# FCM Expert

## Help contents

05/05/2021

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# Welcome

FCM Expert is a software tool for designing, learning and simulating Fuzzy Cognitive Maps (FCMs) devoted to complex systems and pattern classification. This software is completely written in Java language and comprises more than 25,000 source code lines distributed in 120 source files. FCM Expert involves three groups of functions distributed in five menus: ***File***, ***Edit***, ***Build***, ***Run*** and ***Reset***.

The first group is oriented to the design of the FCM-based model, where the expert (user) in a given domain can model a complex system (visual options do not require deep expertise in Mathematics or Computer Science). The second group comprises Machine Learning algorithms for adjusting the model parameters and optimizing its performance. Finally, the third group includes procedures for exploiting the FCM-based system as a tool for supporting decision-making processes.

FCM Expert includes supervised and unsupervised learning algorithms for computing the weights matrix defining the FCM model, optimizing the network topology without losing relevant information, and improving the network convergence. Such *Machine Learning* methods equip FCM Expert with strong experimentation options filling the gap between theory in practice in FCM modeling.

We hope that you find our software useful for your project!
FCM Expert Team.

# Introduction

## Getting Started

- What are Fuzzy Cognitive Maps?
- Check the recommended System requirements for using our software.
- For more information about algorithms, see the publications of Gonzalo Nápoles.

## What are Fuzzy Cognitive Maps?

Fuzzy Cognitive Maps (FCMs) are knowledge-based recurrent neural networks for modeling and simulating dynamic systems. From a connectionist viewpoint, FCMs can be seen as recurrent neural networks consisting of neural concepts and signed weighted connections. Neural concepts represent variables, states, entities related to the physical system under investigation. The weight associated with each connection denotes the strength of the causality between the corresponding neurons. Causal relations are quantified in the [-1,1] interval, while that neurons' activation values can take values in either [0,1] or [-1, 1] depending on the nonlinear transfer function attached to each neuron.

There are three possible types of causal relationships between concepts $C_i$ and $C_j$:

a) If $w_{ij} > 0$ indicates a *positive causality*, then an increase (decrement) on $C_i$ will produce an increment (decrement) on the effect concept $C_j$ with intensity $|w_{ij}|$.
b) If $w_{ij} < 0$ indicates a *negative causality*, then an increase (decrement) on $C_i$ will produce a decrease (increment) on the effect concept $C_j$ with intensity $|w_{ij}|$.
c) If $w_{ij} = 0$ denotes the absence of causal relation between $C_i$ and $C_j$.

Figure 1 displays an FCM-based system concerning *Crime and Punishment*. This FCM comprises seven concepts defining the problem domain connected with causal relationships defined by experts in that domain. Once the causal network has been defined, the expert may perform WHAT-IF simulations and analyze the system behavior through complex, often subjective scenarios.

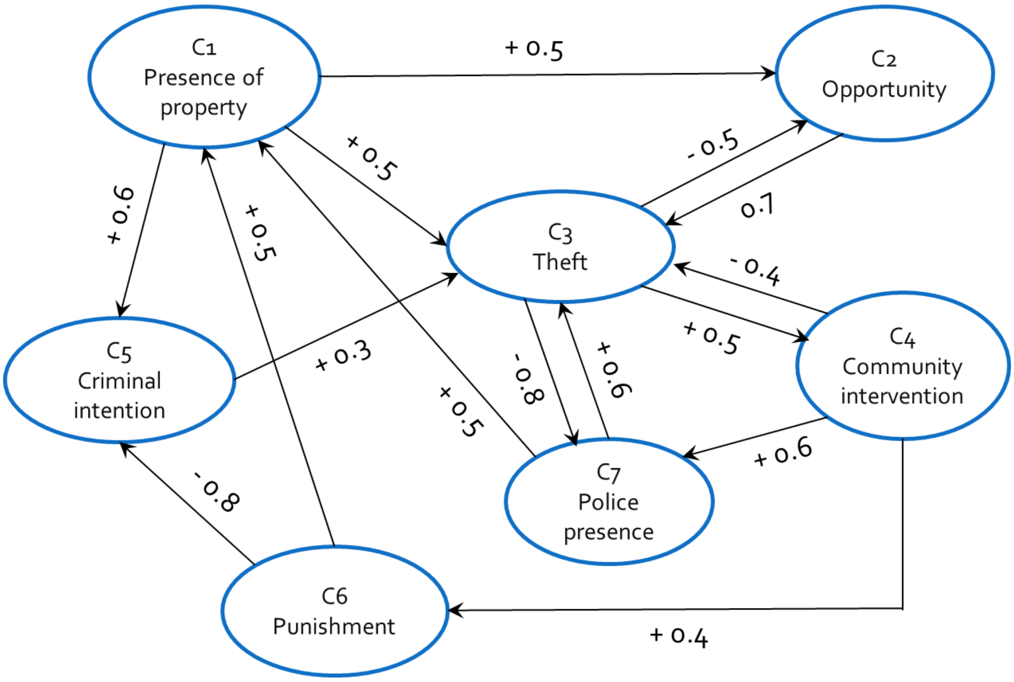



**Figure 1**. Crime and punishment FCM system.

Fuzzy cognitive mapping has some specific advantageous characteristics over traditional mapping methods. For example, they can express the relation between concepts in a clear representation scheme and express hidden relationships. Moreover, their causal semantics can be used to analyze, simulate, and test the influence of parameters and predict the system's behavior.

During the last 30 years, FCMs played a vital role in the applications of diverse scientific areas, such as social and political sciences, engineering, information technology, agriculture, education, forecasting, environment, biology, transportation management, medicine, among others.

The following survey papers cover several aspects in this field:

- G. Felix, G. Nápoles, R. Falcon, K. Vanhoof, W. Froelich, R. Bello: A review on methods and software for Fuzzy Cognitive Maps. *Artificial Intelligence Review*, 2017.
- E. Papageorgiou, J. Salmeron: A review of Fuzzy Cognitive Maps research during the last decade. *IEEE Transactions on Fuzzy Systems* 21, 2012.

## System requirements

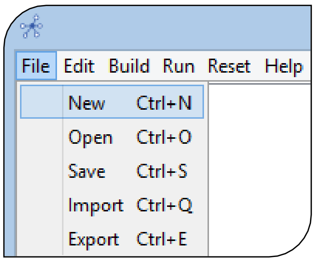
- Java Runtime Environment (JRE) version 8 or above
- 1GB of RAM and 80MB of free disk space
- Windows 7, Windows 8 or Windows 10

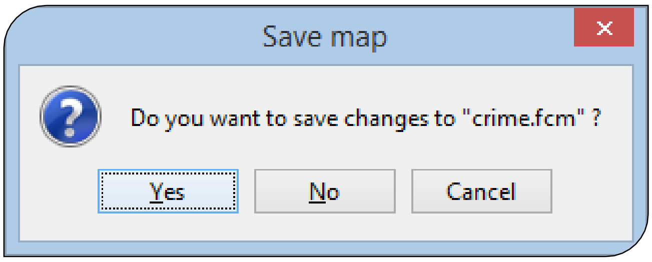
# New, open, save, import and export

FCM Expert uses a serialized binary file with extension **.fcm** to save and recover FCM-based models. This binary file should not be modified when realizing new versions.

## New

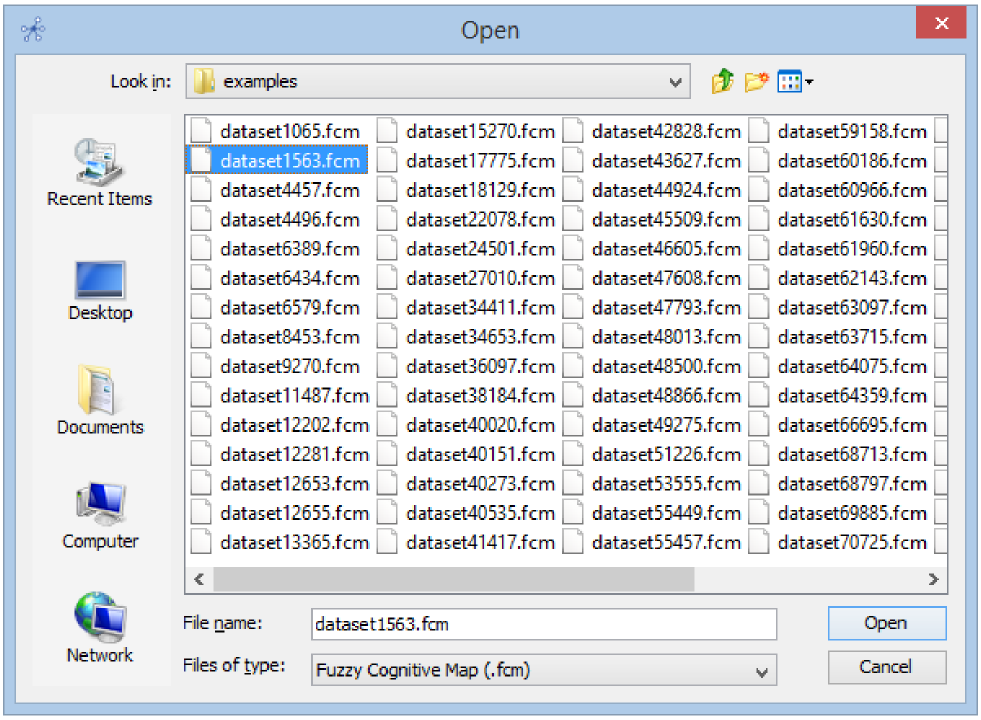
This option clears the canvas for creating a new (empty) FCM without concepts or relations. It can be reached through the menu **File | New** or by clicking the button in the toolbar.
If an FCM is currently open and the changes have not been saved, FCM Expert will display a warning dialog to save the current network before creating a new one.




## Open

This option opens a previously saved FCM-based structure. It can be reached through the menu **File | Open** or clicking the button in the toolbar. A file chooser dialog will be shown.




As mentioned, FCM Expert loads the map from a binary file. Therefore, all structural properties of the map are comprised into a binary format for posterior use with the software.

If an FCM is currently open and the changes have not been saved, FCM Expert will show a warning message indicating to save the current map before opening the specified one.

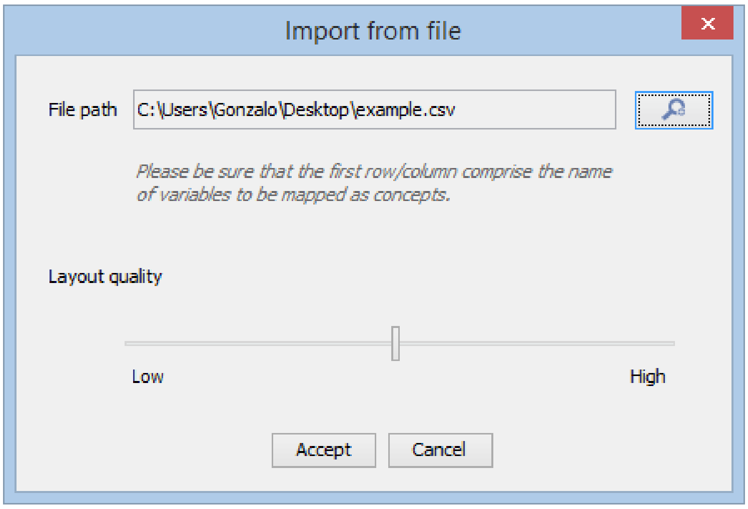
## Save

This option allows saving the structural properties of the current FCM model as a binary serialized file. It can be reached through the menu **File | Save** or clicking the button in the toolbar. A file chooser dialog will be shown. The extension used by the application is "*.fcm*".

## Import

This option allows importing the FCM structure from a CSV. It can be reached through the menu **File | Import**. The structure of the CSV file must be as follows: (1) the first column/row should specific the concepts' names with an identifier of three alphanumeric characters at most, and (2) the weight matrix should be squared and comprising values in the [-1,1] interval; it should be a zero-diagonal matrix.

The user can specify the CSV file path and the "Layout quality". This last option includes a heuristic layout procedure for efficiently drawing the network topology, which minimizes both the distance between concepts and the cuts between graph edges and concepts. This procedure should be time-consuming for FCM models with complex network structures, so it is advisable to keep the quality low.




## Export

This option allows exporting the current FCM as an image in PNG format or as a CSV file. It can be reached through the menu **File | Export** or clicking the button in the toolbar.

# Designing a map from scratch

In this section, we explain how to create and configure an FCM-based model from scratch. Therefore, users can completely design the network just using their knowledge.

## Create new concepts

This option allows creating new concepts with fixed names that can be changed later.

Click on the button in the toolbar to activate this option. After that, each click on the canvas will create a new concept with a generic name "C#", where # is a consecutive integer number (e.g. C1).

As mentioned, the concept can be renamed by clicking the right button over the concept and next changing the field "name" (see Select/move). To guarantee a nice graphical visualization, the identifier of each concept must not be greater than three alphanumeric characters.

## Create new relations

This option creates a relation with a default weight equal to 0.5 that can be changed later.

Click on the button in the toolbar to activate this option. Next, click on the source concept and release, drag the mouse to the target concept, and click to create the relation.

The weight of the relation can be altered manually by clicking the right button over the weight number (see Select/move). Concepts can have causal relations in both directions. If there is already a connection between such nodes, the straight-arrow will be changed to a curved one.

## Select/move

This option allows selecting or moving a map component (i.e., a relation or a concept).

Click on the button on the toolbar to activate this functionality. The mouse cursor will be changed to a hand cursor indicating that you are capable of selecting/moving map components.

### Editing concepts

For editing the properties of concepts, just click with the right button on the desired concept. This will show a dialog comprising three tabs: ***General***, ***Settings,*** and ***Decision***.

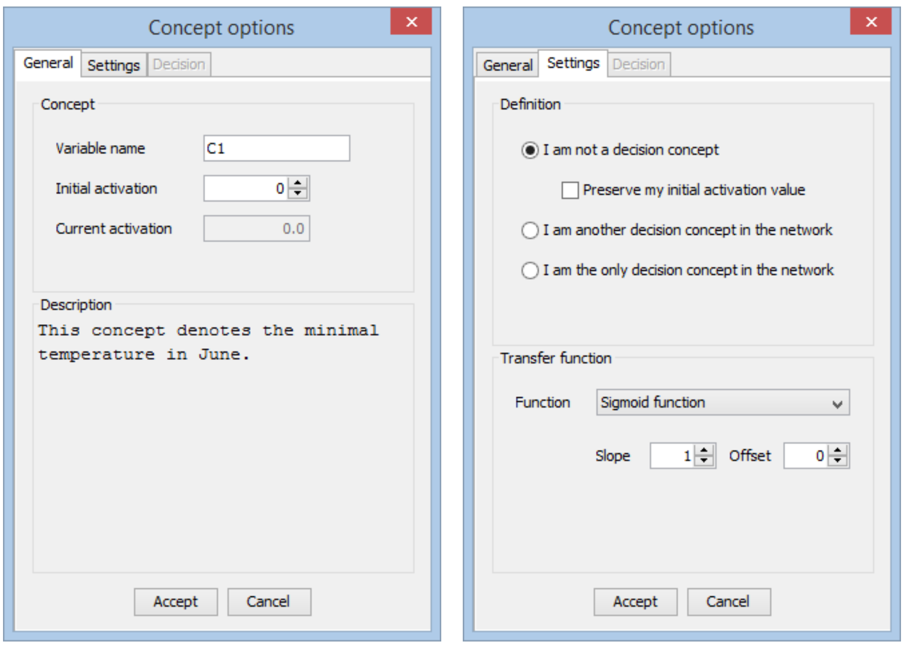
The tab "General" shows the basic properties of the specified concept: its identifier, the full description of the variable being modeled, its initial activation, and the current activation value.

The tab "Decision" allows specifying the concept's role in the topology being modeled. Concepts can be either input concepts or decision ones. Such notions are formalized as follows:

> **Definition 1**. *We say that a neural processing entity* $C_i$ *is an* ***independent input neuron*** *if its activation value does not depend on the other input neurons.*
>
> **Definition 2**. *We say that a neural processing entity* $C_i$ *is a* ***dependent input neuron*** *if other connected neurons influence its activation value.*
>
> **Definition 3**. *We say that a neural processing entity* $C_i$ *is an* ***output neuron*** *if its activation value only depends on the connected input neurons.*

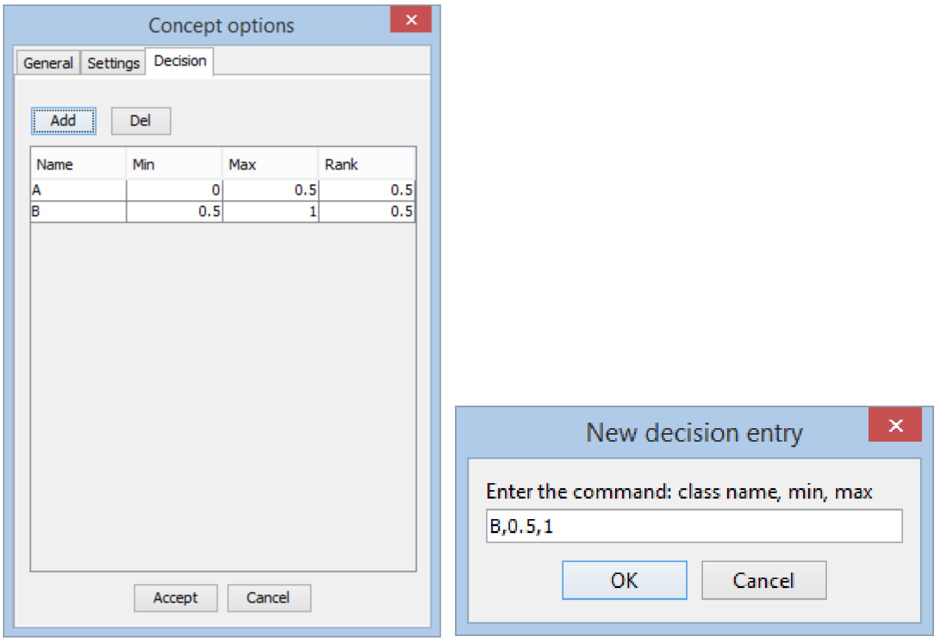
FCM Expert allows handling different architectures for both scenario analysis and pattern classification. In the first case, the FCM does not comprise a decision concept, while in the second case, we implement two architectures for pattern classification that differ in the number of decision concepts.

The *single-output architecture* comprises a single decision concept such that decision classes are defined as closed partitions of the decision space, while in the *class-per-output architecture*, each class is defined by an output neuron. Observe that each neuron may use its own transfer function!



In the *single-output architecture*, we need to configure the decision concept by creating a partition of the decision space according to decision classes. This can be done in the tab “Decision”.

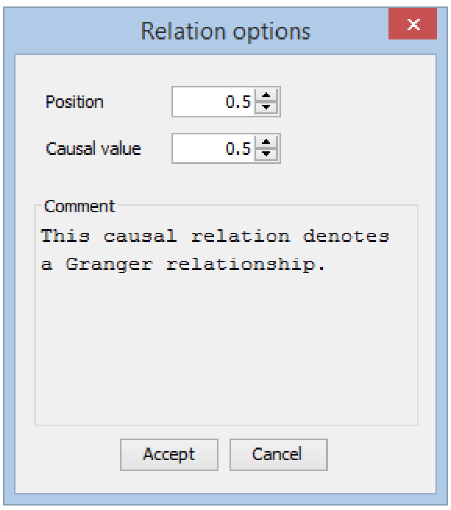
To do that, click on the “Add” button to introduce a new decision entry. Each decision entry is defined by its decision label and by its lower and upper bounds. The following example shows how to configure a decision concept for an FCM-based classifier devoted to solving a binary classification problem.




For further information on this topic, the reader is referred to the following paper: *G. Nápoles, M. León, I. Grau, K. Vanhoof, R. Bello: Fuzzy Cognitive Maps based Models for Pattern Classification: Advances and Challenges. Soft Computing based Optimization and Decision Models, 2018*.

## Editing relations

For editing the properties of relations, click with the right button on the number attached to the desired relation. This will display a window where you can modify the drawing position of the weight, the sign and magnitude of the causal relation, or attach a relevant comment.



### Delete component

This option allows deleting a map component. Click on the button on the toolbar and click on the concept or relation you want to delete. If the selected component is a concept, then the connected causal relations will be automatically deleted as well. Be careful when deleting the decision concept!

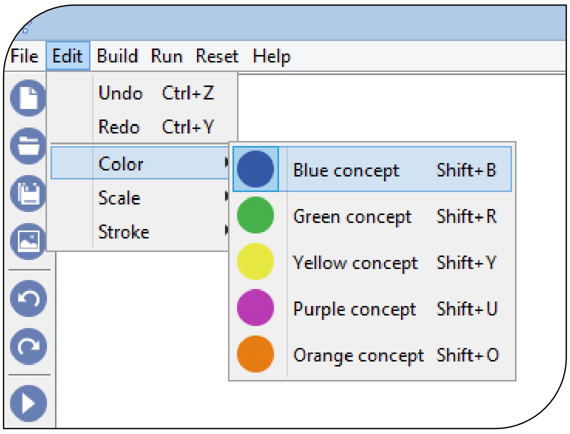
## General functionalities

### Undo/Redo

FCM Expert implements undo and redo options that allow undone any modification. The user can access these options through the buttons or on the toolbar. These options can be reached through the menu **Edit | Undo** and **Edit | Redo**. It should be highlighted that global changes related to the reasoning rules will not be included in the stacks, as they are not attached to the current map.

### Change concept color

The default color of input concepts is blue, but this color can be customized. To do that, go to the menu **Edit | Color** and select your preferred one. Decision concepts will be automatically drawn in red.




### Activate scaled concepts

Concepts can have a standard size, or they can be customized according to their activation value. The default selection is standard. Select your preferred option on the menu **Edit | Scale**.

This option becomes especially useful when performing WHT-IF simulations, so the expert can have insights into the changes in the system without examining the concepts one by one.

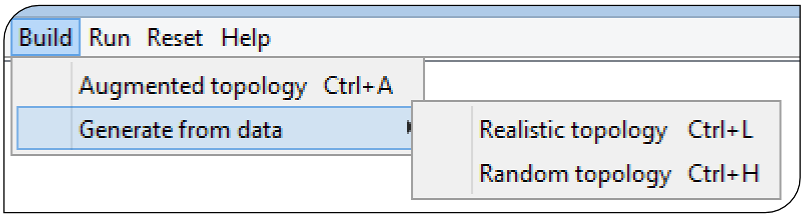
### Change relation thickness

FCM Expert allows customizing the thickness of relations. They can be ***thin***, ***medium,*** or ***wide***. The default thickness is thin. Go to the menu **Edit | Stroke** and select your preferred one.

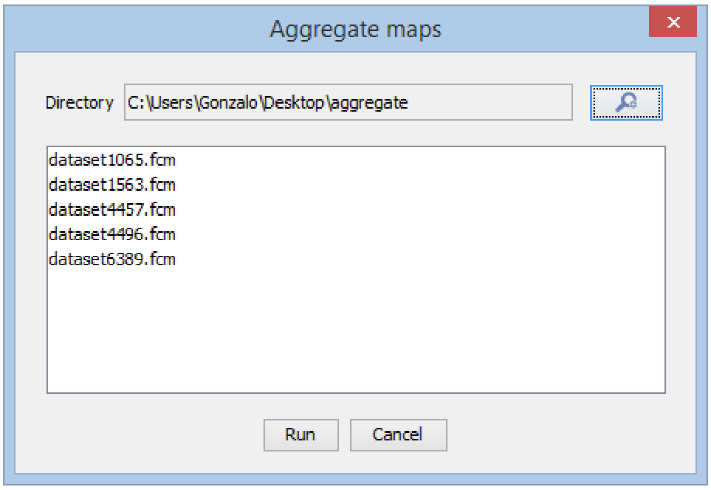
## Building complex networks

### Augmented topology

This option allows combining multiple FCMs into a single knowledge-based representation. According to the literature, it is possible to have better, more consistent models if more than one expert or knowledge source is used. This can be reached from the menu **Build | Augmented topology**.




To select the FCMs to be combined, a file chooser dialog will be shown. Select the folder that contains the maps to be aggregated, which must be in ".*fcm*" format. Once loaded, fcm files will be listed in a separate box, while non-fcm files in the specified folder will simply be ignored.




Internally the software combined multiple weighted FCMs into a single averaged FCM by adding their scaled and augmented adjacency weight matrix. This procedure is based on the mathematical transformation of the causal weight matrixes. If the FCMs to be aggregated are characterized by the same concepts, then the combined FCM representing the entire system can be easily calculated as the average, median or weighted average of their causal matrixes. If the FCMs involve different concepts, then it is necessary to augment each causal matrix by adding a new column and row filled with zeros for each additional concept.

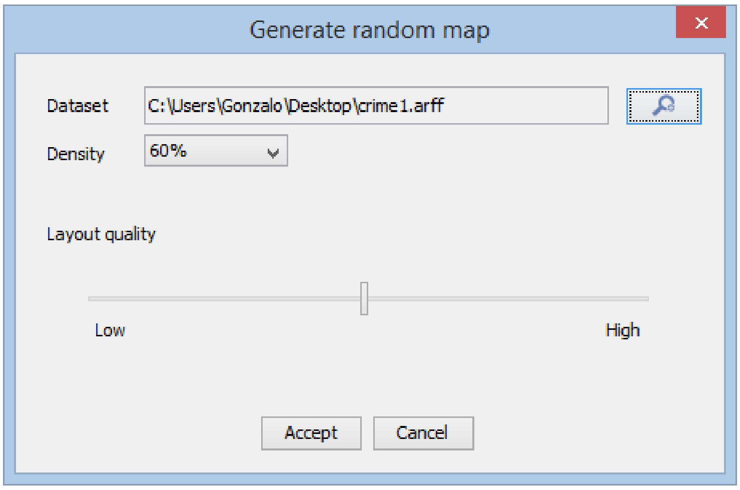
***Note***. *Other aggregation operators might be added in the future.*

## Generate from data

Sometimes, we need to build an FCM-based model fitting a dataset, but do it manually can be tedious, mainly when dealing with large datasets. Moreover, when experimenting with FCMs, researchers need to generate random models with specific density fitting the datasets at hand.

## Random topology

This option allows creating a random topology for a given dataset (in the next sections, we will explain the data file structure). The user must specify the dataset path, the density, and the layout quality. This last option includes a heuristic procedure for efficiently drawing the network topology, which minimizes both the distance between concepts and the cuts between arrows. This procedure should be time-consuming for FCM models with complex network structures, so it is advisable to keep the quality low.




### Realistic topology

This version is not available yet, but we are currently working on it. As far as we know, there is no algorithm for FCM modeling capable of estimating the causal relations from historical observations. Existing learning procedures cannot guarantee that. This option allows discovering authentic causal structures from data, thus resulting in a causal network representing the problem domain.

## Reasoning and parameter settings

### Customize settings

When running experiments or simulations, the expert needs to configure the parameters attached to the FCM reasoning rule. These options can be reached from the menu **Run | Customize settings**.

More explicitly, the domain expert can determine the reasoning rule used to update the activation values of neural concepts and the transfer function used by all concepts in the network. If the sigmoid transfer function is selected, the user can also specify the slope and offset parameters.

More explicitly, FCM Expert includes the following inference rules:

- **Kosko's activation rule**

$$a_i^{(t+1)} = f\left(\sum_{j=1}^{M} w_{ji}\, a_j^{(t)}\right), i \neq j$$

- **Kosko's activation rule with self-memory**

$$a_i^{(t+1)} = f\left(\sum_{j=1}^{M} w_{ji}\, a_j^{(t)} + a_i^{(t)}\right), i \neq j$$

- **Rescaled activation rule with self-memory**

$$a_i^{(t+1)} = f\left(\sum_{j=1}^{M} w_{ji}\left(2a_j^{(t)} - 1\right) + \left(2a_i^{(t)} - 1\right)\right), i \neq j$$

where $f(.)$ can be one of the following transfer functions:

- **Bivalent function**

$$f(x) = \begin{cases} 0, x \geq 0 \\ 1, x < 0 \end{cases}$$

- **Trivalent function**

$$f(x) = \begin{cases} -1, x < 0 \\ 0, x = 0 \\ 1, x > 0 \end{cases}$$

- **Hyperbolic function**

$$f(x) = \frac{e^{2x} - 1}{e^{2x} + 1}$$

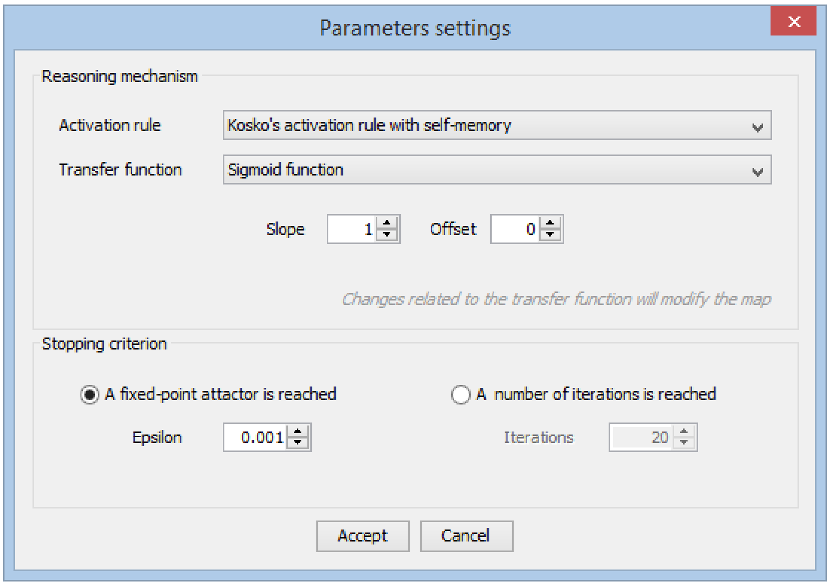
- **Saturation function**

$$f(x) = \begin{cases} 0, & x \leq 0 \\ x, 0 < x < 1 \\ 1, & x \geq 0 \end{cases}$$

- **Sigmoid function**

$$f(x) = \frac{1}{1 + e^{-\lambda(x-h)}}$$

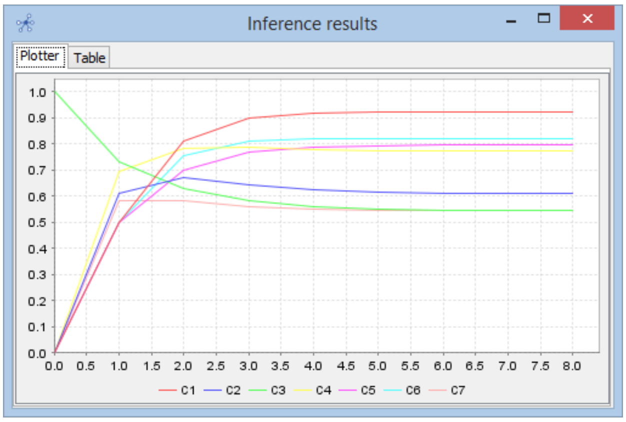
FCM Expert allows determining two stopping criteria for the reasoning process: i) the network converges to a fixed point, or ii) a maximal number of iterations is reached. If the former option is selected and the network does not converge, the inference process will stop after 20 iterations.

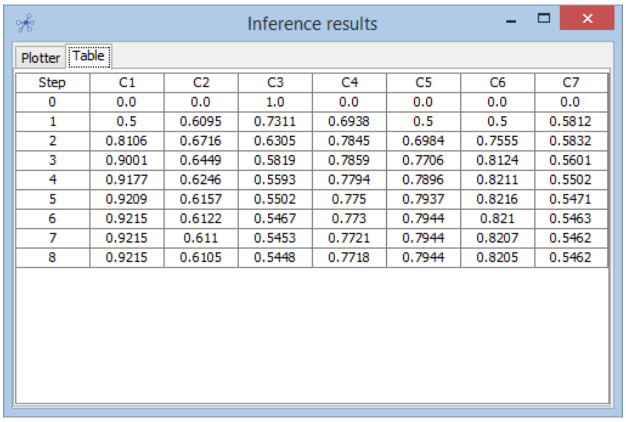



## Perform inference

This option allows performing reasoning using the provided activation values. This option can be reached from the menu **Run | Perform inference** or by clicking on the button in the toolbar. The reasoning process can be restarted at any moment by clicking the button in the toolbar.

Before performing the inference process, the user must specify the activation values of input concepts used to activate the FCM-based system (see Editing concepts). This option will summarize the inference results through a chart and a table with the activation value of concepts at each iteration.



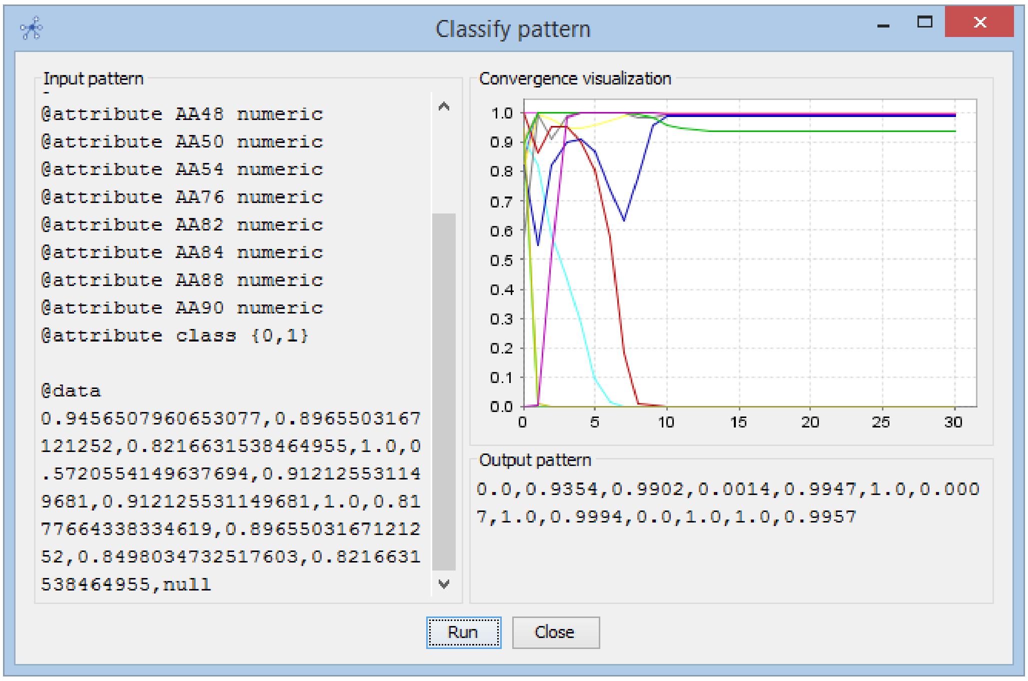

| Step | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
|---|---|---|---|---|---|---|---|
| 0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 1 | 0.5 | 0.6095 | 0.7311 | 0.6938 | 0.5 | 0.5 | 0.5812 |
| 2 | 0.8106 | 0.6716 | 0.6305 | 0.7845 | 0.6984 | 0.7555 | 0.5832 |
| 3 | 0.9001 | 0.6449 | 0.5819 | 0.7859 | 0.7706 | 0.8124 | 0.5601 |
| 4 | 0.9177 | 0.6246 | 0.5593 | 0.7794 | 0.7896 | 0.8211 | 0.5502 |
| 5 | 0.9209 | 0.6157 | 0.5502 | 0.775 | 0.7937 | 0.8216 | 0.5471 |
| 6 | 0.9215 | 0.6122 | 0.5467 | 0.773 | 0.7944 | 0.821 | 0.5463 |
| 7 | 0.9215 | 0.611 | 0.5453 | 0.7721 | 0.7944 | 0.8207 | 0.5462 |
| 8 | 0.9215 | 0.6105 | 0.5448 | 0.7718 | 0.7944 | 0.8205 | 0.5462 |

## Exploit the network

This function allows classifying a completely new instance or simply simulate a state vector. It can be reached from the menu **Run | Exploit the network**. In the first case, the FCM model may comprise decision concepts properly configured, and the input must match with the ARFF format.

The right panel shows the inference results. We plotted the activation values of all concepts in the network and the current activation value with the inferred decision class in the right panel.

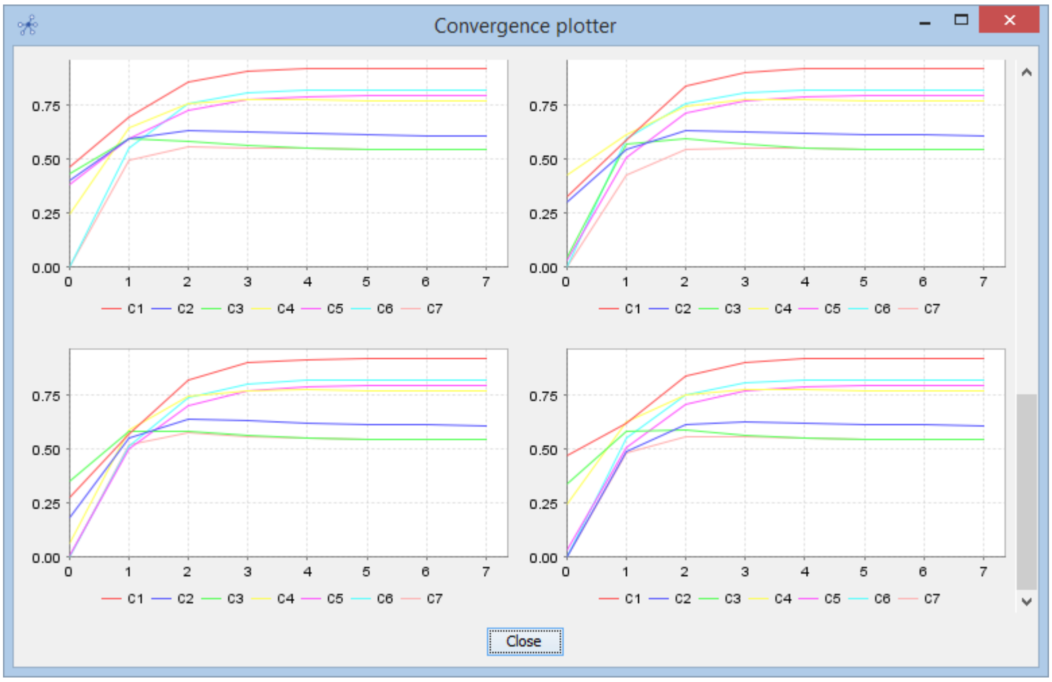
For more information on ARFF files, click here.




## Convergence plotter

This option allows plotting the activation values of all map neurons for each instance stored in a given dataset as a tool to explore the system stability and consistency in simulations. It can be reached from the menu **Run | Convergence plotter** or by clicking on the button in the toolbar.

To trigger this command, the expert must specify the path of the base with the input instances to be evaluated. The knowledge base of historical data should be an ARFF file.



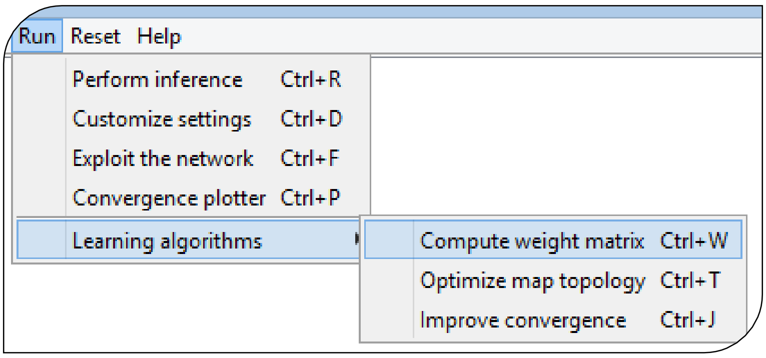

# Learning algorithms

The key features of FCM Expert rely on its Machine Learning algorithms. FCM Expert includes unsupervised and supervised algorithms to compute the weight set defining the FCM model, optimize the network topology and improve the system convergence without losing information.

***Note**: these algorithms are not available in the trial version.*

## Compute weight matrix

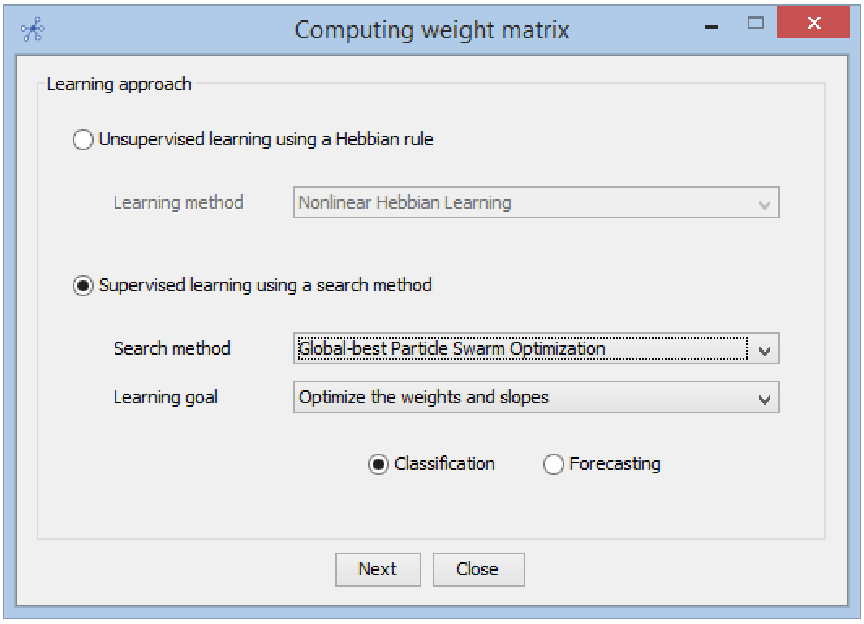
This option allows automatically learning the weight matrix attached to the FCM network. These algorithms are perhaps the most important since they define system behavior. Such methods can be reached from the menu **Run | Learning algorithms | Compute weight matrix**.



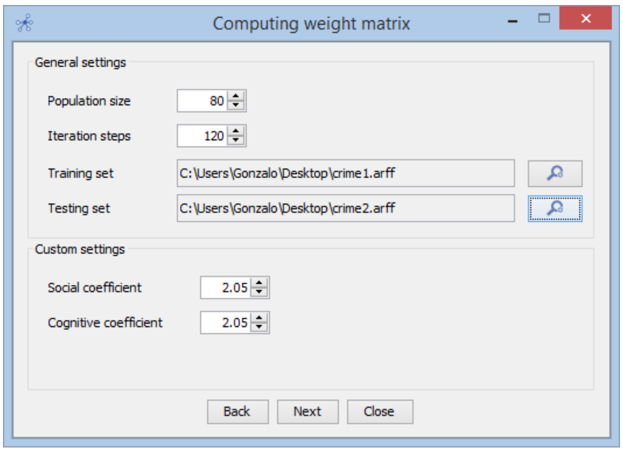

FCM Expert implements the following Hebbian-based algorithms: the ***Differential Hebbian Learning***, the ***Balanced Differential Algorithm***, the ***Nonlinear Hebbian Learning,*** and the ***Improved Nonlinear Hebbian Learning***. In these learning algorithms, the expert must specify two parameters related to the weight decay and the learning rate and the example to be used to train the model.

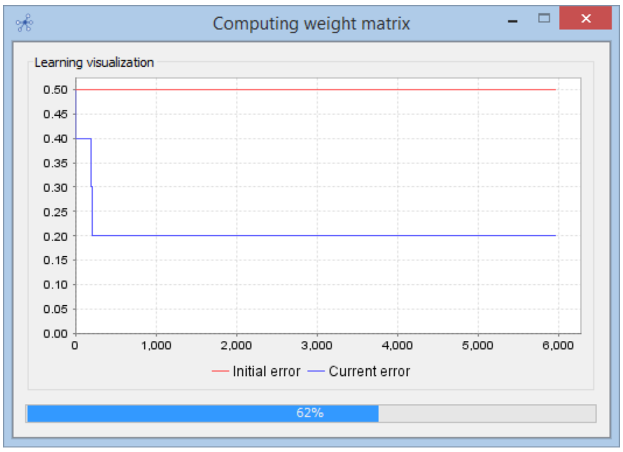
We strongly suggest using supervised algorithms when facing classification problems since Hebbian-based methods[1] often report poor performance in these scenarios. In the *supervised context*, the learning goal is to compute a weight matrix minimizing the dissimilarity between the expected outcomes and the predicted ones. FCM Expert goes a step further since it also allows optimizing the parameters attached to the sigmoid transfer function. This suggests that the expert may select the parameters to be optimized: the weight set, the slope, and offset attached to each sigmoid concept in the cognitive network. If the FCM model does not comprise any sigmoid concept, only the weight set will be optimized.

FCM Expert implements various population-based search methods. These meta-heuristics are *Differential Evolution*, Variable *Mesh Optimization*, *Local-best Particle Swarm Optimization*, Global-best Particle Swarm Optimization, and Real-coded Genetic Algorithms.



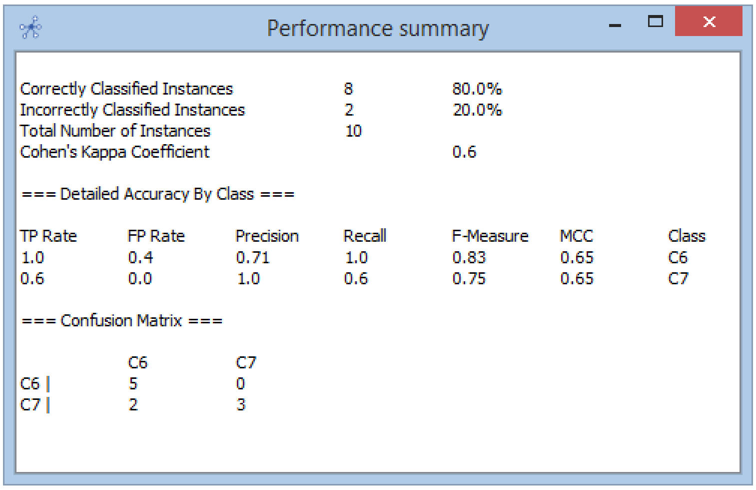

As a next step, the expert must configure the parameters related to the selected search methods, such as the number of artificial agents in the population and the number of iterations. Moreover, the user must specify the path of the historical data file (to be provided as an ARFF file).




In the case of FCM-base classifiers, the expert may specify separate testing set to evaluate the generalization capability of the learned model. F-measure, accuracy, Cohen's Kappa coefficient, recall, and the confusion matrix are some of the statistics used to assess the model.

[1] We will remove Hebbian Learning algorithms from FCM Expert in the next update.




During the learning process, the modifications on weights are updated in real-time. Furthermore, FCM Expert will display a dialog summarizing the learning progress at each step. It should be remarked that, as far as we know, there is no learning method to learn authentic causal structures from historical data automatically. That is why domain experts should examine the “correctness” of each weight.

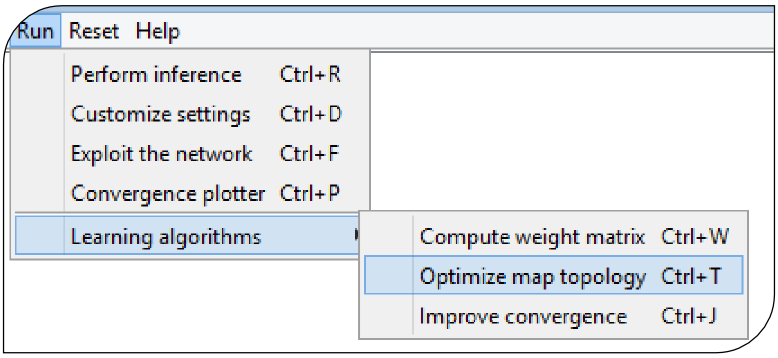
**Further reading**:

- *G. Nápoles, I. Grau, R. Bello, R. Grau: Two-steps learning of Fuzzy Cognitive Maps for prediction and knowledge discovery on the HIV-1 drug resistance. Expert Systems with Applications, 41 (2014) 821–830.*

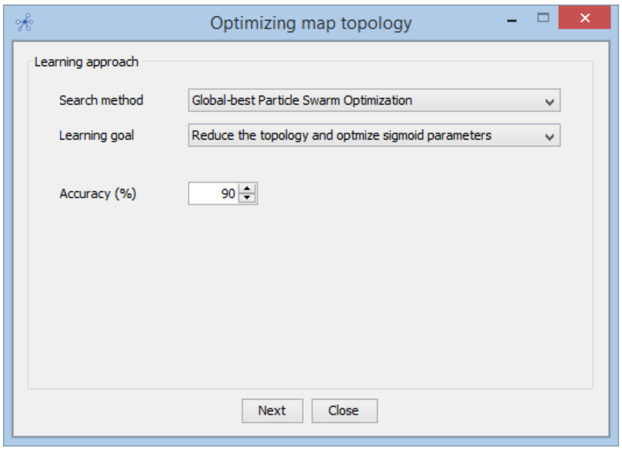
## Optimize network topology

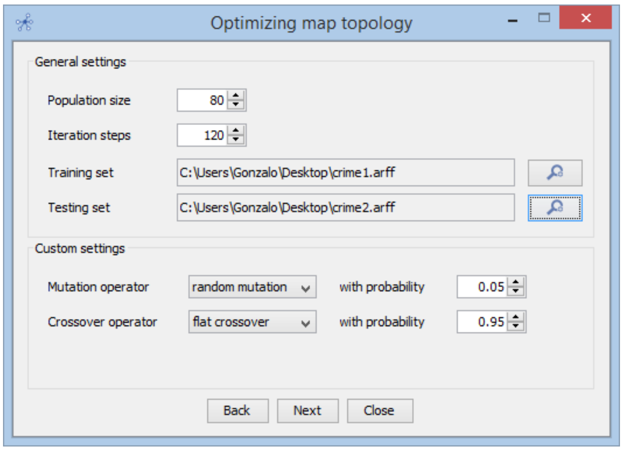
Sometimes, we need to handle FCMs with very complex structures when modeling systems comprised of many variables. In these situations, some concepts could be redundant, thus negatively affecting both the network’s performance and interpretability.

This learning algorithm attempts to overcome this problem by optimizing the network topology (using an optimization approach) without losing relevant information. It can be reached from the menu **Run | Learning algorithms | Optimize map topology**.




The learning goal of this algorithm is to find the minimal subset of concepts capable of preserving, to some extent, the original performance. Since we focus on FCM-based systems used in pattern classification scenarios, the performance could be measured in terms of accuracy. The expert must configure the required parameters, such as the search method and the desired accuracy threshold towards this goal. This algorithm will not produce models with prediction rates below that threshold.




Similarly to the above algorithms, the expert must configure the parameters related to the selected search methods, such as the number of artificial agents in the population, the number of iterations, etc. Moreover, the user must specify the path of the historical data to learn from.

It should be highlighted two novel features of this method. First, we use continuous heuristic search methods (e.g., Particle Swarm Optimization) to solve the constricted, combinatorial problem. This can be achieved by discretizing the continuous space into non-homogeneous partitions, each denoting a specific state, where the size of each partition is heuristically determined. Second, the learning method recalculates the values of sigmoid parameters to compensate for the alterations to the FCM topology. Of course, this second feature is only applicable to FCM-based systems using sigmoid neurons.

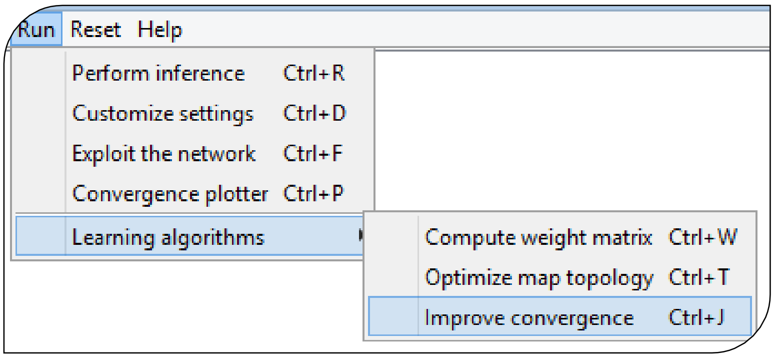
**Further reading**:

- *G. Nápoles, I. Grau, R. Bello, R. Grau: Two-steps learning of Fuzzy Cognitive Maps for prediction and knowledge discovery on the HIV-1 drug resistance. Expert Systems with Applications, 41 (2014) 821–830.*

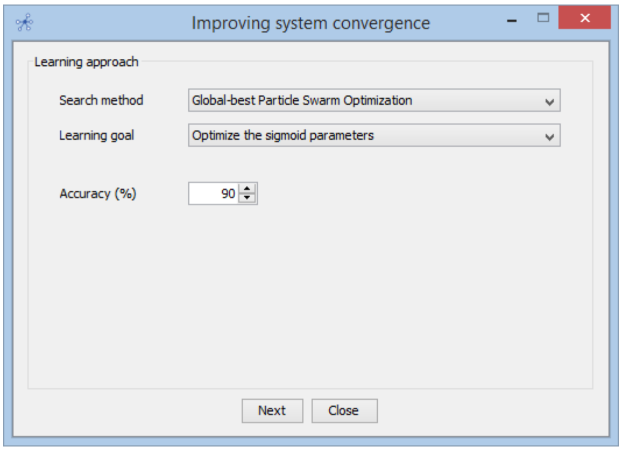
## Improve system convergence

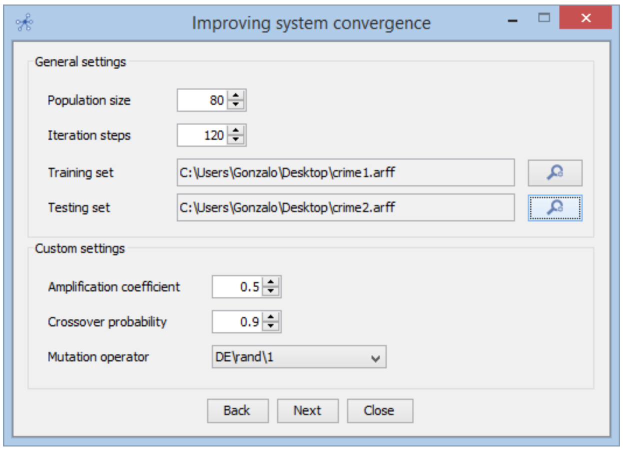
This algorithm allows improving the FCM convergence without losing information. Most error-driven learning methods for computing the weights do not consider stability issues when estimating the final solution. As a result, we obtain FCMs with high prediction rates but unable to provide stable solutions.

The learning goal of this algorithm is to estimate the sigmoid parameters of each sigmoid function leading to improved convergence features without affecting the FCM prediction rates. This method can be reached from the menu **Run | Learning algorithms | Improve convergence**.




FCM Expert implements this learning algorithm for both scenario analysis and pattern classification cases. Like the other supervised learning algorithms, the user must specify a training set where each attribute matches a specific map concept. Additionally, the user must specify the search method and the accuracy level defining the expected deviation to the original responses.




FCM Expert will show a dialog summarizing the learning progress at each step. Besides, the user may specify a test dataset set to evaluate the generalization capability of the learned model.

Recently, we analytically proved that, sometimes, under the weights constriction, the algorithm will be unable to improve the system convergence without harming the accuracy ☹.

**Further reading**:


- *G. Nápoles, R. Bello, K. Vanhoof: How to improve the convergence on sigmoid Fuzzy Cognitive Maps? Intelligent Data Analysis, 18 (2014) S77–S88.*
- *G. Nápoles, E. I. Papageorgiou, R. Bello, K. Vanhoof: On the convergence of sigmoid Fuzzy Cognitive Maps. Information Sciences, 349–350 (2016) 154–171.*
- *G. Nápoles, L. Concepción, R. Falcon, R. Bello, K. Vanhoof: On the Accuracy-Convergence Trade-off in Sigmoid Fuzzy Cognitive Maps. IEEE Transactions on Fuzzy Systems, 2017.*


# Resetting parameters

## Reset inference process

This option allows cleaning the execution tail for the current inference but preserving the initial activation of map concepts. It can be reached through the menu **Reset | Inference process**.

## Reset activation vector

This option allows cleaning the execution tail for the current inference and setting the initial activation of map concepts to zero. It can be reached through the menu **Reset | Activation vector**.

## Randomize weights

This option allows randomizing the weight matrix with values comprised within the [-1,1] interval. It can be reached through the menu **Reset | Weight matrix**.