

Tutorial on Ensemble Learning

Igor Baskin, Gilles Marcou and Alexandre Varnek

Faculté de Chimie de Strasbourg
Laboratoire d'Infochimie
4, rue Blaise Pascal, 67000 Strasbourg, FRANCE

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Introduction

This tutorial demonstrates performance of ensemble learning methods applied to classification and regression problems. Generally, preparation of one individual model implies (i) a dataset, (ii) initial pool of descriptors, and, (iii) a machine-learning approach. Variation of any of these items can be used to generate an ensemble of models. Here, we consider the following ensemble learning approaches: *bagging* and *boosting* (dataset variation), *random subspace* (descriptors variation) and *stacking* (machine-learning methods variation). In some of popular approaches, both dataset and descriptors vary (e.g., random forest).

In all calculations, the *ISIDA descriptors* were used. They represent the counts (occurrences) of some fragments in a molecular graph. Three types of fragments are considered: *sequences* (type 1), *unlimited augmented atoms* (type 2) and *restricted augmented atoms* (type 3). A sequence is the shortest path connected two given atoms. For each type of sequence, the lower (*l*) and upper (*u*) limits for the number of constituent atoms must be defined. The program generates “intermediate” sequences involving *n* atoms ($l \leq n \leq u$) recording both atoms and bonds. Unlimited augmented atom represents a selected atom with its closest environment. Restricted augmented atom is a combination of types 1 and 2: an atom representing an origin of several sequences containing from *l* to *u* atoms. Three subtypes, AB, A and B are defined for each class. They represent sequences of atoms and bonds (AB), of atoms only (A), or of bonds only (B).

Thus, each fragmentation is coded by the pattern $\mathbf{t}xYY\mathbf{l}/\mathbf{u}u$. Here, *x* is an integer describing the type of the fragmentation (1: sequences; 2: unlimited augmented atoms; 3: restricted augmented atoms), *YY* specifies the fragments content (AA: atoms only; AB: atoms and bond; BB: bonds only), *l* and *u* are the minimum and maximum number of constituent atoms.

The following ensemble learning procedures are considered in the tutorial:

- *Bagging* – combination of bootstrapping and averaging used to decrease the variance part of prediction errors [2]
- *AdaBoost* – the most well-known boosting algorithm used to solve classification problems [3]
- *Random Subspace Method* – combination of random subsets of descriptors and averaging of predictions [4]
- *Random Forest* – a method based on bagging (bootstrap aggregation, see definition of bagging) models built using the Random Tree method, in which classification trees are grown on a random subset of descriptors [5].

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- *Additive Regression* – a form of regression gradient boosting: it enhances performance of basic regression methods [6]
- *Stacking* - combines several machine learning methods using the stacking method [7, 8].

The following individual machine learning methods (base learners [9]) are used:

- *JRip* is the Weka implementation of the algorithm Ripper k [10]. This algorithm uses incremental reduced-error pruning in order to obtain a set of classification rules; k is the number of optimization cycles of rules sets.
- *Multiple Linear Regression (MLR)* – classical multiple linear regression without descriptor selection, in which for the sake of numeric stability the diagonal elements of the variance-covariance matrix $X^T X$ are modified by adding a small $1.0e-8$ number (actually a form of the ridge regression).
- *Simple Linear Regression (SLR)* – classical linear regression on a single descriptor.
- *Partial Least Squares (PLS)*
- *M5P* – a kind of regression trees [11]

Part 1. Classification models.

1. Data and descriptors.

The dataset for this tutorial contains 27 ligands of Acetylcholinesterase (AChE) and 1000 decoy compounds chosen from the BioInfo database [1]. This dataset is split into the training set (15 actives and 499 inactives) and the test set (12 actives and 501 inactives). The t3AB12u3 fragments are used as descriptors.

2. Files

The following files are supplied for the tutorial:

- `train-ache.sdf/test-ache.sdf` – Molecular files for training/test set
- `train-ache-t3AB12u3.arff/test-ache-t3AB12u3.arff` – descriptor and property values for the training/test set
- `ache-t3AB12u3.hdr` – descriptors' identifiers

3. Exercise 1: Instability of interpretable rules

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In this exercise, we build individual models consisting of a set of interpretable rules. The goal is to demonstrate that the selected rules depend on any modification of the training data, *e.g.*, the order of the data in the input file.

Step by step instructions

Important note for Windows users: During installation, the ARFF files should have been associated with Weka. In this case, it is highly recommended to locate and double click on the file `train-ache-t3AB12u3.arff` and to skip the following three points.

- In the starting interface of Weka, click on the button *Explorer*.
- In the *Preprocess* tab, click on the button *Open File*. In the file selection interface, select the file `train-ache-t3AB12u3.arff`.

The dataset is characterized in the *Current relation* frame: the name, the number of instances, and the number of attributes (descriptors). The *Attributes* frame allows user to modify the set of attributes using *select* and *remove* options. Information about the selected attribute is given in the *Selected attribute* frame in which a histogram depicts the attribute distribution.

- Click on the tab *Classify*.
- Into the *Test options* frame, select *Supplied test set* and click *Set...*
- In the pop-up window, click the *Open file...* button and select the `test-ache-t3AB12u3.arff` file. Then click *Close*.
- Click *More options...* then in the pop-up window click the *Choose* button near *output predictions* and select *CSV*.
- In the *classifier* frame, click *Chose*, then select the *JRip* method.
- Click *Start* to learn the model and apply this to the test set. Right click on the last line of the *Result list* frame and select *Save result buffer* in the pop-up menu. Name the file as `JRip1.out`.
- Use *ISIDA/Model Analyzer* to visualize both confusion matrix and structures of the compounds corresponding to different blocks of this matrix. Here, on the “...” button and select the `JRip1.out` file and the `test-ache.sdf` file, then click to *Start*.
- In the *Weka Classifier* output frame, check the model opened in *ISIDA/Model Analyzer*. Attributes used by the rules are given the `ache-t3AB12u3.hdr` file which can be opened with any text editor (WordPad preferred).
- In Weka, return to the *Pre-process* tab.

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- Click **Choose** and, select *randomize* in the *filters->unsupervised->instance* folder. Click **Apply**.
- Return to **Classify** and click **Start**. Right click on the last line of the **Result** list frame opens the pop-up menu, in which select **Save result buffer**. Name the file as `JRip2.out`.
- Use the file `ache-t3AB12u3.hdr` and *ISIDA/Model Analyzer* to analyze the rules. They are indeed rather different.

Conclusion. One can conclude that the data reordering is sufficient to modify the interpretable rules model.

4. Exercise 2: Bagging and Boosting

In this exercise, we'll demonstrate that the *bagging* approach (i) overcomes the instability problem discovered in Exercise 1, and, (ii) allows one to order the rules according to their pertinence.

Step by step instructions

Bagging

Step 1: Preparation of one individual model.

- Click on the **Pre-process** tab and then on the **Undo** button. This restores the initial order of the compounds. (This is an alternative of reopening the input file `train-ache-t3AB12u3.arff`).
- Click **Classify**, then **Choose**.
- Select *classifiers->meta->Bagging*.
- Click on the name of the method to the right of the **Choose** button. In the configuration interface, click **Choose** then select *classifiers->rules->JRip*. Set the *numIterations* to 1 and click **OK**.

This operation has created one individual model.

- Right-click on the line last line of the **Result list** and select **Visualize threshold curve** and then **1**.

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The ROC curve is plotted. As one can see, the ROC AUC value (about 0.7) is rather poor which means that a large portion of active compounds cannot be retrieved using only one rule set.

- Save the model output. Right-click on the last line of the *Result list* and select *Save result buffer*. Name your file as JRipBag1.out.

Step 2: Preparation of ensemble of models.

- Produce new bagging models using 3 and 8 models by repeating the previous steps, setting *numIterations* to 3, then to 8. Save the corresponding outputs in files JRipBag3.out and JRipBag8.out, respectively.

One can see that ROC AUC for the consensus model increases up to 0.825 (see Figure 1).

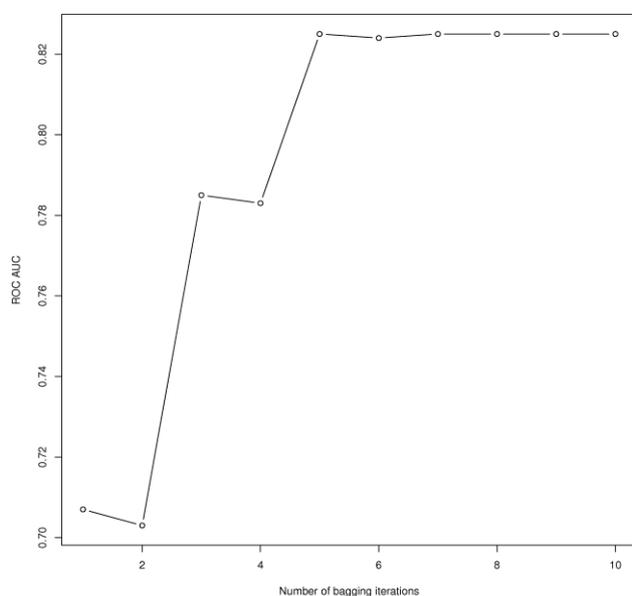


Figure 1. ROC AUC of the consensus model as a function the number of bagging iterations

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Step 3 (optionally): Analysis of the models: retrieval rate as a function of the confidence threshold.

- Use *ISIDA/Model Analyzer* to open `JRipBag3.out` and the `test-ache.sdf` file.
- Navigate through the false negative examples.

The false negative examples are ordered according to the degree of consensus in the ensemble model. A few false negatives could be retrieved by changing the confidence threshold. On the other hand, this leads to the increase of the number of false positives.

- Repeat the analysis using the `JRipBag8.out` file.

As reflected by the better ROC AUC, it is now possible to retrieve maybe one false negative, but at a lower cost in terms of additional false positives. The confidence of prediction has increased. In some sense, the model has become more discriminative.

Step 4 (optionally): Analysis of the models: selecting of common rules.

The goal is to select the rules which occur in, at least, two individual models.

- Open the `JRipBag3.out` in an editor and concatenate all the rules from all the models, then count how many of them are repeated. It should be one or two.
- Do the same for the file `JRipBag8.out`. This time, it should be around ten.

A systematic study show how the “unique” rules rate in the ensemble decreases with the number of bagging iterations (Figure 2). Each bagging iteration can be considered as a sampling of some rule distribution. The final set of rules repeats more often those rules that are most probable. When the sampling is sufficiently representative, the ensemble model converges toward a certain rules distribution.

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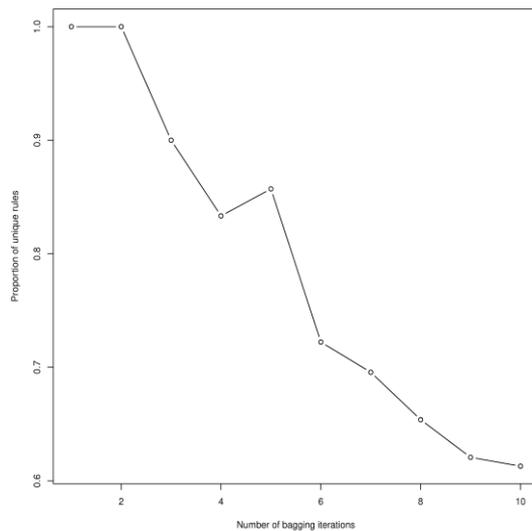


Figure 2. Rate of unique rules as a function of the number of bagging iterations

Boosting

Another approach to leverage predictive accuracy of classifiers is boosting.

- Using Weka, click on the *Classify* tab.
- Click *Choose* and select the method *classifiers->meta->AdaBoostM1*.
- Click *AdaBoostM1* in the box to the right of the button. The configuration interface of the method appears.
- Click *Choose* of this interface and select the method *classifiers->meta->JRip*.
- Set the *numIterations* to 1.
- Click on the button *OK*.
- When the method is setup click *Start* to build an ensemble model containing one model only.
- Right-click on the last line of *Result list* and save the output by choosing *Save result buffer*. Name your file *JRipBoost1.out*.
- Repeat the experiment by setting the parameter *numIterations* to 3 and to 8. Save the outputs as *JRipBoost3.out* and *JRipBoost8.out* respectively.

Notice that the ROC AUC increases more and faster than that with bagging.

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- It is particularly interesting to examine the files JRipBoost1.out, JRipBoost2.out and JRipBoost3.out with *ISIDA/Model Analyzer*.
- Open the files JRipBoost1.out, JRipBoost2.out and JRipBoost3.out with *ISIDA/Model Analyzer*.
- Compare the confidence of predictions for the false negative examples and the true negatives.

Using one model in the ensemble, it is impossible to recover any of the false negatives. Notice that with three models, the confidence of predictions has slightly decreased but the ROC AUC has increased. It is possible to recover almost all of the false negatives, still discriminating most of the negative examples. As the number of boosting iterations increases, it generates a decision surface with greater margin. New examples are classified with greater confidence and accuracy. On the other hand, the instances for which the probability of error of individual models is high, are wrongly classified with greater confidence. This is why, with 8 models, some false negative cannot be retrieved.

A systematic study of the ROC AUC illustrates this effect (Figure 3).

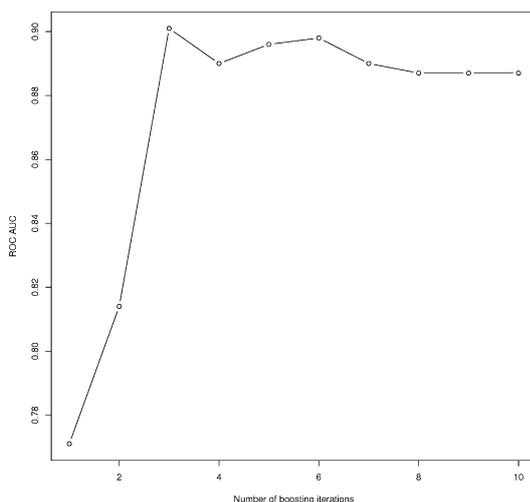


Figure 3. ROC AUC as a function of the number of boosting iterations

4.2. Conclusion

Bagging and boosting are two methods transforming “weak” individual models in a “strong” ensemble of models. In fact JRip is not a “weak” classifier. This somehow damps the effect of ensemble learning.

Generating alternative models and combining them can be achieved in different ways. It is possible, for instance to select random subsets of descriptors.

5. Exercise 3: Random forest

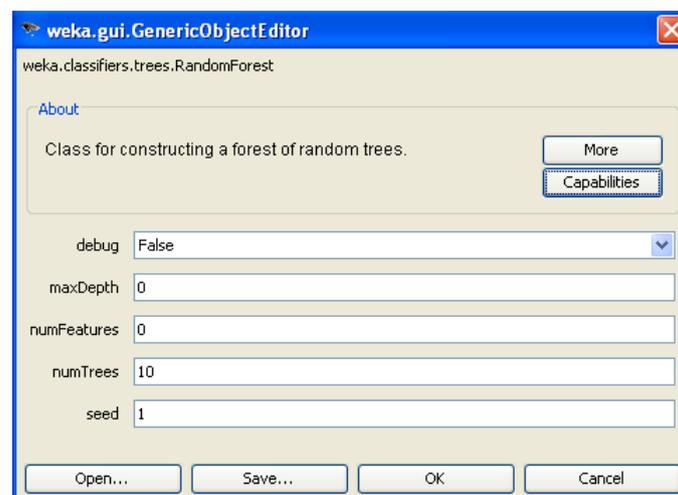
Goal: to demonstrate the ability of the Random Forest method to produce strong predictive models.

Method. The Random Forest method is based on bagging (bootstrap aggregation, see definition of bagging) models built using the Random Tree method, in which classification trees are grown on a random subset of descriptors [5]. The Random Tree method can be viewed as an implementation of the Random Subspace method for the case of classification trees. Combining two ensemble learning approaches, bagging and random space method, makes the Random Forest method very effective approach to build highly predictive classification models.

Computational procedure

Step 1: Setting the parameters

- Click on the **Classify** tab of Weka.
- Make sure that the test set is supplied and that output predictions will be displayed in CSV format.
- Click **Choose** and select the method **classifiers->tree->RandomForest**.
- Click on the word **RandomForest** to the right of the button. A configuration interface appears.



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Step 2: Building a model based on a single random tree.

- Set the *numTrees* to 1, then click the button *OK*.
- Click *Start*.

This setup creates a bagging of one random tree. The random tree is grown as much as possible and 11 attributes are selected at random to grow it. Results should be rather good already.

Correctly Classified Instances	502	97.8558 %
Incorrectly Classified Instances	11	2.1442 %

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	0.988	0.417	0.99	0.988	0.989	0.786	0
	0.583	0.012	0.538	0.583	0.56	0.786	1
Weighted Avg.	0.979	0.407	0.979	0.979	0.979	0.786	

=== Confusion Matrix ===

```
      a  b  <-- classified as
495  6  |  a = 0
     5  7  |  b = 1
```

- Right click on the last line of the Result list frame.
- Select *Save result buffer*. Save the output as *RF1.out*.

Step 3: Building models based on several random trees.

- Build the Random Forest models based on 10 Random Trees. See below

Correctly Classified Instances	504	98.2456 %
Incorrectly Classified Instances	9	1.7544 %

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
	1	0.75	0.982	1	0.991	0.952	0
	0.25	0	1	0.25	0.4	0.952	1
Weighted Avg.	0.982	0.732	0.983	0.982	0.977	0.952	

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=== Confusion Matrix ===

a	b	<-- classified as
501	0	a = 0
9	3	b = 1

All statistical characteristics became considerably stronger

- Save the output as `RF10.out`
- Repeat the study for 100 trees. Save result as `RF100.out`.
- Build Random Forest models for different numbers of trees, varying from 1 to 100.
- Build the plot ROC AUC vs. Number of trees

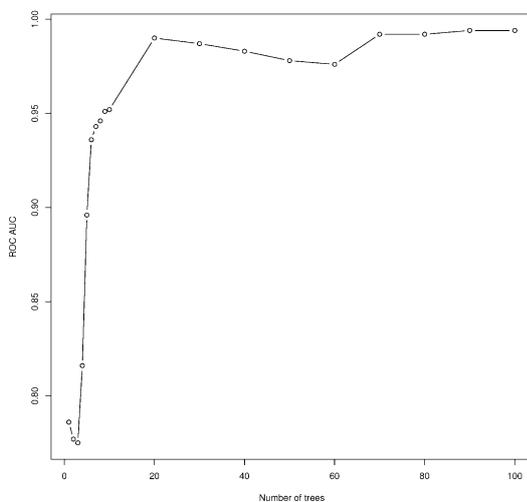


Figure 4. ROC AUC as a function of the number of trees

One may conclude that Random Forest outperforms the previous bagging and boosting methods. First, a single fully grown and unpruned random tree seems as least as useful as a more interpretable small set of rules. Second, the ensemble model is saturated later, using more individual models; on another hand the maximal ROC AUC achieved is extremely high.

- Step 4. Examine the file `RF1.out`, `RF10.out` and `RF100.out` using ISIDA/Model Analyzer.

This single tree forest does not provide any confidence value for the prediction. It is therefore impossible to modulate the decision of the model. When using 10 trees, most false negative can be retrieved accepting roughly one false positive for each of them. At last, using 100 trees in the model, all the same false negatives can be retrieved at the cost of accepting only one

false positive. The last active compound can be retrieved only at the cost of accepting around 40 false positives.

6. Exercise 4: Combining descriptor pools

ISIDA/Model Analyzer can be used also to combine different models. The file `AllSVM.txt` sum up the results of applying different SVM models, trained separately on different pools of descriptors. The file contains a header linking it to a SDF file, giving indications about the number of classes and the number of predictions for each compound and weights of each individual model. These weights can be used to include or exclude individual models from the consensus: a model is included if its corresponding value is larger than 0 and not included otherwise. Next lines correspond to prediction results for each compound.

In each line, the first number is the number of the compound in the SDF file, the second number is an experimental class and the next columns are the individual predictions of each model. Optionally, each prediction can be assigned to a weight, which is represented by additional real numbers on each line.

- Open the `AllSVM.txt` file with *ISIDA/Model Analyzer*.

Several models are accessible. It is possible to navigate among them using the buttons **Next** and **Prev**. It is also possible to use the list box between the buttons to select directly a model. The tick near the name of the model indicates that it will be included into the ensemble of models. It is possible to remove the tick in order to exclude the corresponding model. As can be seen, the overall balanced accuracy is above 0.8 with some individual models performing better than 0.9.

- Click on the button **Vote**. A majority vote takes place. A message indicates that the results are saved in a file `Vote.txt`. The proportion of vote is saved as well.
- Load the file `Vote.txt` in *ISIDA/Model Analyzer* and click the button **Start**. The ensemble model seems to have a suboptimal balanced accuracy.
- Click on the headers of the columns of the confusion matrix to make appear column related statistics. Recall, Precision, F-measure and Matthew's Correlation Coefficient (MCC) are computed for the selected class. The ROC AUC is computed and data are generated to plot the ROC with any tool able to read CSV format.

As can be seen, accepting only 20 false positives, all active compounds are retrieved. It is possible to plot the ROC as in the following figure (Figure 4):

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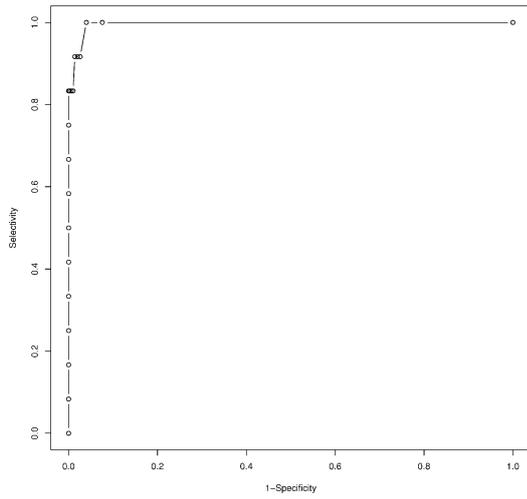


Figure 5. ROC curve for Exercise 4

Part 2. Regression Models

In this part of Tutorial, the **Explorer** mode of the Weka program is used. The tutorial includes the following steps:

- (1) building an individual MLR model,
- (2) performing bagging of MLR models,
- (3) applying the random subspace method to MLR models,
- (4) performing additive regression based on SLR models,
- (5) performing stacking of models.

1. Data and Descriptors

In the tutorial, we used aqueous solubility data (LogS). The initial dataset has been randomly split into the training (818 compounds) and the test (817 compounds) sets. A set of 438 ISIDA fragment descriptors (t1AB12u4) were computed for each compound. Although this particular set of descriptors is not optimal for building the best possible models for this property, however this set of descriptors allows for high speed of all calculations and makes it possible to demonstrate clearly the effect of ensemble learning.

2. Files

The following files are supplied for the tutorial:

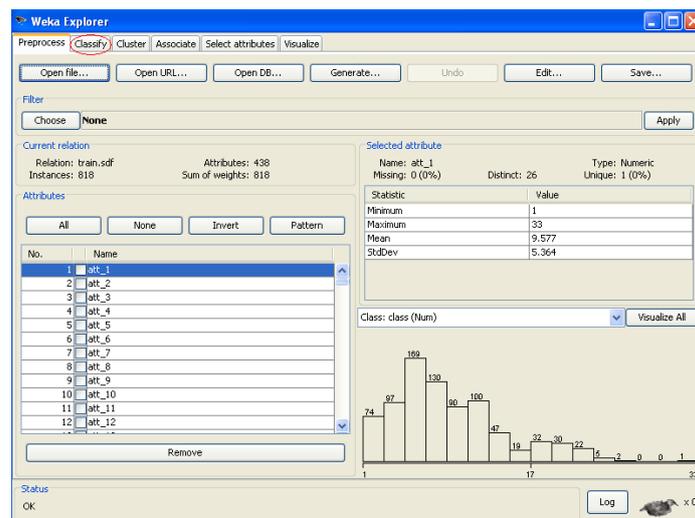
- `train-logs.sdf/test-logs.sdf` – molecular files for training and test sets
- `logs-t1AB12u4.hdr` – descriptors identifiers
- `train-logs-t1AB12u4.arff/test-logs-t1AB12u4.arff` – descriptor and property values for the train/test set

3. Exercise 5: Individual MLR model

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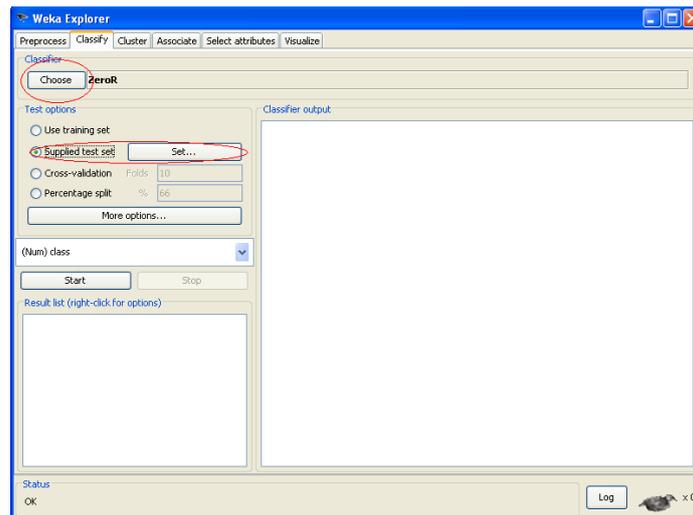
Important note for Windows users: During installation, the ARFF files should have been associated with Weka. In this case, it is highly recommended to locate and double click on the file `train-logs-t1AB12u4.arff`, and to skip the following three points.

- Start *Weka*.
- Press button *Explorer* in the group *Applications*.
- Press button *Open file...* and select the `train-logs-t1AB12u4.arff` file containing descriptor and property values for all training examples. The following window will pop up:



- Switch to the Classification mode by clicking on the *Classify* label.
- In the frame *Test options*, select the option *Supplied test set*. The window should look as the following:

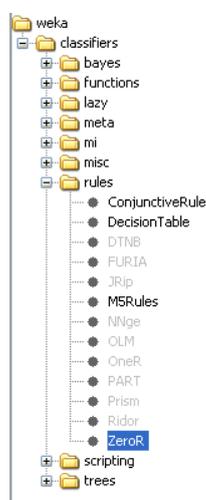
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- Press the button **Set...** right to it.
- In the window that pops up press the button **Open file...** and select the `test-logs-t1AB12u4.arff` file containing descriptor and property values for the test set. Press **Close** to close this window.

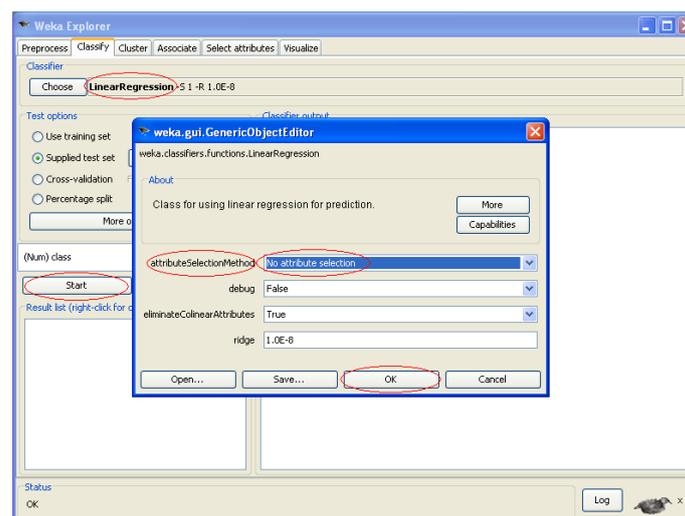
The aim of this part of the tutorial is to build a MLR model on the training set and test it using the specified test set. To do that:

- Click on the **Choose** button in the panel **Classifier**. The following window with the hierarchical tree of available machine learning methods appears:



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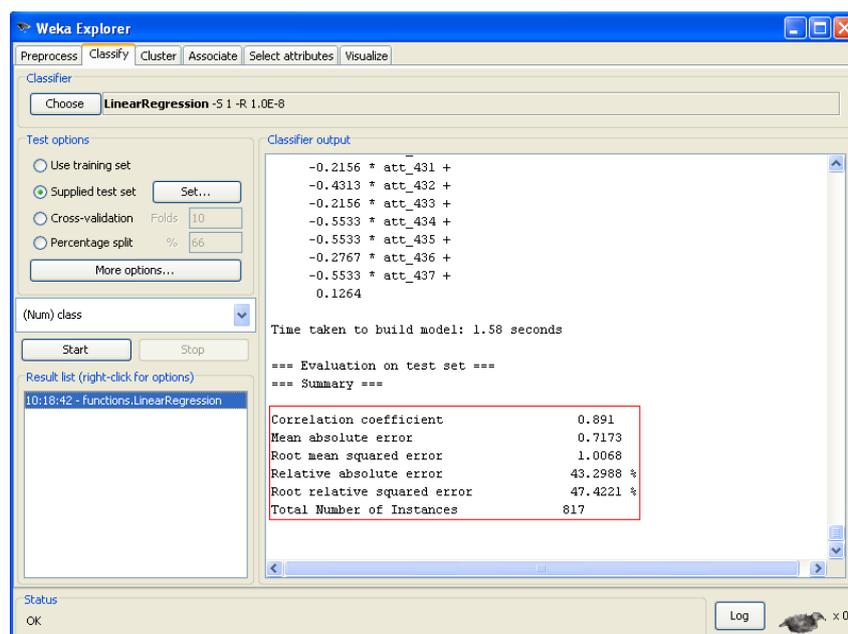
- Choose the method *weka->classifiers->functions->LinearRegression* from the hierarchical tree.
- Click on the word *LinearRegression*. The *weka.gui.GenericObjectEditor* window related to the MLR method, in which the method's parameters can be settled, appears.
- Switch off the descriptor selection option by changing the option *attributeSelectionMethod* to *No attribute selection*. The windows at the screen should be like these:



- Press **OK** to close the window.
- Click on the **Start** button to run the MLR method.

After the end of calculation the window of Weka should look as follows:

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The predictive performance of the model, as estimated using the supplied external test set, is presented at the right panel. One can see that the correlation coefficient (between predicted and experimental values of LogS on the test set) is 0.891, mean absolute error (MAE) of prediction on the test set is 0.7173 LogS units, the root-mean-square error (RMSE) of prediction on the test set is 1.0068 LogS units, the relative absolute error of prediction on the test set is 43.2988%, the root relative squared error of prediction on the test set is 47.4221%. All these characteristics can be used for comparing predictive performances of different regression models. In this tutorial we will use the RMSE error of prediction on the supplied external test set to compare predictive performances of regression models.

4. Exercise 6: Bagging of MLR models

Goal: to demonstrate the ability of ensemble learning based on bagging to decrease prediction errors of MLR models.

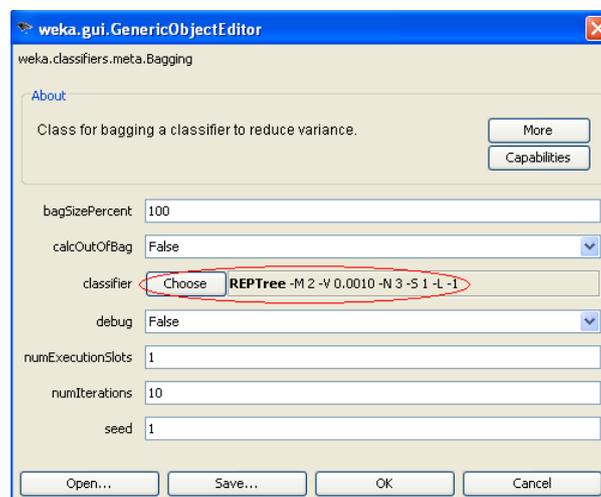
Method. The bagging procedure consists of: (i) generating several samples from the original training set by drawing each compound with the same probability with replacement (so-called bootstrapping), (ii) building a base learner (MLR in our case) model on each of the samples, (iii) averaging the values predicted for test compounds over the whole ensemble of models [4]. This procedure is implemented in Weka by means of a special “meta-classifier” with the name *Bagging*.

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Computational procedure.

Step 1: Setting the parameters.

- Click **Choose** in the panel **Classifier**.
- Choose the method **weka->classifiers->meta->Bagging** from the hierarchical tree of classifiers.
- Click on the word **Bagging**. The *weka.gui.GenericObjectEditor* window related to the bagging procedure with default values of its parameters appears on the screen. Notice that the default classifier for the bagging procedure is REPTree, a sort of regression trees (see below).

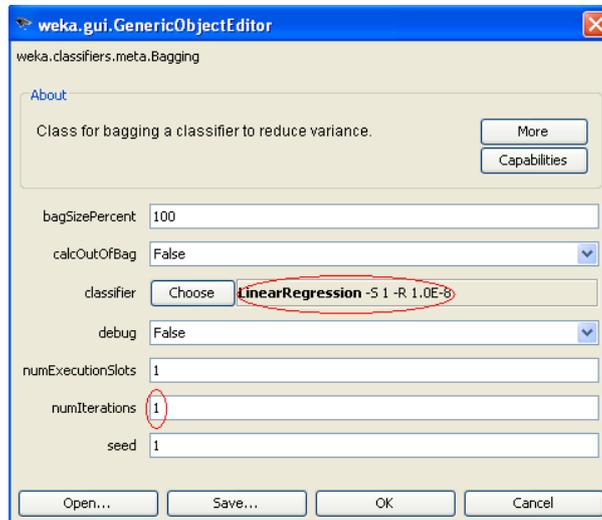


- Change the classifier from REPTree to MLR.
 - Click on the **Choose** button near the word **classifier**.
 - Choose the method **weka->classifiers->functions->LinearRegression** from the hierarchical tree.
 - Click on the word **LinearRegression**.
 - Switch off the descriptor selection option by changing the option **attributeSelectionMethod** to **No attribute selection**.
 - Press **OK** to close the window.

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Step 2: Building a model based on a single bagging sample.

- Change the number of bagging iterations to 1 by editing the field labeled *numIterations* (see below).



- Press **OK** to close the window.
- Click on the **Start** button to run bagging with one MLR model.

The following results are obtained (see the output panel):

Correlation coefficient	0.8254
Mean absolute error	0.8454
Root mean squared error	1.3627
Relative absolute error	51.0352 %
Root relative squared error	64.1859 %

All statistical characteristics are worse in comparison with the individual model. In particular, the RMSE rose from 1.0068 to 1.3627. This could be explained by the fact that the dataset after resampling contains approximately 67% of unique examples, so approximately 33% of information does not take part in learning in a single bagging iteration.

Step 3: Building models based on several bagging iterations.

- Click on **Bagging**.
- Set the number of iterations (near the label *numIterations*) to 10.

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- Press **OK** to close the window.
- Click on the **Start** button to run bagging with 10 iterations.

The results are as follows:

Correlation coefficient	0.9011
Mean absolute error	0.6975
Root mean squared error	0.9503
Relative absolute error	42.1044 %
Root relative squared error	44.7614 %

The statistical characteristics (e.g. RMSE=0.9503) become better than those of both individual MLR model (RMSE=1.0068) and bagging with a single MLR model (RMSE=1.3627).

- Repeat the study with the number of bagging iterations 5, 10, 15, 20, 30, 40, 50.
- Build the plot RMSE vs. *numIterations*

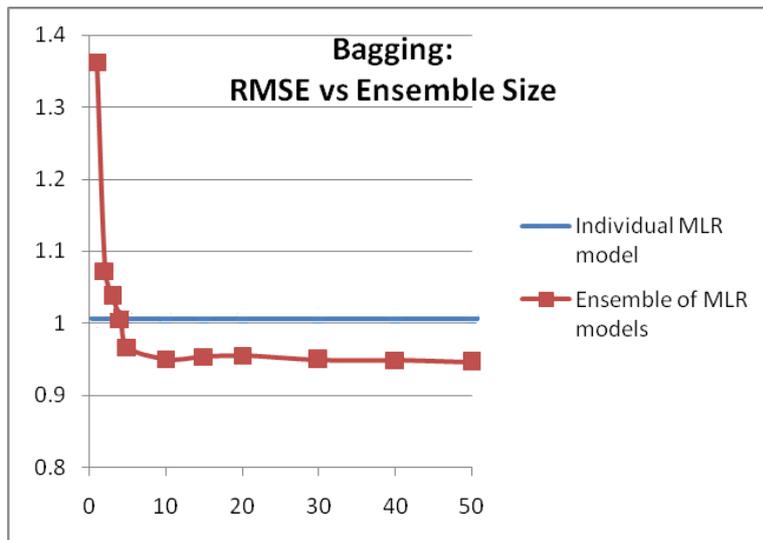


Figure 6. RMSE as a function of the number of models.

One may conclude that ensemble learning by bagging MLR models leads to decrease of prediction errors.

5. Exercise 7: Applying the random subspace method

Tutorial on Ensemble Learning

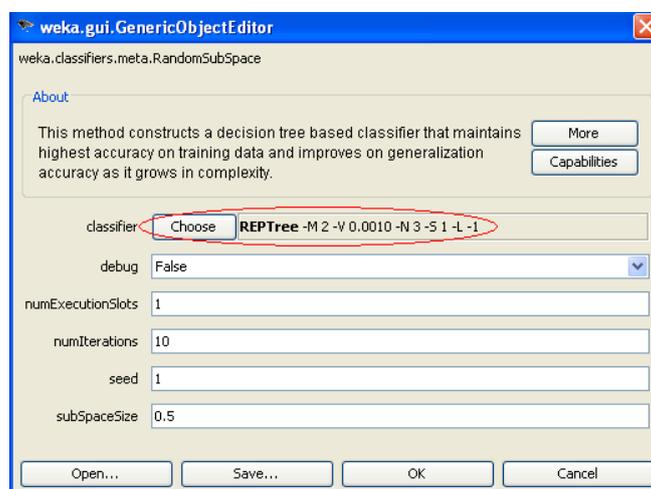
Goal: to demonstrate the ability of ensemble learning based on the random subspace approach to decrease prediction errors of MLR models.

Method. The random subspace procedure consists of: (i) random selection of descriptors subsets from their initial pool, (ii) building a base learner (here, MLR) model on each of these subsets, (iii) application of each individual MLR model to a test set compound following by the averaging of all predictions [4]. This procedure is implemented in Weka in the *RandomSubSpace* “meta-classifier”.

Computational procedure.

Step 1: Setting the parameters.

- Click *Choose* in the *Classifier* panel.
- On the hierarchical tree of classifiers, choose the method:
weka->classifiers->meta->RandomSubSpace.
- Click on *RandomSubSpace*. Notice that the default classifier for the random subspace procedure is *REPTree* (see below).



- Change the classifier from REPTree to MLR.

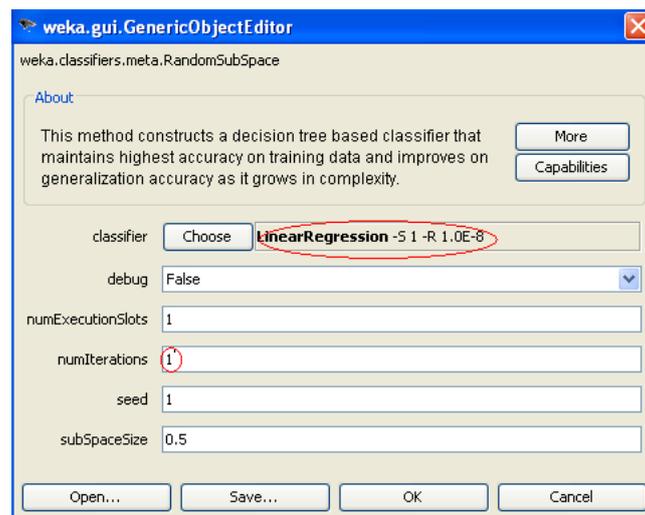
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- Click on the **Choose** button near the word **classifier**.
- Choose the method **weka->classifiers->functions->LinearRegression** from the hierarchical tree.
- Click on **LinearRegression**.
- Switch off the descriptor selection option by changing the option **attributeSelectionMethod** to **No attribute selection**.
- Press **OK** to close the window.

Notice that the default value 0.5 for **subSpaceSize** means that for each model only 50% of descriptors are randomly selected. The performance of the random subspace methods significantly depends on this parameter. Here, we won't optimize **subSpaceSize**, its default value 0.5 will be used in all calculations.

Step 2: Building a model based on a single random subspace sample.

- Change the number of iterations of the random subspace method to 1 by editing the **numIterations** field (see below)



- Press **OK** to close the window.
- Click on the **Start** button to run the random subspace procedure with one MLR model.

The following results are obtained (see output panel):

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Correlation coefficient	0.8477
Mean absolute error	0.8415
Root mean squared error	1.1357
Relative absolute error	50.7968 %
Root relative squared error	53.49 %

The model performance (RMSE = 1.1357) is less good than that obtained for the individual MLR model (RMSE = 1.0068, see Exercise 5). This could be explained by reduction of the number of variables. Indeed, only a half of the descriptor pool is used.

Step 3: Building models based on a several random subspace samples.

- Click on **RandomSubSpace**. Set the number of iterations (*numIterations* = 10).
- Press **OK** to close the window.
- Click on the **Start** button to run the random subspace method with 10 iterations.

The results should be as follows:

Correlation coefficient	0.9024
Mean absolute error	0.6758
Root mean squared error	0.9155
Relative absolute error	40.796 %
Root relative squared error	43.1219 %

The model performance becomes better compared to the previous calculation: RMSE=0.9155.

- Repeat the modeling varying the number of random subspace iterations: *numIterations* = 50, 100, 150, 200, 300 and 400.
- Build the plot RMSE vs *numIterations*

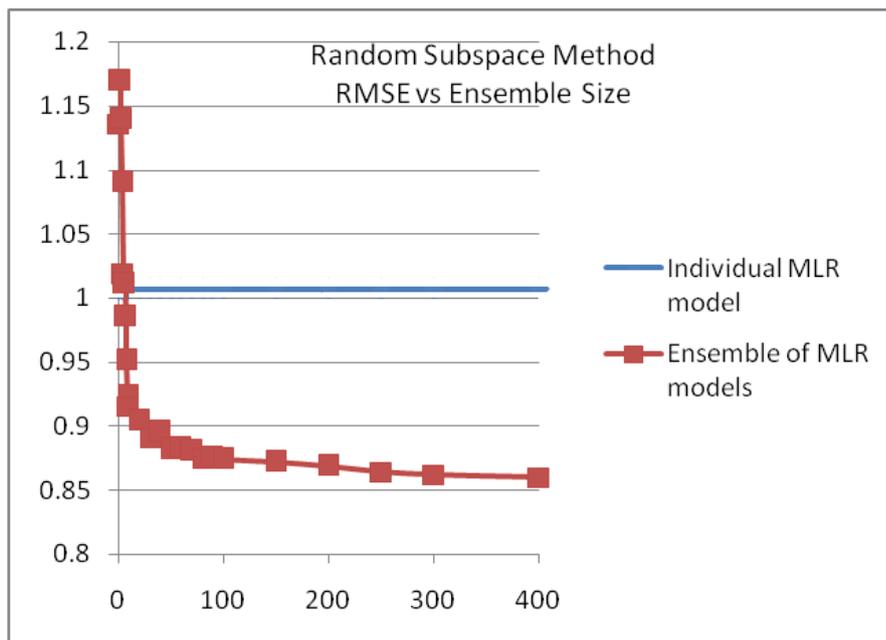


Figure 7. RMSE as a function of the number of models.

One may conclude that the random space method involving ensemble MLR models leads to significant decrease of the prediction errors compared to one individual model.

6. Exercise 8: Additive regression based on SLR models

Goal: to demonstrate the ability of additive regression (a kind of regression boosting) to improve the performance of simple linear regression (SLR) models.

Method. Additive regression enhances the performance of a base regression base method [6]. Each iteration fits a model to the residuals left on the previous iteration. Prediction is accomplished by summing up the predictions of each model. Reducing the shrinkage (learning rate) parameter, on one hand, helps to prevent overfitting and has a smoothing effect but, on the other hand, increases the learning time. Default = 1.0, i.e. no shrinkage is applied. This method of ensemble learning is implemented in Weka in *AdditiveRegression* meta-classifier.

Computational procedure.

Step 1: Setting the parameters.

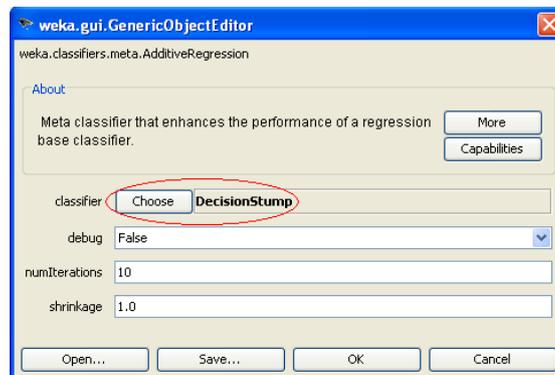
- Click on *Choose* in the *Classifier* panel.

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- On the hierarchical tree of classifiers, choose the method:

weka->classifiers->meta->AdditiveRegression.

- Click on *AdditiveRegression*. Notice that the default classifier (i.e. machine learning method) for the additive regression procedure is *DecisionStump* (see below).



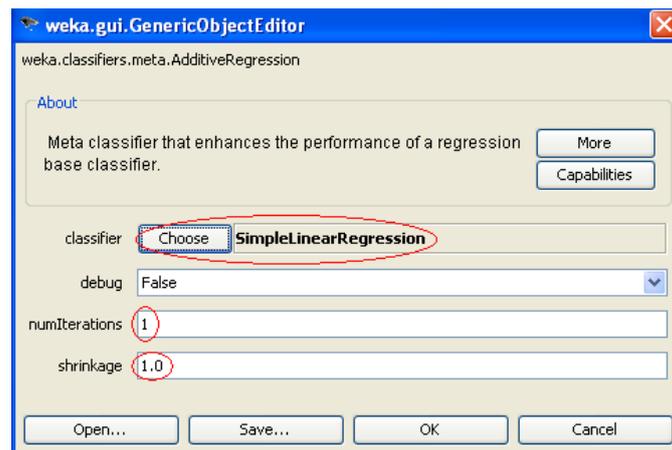
- Change the classifier from *DecisionStump* to *SLR*.
 - Click on the *Choose* button near the word **classifier**.
 - Choose the method *weka->classifiers->functions->SimpleLinearRegression* from the hierarchical tree.

Notice the default value 1.0 for the shrinkage parameter. This means that we are not doing shrinkage at this stage of tutorial.

Step 2: Building a model based on a single iteration of the additive regression method.

- Change the number of iterations of the additive regression method to 1 by editing the field labeled *numIterations* (see below).

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- Press **OK** to close the window.
- Click on the **Start** button to run the additive regression procedure with one SLR model (actually, an individual SLR model).

The following results are obtained (see output panel):

Correlation coefficient	0.5863
Mean absolute error	1.323
Root mean squared error	1.7204
Relative absolute error	79.8654 %
Root relative squared error	81.0341 %

The result is rather bad because the model has been built on only a single descriptor.

Step 3: Building models based on a several random subspace samples.

- Repeat the modeling varying the number of additive regression iterations: *numIterations* = 10, 50, 100, 500, and 1000.
- Change the shrinkage parameter to 0.5 and repeat the study for the same number of iterations.
- Build the plot RMSE vs. *numIterations*

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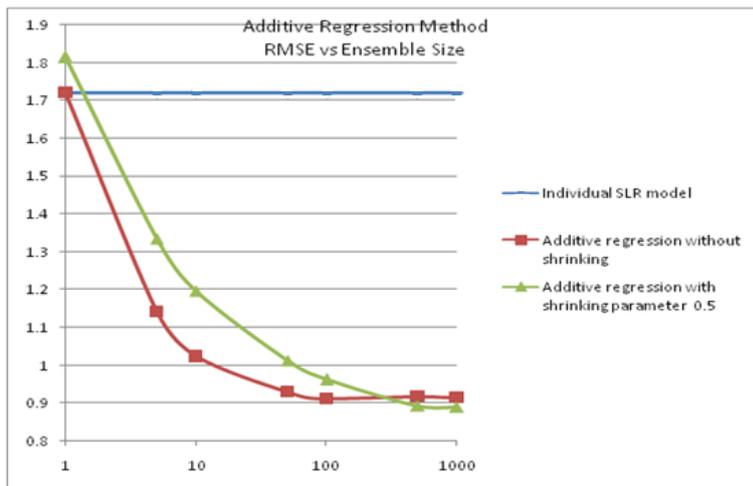


Figure 8. RMSE as a function of the number of models.

One may conclude that the ensemble learning by using the additive regression method with SLR models leads to considerable decrease of prediction errors. The shrinkage parameter helps to lower the prediction errors further.

7. Exercise 9: Stacking of models

Goal: to demonstrate the ability of stacking to improve predictive performance by combining three base classifiers: (i) partial least squares regression (PLS), (ii) regression trees M5P, (iii) multiple linear regression (MLR).

Method. Stacking is historically one of the first ensemble learning methods. It combines several base classifiers, which can belong to absolutely different classes of machine learning methods, by means of a “meta-classifier” that takes as its inputs the output values of the base classifiers [7, 8]. Although stacking is a heuristic method and does not guarantee improvement in all cases, in many practical studies it shows excellent performance. In this tutorial we will use stacking to combine

Step 1: Assessing the predictive performances of individual PLS and M5P models (predictive performance of the MLR model has been assessed in this tutorial earlier see Exercise 5).

- Assess the predictive performance of the PLS method (with the default number of components 20).
 - Click on the *Choose* button in the panel *Classifier*.

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- Choose the method *weka->classifiers->functions->PLSClassifier* from the hierarchical tree.
- Click on the **Start** button to run the PLS method.

The results are as follows:

Correlation coefficient	0.9171
Mean absolute error	0.6384
Root mean squared error	0.8518
Relative absolute error	38.5358 %
Root relative squared error	40.12 %

- Assess the predictive performance of the M5P method.
 - Click on the **Choose** button in the panel **Classifier**.
 - Choose the method *weka->classifiers->trees->M5P* from the hierarchical tree.
 - Click on the **Start** button to run the M5P method.

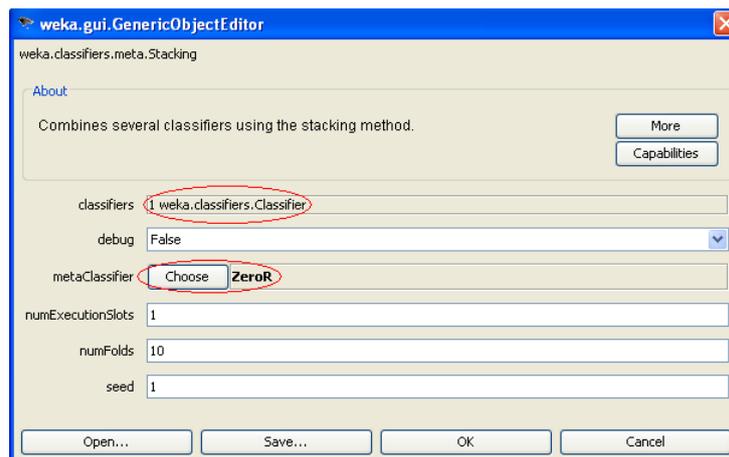
The results are as follows:

Correlation coefficient	0.9176
Mean absolute error	0.6152
Root mean squared error	0.8461
Relative absolute error	37.1349 %
Root relative squared error	39.8532 %

Step 2: Initialize the stacking method.

- Click on the **Choose** button in the panel **Classifier**.
- Choose the method *weka->classifiers->meta->Stacking* from the hierarchical tree of classifiers.
- Click on the word **Stacking**. The *weka.gui.GenericObjectEditor* window related to the stacking procedure with default values of its parameters appears on the screen (see below).

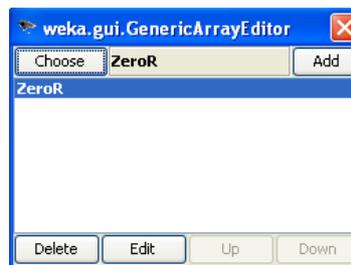
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Step 3: Form a list of base classifiers.

- Click on the field containing the text “1 weka.classifiers.Classifier” right from the label *classifiers*.

A new window containing the list of currently selected classifiers pops up.



- Delete the *ZeroR* method by clicking on the *Delete* button.
- Add the PLS classifier to the empty list of classifiers. Do the following:
 - Click on the *Choose* button near the word **classifier**.
 - Choose the method *weka->classifiers->functions->PLSClassifier* from the hierarchical tree.
 - Click on the *Add* button.
- Add the M5P method to the list of currently selected classifiers. Do the following:
 - Click on the *Choose* button near the word **classifier**.
 - Choose the method *weka->classifiers->trees->M5P* from the hierarchical tree.
 - Click on the *Add* button.

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- Add the MLR method to the list of currently selected classifiers. Do the following:
 - Click on the **Choose** button near the word **classifier**.
 - Choose the method *weka->classifiers->functions->LinearRegression* from the hierarchical tree.
 - Click on the word **LinearRegression**.
 - Switch off the descriptor selection option by changing the option *attributeSelectionMethod* to **No attribute selection**.
 - Press **OK** to close the window.
 - Click on the **Add** button.

At this stage the window should look like this:



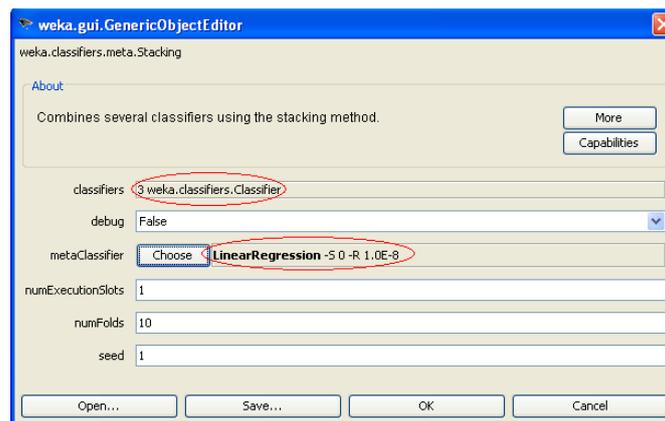
- Close the window by clicking at the cross.

Step 4: Set the meta-classifier for the stacking method to be the multiple linear regression (MLR). Do the following:

- Click on the **Choose** button near the word **metaClassifier**.
- Choose the method *weka->classifiers->functions->LinearRegression* from the hierarchical tree.

At this stage the *weka.gui.GenericObjectEditor* window should be as follows:

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Step 5: Run stacking of methods and assess the predictive performance of the resulting ensemble model.

- Press **OK** to close the window.
- Click on the **Start** button to run the stacking method.

Weka finds the following optimal combination of the base classifiers:

```
0.465 * weka.classifiers.functions.PLSClassifier +
0.445 * weka.classifiers.trees.M5P +
0.0644 * weka.classifiers.functions.LinearRegression +
-0.0932
```

The statistical results are as follows:

Correlation coefficient	0.9366
Mean absolute error	0.562
Root mean squared error	0.746
Relative absolute error	33.9262 %
Root relative squared error	35.1378 %

Step 6: Repeat the study by adding 1-NN. Repeat Step 3 and:

- Choose the method *weka->classifiers->lazy->IBk* from the hierarchical tree.

The results become even better.

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```
class =
    0.2368 * weka.classifiers.lazy.IBk +
    0.0384 * weka.classifiers.functions.LinearRegression +
    0.3713 * weka.classifiers.functions.PLSClassifier +
    0.3559 * weka.classifiers.trees.M5P +
    -0.0589

Time taken to build model: 99.22 seconds

=== Evaluation on test set ===
=== Summary ===

Correlation coefficient          0.9392
Mean absolute error             0.537
Root mean squared error        0.7301
Relative absolute error        32.4193 %
Root relative squared error    34.3861 %
Total Number of Instances      817
```

The results for stacking are presented in Table 1.

Learning algorithm	R (correlation coefficient)	MAE	RMSE
MLR	0.8910	0.7173	1.0068
PLS	0.9171	0.6384	0.8518
M5P	0.9176	0.6152	0.8461
1-NN	0.8455	0.85	1.1889
Stacking of MLR, PLS, M5P	0.9366	0.5620	0.7460
Stacking of MLR, PLS, M5P, 1-NN	0.9392	0.537	0.7301

Conclusion. One may conclude that stacking of several base classifiers has led to considerable decrease of prediction error (RMSE=0.730) compared to that for the best base classifier (RMSE=0.846).

Literature

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- [3] Yoav Freund, Robert E. Schapire: Experiments with a new boosting algorithm. In: Thirteenth International Conference on Machine Learning, San Francisco, 148-156, 1996.
- [4] Tin Kam Ho (1998). *The Random Subspace Method for Constructing Decision Forests*. IEEE Transactions on Pattern Analysis and Machine Intelligence. 20(8):832-844.
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- [10] William W. Cohen: Fast Effective Rule Induction. In: Twelfth International Conference on Machine Learning, 115-123, 1995.
- [11] Ross J. Quinlan: Learning with Continuous Classes. In: 5th Australian Joint Conference on Artificial Intelligence, Singapore, 343-348, 1992.

Appendix

1. Notes for Windows

On Windows, Weka should be located on the usual program launcher, in a folder *Weka-version* (e.g., *weka-3-6-2*).

It is recommended to associate Weka to ARFF files. Thus, by double clicking an ARFF, Weka/Explorer will be launched and the default directory for loading and writing data will be set to the same directory as the loaded file. Otherwise, the default directory will be Weka directory.

If you want to change the default directory for datasets in Weka, proceed as follows:

- Extract from the java archive `weka.jar`, the `weka/gui/explorer/Explorer.props` file. It can be done using an archive program such as WinRAR or 7-zip.
- Copy this file in your home directory. To identify your home directory, type the command `echo %USERPROFILE%` in a DOS command terminal.
- Edit the file `Explorer.props` with WordPad.
- Change the line `InitialDirectory=%c` by `InitialDirectory=C:/Your/Own/Path`

If you need to change the memory available for Weka in the JVM, you need to edit the file `RunWeka.ini` or `RunWeka.bat` in the installation directory of Weka (root privilege may be required). Change the line `maxheap=128m` by `maxheap=1024m`. You cannot assign more than 1.4Go to a JVM because of limitations of Windows.

2. Notes for Linux

To launch Weka, open a terminal and type:

```
java -jar /installation/directory/weka.jar.
```

If you need to assign additional memory to the JVM, use the option `-XmMemorySizem`, replacing `MemorySize` by the required size in megabytes. For instance to launch Weka with 1024 Mo, type:

```
java -jar -Xm512m /installation/directory/weka.jar.
```