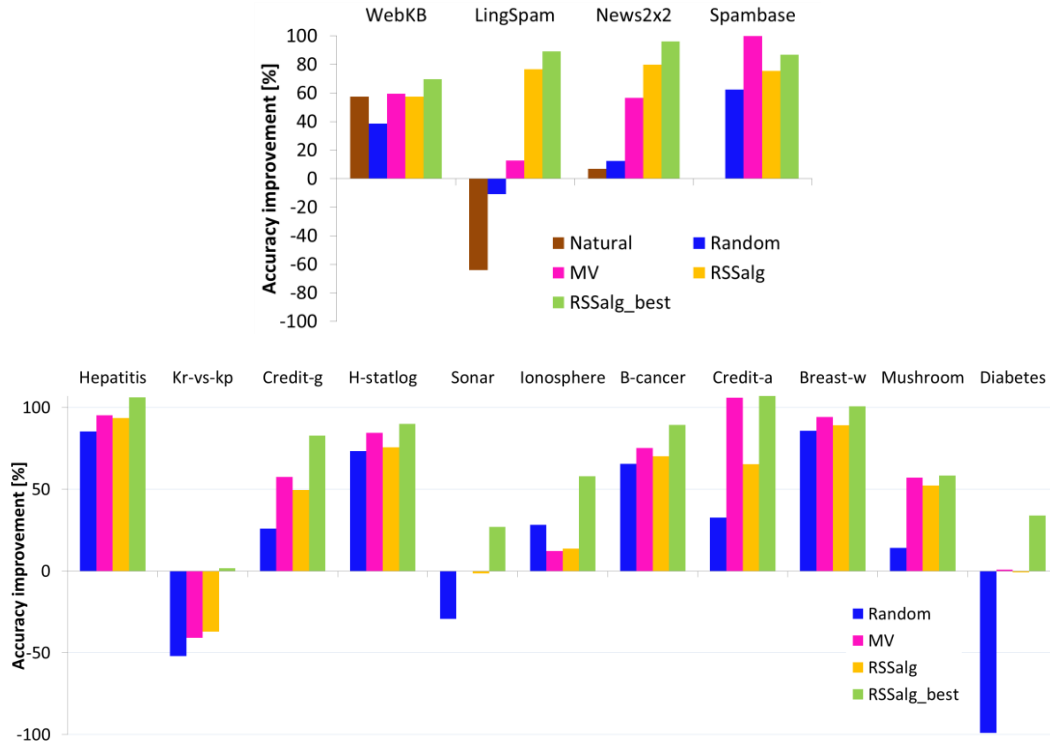


Figure 6. Naive Bayes classifier: percentage improvement of accuracy achieved by considered algorithms. **Top:** natural language datasets characterized by high level of feature redundancy; **Bottom:** UCI datasets.

The results presented in table 3 and figure 6 indicate that:

- A dataset trait that influences the performance of **Random**, **MV**, **RSSalg** and **RSSalg_{best}** is the redundancy of its features (T3). **Random**, **MV**, **RSSalg** and **RSSalg_{best}** perform better on more redundant datasets. This result is expected, as all of these settings are based on co-training ran with random feature split which is shown to be beneficial in case of high feature redundancy [5].
- **RSSalg_{best}** is the best performing setting. It always shows an improvement of accuracy compared to L_{acc} (T1 is satisfied). On more redundant datasets the performance of **RSSalg_{best}** is close to the goal performance All_{acc} (T2 is satisfied on more redundant datasets).
- On more redundant datasets **MV** and **RSSalg** always perform better than L_{acc} – we can say that they meet T1 on more redundant datasets. However, they are less reliable on low redundancy dataset where there are cases when they even degrade the initial accuracy.
- **RSSalg** and **MV** perform better than **Random** setting (the only exception is the Ionosphere dataset). This result is expected since **MV** and **RSSalg** belong to the group of ensemble techniques that tend to reduce the variance compared to single classifiers. We can say that **RSSalg** and **MV** satisfy T5.
- We observe that **Random** performs better than **Natural** on some datasets. The authors of [15] found the same effect and contribute it to the big difference in quality between the individual views in co-training (regarding accuracy).

- In most cases, **RSSalg** did not beat **MV** (T6). Since **RSSalg_{best}** performs better than **MV**, we can conclude that the threshold optimization procedure needs to be improved.
- On more redundant datasets **RSSalg** is close to **RSSalg_{best}** (T7 is satisfied). However, this is not always the case on the less redundant datasets. Improving the threshold optimization procedure would make **RSSalg** more generally applicable (thus satisfying T3).

5.2 Testing the influence of the number of random splits used in RSSalg

In this section, we will analyze how does the number of random splits (m) affect the performance of multi-split settings: **Random**, **MV**, **RSSalg** and **RSSalg_{best}** (trait T4). We perform this experiment by keeping the values of all parameters same as in section 5.1 and only varying m from 5 to 200 in steps of 5¹³. We record the accuracy achieved by each algorithm for each applied value of m . We graphically summarize the obtained results in figures 7 - 10¹⁴. The results indicate that **MV**, **RSSalg** and **RSSalg_{best}** are relatively robust to the value of m even though the performance of **Random** varies significantly. The performance of **MV**, **RSSalg**, and **RSSalg_{best}** is expectedly lower for lower values of m and grows as m grows, however, after a certain point, adding more co-training classifiers makes little difference. Another result we were able to observe from this experiment is that the performances of **MV**, **RSSalg** and **RSSalg_{best}** are correlated to the performance of **Random**.

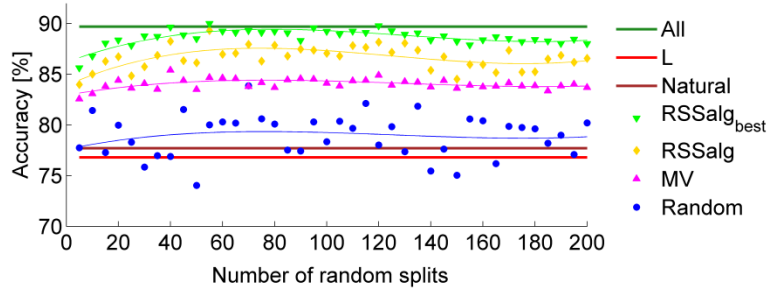


Figure 7. News2x2 dataset: exploring the impact of the number of performed random splits

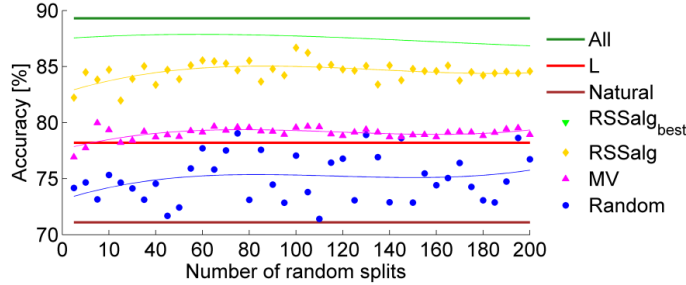


Figure 8. LingSpam dataset: exploring the influence of the number of performed random splits

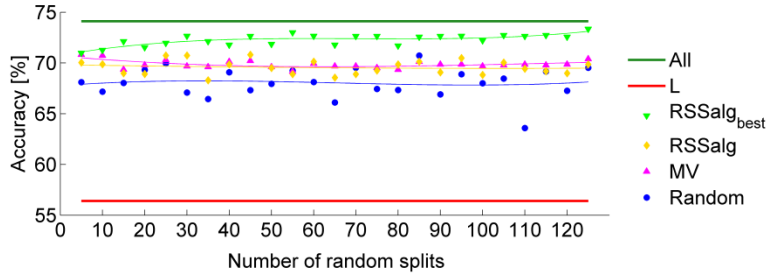


Figure 9. Breast-cancer dataset: exploring the influence of the number of performed random splits

¹³ The maximal number of splits performed on the Breast-cancer dataset was 125 due to small dimensionality (nine features), and 35 on the Diabetes dataset which contains only eight features

¹⁴ Due to the magnitude of the task we have selected a representative subset of the datasets presented in section 5.1.1

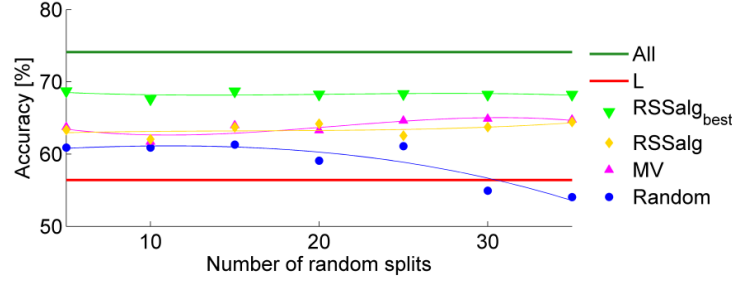


Figure 10. Diabetes dataset: exploring the influence of the number of performed random splits

5.3 Testing the influence of different underlying classification models

In co-training studies, the most commonly used classification model used for training individual views in co-training is Naïve Bayes (NB) [3][5][6]¹⁵. Authors in [6] have experimented with NB, SVM [6]¹⁶ and RBF Nets [6]¹⁷ and found that co-training performance depends on the choice of the underlying classifiers. In this section, we will analyze the influence of the underlying classification models on the performance of algorithms implemented in *RSSalg software*. Similarly to [6] we will consider NB, SVM, and RBF Nets. In this experiment, we keep the values of all parameters same as in section 5.1 and only vary the view classification models¹⁸. We present the experiments with NB in section 5.1.5, the experiments performed using SVM in table 4 and graphically summarized them in figure 11, and the experiments performed using RBF Nets in table 5¹⁹ and graphically summarized them in figure 12.

Table 4. The performance of the algorithms (accuracy \pm standard deviation) obtained using SVM for underlying view classifiers in co-training

Datasets	L _{acc}	All _{acc}	Natural	Random	MV	RSSalg	RSSalg best
WebKB	82.7 \pm 12.0	97.0 \pm 0.4	86.2 \pm 4.1	85.0 \pm 5.0	85.8 \pm 4.3	88.9 \pm 5.1	92.0 \pm 2.9
LingSpam	67.5 \pm 8.0	94.8 \pm 1.0	81.3 \pm 2.6	81.8 \pm 3.8	85.6 \pm 2.4	85.9 \pm 0.9	87.7 \pm 2.0
News2x2	78.5 \pm 5.4	96.7 \pm 0.5	65.9 \pm 6.8	72.4 \pm 4.9	77.9 \pm 2.5	83.9 \pm 2.0	85.8 \pm 1.9
Spambase	74.2 \pm 6.7	89.9 \pm 1.0		68.2 \pm 13.5	74.0 \pm 4.5	78.6 \pm 5.7	81.7 \pm 3.5
Hepatitis	68.8 \pm 17.5	85.3 \pm 3.3		78.7 \pm 2.2	79.8 \pm 1.0	80.3 \pm 3.1	84.3 \pm 2.8
Kr-vs-kp	65.9 \pm 4.4	95.5 \pm 0.9		56.2 \pm 4.3	61.5 \pm 3.8	65.5 \pm 4.2	66.2 \pm 4.1
Credit-g	55.0 \pm 12.8	73.5 \pm 1.3		68.2 \pm 2.1	70.1 \pm 0.2	69.2 \pm 1.4	71.3 \pm 1.3
Heart-statlog	75.2 \pm 5.2	83.5 \pm 3.6		74.6 \pm 2.6	76.8 \pm 3.3	79.1 \pm 3.8	81.9 \pm 3.8
Sonar	54.6 \pm 7.1	78.2 \pm 3.9		50.5 \pm 7.2	58.2 \pm 10.6	56.4 \pm 8.9	61.7 \pm 8.5
Ionosphere	70.9 \pm 7.3	87.7 \pm 3.0		65.5 \pm 6.1	67.9 \pm 7.7	77.3 \pm 7.6	81.3 \pm 5.9
Breast-cancer	56.6 \pm 9.7	69.3 \pm 3.9		68.4 \pm 3.1	70.4 \pm 1.9	67.7 \pm 4.8	72.1 \pm 4.7
Credit-a	75.6 \pm 7.6	84.6 \pm 2.8		66.6 \pm 10	70.3 \pm 4.2	79.3 \pm 4.9	81.1 \pm 6.0
Breast-w	90.2 \pm 7.8	96.5 \pm 0.7		95.9 \pm 0.8	96.6 \pm 0.8	96.1 \pm 1.0	96.6 \pm 0.8
Mushroom	77.1 \pm 10.3	100.0 \pm 0.0		76.7 \pm 11.4	86.9 \pm 6.3	84.1 \pm 9.4	86.4 \pm 8.1
Diabetes	59.1 \pm 9.4	76.8 \pm 1.6		65.8 \pm 1.7	65.8 \pm 1.6	66.0 \pm 2.2	68.1 \pm 2.4

¹⁵ The implementation of Naïve Bayes is available in Weka's class `weka.classifiers.bayes.NaiveBayes`

<http://weka.sourceforge.net/doc.dev/weka/classifiers/bayes/NaiveBayes.html>

¹⁶ The implementation of SVM can be found in Weka's class `weka.classifiers.functions.SMO`

<http://weka.sourceforge.net/doc.dev/weka/classifiers/functions/SMO.html>

¹⁷ The implementation of RBF Nets can be found in Weka's class `weka.classifiers.functions.RBFNetwork`

<http://weka.sourceforge.net/doc.stable/weka/classifiers/functions/RBFNetwork.html>

¹⁸ The created experiment (division in folds and L, U, and T in each fold) is the same as used in experiments with NB

¹⁹ Weka's RBFNetwork was unable to build a classifier with a small amount of labeled data on Hepatitis, Credit-g, and Sonar datasets. Thus we have excluded these datasets from the evaluation

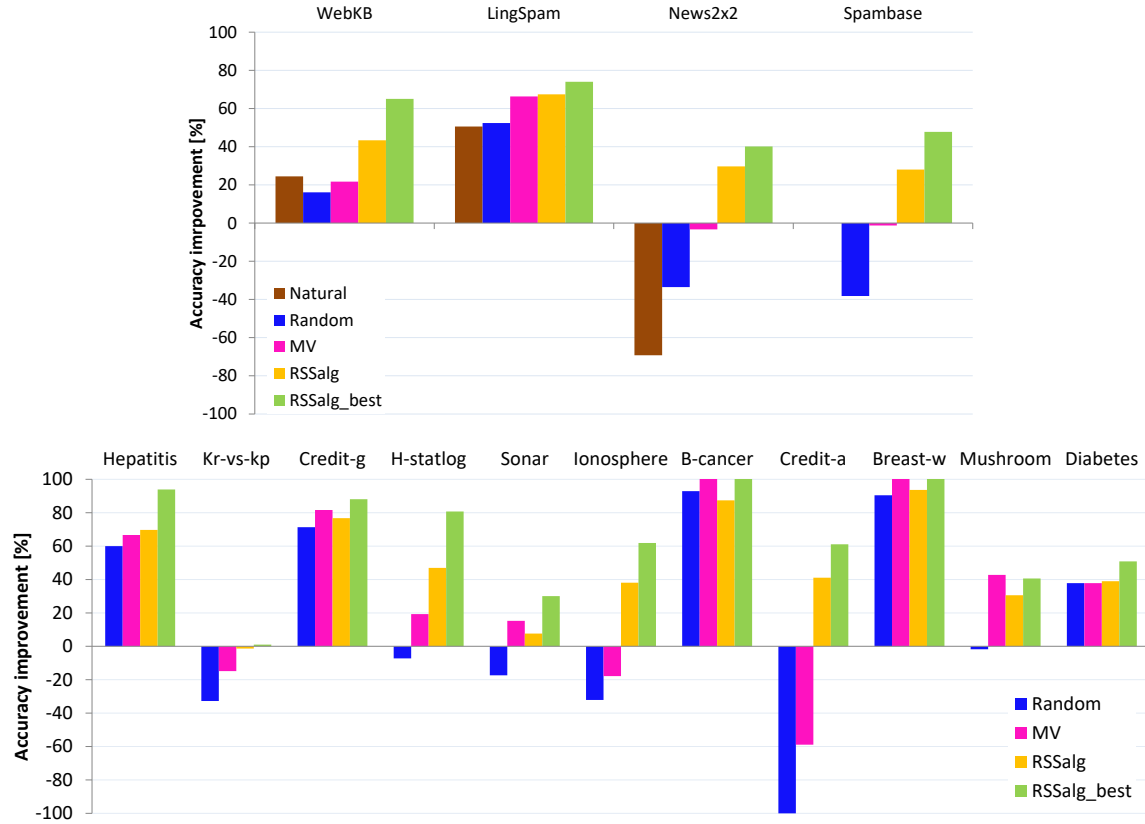


Figure 11. SVM classifier: percentage improvement of accuracy achieved by considered algorithms. **Top:** natural language datasets characterized by high level of feature redundancy; **Bottom:** UCI datasets.

SVM classifier: the results presented in table 4 and figure 11 indicate that:

- When using SVM classifier, the redundancy of the features does not seem to have the influence on algorithm performance (contrary to results obtained using NB)
- The best performing setting is again **RSSalg_{best}**. It is always able to improve the accuracy of the initial classifier (T1 is satisfied), but it is not always close to the goal performance (**All_{acc}**) as it mostly was when using NB.
- **RSSalg** is more stable when using SVM – except for the small degradation of accuracy (0.4) on Kr-vs-kp dataset it was always able to improve the initial accuracy. Thus we can say that it satisfies T1. Its performance is close to **RSSalg_{best}** (T7 is satisfied). **RSSalg** performs better than **MV** (T6 is satisfied) considering that MV is less reliable regarding the degradation of initial accuracy.
- **MV** is less reliable and sometimes results in the degradation of initial accuracy (T1 is not always satisfied). The same goes for **Random** setting. As expected, **MV** and **RSSalg** always outperform **Random** (T5 is satisfied).
- As in experiments with NB, we can observe that **Random** sometimes outperforms **Natural**.

Table 5. The performance of the algorithms (accuracy \pm standard deviation) obtained using **RBF Nets** for underlying view classifiers in co-training

Datasets	L_{acc}	All_{acc}	Natural	Random	MV	RSSalg	RSSalg best
WebKB	73.0 \pm 10.4	85.6 \pm 1.6	74.8 \pm 4.9	70.2 \pm 5.7	77.9 \pm 3.5	79.9 \pm 4.6	86.7 \pm 2.7
LingSpam	77.8 \pm 7.9	89.6 \pm 0.7	84.4 \pm 1.8	82.8 \pm 1.4	83.5 \pm 0.3	83.5 \pm 1.2	85.1 \pm 0.7
News2x2	76.9 \pm 5.3	97.7 \pm 0.8	84.9 \pm 8.3	81.9 \pm 9.0	91.1 \pm 2.8	93.1 \pm 2.3	94.6 \pm 1.4
Spambase	64.8 \pm 12.1	81.1 \pm 1.9		60.1 \pm 14.5	78.1 \pm 7.8	74.9 \pm 6.0	78.8 \pm 4.19
Kr-vs-kp	62.2 \pm 4.3	82.4 \pm 2.6		54.8 \pm 7.4	61.5 \pm 5.0	62.1 \pm 5.3	65.4 \pm 4.2
Heart-statlog	73.5 \pm 6.9	83.4 \pm 2.8		74.4 \pm 7.4	81.5 \pm 4.5	75.6 \pm 5.2	82.6 \pm 4.2
Ionosphere	71.1 \pm 7.3	91.6 \pm 1.8		73.6 \pm 15	80.8 \pm 9.3	75.1 \pm 7.6	84.8 \pm 6.0
Breast-cancer	52.2 \pm 11.5	73.3 \pm 2.8		67.1 \pm 6.3	69.9 \pm 4.1	68.7 \pm 4.6	72.8 \pm 3.2
Credit-a	62.4 \pm 6.6	80.9 \pm 3.8		62.0 \pm 15.6	77.5 \pm 3.3	73.9 \pm 4.2	78.2 \pm 3.5
Breast-w	84.7 \pm 12.2	95.3 \pm 1.9		83.0 \pm 20.6	96.1 \pm 1.5	94.4 \pm 2.5	96.3 \pm 1.4
Mushroom	79.7 \pm 9.6	98.3 \pm 0.2		76.6 \pm 8.7	83.3 \pm 5.5	83.1 \pm 8.1	84.8 \pm 7.1
Diabetes	57.7 \pm 7.2	73.3 \pm 1.5		59.2 \pm 8.2	67.6 \pm 3.6	65.0 \pm 5.8	70.5 \pm 3.1

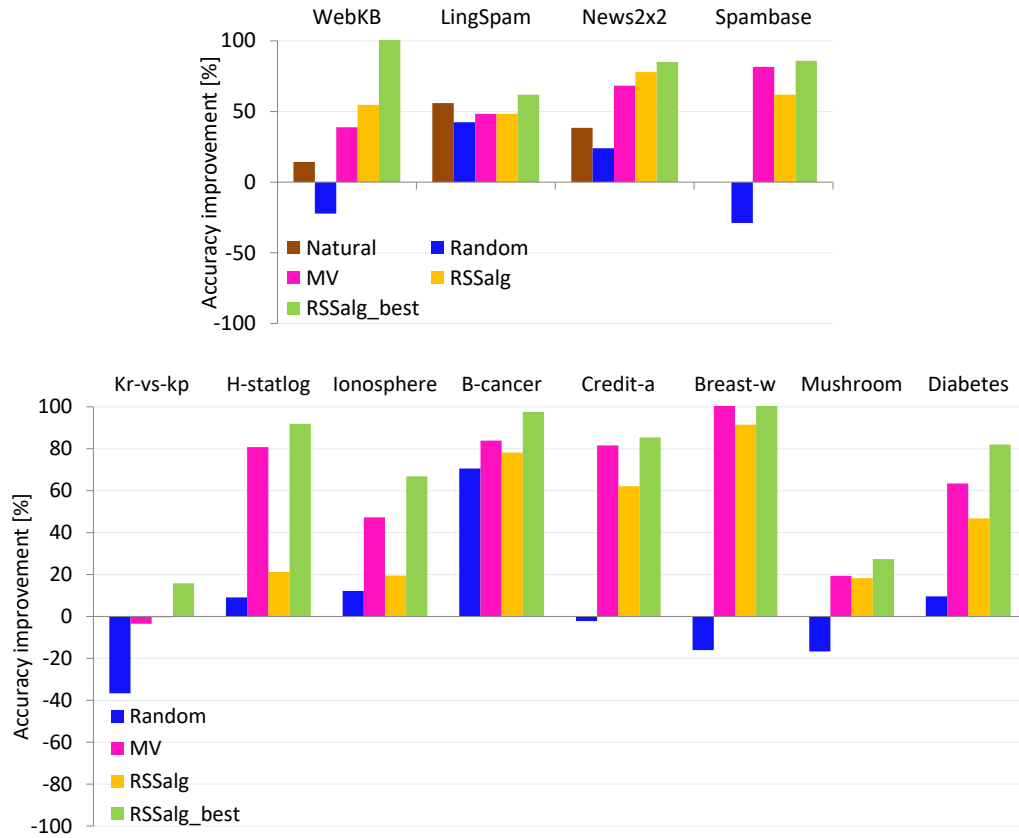


Figure 12. RBF classifier: percentage improvement of accuracy achieved by considered algorithms. **Top:** natural language datasets; **Bottom:** UCI datasets

RBF classifier: the results presented in table 5 and figure 12 indicate the following:

- Similarly to SVM and contrary to NB, the redundancy of the features does not seem to have the influence on algorithm performance
- The best performing setting is again **RSSalg_{best}**. It is always able to improve the accuracy of the initial classifier (T1 is satisfied), but it is not always close to the goal performance (**All_{acc}**).

- Except for the small degradation of accuracy (0.1) on Kr-vs-kp dataset, **RSSalg** was always able to improve the initial accuracy. Thus we can say that it satisfies T1. Its performance is close to **RSSalg_{best}** (T7 is satisfied). These conclusions about **RSSalg** are similar to those obtained using SVM.
- Except for Kr-vs-kp dataset, **MV** has always improved the initial accuracy and thus satisfied T1. When using RBF classifier **MV** is close to or better than **RSSalg**. Thus T6 is not satisfied. This result is similar to the results obtained using NB.
- When using an RBF classifier, **Natural** always outperformed **Random** and was always able to improve the accuracy (T1 is satisfied). This result confirms the result obtained in [6] where authors show that RBF outperforms SVM and NB in a co-training setting with a natural feature split.

To summarize, our experiments with different underlying classifiers indicate that out of considered algorithms:

- **RSSalg** is the best choice when using SVM
- **MV** is the best choice when using RBF nets
- When using NB, **RSSalg** yields somewhat better performance on more redundant datasets, and it is comparable to **MV** on less redundant datasets.
- **Natural** performs worse than **RSSalg** and **MV**. It has displayed best results when applied with RBF nets.
- **Random** displayed the best performance when applied with NB on more redundant datasets.
- In all experiments, **RSSalg_{best}** was the best performing setting. While it is not a realistic setting (it utilizes test data labels for determination of threshold values) it shows the potential of **RSSalg**. An improved threshold determination procedure would boost the performance of **RSSalg** and make it more widely applicable.

6 Creating the property files and running the experiment: a tutorial on News 2x2 dataset

In this section, we will give a step-by-step tutorial on building and running a new experiment with *RSSalg software*. We will demonstrate this on the example of running News2x2 experiment. Section 6.1 describes the problem we are trying to solve and the experimental setting for evaluating the solution. Section 6.2 describes how to install and start *RSSalg software*. Section 6.3 describes how to set the experiment and parameter values in *RSSalg software*. Finally, section 6.4 describes how to run the created experiment and interpret the software output.

6.1 Problem setting

News 2x2 dataset is a semi-artificial dataset introduced in [5]. It was artificially created to be a binary classification problem with class-conditional independence, ideal for testing the performance of co-training. The examples are categorized in two classes named “positiveClass” and “negativeClass.”

Our goal is to minimize the number of examples needed for quality classification. That is, starting from a small number of labeled instances and a sufficiently large number of unlabeled instances our goal is to achieve roughly the performance of a supervised classifier trained using both labeled and unlabeled instances with the correct label assigned.

6.1.1 Experimental setting

We will test our solution using a 10-fold-cross validation procedure introduced in [6]. In this experiment, the data is divided into ten stratified folds. In each round of cross-validation, a different fold will be used for the selection of initial labeled data: five instances belonging to “positiveClass” and five instances belonging to the “negativeClass.” The rest of the data from this fold, as well as five adjacent folds, will be used as unlabeled data. The four remaining folds are used as test data.

The total number of instances in News2x2 dataset is 2000 (200 per fold). Thus, starting from just ten labeled instances, we strive to achieve the performance of a supervised classifier trained on 1200 instances (6 folds

used as labeled and unlabeled data). News2x2 is a balanced dataset with an equal number of instances belonging to “positiveClass” and “negativeClass,” thus, we will use accuracy as the measure of performance.

6.1.2 Co-training parameters

Each tested co-training style algorithm will use the following parameter values:

- the number of iterations of co-training algorithm k is 20;
- a small unlabeled pool u of 50 instances is used;
- growth size p/n : in each iteration of co-training five instances most confidently labeled as “positiveClass” and five instances most confidently labeled as “negativeClass” will be added to the initial training set
- Naïve Bayes classifier will be used for both views

In **Random**, **MV** and **RSSalg** settings, each round of co-training is performed using the parameters listed in this section. All of these parameter values were empirically chosen. The same parameter values were used in [6] when applying co-training on News2x2 dataset.

6.2 Installing and starting *RSSalg* software

RSSalg software requires Java Runtime Environment (JRE) 1.7 or above²⁰. Once Java is installed, you can build the project by using Apache Ant or by loading the source code into your favorite IDE (section 6.2.1). After building you can run the project by using the packaged JAR executable (section 6.2.2) or by using the provided Apache Ant script (section 6.2.3).

6.2.1 Building the project

Figure 13 shows the folder structure of *RSSalg* software. The folder named ‘src’ contains *RSSalg* software source code. The folder entitled ‘data’ holds the datasets, property files, and algorithm outputs. The external libraries needed for code compilations are located inside the ‘lib’ folder.

The easiest way to build and run the project is by using Apache Ant²¹. You will firstly need to install Ant. After installing Ant, open the terminal and navigate to the root of the project. There you will find the Ant script named “build.xml”²². This script assumes there is a folder named ‘lib’ next to the source folder ‘src’ containing weka.jar as in figure 13 (version 3.7.0). To compile and package the software in an executable JAR file one should run *jar* target defined in ‘build.xml’ script. In the terminal type the command:

ant.

This will compile and package the code in an executable *RSSalg.jar* located inside the folder <project_root>/dist/jar/.

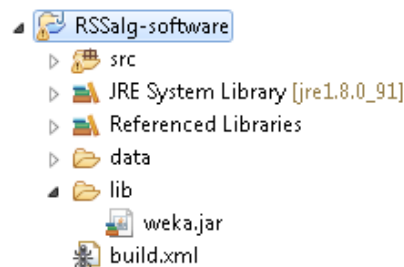


Figure 13. *RSSalg* software folder structure

Optionally, you load the source code from the *src* folder²³ into your favorite IDE. Note that *RSSalg* software implementation depends on Weka (version 3.7.0). Thus, you will need to add the weka.jar library (located inside the folder <project_root>/lib²⁴) to your project.

²⁰ To install Java go to <http://www.oracle.com/technetwork/indexes/downloads/index.html#java>

²¹ Apache Ant can be obtained from <http://ant.apache.org/>

²² <https://github.com/slivkaje/RSSalg-software/blob/master/build.xml>

²³ <https://github.com/slivkaje/RSSalg-software/tree/master/src>

6.2.2 Running the project by using the built executable

To run *RSSalg software* you can use the packaged `RSSalg.jar` executable obtained from the software release or by building the project (section 6.2.1).

To start experiment execution, a user must define several property files containing the desired values for algorithm parameters and experiment setting. The detailed description of the required files will be given in section 6.3 and commented examples of these files for running News2x2 experiment described in this document are available in `dist/data/News2x2/experiment` folder²⁵.

RSSalg software can be run in two modes: GUI mode (section 6.2.2.1) or console mode (section 6.2.2.2). GUI mode allows for the easy, intuitive creation of the needed property files, as well as algorithm execution. Alternatively, a user may choose to create the property files by hand using his favorite text editor. Console mode assumes that the needed property files are already created.

6.2.2.1 GUI mode

In order to run *RSSalg software* in GUI mode, in command prompt navigate to the location of the downloaded executable `RSSalg.jar` and type the following command:

```
java -jar RSSalg.jar
```

If you chose to load the source code in your favorite IDE, a starting point for running GUI is the class `RSSalgFrame`, located inside package `application.GUI`.

6.2.2.2 Console mode

To run the console mode, a user must firstly define the property files. To run *RSSalg software* in console mode, in command prompt navigate to the location of the downloaded executable `RSSalg.jar` and type the following command:

```
java -jar RSSalg.jar <properties_folder> <experiment_properties>
```

where:

`<properties_folder>` represents the folder containing the following property files (needed for execution of all experiments): `data.properties`, `cv.properties`, `co-training.properties` and `GA.properties`. For the detailed description of these files, please refer to section 6.3.

`<experiment_properties>` represents the property file containing the desired settings for the particular experiment that should be run (which algorithm to run, etc.). Section 6.3.4 gives the detailed description of this file.

For example, if a user wishes to execute the L_{acc} setting on News2x2 dataset he should download the `/data` folder²⁶ and place it in the same folder as `RSSalg.jar` and type the following command:

```
java -jar RSSalg.jar ./data/News2x2/experiment experiment_L.properties
```

If you chose to load the source code in your favorite IDE, a starting point for running *RSSalg software* in console mode is the class `StartExperiment`, located inside the `application` package.

6.2.3 Running the project by using Apache Ant

Open the terminal and navigate to the root of the project (containing `build.xml`):

- You can run *RSSalg software* in GUI mode by typing the command:

```
ant run_GUI
```
- You can run *RSSalg software* in console mode by typing the command

```
ant run_console.
```

²⁴ <https://github.com/slivkaje/RSSalg-software/blob/master/lib/weka.jar>

²⁵ <https://github.com/slivkaje/RSSalg-software/tree/master/dist/data/News2x2/experiment>

²⁶ Located inside <https://github.com/slivkaje/RSSalg-software/tree/master/dist> folder

In this case, you need to modify the arguments of target `run_console` located in `build.xml` to correspond to the adequate *properties folder* and *experiment* properties. Figure 14 shows an example how the `run_console` target should look like for running L_{acc} setting on the News2x2 dataset. The experiment that will be run is determined by the two arguments (`<arg>` elements): *properties folder* and *experiment properties* (see section 6.2.2).

```
<target name="run_console">
  <java jar="./dist/jar/RSSalg.jar" fork="true">
    <arg value="./data/News2x2/experiment"/>
    <arg value="experiment_L.properties"/>
  </java>
</target>
```

Figure 14. An example of the `run_console` target (`build.xml`)

6.3 Specifying parameter values in *RSSalg* software

RSSalg software was designed to be easily configurable - a user can supply the values for all co-training and RSSalg parameters through the usage of property files. Algorithm properties are organized into five basic groups:

- **dataset settings** provide the basic dataset properties: dataset file location, the names of class and id attribute, etc. They can be found in the file called ‘data.properties’ described in section 6.3.1.6
- **cross-validation experiment settings** dictate how *RSSalg* software will construct the cross-validation experiment: the number of folds used in n-fold-cross validation, the number of initially labeled instances per each class, etc. These settings are saved in the file entitled ‘cv.properties’ described in section 6.3.2.1
- **co-training settings** dictate the properties of the co-training algorithm: number of iterations, the size of the unlabeled pool u , etc. These settings are saved in the file entitled ‘co-training.properties’ described in section 6.3.3.1
- **experiment settings** define the conducted experiment: the algorithm that should be run, performance measures to be calculated, etc. These settings are saved in property file described in section 6.3.4.7
- **genetic algorithm settings** are only needed for **RSSalg** setting and provide the underlying properties of the genetic algorithm that is the basis of threshold optimization process in RSSalg [4]. These settings are saved in the file entitled ‘GA.properties’ described in section 6.3.5.1.

The application GUI allows the easy creation of the needed property files. Figure 15 illustrates the main window that is opened on the startup of *RSSalg* software application. To run the News2x2 experiment, the user must firstly provide the dataset properties by selecting “...” button on the right-hand side of „Data settings:“ label (see figure 15).

6.3.1 Specifying dataset settings

Figure 16 illustrates the dialog for dataset properties entry. The user can choose between the two options: (1) prepare a new cross-validation experiment (explained in section 6.3.1.1) or (2) load previously constructed cross-validation experiment from files (described in section 6.3.1.2). After selection, the user can define general dataset properties (class and id attribute names, random number generator seed, etc.) which are described in section 6.3.1.3. Section 6.3.1.4 describes how the user can specify a classification model used for each of the individual views. Finally, section 6.3.1.5 describes how to save the selected settings and describes the resulting property files. Section 6.3.1.5 also describes how to load a previously created property file.

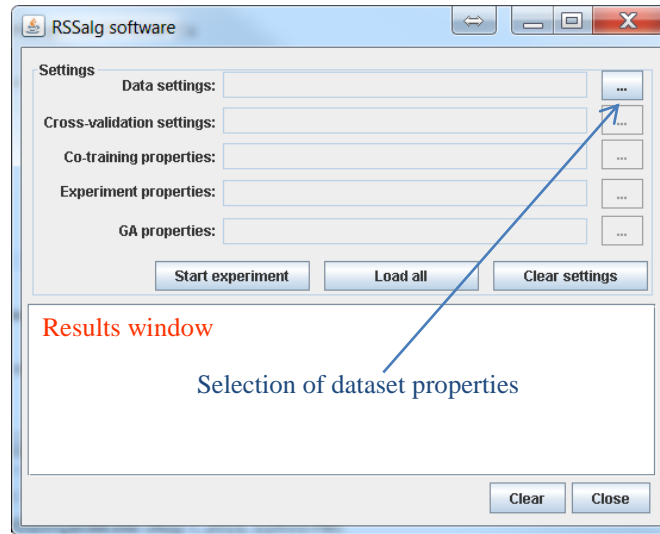


Figure 15. The main window of *RSSalg software* application

Dataset settings

☒ **New experiment** ← 1. Choose new experiment creation

Number of views:

Data files:

view	file
0	C:\workspace\RSSalgSoftware\data\News2x2\News2x2_ViewA.arff
1	C:\workspace\RSSalgSoftware\data\News2x2\News2x2_ViewB.arff

2. Add data files. News2x2 dataset consists of two views (A and B), thus two files are added, each corresponding to one view of the News2x2 dataset

☐ **Load experiment**

Folder:

Dataset

Class attribute name:

ID attribute name:

When tied classify as:

All experiments

Results folder:

Random number generator seed:

Learning models

Combined views model: ☒ Use for all views

view	learning model
------	----------------

Figure 16. Dataset settings input form: creation of the new cross-validation experiment for News2x2 dataset

6.3.1.1 Creating a new cross-validation experiment

Figure 16 illustrates the process of preparing a new cross-validation experiment for News2x2 dataset. Choosing the “New experiment” radio button will allow the user to define the dataset that is to be partitioned in the desired number of folds for the cross-validation experiment.

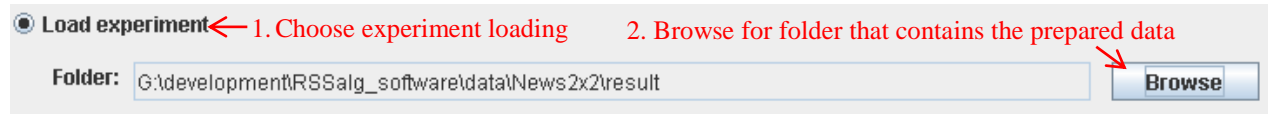
By selecting the “Add” button user can provide one or two dataset files²⁷. It is assumed that all user provided dataset files contain same instances but unique sets of attributes (i.e. they correspond to the different views of the same dataset). The only common attributes for all provided datasets should be the class attribute (obligatory in all views) and the id attribute (optional²⁸).

Currently, *RSSalg software* only allows two views of the data. If the user provides only one dataset file, *RSSalg software* will automatically create the second view by using only class and id attribute. Later, during experiment execution, other features might be added to the second view if needed (e.g. when performing a random feature split). If the user provides two views, the provided features separation is considered to be the “natural feature split” of the dataset.

The prepared cross-validation experiment will be saved to disk inside the folder specified as the *result folder*. Please refer to section 6.3.1.2 for the structure of the recorded cross-validation experiment and to section 6.3.1.3 for the explanation on specifying the *result folder*.

6.3.1.2 Loading an already prepared cross-validation experiment

User is allowed to load an already prepared cross validation experiment by selecting the “Load experiment” radio button (figure 17).



☒ Load experiment ← 1. Choose experiment loading 2. Browse for folder that contains the prepared data
 Folder:

Figure 17. Loading an already prepared experiment (part of the dataset settings input form, figure 16)

The user must define the directory to load the prepared experiment from by clicking on the “Browse” button. The chosen directory must have the following structure (figure 18): it contains subdirectories that are named *fold_0*, *fold_1*, etc. Subdirectory *fold_i* contains all the data needed for running and testing the algorithms on the *i*th fold of *n*-fold cross-validation experiment, $i \in \{0, \dots, n-1\}$. Each subdirectory must contain $3 \times$ the number of views ARFF files, for example, in the case of 2 views the files are named:

- labeled_view0.arff, labeled_view1.arff (two views of labeled data);
- unlabeled_view0.arff, unlabeled_view1.arff (two views of unlabeled data);
- test_view0.arff, test_view1.arff (two views of test data);

Optionally, two more files may be provided named *pool_view1.arff* and *pool_view2.arff*, which correspond to a small pool of unlabeled data *u*’.

It is assumed that the two views of the same data contain the same instances described by different sets of attributes. The only common attributes for all views should be the class attribute whose presence is obligatory in all views and the id attribute which is optional.

²⁷ Currently, only ARFF file format is accepted. Originally developed for Weka [7], ARFF format is widely used in many data mining tools, e.g. Weka and RapidMiner (<http://rapidminer.com/>). Using these data mining tools it is easy to convert the datasets written in other file formats to ARFF format.

²⁸ If the dataset does not contain the id attribute, it is assumed that the provided views have the same ordering of instances, i.e., the *n*-th instance in the first view corresponds to the *n*-th instance in all other views

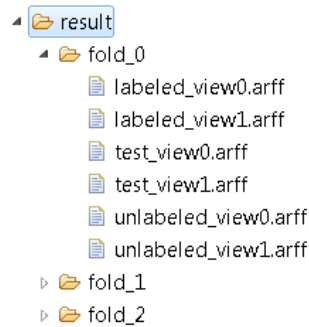


Figure 18. File structure of the directory *result* that contains an already prepared 3-fold-cross-validation experiment for the dataset that has two views

6.3.1.3 Defining general data properties

After the selection of whether to create a new or load an existing cross-validation experiment, the data properties listed in figure 19 should be provided:

- name of the class and id attribute – selection of the dataset will cause the list of possible class and id attribute names to populate. As the class and id attributes are the only attributes that should be present in both views, the list's selections are filled with attributes found in both views. The class attribute name is also limited to nominal attributes. If the id attribute is not present in the dataset ('generate ID' choice, figure 19), the dataset will be automatically tagged with id attribute named 'ID' (numerical, incremental).
- optionally, one can specify the class which should be assigned to the instances for which the algorithm provides an equal probability for all classes;
- the result folder – the directory to which the created experiment will be written (according to the file structure described in section 6.3.1.3) along with the experiment results.
- the random number generator seed – this parameter ensures that the sequence of created random numbers stays the same for each of the experiments, making all experiments exactly replicable.

1. Specify the class attribute name

2. Specify the ID attribute name

3. Specify the name of the class to classify the instances to when all class probabilities are equal

4. Specify the results folder – all experiment data and results will be recorded in this folder

5. Specify the random number generator seed

Figure 19. Entering the general data properties (part of the dataset settings input form, figure 16)

6.3.1.4 Choosing classification models

The user can opt to use the same classification model for the combined classifier as well as the individual views. On the left side of figure 20, we can see the example of selecting the same model for the combined classifier and all individual views. On the right side of figure 20, we can see the example of using different classification models: SVM for the first view, RBF for the second view and Naïve Bayes for the combined classifier. The user can provide arbitrary classifiers from Weka libraries [7] or any class implementing Weka's *Classifier* interface. A full name of the implementation class as well as the package structure must be provided.

Learning models

Combined views model: ☒ Use for all views

weka.classifiers.bayes.NaiveBayes

view	learning model
	weka.classifiers.bayes.NaiveBayes

Learning models

Combined views model: ☐ Use for all views

weka.classifiers.bayes.NaiveBayes

view	learning model
0	weka.classifiers.functions.SMO
1	weka.classifiers.functions.RBFNetwork

Figure 20. Choosing classification models (part of the dataset settings input form, figure 16)

Individual learning models are used for training individual view classifiers in co-training. A combined model is a model used for training on the whole feature set (merged views), i.e. a training model used in supervised experiments L_{acc} and All_{acc} , as well as the model used for the final classifier in **RSSalg**.

For News2x2 experiment, a Naïve Bayes classifier is specified to be used for both individual views as well as for the final classifier, as shown in in figure 20, left.

6.3.1.5 Saving/loading the data settings

After specifying the desired settings, the user can save them in *.properties* file by clicking on the “Save and close” button on the bottom right side of dataset settings dialogue (figure 16). The user can specify the directory the settings will be saved to in the file automatically named ‘data.properties.’

User can also load the existing *.properties* file by clicking on “Load from file” button located on the bottom right side of dataset settings dialogue (figure 16). The user will be prompted to select a directory which must contain the file named ‘data.properties’ from which the properties will be loaded.

Once the dataset properties have been successfully saved, application returns to the main window and the user is allowed to specify other properties, figure 21.

Settings

Dataset settings: alg_software\data\News2x2\experiment\data.properties ...

Cross-validation settings: ...

Co-training properties: ...

Experiment properties: ...

GA properties: ...

Start experiment Load all Clear settings

Figure 21. The main window of the application after the successful save of data properties

6.3.1.6 The resulting data.properties file

Table 6 lists all available data properties as written in ‘data.properties’ file, their meaning and possible values. An example of data.properties file with comments is distributed with *RSSalg software* and can be found in /dist/data/News2x2/experiment folder.

Table 6. The meaning of properties saved in ‘data.properties’ file

Property name	Description	Value
resultFolder	Folder in which the performed cross-validation experiment and results will be recorded	String representing a folder location
classNames	Names of the categories	Quoted Strings separated with whitespace character
combinedClassifier	The combined classifier: supervised model trained on full attribute set acquired by merging all views. It is used in L_{acc} and All_{acc} settings, as well as the final classifier in RSSalg	String: a full-package name of the class implementing Weka’s Classifier interface
classifiers	Classification models used for individual views. If only one classifier is listed and there is more than one view, the same classification model will be used for all individual views. Otherwise, the number of strings in the <i>classifiers</i> parameter as and <i>dataFiles</i> parameter must be same	Quoted Strings separated with whitespace characters. Each String should be a full-package name of the class implementing Weka’s Classifier interface
noViews	The number of views (currently fixed to 2)	2
classAttributeName	Class attribute name	String
dataFiles	Files containing the data. Each file corresponds to one view of the data. The views should contain same instances but different sets of attributes. The only attributes which should appear in both views are class and (optionally) id attribute (class and id values of one instance should be same in all views). If the id attribute is not present in the dataset it is assumed that the <i>n</i> th instance of the first view corresponds to the <i>n</i> th instance in all other views.	Quoted Strings separated with whitespace characters. Each string should be an ARFF file location
randomGeneratorSeed	Seed for random number generator	Integer
loadPresetExperiment	If true, the experiment will be loaded from the <i>resultFolder</i> (properties <i>dataFiles</i> , <i>noViews</i> and all properties from cv.properties file will be ignored). If false, a new cross-validation experiment will be prepared	Boolean value (true/ false)
idAttributeName	ID attribute name. If the property value is unspecified, an id attribute named ‘ID’ will be automatically generated	String

6.3.2 Specifying cross-validation experiment settings

The cross-validation experiment settings are used if the user chose the “New experiment” option (section 6.3.1.1). Otherwise (if the user chose the “Load experiment” option, section 6.3.1.2), the user will still be able to access these settings in order to review the loaded experiment, but will be unable to change them.

Figure 22 shows the dialogue for cross-validation settings entry populated with the settings needed for News2x2 experiment. In each round of 10-fold-cross validation, six adjacent folds will be used as the unlabeled data and four adjacent folds will be utilized as the test data (the total number of folds is always equal to the number of unlabeled and test folds). The labeled dataset will be constructed by randomly selecting five instances labeled as ‘positiveClass’ and five instances labeled as ‘negativeClass’. The application will automatically populate the possible category names (‘class name’ column in the table on figure 22), the user only needs to specify the number of labeled instances per each class.

The user can also select the option of removing the value of the class attribute for all instances that belong to the unlabeled set. However, in this case, the supervised experiment *All* which uses the labels of unlabeled data cannot be ran properly (it will return the same result as the *L* experiment as the model will be trained on the same small labeled set). Keeping or removing the labels from unlabeled data does not affect the results of any other experiments that do not use these labels.

Cross-validation settings

Labeled instances

class name	no. labeled
positiveClass	5
negativeClass	5

Unlabeled folds: ☐ Remove labels

Test folds:

Number of folds:

Figure 22. The cross-validation input form with values entered for the News2x2 experiment

The user can save the specified cross-validation settings by clicking on the “Save and close” button on the bottom right side of cross-validation input form (figure 22). User is prompted to specify the directory the settings will be saved to in the file automatically named ‘cv.properties.’

6.3.2.1 The resulting cv.properties file

Table 7 lists all available cross-validation properties as written in ‘cv.properties’ file, their meaning and possible values. An example of cv.properties file with comments is distributed with *RSSalg software* and can be found in /dist/data/News2x2/experiment folder.

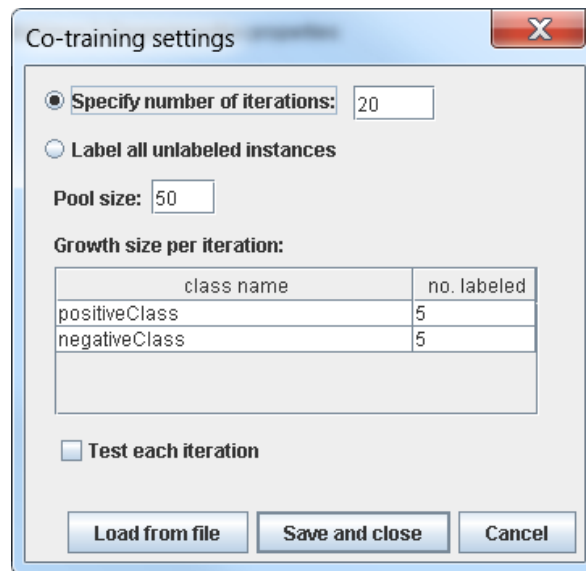
Table 7. The meaning of properties saved in ‘cv.properties’ file

Property name	Description	Value
className	Names of the categories	Quoted Strings separated with whitespace characters
noLabeled	Number of labeled examples randomly chosen per each class – the <i>i</i> th value from the list corresponds to the <i>i</i> th category listed in <i>className</i> parameter	Integer values separated with whitespace characters
noTest	Number of adjacent folds merged and used as test data	Integer value
noUnlabeled	Number of adjacent folds merged and used as unlabeled data	
noFolds	Total number of folds (<i>n</i>) for <i>n</i> -fold-cross validation	Integer value
removeLabels	If true, the label will be removed from all unlabeled instances (this will disable the execution of <i>All</i> experiment)	Boolean value (true/false)

The user can load the existing *.properties* file by clicking on the “Load from file” button on the bottom right side of cross-validation input form (figure 22). The user will be prompted to select a directory which must contain the file named ‘cv.properties’ from which the properties will be loaded.

6.3.3 Specifying co-training settings

The co-training settings are used for all underlying co-training experiments. For example, in *RSSalg* a predefined number of co-training classifiers is trained, each using these settings. The same co-training settings are used for running *Natural* setting or if running the *Random* setting. The input form for co-training settings entry is shown in figure 23.



Co-training settings

☒ Specify number of iterations: 20

☐ Label all unlabeled instances

Pool size: 50

Growth size per iteration:

class name	no. labeled
positiveClass	5
negativeClass	5

☐ Test each iteration

Load from file Save and close Cancel

Figure 23. The co-training settings input form with values entered for the News2x2 experiment

As stopping criteria for co-training, the user can either specify the desired number of iterations (20 for the News 2x2 dataset, figure 23) or specify to stop co-training when all unlabeled instances have been labeled (option “Label all unlabeled instances”). The size of the small unlabeled pool u' may be specified (50 for the News2x2 experiment, figure 23). If the specified size of the small unlabeled pool is 0, the pool won’t be used, and the underlying co-training classifiers will select and label instances directly from the unlabeled set.

The “Growth size per iteration” defines the number of most confidently labeled instances per each class that will be labeled and transferred to the labeled set in each co-training iteration. The “class names” column is automatically populated, and the user only needs to specify the number of instances.

Check box “Test each iteration” allows the user to oversee the progress of each co-training classifier training by testing the classifier in each iteration. These results are documented in the log files named ‘CTlog_split_ i .txt’ in the results folder (specified through data settings, section 6.3.1.3). For example, if the **RSSalg** setting was ran using three different random splits, three different co-training classifiers will be trained, and the progress of their training will be saved in three different log files, one for each split, as shown in figure 24.

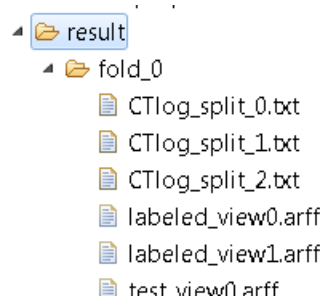


Figure 24. The results of testing each iteration of co-training classifiers

Figure 25 shows an example of one of these log files. Individual co-training classifiers, as well as the combined co-training style classifier²⁹, are tested in each iteration. The calculated measures (in this example accuracy and $f1$ -measure for the ‘positiveClass’) are defined by settings of the performed experiment (section 6.3.4).

²⁹ The combined co-training style classifier classifies each test instance by multiplying the class probabilities output by individual underlying classifiers. The instance is assigned the class with the highest probability obtained this way

```

Starting co-training experiment for fold 0 split: 0
View1: accuracy: 80; f1-measure for class positiveClass: 80.3;
View2: accuracy: 73; f1-measure for class positiveClass: 71.2;
Combined: accuracy: 81.25; f1-measure for class positiveClass: 80.05;

Classifiers after iteration: 1:
View1: accuracy: 74.38; f1-measure for class positiveClass: 75.03;
View2: accuracy: 72.75; f1-measure for class positiveClass: 71.83;
Combined: accuracy: 76; f1-measure for class positiveClass: 74.05;

Classifiers after iteration: 2:
View1: accuracy: 73.62; f1-measure for class positiveClass: 72.42;
View2: accuracy: 74.62; f1-measure for class positiveClass: 72.82;
Combined: accuracy: 74.88; f1-measure for class positiveClass: 71.57;

...

End accuracy:
View1: accuracy: 78.5; f1-measure for class positiveClass: 79.38;
View2: accuracy: 80.38; f1-measure for class positiveClass: 80.45;
Combined: accuracy: 81.62; f1-measure for class positiveClass: 81.13;

CT running time 62.63s

```

Figure 25. The example of the log file obtained by testing each iteration of co-training

User can save the specified co-training settings by clicking on the “Save and close“ button on the bottom right side of co-training input form (figure 23). The user is prompted to specify the directory the settings will be saved to in the file automatically named ‘co-training.properties’.

User can load the existing *.properties* file by clicking on the “Load from file“ button located on the bottom right side of co-training settings input form (figure 23). The user will be prompted to select a directory which must contain the file named ‘co-training.properties’ from which the properties will be loaded.

6.3.3.1 The resulting co-training.properties file

Table 8 lists all available co-training properties as written in ‘co-training.properties’ file, their meaning and possible values.

Table 8. The meaning of properties saved in ‘co-training.properties’ file

Property name	Description	Value
className	Names of the categories	Quoted Strings separated with whitespace characters
Growth size	The number of most confidently labeled examples belonging to each class that will be labeled and transferred to the labeled set in each co-training iteration. The <i>i</i> th value from the list corresponds to the <i>i</i> th category listed in <i>className</i> parameter	Integer values separated with whitespace characters
labelAllUnlabeledData	If set to <i>true</i> , co-training process will continue until all examples from unlabeled set are labeled (<i>coTrainingIterations</i> parameter will be ignored); if false, co-training will run for a predefined number of iterations defined in <i>coTrainingIterations</i> parameter	Boolean value (true/false)
coTrainingIterations	Number co-training iterations <i>k</i>	Integer value
poolSize	Size (number of instances) of unlabeled pool <i>u</i> . If set to 0, the pool is not used, and the instances are sampled directly from the unlabeled set	Integer value
testEachIteration	If true – the obtained co-training classifiers will be tested in each iteration and the results will be written to log files	Boolean value (true/false)

6.3.4 Specifying experiment settings

The experiment settings allow the user to define the conducted experiment. Figure 26 shows the input form for experiment settings entry.

Algorithm: L

1. Selecting the algorithm

Measure	For class
Accuracy	avg
F1-measure	positiveClass
F1-measure	negativeClass

2. Specifying performance measures

Measure: Accuracy For class: not specified Add Remove

3. Specifying a feature split

Feature split: None Number of splits: 0

4. Loading a pre-recorded classifier statistics

☐ Load classifiers File name: ...

5. Recording results

☐ Write training/test statistics

☐ Write enlarged training set

Load from file Save and close Cancel

Figure 26. The experiment settings input form

1. Selecting the algorithm

Using the “Algorithm” selection list user can choose to run one of the experiments listed in section 2.3. In the selection list ‘L’ denotes L_{acc} setting, ‘All’ denotes All_{acc} setting, ‘Co-training’ is used for *Natural* and *Random* settings, ‘MV’ is used for *MajorityVote* setting, ‘RSSalg’ is used for running **RSSalg** setting and ‘RSSalg_best’ is used for running **RSSalg_{best}** setting.

2. Specifying performance measures

RSSalg software can calculate several measures of algorithm performance. Currently, supported measures are accuracy, *f1*-measure, precision, and recall. The user can also specify an arbitrary measure that implements *classificationResult.measures.MeasureIF* interface provided in *RSSalg* software implementation.

For category-specific measures such as *f1*-measure user can specify the category to calculate the measure for or select “not specified” choice in order to obtain the average measure for all classes (e.g. in figure 27 user chooses to obtain an average of *f1*-measure for ‘positiveClass’ and *f1*-measure for ‘negativeClass’). The category list is automatically obtained from the data settings by examining the provided class attribute.

Measure: F1-measure For class: not specified

not specified

positiveClass

negativeClass

Feature split:

Figure 27. Choosing to calculate an average of *f1*-measure for ‘positiveClass’ and *f1*-measure for ‘negativeClass’

User may provide several measures which will be calculated. For example, in figure 26, the user has chosen to calculate the accuracy and *f1*-measure for both positive and negative class in L_{acc} experiment.

3. Specifying a feature split

By specifying values in ‘Feature split’ list choice and ‘Number of splits’ field user can specify the feature split that will be performed before running the chosen algorithm, and the number of times this process will be repeated, respectively.

4. Loading a pre-recorded classifier statistics

“Load classifiers” check box denotes whether to load a previously recorded classifier statistic or not. Selecting to use the classifier statistic will enable the user to specify the XML file that contains the recorded statistic.

A *training* classifier statistic provides the information about each instance *labeled during the training process* of the classifier (instances formally belonging to the unlabeled set, labeled and added to train data by the algorithm). This information encompasses the label that was assigned to the instance by a classifier, as well as the classifiers confidence for each possible category. For example, in each round of co-training, both underlying classifiers are allowed to select and label instances from unlabeled set and transfer them to the labeled set. A training classifier statistic encompasses a label for each such instance and the confidence of the underlying classifier that assigned the label. This information can be used later to aggregate the votes of several co-training classifiers. For example, in RSSalg multiple co-training classifiers are built. Statistics about building these classifiers is recorded and then used for building the final training set in RSSalg.

A *testing* classifier statistic provides the information about each instance from the test set *labeled during the algorithm evaluation*. As training statistics, this information encompasses the label assigned to the instance, as well as the classifiers confidence for the assigned label. In the case where the label is assigned by the ensemble of classifiers, all confidences are recorded. For example, when applying a trained co-training classifier to the test set, confidences of both underlying single-view classifiers for each category are recorded. This information can be later used in order to aggregate the classifier votes on the test set. For example, in MV multiple co-training classifiers are built. Each trained classifier is applied to the test set and statistics about testing these classifiers is recorded. This statistics is later used for labeling test instances by a simple majority vote of the created classifiers.

5. Recording results

The user can choose to record both training and testing classifier statistic for the executed algorithm by selecting the “Write training/test statistics” option. The statistic will be saved in the directory defined by the result folder (property resultFolder, table 6) to the file whose name will be automatically determined by the executed algorithm (please refer to following subsections for the file names in which the statistics of the algorithms will be recorded). Figure 28 shows an example of written test classifier statistics for the *L* setting.

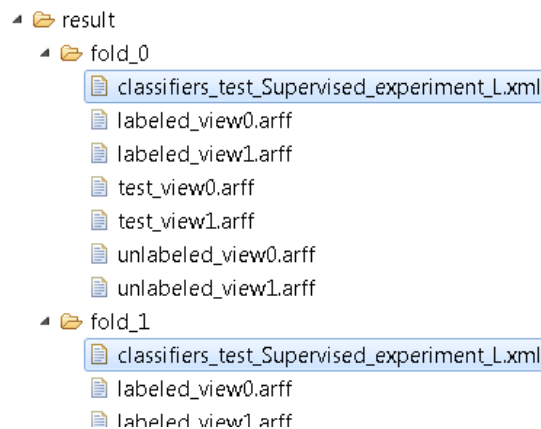


Figure 28. Example of written test classifier statistics for the *L* setting

Finally, RSSalg software provides the user with an option to save the enlarged training set obtained during the algorithm execution, i.e. the training set consisting of both labeled data and unlabeled instances labeled and added to the training set during algorithm execution time. The enlarged dataset will be saved in the directory defined by the result folder (property resultFolder, table 6) to the file whose name will be automatically determined by the executed algorithm (see later subsections for the file names for specific algorithms). Figure 29 shows an example of written enlarged training sets for the Natural setting.

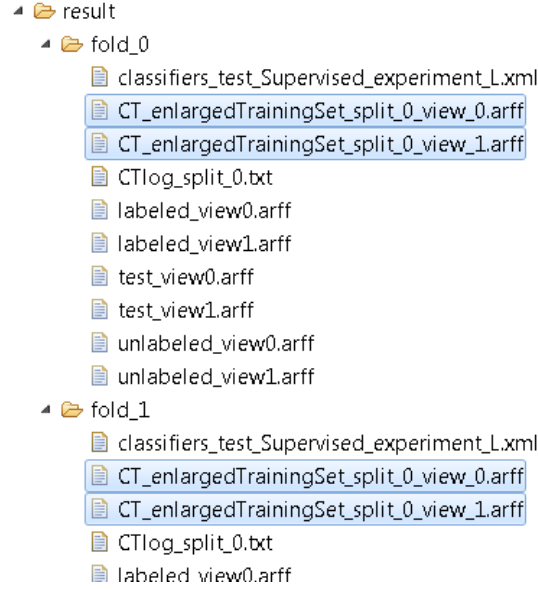


Figure 29. Example of written enlarged training sets for the *Natural* setting

6. Saving and loading properties

The user can save the specified experiment settings by clicking on the “Save and close“ button on the bottom right side of experiment settings input form (figure 26). The user is prompted to specify the directory the settings will be saved to in the file automatically named according to the algorithm name.

The user can load the existing *.properties* file by clicking on the “Load from file“ button on the bottom right side of co-training settings input form (figure 26). The user will be prompted to select a *.properties* file containing the desired experiment.

6.3.4.1 Running the L_{acc} setting

The input form for experiment settings entry with the selection of L setting is shown in figure 26. In L_{acc} setting, all features are merged in a unique attribute set and the classifier is trained on the labeled portion of the data (i.e. feature values from all other views are copied to the first view which is used for training). The ‘Feature split’ choice list and the ‘Number of splits’ field are disabled and set to ‘None’ and 0, respectively, as the supervised labeled experiment does not rely on a feature split.

As the L_{acc} setting does not rely on training or testing classifier statistics, ‘Load classifiers’ choice is disabled. Since none of the unlabeled instances is labeled and added to the training set during the L_{acc} setting execution, ‘Write enlarged training set’ option is disabled. For the same reason, if the ‘Write training/test statistics’ option is chosen, only the *test* statistics will be written. The test statistic file is automatically named ‘classifiers_test_Supervised_experiment_L.xml’, figure 28.

Figure 26 shows the experiment settings input form populated with the values needed to run the L setting for the News2x2 experiment. When the user chooses to save the input properties for the L setting, a *.properties* file is automatically named ‘experiment_L.properties.’

6.3.4.2 Running the All_{acc} setting

The input form for experiment settings entry adjusted for performing the All_{acc} setting for the News2x2 experiment is shown in figure 30.

Experiment settings

Algorithm: All

Measures

Measure	For class
Accuracy	avg

Measure: Accuracy For class: not specified Add Remove

Feature split: None Number of splits: 0

☐ Load classifiers

File name: ...

☐ Write training/test statistics

☐ Write enlarged training set

Load from file Save and close Cancel

Figure 30. The experiment settings input form adjusted for running the *All* setting on News2x2 dataset

In All_{acc} setting, all features are merged in a unique attribute set. Also, all unlabeled instances are transferred to the labeled data and their correct manually-assigned labels are used. Note that if the ‘Remove labels’ option was chosen when creating a cross-validation experiment (section 6.3.2), All_{acc} setting will reduce to the L_{acc} setting as the labels for unlabeled data are unavailable.

The ‘Feature split’ choice list and the ‘Number of splits’ field are disabled and set to ‘None’ and 0, respectively, as the supervised experiment All_{acc} does not rely on a feature split. As the All_{acc} setting does not rely on training or testing classifier statistics, ‘Load classifiers’ choice is also disabled.

Because the unlabeled instances are simply copied to the training set during the All_{acc} setting execution ‘Write enlarged training set’ option is disabled. For the same reason, if the ‘Write training/test statistics’ option is chosen, only the *test* statistics will be written. The test statistic file is automatically named ‘classifiers_test_Supervised_experiment_All.xml.’

When the user choses to save the input properties for the All_{acc} setting, a *.properties* file is automatically named ‘experiment_All.properties.’

6.3.4.3 Running the Natural setting (co-training with a natural feature split)

The input form for experiment settings entry adjusted for performing the *Natural* setting for News2x2 experiment is shown in figure 31.

Experiment settings

Algorithm: Co-training

Measures

Measure	For class
Accuracy	avg

Measure: Accuracy For class: not specified Add Remove

Feature split: Natural Number of splits: 1

☐ Load classifiers

File name: ...

☒ Write training/test statistics

☐ Write enlarged training set

Load from file Save and close Cancel

Figure 31. The experiment settings input form adjusted for running the *Natural* setting on News2x2 dataset

For running the *Natural* setting, ‘Algorithm’ is set to ‘Co-training’ and ‘Feature split’ choice is set to ‘Natural.’ In this case, the ‘Number of splits’ field is disabled and set to ‘1’ as there is only one “natural” split. Running co-training with natural feature split in *RSSalg software* does not perform a feature split – it is assumed that the user has previously provided the two views (see section 6.3.1.1) and this separation is considered to be the “natural feature split” of the dataset.

The co-training algorithm does not rely on training or testing classifier statistics generated by other classifiers. Thus the ‘Load classifiers’ choice is disabled.

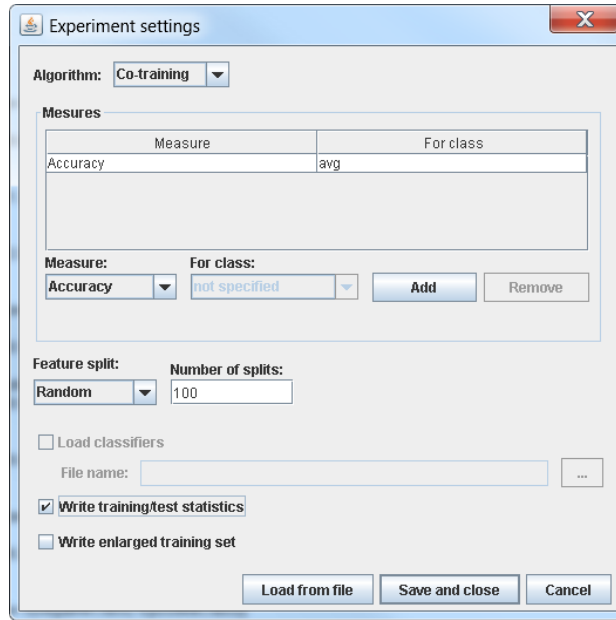
User can choose to save both *training* and *testing* classifier statistic by selecting the ‘Write training/test statistic’ choice. The resulting files are named ‘classifiers_CoTraining.xml’ and ‘classifiers_test_CoTraining.xml’, respectively.

The user can also choose to save the enlarged training set obtained with co-training by selecting the ‘Write enlarged training set’ option. The resulting files will be named ‘CT_enlargedTrainingSet_split0_view_0.arff’ (the first view) and ‘CT_enlargedTrainingSet_split0_view_1.arff’ (the second view).

When the user chooses to save the input properties for the *Natural* setting, a *.properties* file is automatically named ‘experiment_Co-training_Natural.properties.’

6.3.4.4 Running the Random setting (co-training with a random feature split)

The input form for experiment settings entry adjusted for performing the *Random* setting for News2x2 experiment is shown in figure 32.



The 'Experiment settings' dialog box is shown. The 'Algorithm' dropdown is set to 'Co-training'. The 'Measures' section contains a table with one row: 'Accuracy' for the 'Measure' and 'avg' for the 'For class'. Below the table, the 'Measure' dropdown is set to 'Accuracy' and the 'For class' dropdown is set to 'not specified'. There are 'Add' and 'Remove' buttons. The 'Feature split' dropdown is set to 'Random' and the 'Number of splits' text box contains '100'. There are three checkboxes: 'Load classifiers' (unchecked), 'Write training/test statistics' (checked), and 'Write enlarged training set' (unchecked). At the bottom, there are 'Load from file', 'Save and close', and 'Cancel' buttons.

Measure	For class
Accuracy	avg

Figure 32. The experiment settings input form adjusted for running the *Random* setting on News2x2 dataset

For running the *Random* setting, 'Algorithm' is set to 'Co-training' and 'Feature split' choice is set to 'Random.' In this case, the 'Number of splits' field is enabled, and user can enter an arbitrary number of random splits to perform. For News2x2 experiment, the number of splits is set to 100 which will create 100 different random splits (i.e. 100 different co-training classifiers). The resulting performance of *Random* will be the average performance of built classifiers.

The co-training algorithm does not rely on training or testing classifier statistics generated by other classifiers. Thus, the 'Load classifiers' choice is disabled.

The user can choose to save both *training* and *testing* classifier statistic by selecting the 'Write training/test statistic' choice. The resulting files are named 'classifiers_CoTraining_DifferentRandomSplits.xml' and 'classifiers_test_CoTraining_DifferentRandomSplits.xml', respectively, and are located in the results folder. For News2x2 experiment the option 'Write training/test statistics' is chosen as we would later like to exploit the created *training* statistics for **RSSalg** and **RSSalg_{best}** experiments and created *test* statistics for **MV** experiment. The name and the location of the resulting train and test statistic is shown in figure 33.

```

result
├── fold_0
│   ├── classifiers_CoTraining_DifferentRandomSplits.xml
│   ├── classifiers_test_CoTraining_DifferentRandomSplits.xml
│   ├── labeled_view0.arff
│   ├── labeled_view1.arff
│   ├── test_view0.arff
│   ├── test_view1.arff
│   ├── unlabeled_view0.arff
│   └── unlabeled_view1.arff
├── fold_1
│   ├── classifiers_CoTraining_DifferentRandomSplits.xml
│   ├── classifiers_test_CoTraining_DifferentRandomSplits.xml
│   ├── labeled_view0.arff
│   ├── labeled_view1.arff
│   ├── test_view0.arff
│   ├── test_view1.arff
│   ├── unlabeled_view0.arff
│   └── unlabeled_view1.arff
├── fold_2
└── fold_3

```

Figure 33. The result of saving the training and test statistics for co-training ran with multiple random splits

User can also choose to save the enlarged training set obtained with co-training by selecting the ‘Write enlarged training set’ option. The resulting files will be named ‘CT_enlargedTrainingSet_split*i*_view_0.arff’ (the first view) and ‘CT_enlargedTrainingSet_split*i*_view_1.arff’ (the second view) where *i* is the number of the performed random split. In News2x2 *Random* experiment $i \in \{0, \dots, 99\}$.

When the user chooses to save the input properties for the *Random* setting, a *.properties* file is automatically named ‘experiment_Co-training_Random.properties’.

6.3.4.5 Running the MV setting (majority vote of co-training classifiers)

The input form for experiment settings entry adjusted for performing the *MV* setting for News2x2 experiment is shown in figure 34.

Figure 34. The experiment settings input form adjusted for running the *MV* setting on News2x2 dataset

In *MV* setting, an instance from the test set is classified by a simple majority vote of an ensemble of trained co-training classifiers. As the *test* statistic is needed (information on how each classifier from the ensemble classifies instances from the test set), it is necessary to load it. Thus the choice ‘Load classifiers’ is checked and disabled and by clicking on “...” button user is prompted to select a file containing the test statistic. *RSSalg software* automatically saves the *test* statistic of the resulting classifiers in the results folder in XML files with names starting with ‘classifiers_test’ (see figure 33). Thus, the user can select only XML files whose names start with ‘classifiers_test’ and are located in fold_0 subdirectory in the results folder³⁰. In this experiment (figure 34), we assume that the *Random* setting was already run and that its test statistic has been recorded in ‘classifiers_test_CoTraining_DifferentRandomSplit.xml’ file.

When test statistic is selected, *RSSalg software* will automatically read the test statistics from fold_0 and populate the ‘Number of splits’ field with the number of classifiers from the loaded ensemble.

User can choose to save *testing* classifier statistic by selecting the ‘Write training/test statistic’ choice³¹. The resulting files are named ‘classifiers_test_Majority_vote_of_Co-training_classifiers_on_test_set_DifferentRandomSplits.xml’ and are located in the results folder. As *MV* does not label and add unlabeled instances to the training set, ‘Write enlarged training set’ option is disabled.

When the user choses to save the input properties for the *MV* setting, a *.properties* file is automatically named ‘experiment_MV.properties.’

³⁰ It is assumed that the appropriate file names are the same in other subdirectories which correspond to other folds in cross-fold-validation. Also, it is assumed that there is a minimum one fold (which corresponds to subdirectory fold_0)

³¹ Training statistics is not saved as it would be the same statistic which was loaded for **MV** setting

6.3.4.6 Running RSSalg and RSSalg_{best} settings

The user can opt to run **RSSalg** or **RSSalg_{best}** setting by using ‘RSSalg’ or ‘RSSalg_{best}’ as the algorithm choice, respectively. The input form for experiment settings entry adjusted for performing the **RSSalg** setting for News2x2 experiment is shown in figure 35.

Measure	For class
Accuracy	avg

Figure 35. The experiment settings input form adjusted for running the *RSSalg* setting on News2x2 dataset

RSSalg relies on using the training statistic of multiple co-training classifiers. The user can choose to load a previously saved statistic (e.g. if the user has already run the *Random* setting and would like to use the same classifiers for **RSSalg**) by choosing the ‘Load classifiers’ option. Since *RSSalg software* automatically saves the *training* statistic in the results folder in XML files with names starting with ‘classifiers_’ (see figure 33), the user can only select XML files whose names start with ‘classifiers_’ and are located in fold_0 subdirectory in the results folder³². When training statistic is selected, *RSSalg software* will automatically read the test statistics from fold_0 and populate the ‘Number of splits’ field with the number of classifiers from the loaded ensemble. In this experiment (figure 35), we assume that the *Random* setting was already run and that its training statistic has been recorded in ‘classifiers_test_CoTraining_DifferentRandomSplit.xml’ file. We will use these statistics to form the final training set in **RSSalg**.

If the ‘Load classifiers’ option is not selected, **RSSalg** will create a new training statistics by running co-training with different random splits for the number of times user specified in the ‘Number of splits’ field. Assuming that the random seed is unchanged and that user chose the same number of splits as in *Random* experiment, the newly created statistic will be the same as the same sequence of random numbers is generated.

User can choose to save *train* and *test* classifier statistic by selecting the ‘Write training/test statistic’ choice. The resulting files are named ‘classifiers_RSSalg_left_out_instances_DifferentRandomSplits.xml’ and ‘classifiers_test_RSSalg_left_out_instances_DifferentRandomSplits.xml’, respectively, for **RSSalg** setting and ‘classifiers_RSSalg_best_DifferentRandomSplits.xml’ and ‘classifiers_test_RSSalg_best_DifferentRandomSplits.xml’ for **RSSalg_{best}** setting. The saved files are located in the results folder.

The selection of ‘Write enlarged training set’ option will result in saving the final classifier of **RSSalg** or **RSSalg_{best}** in the files named ‘RSSalg_left_out_instances_enlargedTrainingSet.arff’ and ‘RSSalg_{best}_enlargedTrainingSet.arff,’ respectively.

When the user chooses to save the input properties for the **RSSalg** or **RSSalg_{best}** setting, a *.properties* file is automatically named ‘experiment_RSSalg.properties’ and ‘experiment_RSSalg_{best}.properties,’ respectively.

³² It is assumed that the appropriate file names are the same in other subdirectories which correspond to other folds in cross-fold-validation. Also, it is assumed that there is a minimum one fold (which corresponds to subdirectory fold_0)

6.3.4.7 The resulting experiment property file

Table 9 lists all available experiment properties, their meaning, and possible values.

Table 9. The meaning of properties saved in experiment *.properties* file

Property name	Description	Value
algorithm	The performed algorithm	String value: a full package name of algorithm implementation. Possible values: <ul style="list-style-type: none"> <code>algorithms.SupervisedAlgorithm_L</code> (<i>L_{acc}</i>) <code>algorithms.SupervisedAlgorithm_All</code> (<i>All_{acc}</i>) <code>algorithms.co_training.CoTraining</code> (<i>Random, Natural</i>) <code>algorithms.RSSalg.MajorityVote</code> (<i>MV</i>) <code>algorithms.RSSalg.RSSalg</code> (<i>RSSalg, RSSalg_{best}</i>) The arbitrary class which extends the <code>algorithms.Algorithm</code> class
measures	The list of performance measures that should be calculated	Quoted Strings separated with whitespace characters. Each String should be a full package name of a performance measure. Possible values: <ul style="list-style-type: none"> <code>classificationResult.measures.AccuracyMeasure</code> <code>classificationResult.measures.F1Measure</code> <code>classificationResult.measures.Precision</code> <code>classificationResult.measures.Recall</code> Arbitrary implementation of <code>classificationResult.measures.MeasureIF</code>
measuresForClass	Categories for category-specific measures such as <i>f1</i> -measure	Quoted Strings separated with whitespace characters. Each String denotes the category for which the performance measure is calculated (the <i>i</i> th String corresponds to the <i>i</i> th String in <i>measures</i> property). If the measure is category-independent (e.g. accuracy) or if an average for all categories should be calculated, specify the value as “avg”
featureSplitter	Algorithm for feature splitting	String value: a full package name of a feature splitting algorithm. Possible values: <ul style="list-style-type: none"> <code>featureSplit.RandomSplit</code> (random split) <code>featureSplit.DifferentRandomSplitsSplitter</code> (unique random splits) Arbitrary implementation of <code>featureSplit.SplitterIF</code>
noSplits	Number of feature splits	Integer value
loadClassifiers	If true, load a <i>training</i> classifier statistic from <i>ClassifiersFileName</i>	Boolean value (true/false)
ClassifiersFilename	A classifier statistics to be loaded if <i>loadClassifier=true</i> .	String value representing the XML file containing the classifier statistics. Note: For <i>MV</i> use <i>loadClassifier=false</i> and specify the <i>test</i> classifier statistic in this property
writeClassifiers	If true, record <i>train</i> and <i>test</i> classifier statistics obtained during algorithm execution	Boolean value (true/false)
writeEnlargedTrainingSet	If true, record the enlarged training set obtained by labeling unlabeled instances during algorithm execution	Boolean value (true/false)
voter	Algorithm that aggregates votes assigned by multiple classifiers	String value: a full package name of the voting algorithm. Possible values: <ul style="list-style-type: none"> <code>algorithms.RSSalg.resultStatistic.Label.MajorityVotes</code> Arbitrary implementation of <code>algorithms.RSSalg.resultStatistic.Label.VoterIF</code>
candidateEvaluator	Algorithm that evaluates candidates for GA optimization of thresholds in <i>RSSalg</i> . This property value is used only for RSSalg setting.	String value: a full package name of the algorithm. Possible values: <ul style="list-style-type: none"> <code>algorithms.RSSalg.GA.RSSalgCandidateEvaluator</code> (RSSalg setting) <code>algorithms.RSSalg.GA.TestSetAccuracyCandidateEvaluator</code> (RSSalg_{best} setting) Arbitrary implementation of <code>algorithms.RSSalg.GA.CandidateEvaluatorIF</code>

6.3.5 Specifying genetic algorithm settings

The GA settings are needed for the execution of **RSSalg** and **RSSalg_{best}** experiments as the genetic algorithm is used as the optimization algorithm for threshold selection in these algorithms. Figure 36 shows the dialogue for genetic algorithm settings entry populated with the settings needed for News2x2 experiment:

- Each generation will encompass 50 individuals;
- GA will be run for maximally 50 iterations;
- If there is no improvement in 5 generations, GA will stop;
- The crossover and mutation thresholds are 0.3 and 0.02, respectively;
- The testing threshold [4] used in RSSalg is 20%;
- Elitism will be used³³;
- When evaluating a model resulting from the threshold pair candidate, accuracy is used as the optimization measure;
- Accuracy measure does not depend on a particular category, thus ‘Optimization measure for class’ is set to ‘not specified’.

The user can also select the option of keeping the log about the GA execution. The result log will be written to the file named ‘ThresholdOptimiserlog.txt’ in the result folder³⁴.

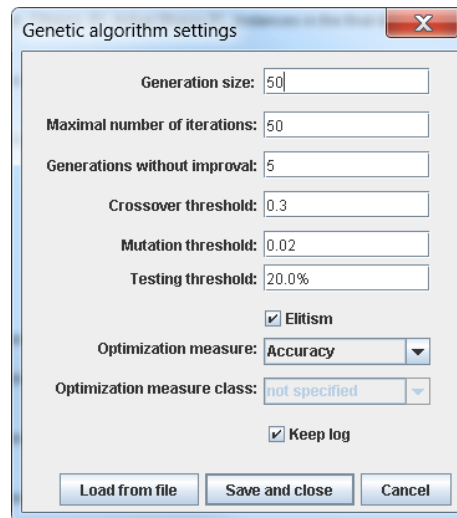


Figure 36. The GA settings input form with values entered for the News2x2 experiment

The user can save the specified GA settings by clicking on the “Save and close“ button on the bottom right side of GA settings input form (figure 36). User is prompted to specify the directory the settings will be saved to in the file automatically named ‘GA.properties’.

The user can load the existing *.properties* file by clicking on the “Load from file“ button on the bottom right side of GA settings input form (figure 36). User will be prompted to select a directory which must contain the file named ‘GA.properties’ from which the properties will be loaded.

³³ The best individual from the generation will be copied to the next generation

³⁴ The full path to each file is <results_folder>/fold_<currentFold>/ThresholdOptimiserlog.txt

6.3.5.1 The resulting GA.properties file

Table 10 lists all available GA properties as written in ‘GA.properties’ file, their meaning and possible values.

Table 10. The meaning of properties saved in ‘GA.properties’ file

Property name	Description	Value
generationSize	Number of candidates in each GA generation	Integer value
iterations	Maximal number of GA iterations	Integer value
noImprovalGenerations	If the solution does not improve in last <i>noImprovalGenerations</i> , stop GA. If set to -1 GA will iterate for the exact number of iterations specified in ‘iterations’ property	Integer value (-1 or greater than 0)
crossoverTS	Crossover threshold in GA	Double value in the range (0,1)
mutationTS	Mutation threshold in GA	Double value in the range (0,1)
testingTS	Testing threshold in RSSalg	Double value in the range (0,1)
elitism	If set to true use elitism (copy the best individual from current generation to the next generation)	Boolean value (true/false)
optimizationMeasure	Each candidate in RSSalg represents a threshold pair which defines the training set used the final model in RSSalg. This property defines the evaluation measure for this model.	String value: full-package name of the implementation of a performance measure. Possible values: <ul style="list-style-type: none"> <code>classificationResult.measures.AccuracyMeasure</code> <code>classificationResult.measures.F1Measure</code> <code>classificationResult.measures.Precision</code> <code>classificationResult.measures.Recall</code> Arbitrary implementation of <code>classificationResult.measures.MeasureIF</code>
optimizationMeasureClass	Categories for category-specific measures such as <i>f1</i> -measure	String value: the category for which the performance measure is calculated. If the measure is category-independent (e.g. accuracy) or if an average of the measure value for all categories should be calculated, specify the value as “avg”
logGA	If true, log the process of GA optimization	Boolean value (true/false)

6.4 Running the experiment in RSSalg software

To execute the desired experiment, the user must firstly specify the desired settings. Dataset settings and co-training settings are obligatory for all experiments. Cross-validation experiment settings are mandatory if the user has chosen to create a new cross-validation experiment (section 6.3.2). The experiment that will be run is determined by the currently selected experiment settings. Genetic algorithm settings are only required in case of running **RSSalg** or **RSSalg_{best}** experiment.

Please refer to section 6.3 for detailed description of entering the desired settings. By clicking on ‘Load all’ button (figure 15) the user may load all previously created settings: user is prompted to select the directory to re-load the saved properties from. *RSSalg software* will load the following *.properties* files from the chosen directory: data settings from the file ‘data.properties,’ the cross-validation settings from the file ‘cv.properties,’ the co-training settings from the file ‘co-training.properties,’ the settings of the *L* experiment from the file ‘experiment_L.properties’ and the genetic algorithm settings from the file ‘GA.properties’. User can clear all selecting settings by clicking on ‘Clear settings’ button (figure 15).

The experiment execution is started by clicking on the ‘Start experiment’ button. Experiment results will be shown in the results window, figure 15. If the user wishes to clear the results window, he can do so by clicking on the “Clear” button on the bottom right side of the main window of *RSSalg software* application (figure 15).

In case the user has chosen to create a new cross-validation experiment (section 6.3.1.1) when the experiment starts, the created cross-validation experiment will be written to the specified result folder (section 6.3.1.3) as shown in figure 37. The file structure of the written data is explained in section 6.3.1.2. For the later experiments, the user may want to select the option of loading the prepared experiment from the result folder as described in section 6.3.1.2. Assuming that the user does not change the random generator seed or other data and cross-validation settings, choosing to load a prepared experiment or generating a new one for each experiment does not affect the results. Each time the experiment is created using the same sequence of random numbers, so each time the instances layout across different folds and train/unlabeled/test data is the same. However, it is recommended to create the experiment only once and later load the prepared experiment as the experiment creating procedure may be slow for the larger datasets.

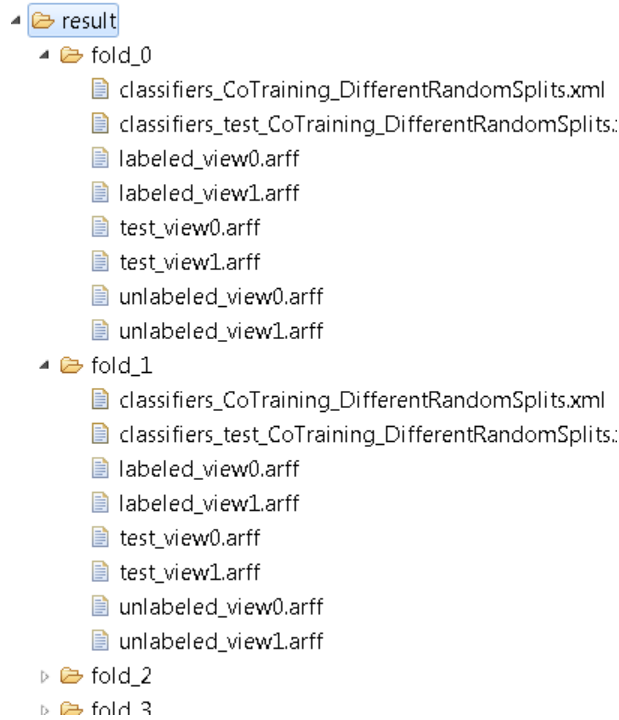


Figure 37. The result of creating a new cross-validation experiment

Each time an experiment is run, the resulting micro and macro averaged measures are shown in the results window. The example output (obtained by executing L_{acc} experiment of News2x2 dataset) is shown in figure 5. Each time an experiment is run, its resulting performance is recorded in 'Results.xml' file located inside the result folder. At the end of performing the experiment, *RSSalg software* will list all of the results recorded in 'Results.xml' (figure 5).

Figure 38 shows an example of 'Results.xml' file obtained after running several different experiments. The experiments recorded in the 'Results.xml' are organized according to some basic settings: the number of co-training iterations, the growth size and number of performed splits. The name of the applied algorithm is also saved. Thus, only running the experiment with the same name and recorded properties will rewrite the results of that experiment, otherwise the experiment results will be appended to the list. Note that for each experiment different measures may be calculated – running the experiment with the same settings will only modify the measure which is being calculated.

Table 11 lists the results obtained by running the experiments described in this document on the News2x2 dataset. One of the advantages of *RSSalg software* is the exact reliability of the obtained results. The random generator seed parameter ensures that the experiments are always executed using the same sequence of random numbers. Thus, specifying the same settings as the ones given in this document should always yield the same results.

Table 11. Results of presented experiments on News2x2 dataset

	L_{acc}	All_{acc}	Natural	Random	MV	RSSalg	RSSalg _{best}
News2x2	76.8±5.1	89.7±1.7	77.7±10.8	78.4±8.0	84.1±5.2	84.7±3.8	89.2±2.0

```
<?xml version="1.0" encoding="UTF-8" standalone="yes"?>
<Results>
  <Experiments noIterations="20" classNames="positiveClass negativeClass" growthSize="5 5" noSplits="1">
    <experiment name="Supervised_experiment_L">
      <measure name="accuracy" microAveraged="76.8375" macroAveraged="76.8375" stdDev="5.1048213865804">
      <measure name="f1-measure for class positiveClass" microAveraged="74.83362759744668" macroAveraged="74.83362759744668" stdDev="1.658102999079235">
      <measure name="f1-measure for class negativeClass" microAveraged="78.5457913627417" macroAveraged="78.5457913627417" stdDev="10.746454518687">
    </experiment>
    <experiment name="Supervised_experiment_All">
      <measure name="accuracy" microAveraged="89.725" macroAveraged="89.725" stdDev="1.658102999079235">
    </experiment>
    <experiment name="CoTraining">
      <measure name="accuracy" microAveraged="77.7125" macroAveraged="77.7125" stdDev="10.746454518687">
    </experiment>
  </Experiments>
  <Experiments noIterations="20" classNames="positiveClass negativeClass" growthSize="5 5" noSplits="100">
    <experiment name="CoTraining_DifferentRandomSplits">
      <measure name="accuracy" microAveraged="78.88125" macroAveraged="78.35" stdDev="7.97561387397024">
    </experiment>
    <experiment name="RSSalg_left_out_instances_DifferentRandomSplits_accuracy_optimized">
      <measure name="accuracy" microAveraged="87.4" macroAveraged="87.4" stdDev="3.8531192270390204"/>
    </experiment>
    <experiment name="RSSalg_best_DifferentRandomSplits_accuracy_optimized">
      <measure name="accuracy" microAveraged="89.1625" macroAveraged="89.1625" stdDev="2.0883689143018">
    </experiment>
    <experiment name="Majority_vote_of_Co-training_classifiers_on_test_set_DifferentRandomSplits">
      <measure name="accuracy" microAveraged="84.05" macroAveraged="84.05" stdDev="5.234832587793254"/>
    </experiment>
  </Experiments>
</Results>
```

Figure 38. The ‘Results.xml’ file located in the results folder, obtained after running the experiments on News2x2 dataset described in this section

7 RSSalg software architecture

In this section, we will give an overview of the *RSSalg software* architecture (sections 7.1-7.8) and implementation details (section 7.8). In section 7.9 we explain how *RSSalg software* can be extended programmatically. Figure 39 presents the main classes of *RSSalg software*³⁵. The starting entry of the program is the *StartExperiment* class (section 0) which orchestrates training and evaluation of the selected algorithm on the selected dataset:

- The dataset is represented by *CoTrainingData* class (section 7.1).
- Experiment preparation (dividing the loaded dataset into labeled, unlabeled, and test data) is implemented in *CrossValidationSeparator* class.
- Model training:
 - Before running certain algorithms, we want to make sure that the appropriate feature split is performed (e.g. if we want to execute co-training with a random feature split). Different feature splitting methods are represented by classes that implement *SplitterIF* interface (section 7.5).
 - The applied algorithm itself is represented by *Algorithm* class (section 7.2).
 - During algorithm execution, a classifier (or an ensemble of classifiers) is trained. The details of the training process can be stored in *Classifiers* object for later analysis (section 7.3). This is represented by *train data* association in figure 39.
- Model testing:

³⁵ Due to space restrictions and clarity some details some (less important) classes and methods have been omitted from the diagram

- The result of applying the trained model on test data (predicted labels and classifier confidence) is represented by `ClassificationResult` class.
- *RSSalg software* supports a number of standard metrics for calculating algorithm performance (accuracy, *f1*-measure, precision and recall). These metrics are represented by classes implementing the `MeasureIF` interface (section 7.4).
- The trained classifier (or ensemble) is evaluated on the test data. The details of the testing process (e.g. confidences of each classifier from the ensemble) can be stored in `Classifiers` object for later analysis (section 7.3). This is represented by *test data* association in figure 39.

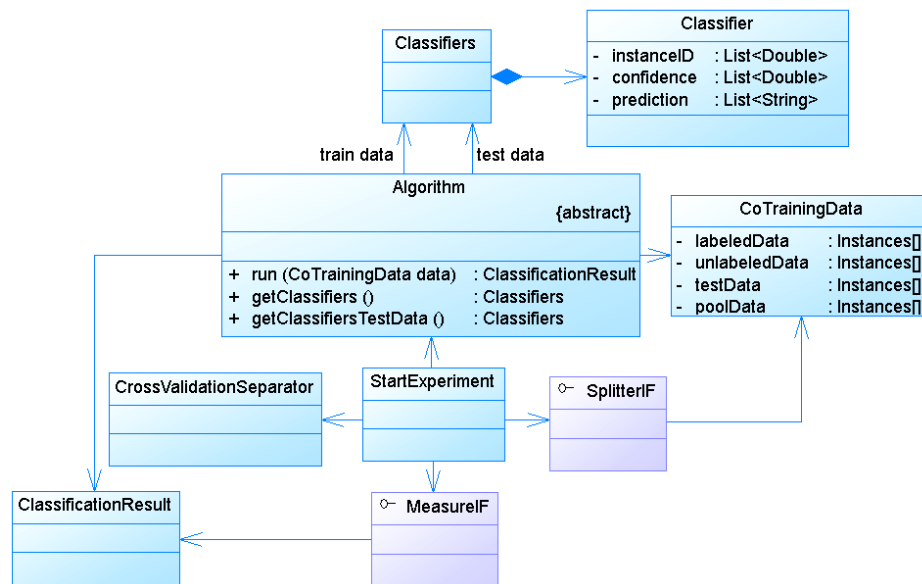


Figure 39. Main classes in *RSSalg software*

7.1 CoTrainingData class

`CoTrainingData` class presents the dataset ready for the execution of a co-training style algorithm. The dataset is divided into several parts:

- labeled data;
- unlabeled data;
- (optionally used) small unlabeled pool data u' ;
- test data.

Each dataset part is represented by an array of Weka's [7] `Instances` objects (figure 39). Elements of this array correspond to different views of the data. For example, if the feature set is split into two views, labeled, unlabeled, unlabeled pool and test datasets each consist of an array containing two `Instances` objects. Both `Instances` objects include the same instances described by different attributes³⁶.

The `CoTrainingData` class encompasses a number of useful methods for co-training data manipulation. Some examples are:

- assigning a label to an unlabeled instance and simultaneously transferring that instance to the labeled set;
- testing the performance of the current classifier (a supervised classifier trained using currently available labeled data);

³⁶ Except for the id and label attribute

- testing the performance of individual views (the performance of a single view is the performance of a supervised classifier trained using only attributes from that view and currently available labeled data);
- moving an attribute from one view to another; etc.

7.2 Algorithm class

The algorithm that is being trained and evaluated during *RSSalg software* execution is represented by abstract `Algorithm` class. All concrete implementations of the settings (**L_{acc}**, **All_{acc}**, **Random**, **Natural**, **MV**, **RSSalg** or **RSSalg_{best}**) inherit the `Algorithm` class.

The primary method of `Algorithm` class is the `run` method. This method executes the algorithm on the dataset supplied via `CoTrainingData` object. During the execution of the `run` method, an ensemble of classifiers will be trained in an algorithm-specific way using the supplied labeled and unlabeled data and applied to the test data. The result of the `run` method is the `ClassificationResult` object.

The classes inheriting the abstract `Algorithm` class (concrete strategy classes) form the obtained classifier ensemble in the following way:

- `SupervisedAlgorithm_L`: a single supervised classifier trained using only labeled instances (**L_{acc}** setting);
- `SupervisedAlgorithm_All`: a single supervised classifier trained using both labeled and unlabeled instances with correct label assigned (**All_{acc}** setting);
- `CoTraining`: a single classifier trained in co-training fashion using labeled and unlabeled instances (**Random** and **Natural** settings both use the `CoTraining` class for the implementation of the underlying algorithm. They differ in the pre-applied feature splitting method);
- `RSSalg`: the implementation of `RSSalg` (**RSSalg** and **RSSalg_{best}** settings both use this class for the underlying algorithm implementation. Section 7.7 explains the difference between their implementation);

`MajorityVote`: multiple classifiers trained using the `CoTraining` class. The ensemble prediction is obtained by a majority vote (**MV** setting). A user might choose to record the details of the ensemble training process. Those details can be obtained after execution of the `run` method by calling the `getClassifiers` method. The `getClassifiers` method results with `Classifiers` object (*train data* association in figure 39). In this `classifiers` object we record the details about each instance transferred from the unlabeled to the labeled set during the training process. For example, in `RSSalg` this “classifier statistics” is used to derive the final training set.

Similarly, we can record the details of the testing process. The details about classifying test instances can be accessed via the `getClassifiersTestData` method (*test data* association in figure 39) which returns the `Classifiers` object. For example, this “classifier test statistics” can be used by the `MajorityVote` algorithm to derive the label of each test instance in a majority vote fashion.

7.3 Classifiers class

`Classifiers` class represents an ensemble of individual classifiers. An individual classifier from the ensemble is represented by the `Classifier` class (figure 39).

Each setting implemented in *RSSalg software* produces an ensemble of classifiers. For example, the **Random** setting produces *m* co-training classifiers (obtained using *m* random splits). Some settings will produce the ensemble consisting of only one classifier, for example, in the **Natural** setting, we train only one co-training classifier using the natural feature split.

While training an individual semi-supervised classifier, we can store the “training statistics” in the `Classifier` class: for each unlabeled instance that was labeled and transferred to the labeled set we save the predicted label and classifier confidence of assigning that label. Similarly, when evaluating an individual classifier on a set of test instances, we use `Classifier` object to store the “testing statistics”: how an individual classifier of the ensemble classified each test instance (prediction and confidence).

Classifiers object may be stored on disk as an XML file for the later in-depth analysis. This object may also be used as input for other algorithms. For example, **RSSalg** can use the “training statistics” produced by **Random** setting, while **MV** can use the “testing statistics” produced by **Random** setting.

7.4 MeasureIF interface

MeasureIF represents a metrics for calculating algorithm performance. Concrete implementations of MeasureIF are:

- AccuracyMeasure,
- F1Measure,
- Precision
- Recall.

MeasureIF interface exposes the method `getMeasure` which takes the `ClassificationResult` object as an input parameter and returns a single real number that represents algorithm performance.

7.5 SplitterIF interface

SplitterIF interface accounts for a feature splitting method. Concrete implementations of SplitterIF are:

- RandomSplit (randomly divides the feature set in two views of roughly equal size) and
- DifferentRandomSplitsSplitter (using the RandomSplit class it generates multiple unique random feature splits).

SplitterIF interface exposes the method `splitDataset` which accepts the `CoTrainingData` object as one of its input parameters and applies the algorithm-specific feature split on the supplied data.

7.6 StartExperiment class

StartExperiment class is the starting point that orchestrates the execution of the program. The execution of the program is represented by an activity diagram in figure 40. It involves the following steps:

1. **Reading user-specified properties.** Values of the algorithm properties are loaded in several classes that follow the singleton design pattern to ensure that all parts of the system use the same parameter settings during the system life cycle. These classes are:
 - DatasetSettings: provides the dataset properties such as file locations, the name of the class attribute, etc.;
 - CVSettings: contains settings needed for the creation of a new cross-validation experiment. For example, the number of folds, the number of randomly chosen labeled instances, etc.;
 - CoTrainingSettings: provides the settings needed for running the co-training algorithm. For example, the number of co-training iterations, the number of most confident instances labeled in each iteration, etc.;
 - ExperimentSettings: provides the specifics of the applied algorithm such as the concrete strategy classes that will be used during the execution (algorithm, splitting algorithm and performance measures);
 - GASettings: provides the parameters for the GA used for threshold optimization in RSSalg.
2. **(Optional) Setting the cross-validation experiment.** If the user has specified that *RSSalg software* should create a new cross-validation experiment, the `CrossValidationSeparator` class will be used to generate a new experiment.
3. **Running the experiment.** In each round of cross-validation *RSSalg software* executes the following steps:
 - (1) An appropriate `CoTrainingData` object (i.e. fold data) is loaded;
 - (2) (Optional) a feature split is performed by the chosen feature splitter algorithm on `CoTraningData` object;

- (3) The run method of the selected algorithm is executed using the CoTrainingData object. The result is the ClassificationResult object and Classifier objects that store details about the training and testing process;
- (4) Performance measures are obtained based on the obtained ClassificationResult object;
- (5) (Optional) Train and test “classifier statistics” are saved on disk

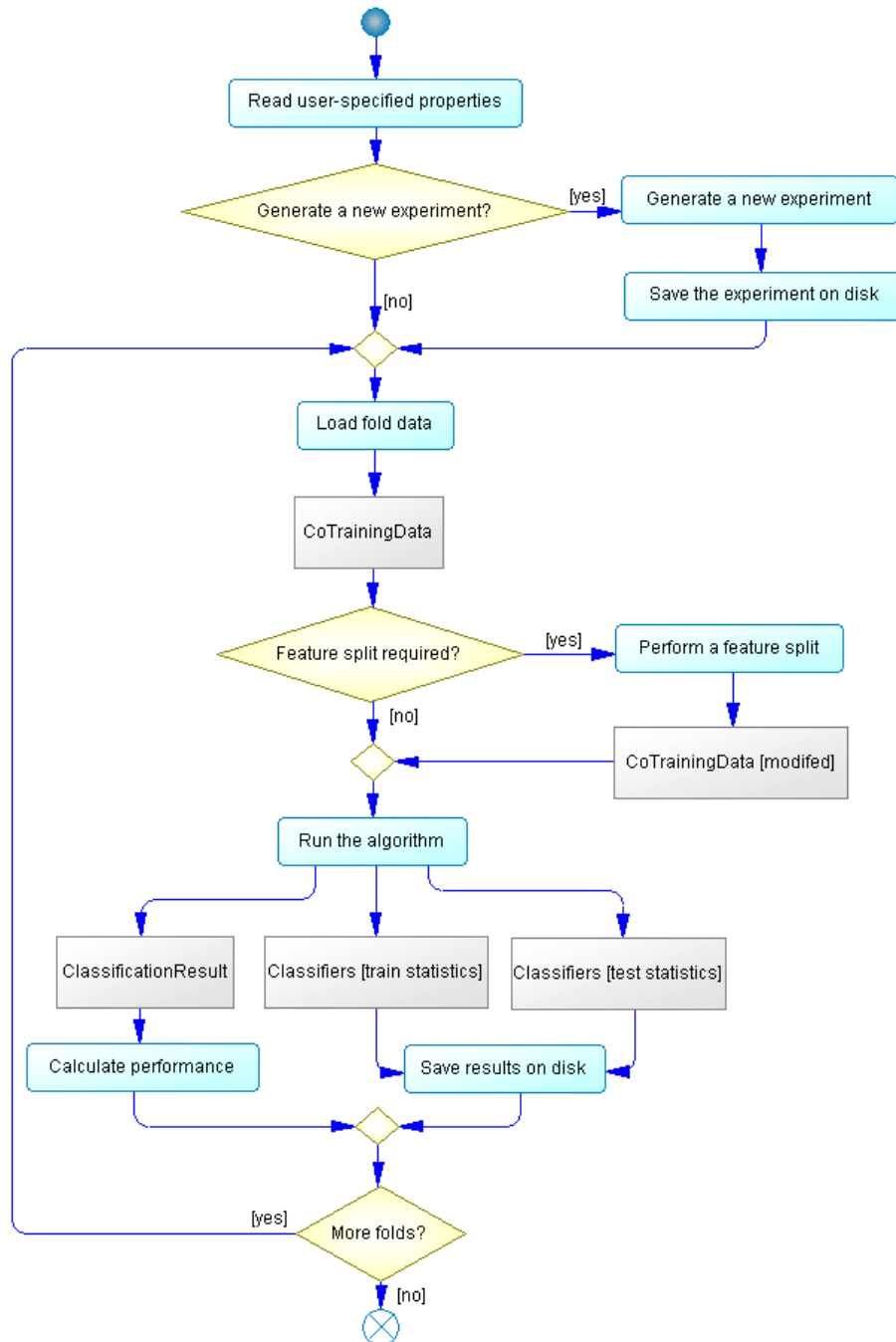


Figure 40. Activity diagram: running the experiment

7.7 RSSalg implementation

In this section, we will display the details of RSSalg implementation. RSSalg is implemented in `RSSalg` class which inherits the abstract `Algorithm` class (figure 39). The execution flow of the `run` method implemented in `RSSalg` is represented by the activity diagram in figure 41.

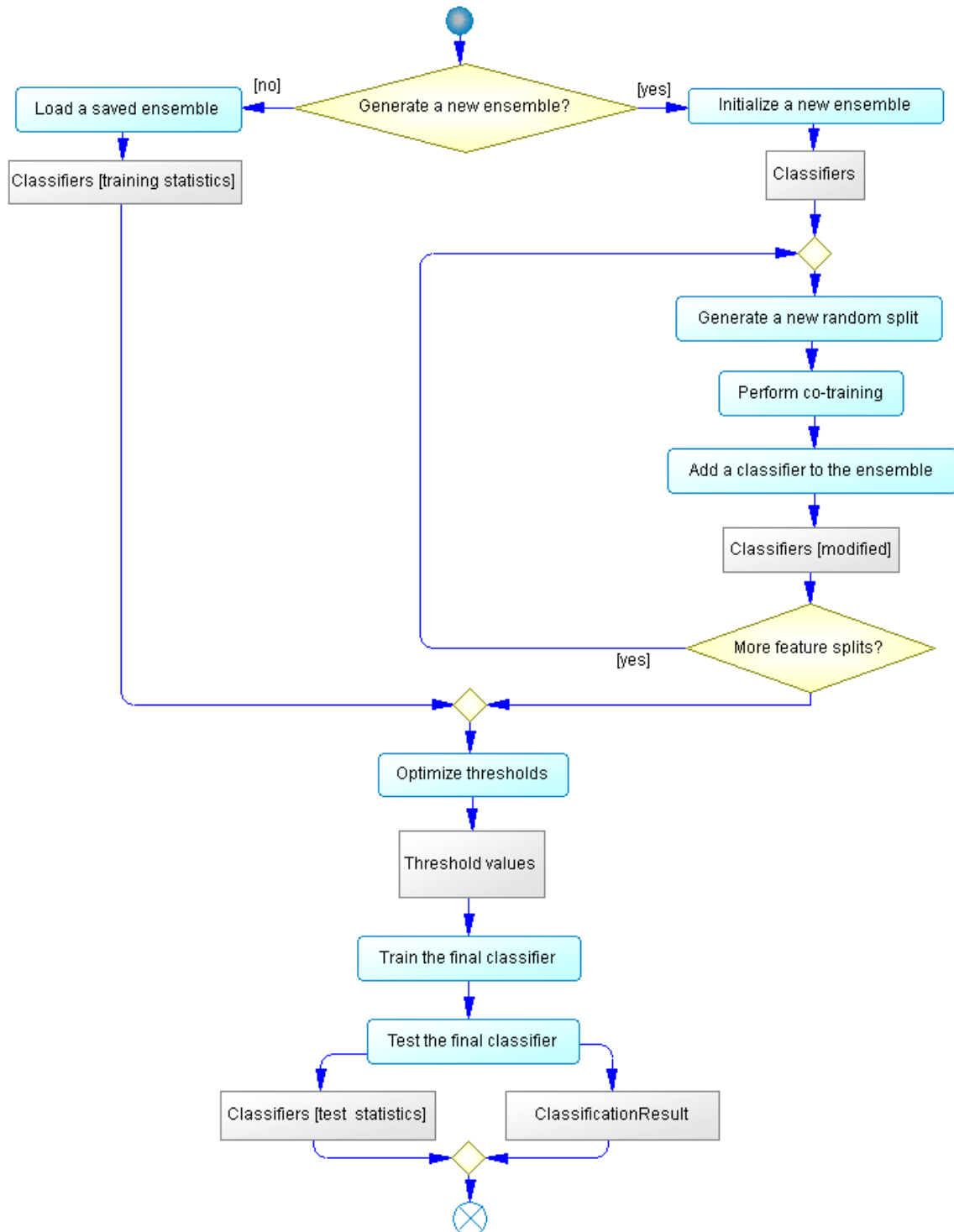


Figure 41. Activity diagram: the `run` method of `RSSalg` class

When running the **RSSalg** setting, an already created ensemble can be loaded (for example, an ensemble produced earlier when running the **Random** setting). Otherwise, multiple unique random feature splits are created by applying the `DifferentRandomSplitsSplitter` class on the data supplied through `CoTrainingData` object. Each generated split is used to perform co-training (using `CoTraining` class implementation). The resulting training classifier statistics is recorded in the `Classifiers` object. Alternatively, the user can choose to load a previously generated classifier statistics from a file.

After creating (or loading) an ensemble, the thresholds which determine the training set of the final model are determined by the GA optimization process. Using the labeled and unlabeled set supplied through the `CoTrainingData` object input parameter and the determined threshold values, the training set for the final model is created. The final model is trained and evaluated (using the test data supplied through the `CoTrainingData` object parameter). The output of the algorithm is the `CoTrainingResult` object which can be used for performance measure evaluation and the `Classifier` object which stores the details of evaluating all classifiers from the ensemble.

Figure 42 presents the main classes involved in the threshold optimization process. The class `GAThresholdOptimizer` implements the GA threshold optimization process in `RSSalg`. Each threshold pair represents a candidate in GA optimization process (class `Candidate`). Each candidate is evaluated using the implementation of `CandidateEvaluatorIF` interface. The `evaluateCandidate` method in this interface takes as input parameters the `CoTrainingData`, `Classifiers` and `Candidate` objects as well as the implementation of `MeasureIF`. The concrete implementation of `CandidateEvaluatorIF` should, according to the candidate threshold pair and the recorded statistics adjust the labeled and test portion of `CoTrainingData` for final model training and testing; the final model will be evaluated using the provided implementation of `MeasureIF`.

There are two concrete implementations of `CandidateEvaluatorIF`:

- `RSSalgCandidateEvaluator`: used for running the threshold process described in section 2.2.1;
- `TestSetAccuracyCandidateEvaluator`: which uses the hand-labeled test data provided through `CoTrainingData` object. It is used for running the `RSSalgbest` setting in [4].

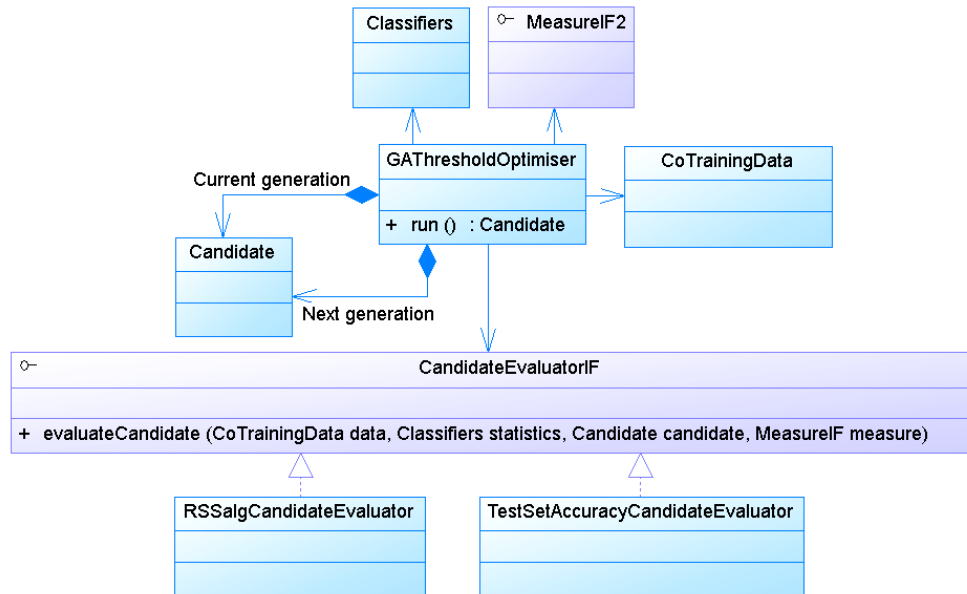


Figure 42. Primary classes in `RSSalg` threshold optimization

7.8 *RSSalg* software implementation details

RSSalg software is implemented in Java and requires Java Runtime Environment 1.7 or higher to work. The implementation relies on Weka library version 3.7.0³⁷:

- (1) The datasets are internally represented using .ARFF file format and corresponding Weka's `Instances` class³⁸. This is the commonly used representation widely accepted in the data mining community;
- (2) Weka library provides implementations of individual view classifiers used in co-training. In *RSSalg* software any class implementing Weka's `Classifier` interface³⁹ can be used for underlying classifiers.

A disadvantage of *RSSalg* software is its rather slow performance due to relying on Weka data representation. A bottleneck of this representation is transferring instances between different feature sets. In the future, we plan to address this issue by implementing a custom optimized version of the internal data representation.

7.9 Extending *RSSalg* software

One of the goals of *RSSalg* software design was to make it easily extendable to allow researchers easy experimenting with their co-training based solutions. We strived to achieve this goal by using the strategy design pattern and exposing the interfaces that allow adding new implementations without changing the existing code. You can extend *RSSalg* software by adding a new algorithm (section 7.9.1), feature-splitting method (section 7.9.2), performance measure (section 7.9.3) or a new threshold optimization procedure for *RSSalg* (section 7.9.4).

7.9.1 Adding a new algorithm

We will explain how to add a new algorithm on the example of L_{acc} setting implementation given in figure 43. Each algorithm in *RSSalg* software inherits an abstract `Algorithm` class. In the inherited `run` method we implement all the steps needed for algorithm training and evaluation:

1. In the first try/catch block we make a call to the `run` method inherited from the `Algorithm` class. This method contains some implementation steps common for all algorithms, for example, (depending on user settings) it will initialize a new ensemble of classifiers or load an existing one.
2. After that, we record the starting time. At the end of the `run` method, we also record the execution end time and determine the time needed for running the algorithm as the difference between these two values. The running time recorded in `runningTime` property of the `Algorithm` class is accessible via the call to `getRunningTimeMillis` method of `Algorithm` class.
3. The `run` method receives the dataset (divided into labeled, unlabeled and test data) as one of its input parameters: the data object that belongs to `CoTrainingData` class. In L_{acc} setting our goal is to train a supervised classifier on the labeled portion of the data and evaluate it on the test portion of the data. This is already implemented in the `testLabeledMergedViews` method of the passed data object which returns the `ClassificationResult` object as a result.
4. The obtained `ClassificationResult` object is returned as a result of the `run` method. This object contains the information needed for calculating various performance measures.
5. As we have explained in section 4, we can record the details about training ("training statistics") and testing ("test statistics") of an algorithm. Since the "training statistics" refers to the training process of an SSL algorithm – labeling and transferring unlabeled instances to labeled data, we do not record this for L_{acc} which is a supervised setting. The "test statistic" contains the details about the evaluation of each classifier from the ensemble and is represented by the `classifierTestData` object in figure 43.

Another method that should be implemented is the abstract `getName` method which should return the algorithm name as a `String`. The returned `String` is used for automatic naming of the XML files in which the obtained "training/test statistics" will be recorded.

³⁷ To run the distributed executable (<https://github.com/slivkaje/RSSalg-software/blob/v1.0/dist/RSSalg.jar>), Weka does not have to be installed

³⁸ <http://weka.sourceforge.net/doc.dev/weka/core/Instances.html>

³⁹ <http://weka.sourceforge.net/doc.dev/weka/classifiers/Classifier.html>

Some algorithms may use previously recorded “training/test statistics,” for example, **MV** uses the “test statistics” previously created by **Random** setting. The `Algorithm` class provides `SetClassifiers` method for setting the value of the used “statistics,” and it may be overridden for algorithm-specific purposes. In figure 43, since L_{acc} setting does not use train or test “statistics,” we have overridden the method to display the warning if the user tries to provide it.

Once an algorithm is implemented in a particular class, it can be used by specifying the full package name of that class in the `algorithm` property located in experiment properties (section 6.3.4.7).

```
public class SupervisedAlgorithm_L extends Algorithm{ Abstract algorithm class is inherited

    public ClassificationResult run(CoTrainingData data, int fold, int splitNo, boolean recordClassifiers){
        try {
            super.run(data, fold, splitNo, recordClassifiers);
        } catch (Exception e) {
            System.out.println("WARNING: Trying to read the classifiers from file. Algorithm "
                + "does not rely on the recorded classifier statistic, ignoring classifiers");
        }
        long startTime = System.currentTimeMillis();

        ClassificationResult result = null;
        if(recordClassifiers)
            result = data.testLabeledMergedViews(true);
        else
            result = data.testLabeledMergedViews(false);

        if(classifierTestData != null)
            classifierTestData.addPredictions(result.getPredictions());

        long endTime = System.currentTimeMillis();
        runningTime = endTime - startTime;

        return result; Algorithm training and evaluation is implemented in the run method
    }

    public String getName() {
        return "Supervised_experiment_L";
    }

    @Override
    protected void setClassifiers(ClassifierEnsembleList classifiers) {
        if(classifiers != null)
            System.out.println("WARNING: " + getName() + " algorithm does not rely on the "
                + "recorded classifier statistic. Ignoring classifiers");
    }
}
```

Figure 43. Implementation of L_{acc} (supervised learner trained on labeled portion of the data)

7.9.2 Adding a new feature-splitting method

An implementation of the feature splitting method should be contained in the class implementing `SplitterIF` (section 7.5). This interface exposes two abstract methods: `getName` and `splitDatasets`.

The `getName` method returns a name of the feature splitting algorithm as a `String`. The returned `String` is used for automatic naming of the XML files in which the obtained “training/test statistics” will be recorded.

The `splitDatasets` method should contain the implementation of the feature splitting methodology. Its two most important input parameters are:

- `CotrainningData` object (section 7.1) that contains the dataset to perform the feature splitting method on. The `splitDatasets` method should modify this object so that the views correspond to the created feature split.
- `FeatureGraph` object represents the undirected weighted graph in which features represent vertices, and the weight of an edge connecting two features represents some measure of dependence between those two features. For example, the `maxInd` algorithm proposed in [6] is a

feature splitting methodology for co-training based on the assumption that the two views in co-training should be maximally independent given the class label. As the measure of the class-conditional dependence of two features, authors propose to use the Conditional Mutual Information (*CondMI*) [16]. In this case, we would construct the feature graph in which the weight of an edge connecting two features would be the *CondMI* measure calculated for these two features. In the implementation of random feature split, this parameter is ignored as it does not depend on any inter-feature measure.

Once a feature splitting methodology is implemented in a particular class, it can be used by specifying the full package name of that class in the *featureSplitter* property located in experiment properties (section 6.3.4.7).

7.9.3 Adding a new performance measure

A class representing the performance measure should implement *MeasureIF* interface (section 7.4). *MeasureIF* exposes the following methods that a performance measure class should implement:

- *getName* – returns the performance measure name as Java *String*.
- *dependsOnClass* – This method should return false if the performance measure is not category-dependent (e.g. accuracy) and true if it is category-dependent (e.g. *f1*-measure).
- *setClassName* – This method is used to specify the category name for the calculation of category-dependent measures. The passed value may be the name of the category (for which we want to calculate the measure) or the *String* value “avg” (meaning that we want to calculate the measure averaged over all categories).
- *getClassName* – Returns the category value for which the measure is being calculated or the *String* “avg” if an averaged measure over all categories is being calculated.
- *getMeasure* – This measure accepts the *ClassificationResult* object as an input parameter. This object summarizes the results of evaluating a trained classifier on the set of test instances (the number of correctly and incorrectly labeled instances per each class and prediction confidences). Based on this object, in the *getMeasure* method, a double value representing the algorithm performance is calculated and returned as a result.

Once a performance measure is implemented in a particular class, it can be used by simply specifying the full package name of that class in the *measures* property located in experiment properties (section 6.3.4.7).

7.9.4 Adding a new threshold optimization technique

As explained in section 2.2.1, *RSSalg* uses a GA for threshold optimization. A threshold pair is considered a candidate in the GA evaluation process. Setting certain threshold values will determine which portion of the most confidently labeled instances will be kept in the final training set. The open question is how we can evaluate the model trained on this final set. The classes implementing a particular model-evaluation methodology should implement the *CandidateEvaluatorIF* interface.

CandidateEvaluatorIF interface exposes two methods:

- *getName* – returns the name of the method as Java *String*.
- *evaluateCandidate* – the method in which the final model evaluation is performed. The input parameters of this method are: a *CoTrainingData* object which contains the instances of the dataset; *Classifiers* object which contains details about training the classifier ensemble; the implementation of the performance measure (*MeasureIF*) which defines whether a model should be evaluated by its accuracy, precision or some other measure; and the *Candidate* object which represents the candidate threshold pair which defines the instances that will be used for model training.

Once a final model evaluation procedure is implemented in a particular class, it can be used by simply specifying the full package name of that class in the *candidateEvaluator* property located in experiment properties (section 6.3.4.7).

8 References

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