

ADAMS

Advanced **D**ata mining **A**nd **M**achine learning **S**ystem

Module: adams-weka



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Chapter 1

Introduction

The *adams-weka* module offers most of the functionality found in WEKA [2]: pre-processing, classification and regression, clustering, attribute selection, data visualization and visualization of results/models. But it does not stop there: the module also contains other features for optimization, experiment generation that are not available from WEKA, be it Explorer or KnowledgeFlow. It is assumed that you are familiar with WEKA ¹ and machine learning in general, as common terms are not explained again.

If you have used WEKA's KnowledgeFlow before, then you will have to forget (mostly) everything that you know about setting up workflows. ADAMS does things quite differently in comparison to the WEKA. Additionally, ADAMS offers a range of general purpose actors that allow you to go further.

The manual is split into two parts: *classification and regression* comprising the first one and *clustering* the second.

¹If you haven't used WEKA before, check out the Data Mining book [3], which gives you a good introduction to machine learning, data mining and WEKA.

Chapter 2

Classification and Regression

WEKA's main strength lies in its large number of classification and regression schemes. Most of the documentation will cover this functionality therefore.

We start out with some basic WEKA functionality, like loading and preprocessing data, building models and evaluating them. That includes visualization of the results and models as well. After that we will cover more advanced features like learning curves, experiment generation and evaluation, optimization of classifiers and also the current provenance support in ADAMS.

2.1 Basic

In this section we describe how to perform basic WEKA functionality that you are used to perform with the Explorer, but in the workflow context. Instead of having to repeat the same steps, like loading and preprocessing data, whenever you update your data, a flow allows you to define the steps apriori and then merely re-execute them time and time again. Also, flows make it very easy to *document* all the steps that you perform, not just merely recording what you are doing.

2.1.1 Loading data

Before we can build any models, we have to have data at hand, of course. So the first step will be to obtain data from somewhere, whether that is by loading a local dataset or by downloading a remote dataset.

To start, we will be loading files that are stored locally. The actor used for loading datasets is the *WekaFileReader* transformer. This actor does not have an option for the file to load. Instead, it expects a file name, string or URL object to arrive at its input port. In order to supply a local file, we use the *SingleFileSupplier* source, which allows us to specify a single file that gets forwarded in the flow. If required, one can also use the *MultiFileSupplier* or *DirectoryLister* sources ¹, which can forward multiple file names instead of just one. The latter one is especially handy, if the files are not known in advance, e.g., generated on the fly. In order to display the loaded data, we use the *WekaInstancesDisplay* sink actor, which displays the data in a nice tabular format. Figure 2.1 shows the flow for loading the dataset and Figure 2.2 the generated output.

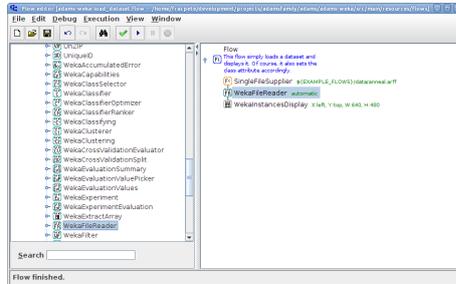


Figure 2.1: Flow for loading a local dataset.

The screenshot shows the WEKA WekaInstancesDisplay window. The title bar reads 'File: wekainstancesdisplay'. The window displays a table with the following data:

Relation: annual	1: family	2: product-type	3: steel	4: carbon	5: hardness	6: temper_rolling	7: condition	8: form
	Nominal	Nominal	Nominal	Numeric	Numeric	Nominal	Nominal	Nominal
1	C	JA	0.0	0.0?	S	?	?	
2	P	C	PR	0.0	0.0?	S	?	
3	P	C	PR	0.0	0.0?	S	?	
4	P	C	JA	0.0	60.0?	P	?	
5	P	C	JA	0.0	60.0?	P	?	
6	P	C	JA	0.0	45.0?	S	?	
7	P	C	PR	0.0	0.0?	S	?	
8	P	C	JA	0.0	0.0?	S	?	
9	P	C	PR	0.0	0.0?	S	?	
10	P	C	JA	0.0	0.0?	S	?	
11	P	C	PR	0.0	0.0?	S	?	
12	P	C	PR	0.0	0.0?	S	?	
13	P	C	PR	0.0	0.0?	S	?	
14	P	C	JA	0.0	45.0?	S	?	
15	P	C	JA	0.0	0.0?	S	?	
16	P	C	JA	0.0	0.0?	S	?	
17	P	C	JA	10.0	0.0?	P	?	
18	P	C	JA	0.0	60.0?	P	?	
19	P	C	JA	0.0	0.0?	S	?	
20	P	C	JA	0.0	70.0?	P	?	
21	P	C	JA	0.0	0.0?	S	?	
22	P	C	K	55.0	0.0?	P	?	
23	P	C	JA	0.0	65.0?	P	?	

Figure 2.2: The dataset that got loaded from disk.

In this example ² we let the *WekaFileReader* determine the correct file loader automatically, based on the file extension. If this automatic determination should fail, you can always check the “useCustomLoader” checkbox and then configure the appropriate loader yourself.

Another feature of this actor is the ability to output the dataset row by row (option “incremental”). This is very handy in case of very large files, where loading into memory could pose a problem. Even though the incremental feature

¹adams-weka-crossvalidate_classifier_multiple_datasets.flow

²adams-weka-load_dataset.flow

works for any file type that WEKA can read, truly incremental, i.e., memory-efficient, loading is only possible if the underlying loader also supports incremental loading. In any other case, the dataset gets loaded fully into memory before being forwarded row by row.

Nowadays, a lot of data is available online. Instead of relying on local files, one can use the flow also to download remote files. Some of the WEKA file loaders, like the *ArffLoader*, natively support the download via a URL. Figure 2.3 shows a flow ³ that downloads (and displays) an ARFF file available from a URL that was supplied by the *SingleURLSupplier*. If the required dataset is encapsulated in an archive, e.g., a ZIP file and not just compressed with GZIP, then one has to download the archive first and extract the correct file before working with it. The flow ⁴ in Figure 2.4 downloads an archive from WEKA’s sourceforge.net web site ⁵ using the *DownloadFile* sink and extracts all the datasets which filename fit a regular expression. The extracted files are then displayed in a *HistoryDisplay* sink.

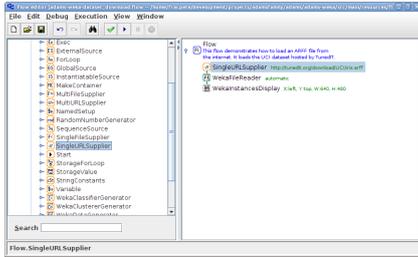


Figure 2.3: Flow for loading a local dataset.

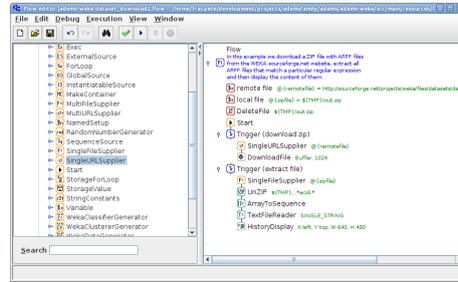


Figure 2.4: The dataset that got loaded from disk.

Finally, artificial data can be generated within ADAMS as well. Using the *WekaDataGenerator* source, any WEKA data generator can be used to output data. The flow ⁶ depicted in Figure 2.5 generates a small dataset using the “Agrawal” data generator.

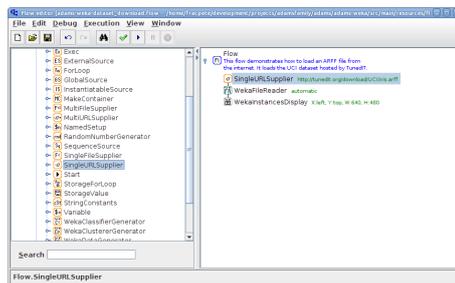


Figure 2.5: Flow for generating and displaying an artificial dataset.

³adams-weka-dataset_download.flow

⁴adams-weka-dataset_download2.flow

⁵WEKA on sourceforge.net: <http://sourceforge.net/projects/weka/>

⁶adams-weka-data-generator.flow

2.1.2 Building models

After having sorted out the loading of the data, it is time to check out how to build models. Since we are using supervised algorithms, we have to make sure that the datasets have a class attribute set. The *WekaClassSelector* actor allows the setting of the class attribute, in the default setting it simply uses the last attribute as the class attribute. With the *WekaClassifier* actor you can choose a classifier to be built. By default, the *WekaClassifier* actor outputs a container that comprises the built model and the header of the training set. In order to extract either of the container items, you need to use the *ContainerValuePicker* control actor. Figure 2.6 demonstrates how to train a J48 classifier on dataset and then displaying the built model (see Figure 2.7) ⁷.

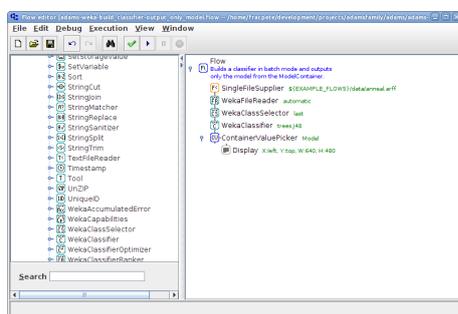


Figure 2.6: Flow for building J48 model on a dataset and outputting the model.

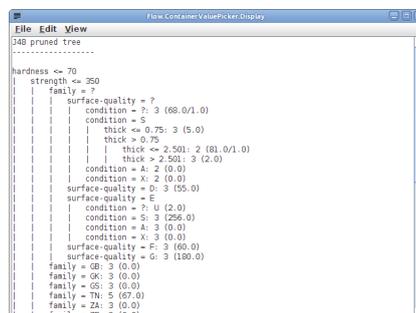


Figure 2.7: J48 model output.

A built model can be saved to disk (and then re-used later) using the *WekaModelWriter*. The file generated can also be loaded in the WEKA Explorer again and applied to another test set there ⁸.

2.1.3 Preprocessing

A very important, but often underrated step is preprocessing. Unless your data is properly cleaned up and in the right format, your models will not be very meaningful. Preprocessing steps can be done within the flow using the *WekaFilter* transformer, which wraps around a single WEKA filter. One either chains multiple actors together or uses the *weka.filters.MultiFilter* meta-filter to executed several filter sequentially in a single actor.

In Figure 2.8 we are investigating the impact of preprocessing on the “slug” dataset [4]. The flow ⁹ cross-validates *LinearRegression* on the original and log-transformed data. The log-transformed data is generated by applying the *AddExpression* filter on each of the two attributes of the dataset and then deleting the original ones. In each case, original or preprocessed, it displays the evaluation summary and classifier errors.

Figures 2.9 and 2.10 show the evaluation summary, for the original and the log-transformed data. The log-transformed dataset gets not only a better correlation coefficient, but also smaller errors.

⁷adams-weka-build-classifier-output_only_model.flow

⁸adams-weka-build-classifier-save_model.flow

⁹adams-weka-filter_data.flow

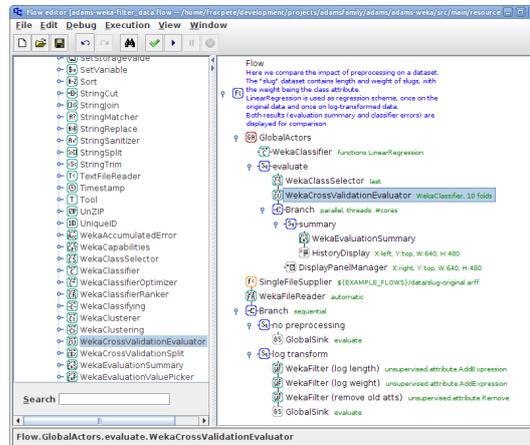


Figure 2.8: Flow for comparing results generated from original and preprocessed “slug” data [4].

Summary	
Correlation coefficient	0.9056
Mean absolute error	0.9559
Root mean squared error	1.2725
Relative absolute error	38.3959 %
Root relative squared error	41.6248 %
Total Number of Instances	100

Figure 2.9: Evaluation summary on “slug” dataset (original).

Summary	
Correlation coefficient	0.9685
Mean absolute error	0.2505
Root mean squared error	0.4225
Relative absolute error	17.0962 %
Root relative squared error	24.6952 %
Total Number of Instances	100

Figure 2.10: Evaluation summary on “slug” dataset (log-transformed).

Figures 2.11 and 2.12 display the classifier errors. It is obvious from the funny log-shaped curve, that LinearRegression built on the original data is not a very good model. Something that is not so obvious by just looking at the correlation coefficient: 0.9056 is not bad.

This flow can be quickly extended to accommodate other preprocessing techniques, all very easily comparable in the graphical output.

In this example the preprocessing was rather specific. On the other hand, if you are working mainly in a particular data domain, like spectral analysis of some kind, then certain preprocessing steps will always be same. In this case, it makes sense to store these externally in a *preprocessing library* which you then link to using external actors (see manual for the *adams-core* module for more details). This reduces duplication and you will only have to update the preprocessing step in a single location.

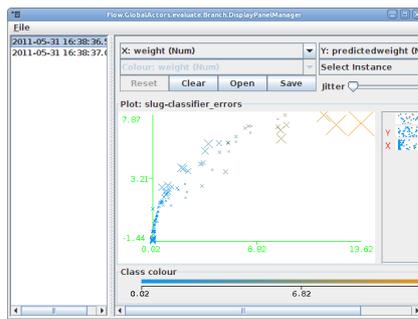


Figure 2.11: Classifier errors on “slug” dataset (original).

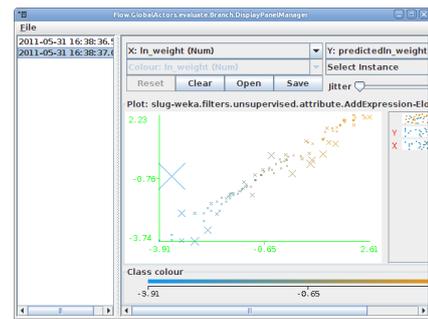


Figure 2.12: Classifier errors on “slug” dataset (log-transformed).

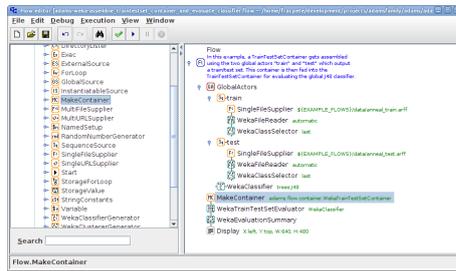


Figure 2.22: Flow for evaluating classifier on separate train/test set.

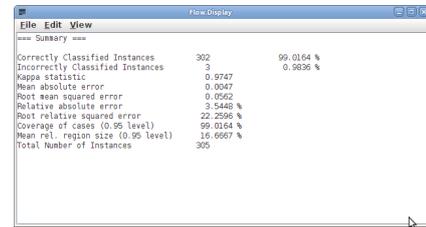


Figure 2.23: Summary output of classifier evaluated on separate train/test set.

Another interesting visualization is the *WekaAccumulatedError* transformer. This transformer takes also an *Evaluation* object and then turns it into a special sequence of plot containers: it creates a sequence of the prediction errors that were obtained during an evaluation and outputs them sorted, from smallest to largest¹⁵. The Figures 2.24 and 2.25 show the flow and the generated output respectively. As you can see from the graph, GaussianProcesses generates consistently larger errors than LinearRegression, which only seems to have a few big outliers (steep increase at the end).

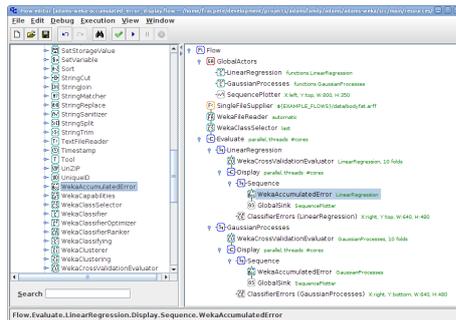


Figure 2.24: Flow for displaying the “accumulated error” of a two classifiers.

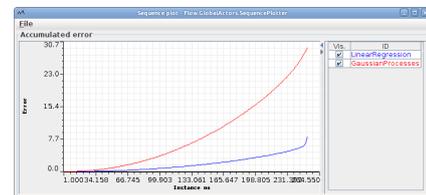


Figure 2.25: The “accumulated error” of LinearRegression and GaussianProcesses.

¹⁵ adams-weka-accumulated_error_display.flow

2.2 Advanced

2.2.1 Learning curves

incremental ¹⁷ and non-incremental ¹⁸

2.2.2 Experiments

experiment generation ¹⁹, execution and evaluation ²⁰

2.2.3 Optimization

setup generators ²¹, ranker ²², optimizer ²³

2.2.4 Provenance

provenance display ²⁴

¹⁷adams-weka-build_classifier_incrementally.flow

¹⁸adams-weka-classifier_learning_curve.flow

¹⁹adams-weka-experiment_generation.flow

²⁰adams-weka-experiment.flow

²¹adams-weka-classifier_setup_generation.flow

²²adams-weka-classifier_setup_ranking.flow

²³adams-weka-classifier_optimizer.flow

²⁴adams-weka-crossvalidate_classifier_display_provenance.flow

Chapter 3

Clustering

Clustering behaves very much like Classification/Regression, the only difference being that it is an unsupervised learning process. This means that the flows won't contain a *WekaClassSelector* actor to set the class attribute in the loaded data. Due to the similarity, the section here will cover only the basics of clustering.

3.1 Building models

Building clustering models is as easy as building classification/regression models. Instead of the *WekaClassifier* transformer, you use the *WekaClusterer* one.

Figures 3.1 and 3.2 show a flow ¹ that builds a *SimpleKMeans* clusterer on a dataset (the class attribute gets removed using a *WekaFilter* actor) and the generated model gets displayed.

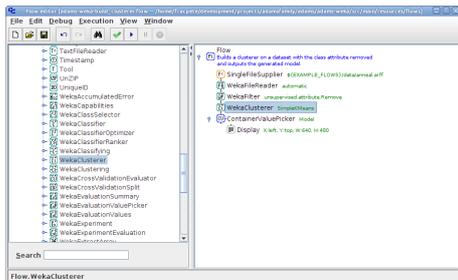


Figure 3.1: Building a clusterer and outputting the model.

Attribute	Full Data (898)	Cluster# 0 (484)	Cluster# 1 (414)
family	?	?	?
product-type	C	C	C
steel	A	R	A
carbon	3.6347	0.8958	7.7026
hardness	11.7762	1.5806	23.6957
temper_rolling	?	?	?
condition	S	S	?
formability	2	2	?
strength	30.6682	1.0331	65.314
non-ageing	?	?	?
surface-finish	?	?	?
surface-quality	E	E	G

Figure 3.2: Cluster model output.

If the base cluster algorithm is an incremental one, i.e., one that implements the *weka.clusterers.UpdateableClusterer* interface, you can build your clustering model incrementally as well. The flow ² in Figure 3.3 builds the CobWeb cluster algorithm incrementally and outputs the generated models every 25 instances (see Figure 3.4).

¹adams-weka-build_clusterer.flow

²adams-weka-build_clusterer_incrementally.flow

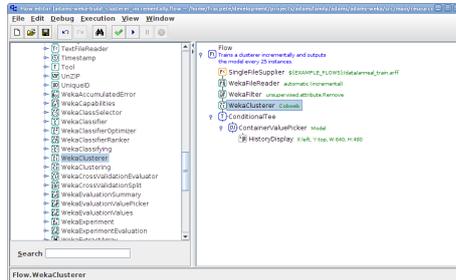


Figure 3.3: Building a clusterer incrementally and outputting the model.

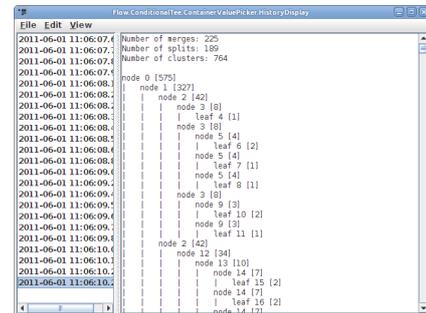


Figure 3.4: Cluster model outputs, generated every 25 instances.

3.2 Clustering data

Clustering new data is done using the *WekaClustering* transformer, which takes a single instance as input and outputs the generated clustering information in form of a container (*WekaClusteringContainer*). You can either specify a serialized clusterer model to use or a global actor to obtain the clusterer from. The flow ³ in Figure 3.5 shows how to build a clusterer and use it to cluster new data, outputting the cluster distributions (see Figure 3.6 for the generated output).

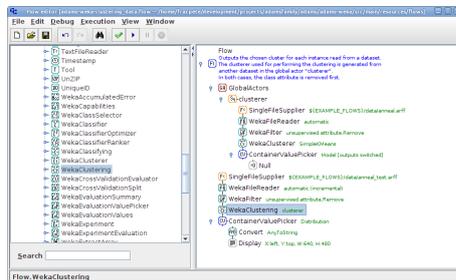


Figure 3.5: Flow for clustering new data.

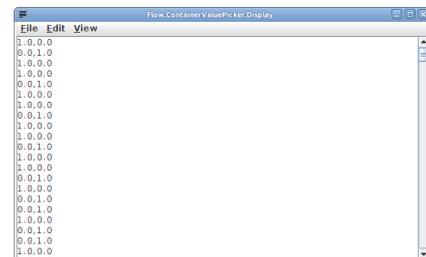


Figure 3.6: Generated cluster.

³adams-weka-clustering_data.flow

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