

NeuroMem[®] Knowledge Builder

*Experiment Machine Learning with a NeuroMem neural
network*



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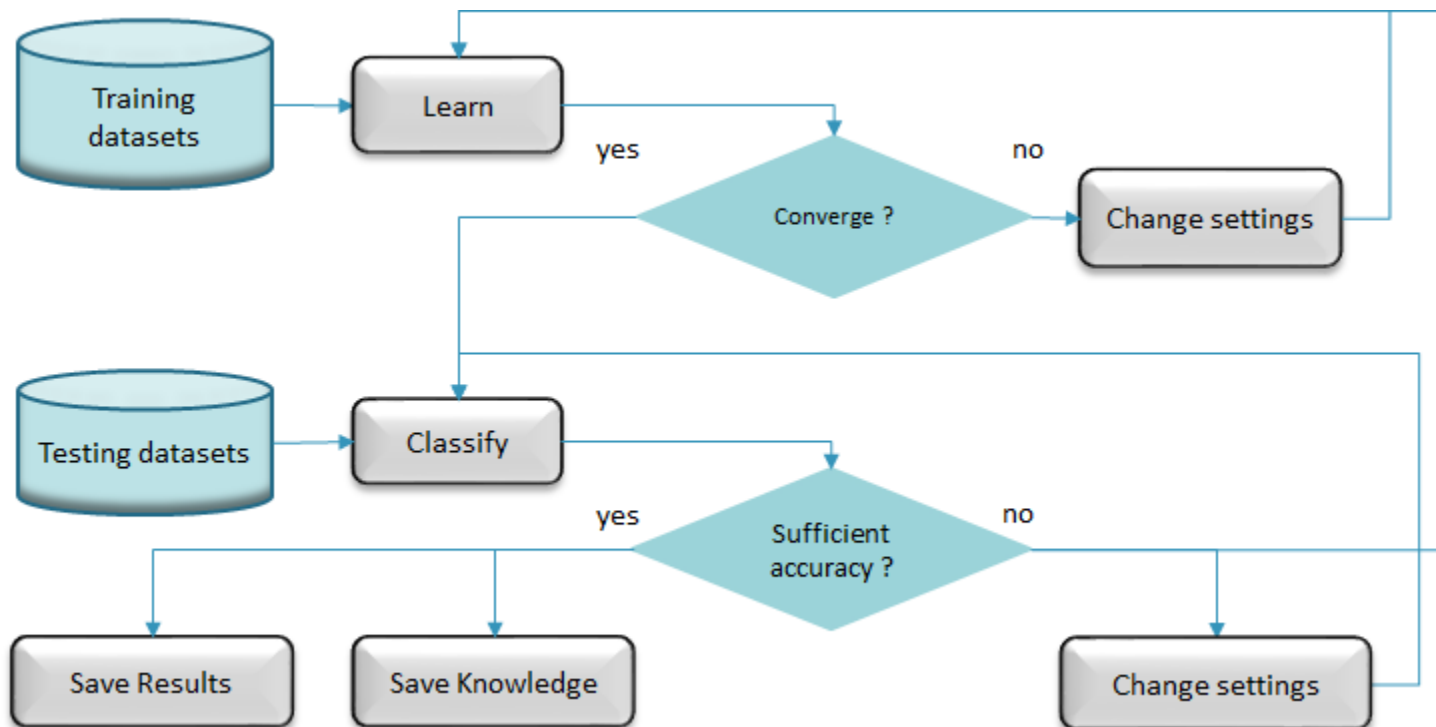
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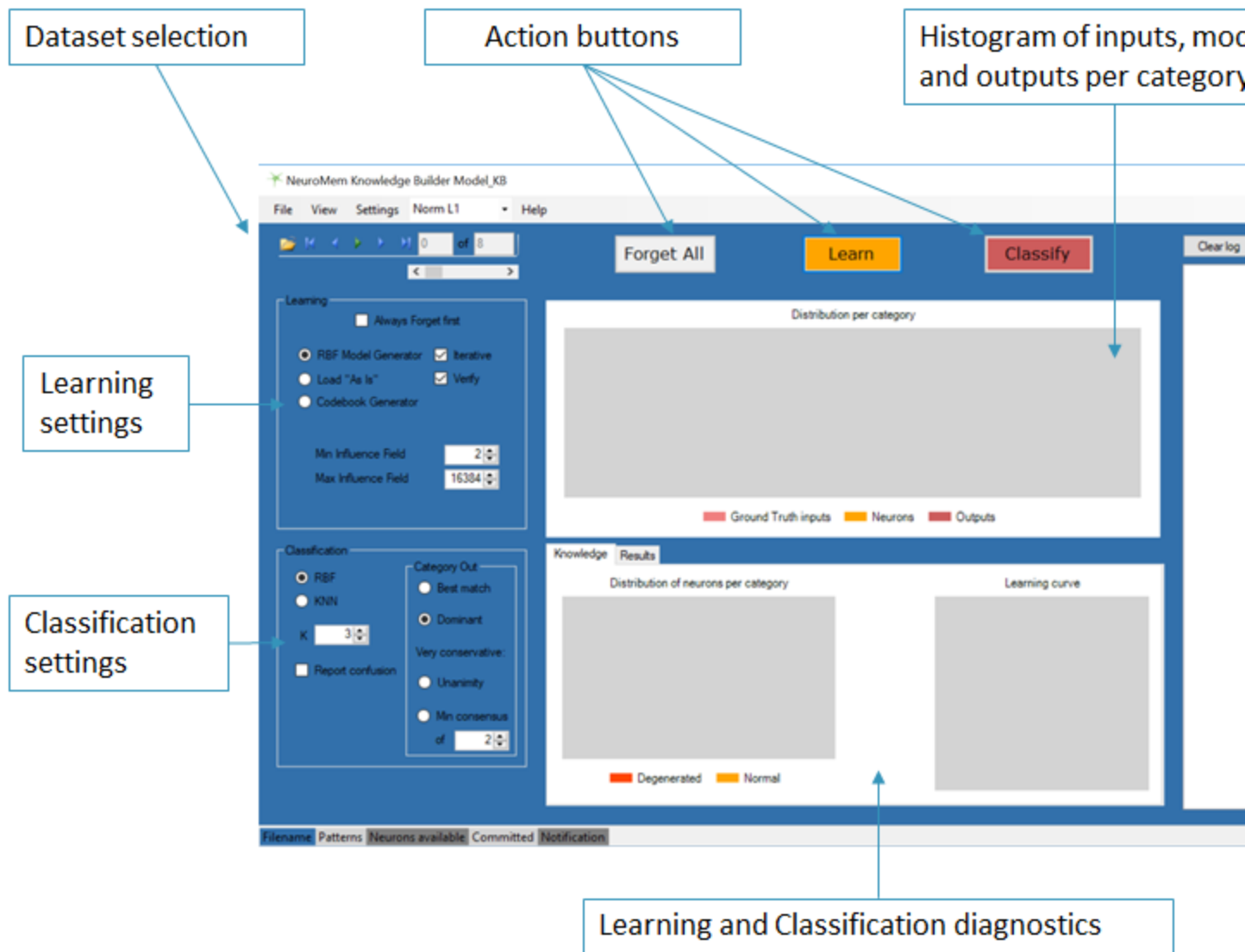
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1 Very simple work flow, few mouse clicks, rich and detailed diagnostics



2 Powerful machine learning with the simplest user interface



3 Prepare your datasets

The application can load files saved in comma delimited format and complying with the simple format described below. Examples of datasets are supplied with the application.

Because the NeuroMem neurons each have a memory capable of holding patterns of 256 bytes, your pattern data P must be converted to fit in an array of dimension L with $L < 256$ and with values ranging between [0, 255].

PatternID	ParentID	Context (*)	CatGT	Length	P[0]	P[1]	...	P[L]
-----------	----------	-------------	-------	--------	------	------	-----	------

(optional content)	(optional content)	(optional content)						
Index of the pattern in the input list	User-defined index (a file name, XY position, time stamp, etc.)	Value identifying the type of feature encrypted in the vector.	Ground Truth Category value assigned to the vector	Number of components L in the vector	L values of the vector components			
Default= automatic increment of 1, starting at 0	Default =0	Range=[1, 127] Default = 1	Range=[1,32768] 0 = "background" 0xFFFF = "unspecified"	Default Range=[1,256] for all NeuroMem platform, except Intel QuarkSE/Curie =[1,128]	Values ranging between [0,255]			

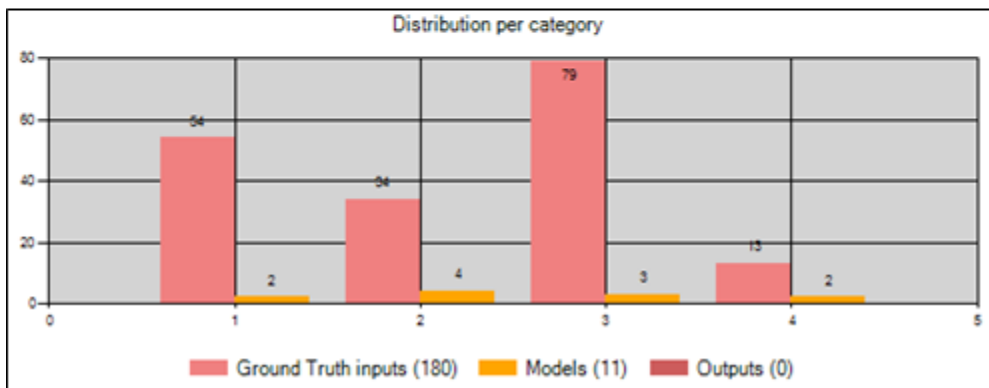
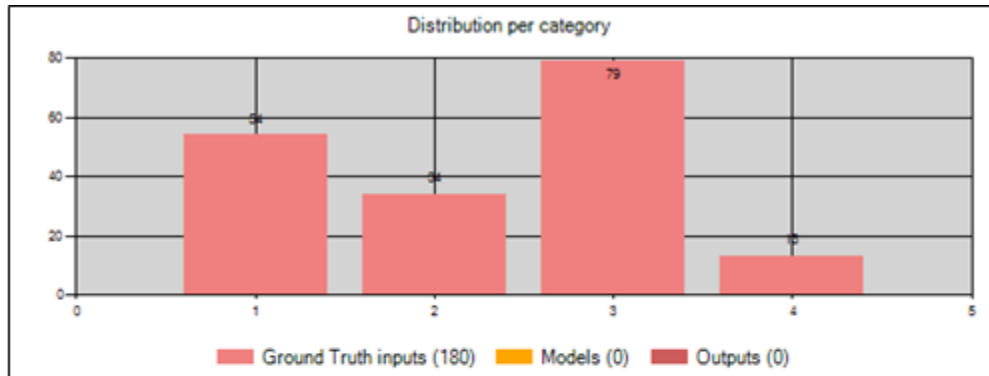
4 Load your training set and survey



Inputs:
Vectors, with a
Ground Truth c

This simple display immediately shows if all categories are evenly represented in the training set or not.

5 Learn in RBF mode



Inputs:
Vectors, with a
Ground Truth c

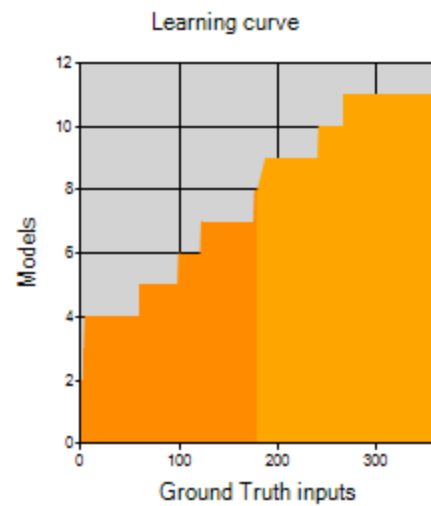
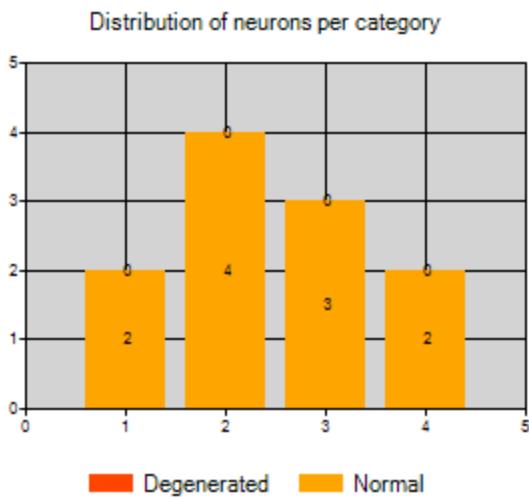
Learn

Models:
Inputs retained
to describe the

5.1 Learning diagnostics at a glance

Upon learning, the Knowledge Tab is updated and reports the distribution of the committed neurons per category and the learning curve.

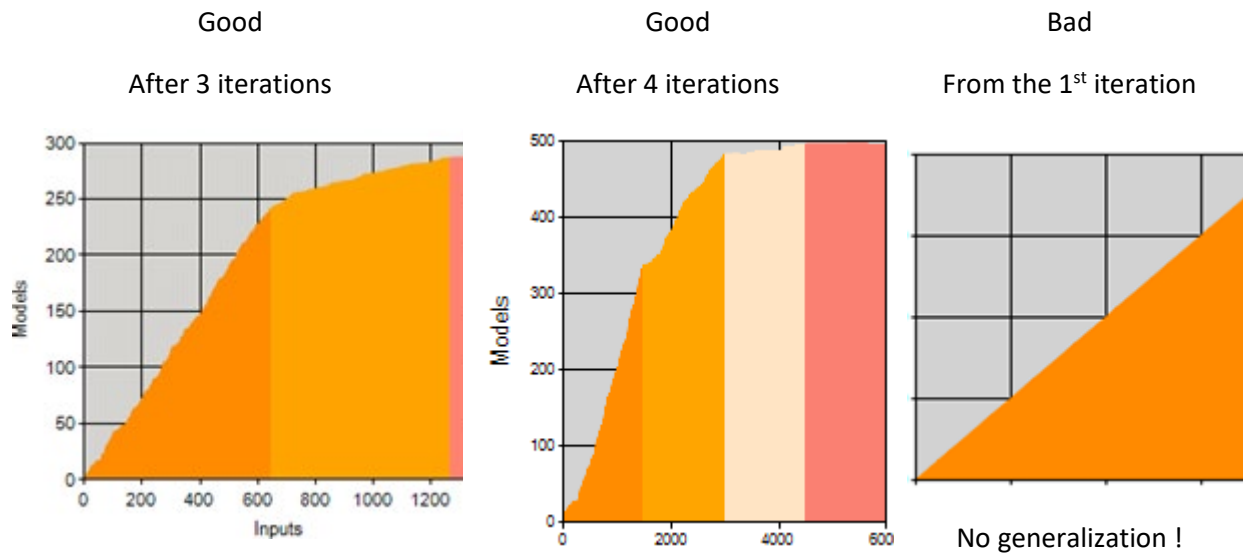
- 1) The reporting of degenerated neurons in the histogram is a flag that some of the categories in the learned dataset have overlap in the decision space and you can expect uncertainties between them.
- 2) The learning curve reports how many neurons are committed as input patterns are learned. This curve should be asymptotic (see next paragraph). Provided that the "Iterative" checkbox is marked, the Number of colors in the plot indicates how many iterations were necessary until the learning converges and no more neurons need to be committed to model the decision space.



5.2 Check learning curve

Verify at a glance that the learning curve is correct. An asymptotic curve reflects that the neurons can model your training set while over-generalizing and converging.

- X-axis: learned vectors
- Y-axis: retained vectors to model the knowledge



5.3 Observe the learning compression factor per category

The bars of the histogram of the Models should be significantly lower than the ones of the Ground truth categories. This means that the neurons are capable of generalization and validates the relevancy of the input vectors to model the GT categories.

The ratio between the number of input patterns (green) and the number of models retained by the neurons (orange) is an indicator of how well the neurons can model a specific category given the learned training set.

The smaller the ratio (Neurons/Inputs), the better the generalization performed by the neurons. Note that the accuracy of this generalization still must be verified with a Diagnostics after recognition.

<p>Good generalization across all categories:</p> <p>A few neurons model a large number of inputs.</p> <p>Will they be sufficient to deliver a good accuracy in recognition of new vectors?</p>	 <table border="1"> <thead> <tr> <th>Models</th> <th>Neurons</th> <th>Inputs</th> </tr> </thead> <tbody> <tr> <td>1</td> <td>54</td> <td>2</td> </tr> <tr> <td>2</td> <td>34</td> <td>4</td> </tr> <tr> <td>3</td> <td>79</td> <td>3</td> </tr> <tr> <td>4</td> <td>13</td> <td>2</td> </tr> </tbody> </table>	Models	Neurons	Inputs	1	54	2	2	34	4	3	79	3	4	13	2																		
Models	Neurons	Inputs																																
1	54	2																																
2	34	4																																
3	79	3																																
4	13	2																																
<p>Poor generalization across all categories:</p> <p>A ratio (Models ÷ Input) too close to 1.</p> <p>Does the ratio improve when learning more Inputs?</p>	 <table border="1"> <thead> <tr> <th>Models</th> <th>Neurons</th> <th>Inputs</th> </tr> </thead> <tbody> <tr> <td>1</td> <td>129</td> <td>116</td> </tr> <tr> <td>2</td> <td>134</td> <td>118</td> </tr> <tr> <td>3</td> <td>118</td> <td>106</td> </tr> <tr> <td>4</td> <td>143</td> <td>132</td> </tr> <tr> <td>5</td> <td>148</td> <td>134</td> </tr> <tr> <td>6</td> <td>117</td> <td>108</td> </tr> <tr> <td>7</td> <td>218</td> <td>172</td> </tr> <tr> <td>8</td> <td>190</td> <td>164</td> </tr> <tr> <td>9</td> <td>144</td> <td>121</td> </tr> <tr> <td>10</td> <td>160</td> <td>137</td> </tr> </tbody> </table>	Models	Neurons	Inputs	1	129	116	2	134	118	3	118	106	4	143	132	5	148	134	6	117	108	7	218	172	8	190	164	9	144	121	10	160	137
Models	Neurons	Inputs																																
1	129	116																																
2	134	118																																
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5	148	134																																
6	117	108																																
7	218	172																																
8	190	164																																
9	144	121																																
10	160	137																																
<p>Uneven generalization across categories:</p> <p>Accuracy and confusion may vary depending on the categories</p>	 <table border="1"> <thead> <tr> <th>Models</th> <th>Neurons</th> <th>Inputs</th> </tr> </thead> <tbody> <tr> <td>1</td> <td>37</td> <td>13</td> </tr> <tr> <td>2</td> <td>182</td> <td>94</td> </tr> <tr> <td>3</td> <td>144</td> <td>105</td> </tr> <tr> <td>4</td> <td>206</td> <td>76</td> </tr> </tbody> </table>	Models	Neurons	Inputs	1	37	13	2	182	94	3	144	105	4	206	76																		
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1	37	13																																
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In addition to the histogram of the committed neurons per category, the text log reports statistics about their maximum dimensions of the AIFs per category, the existence of degenerated neurons per category of any, and the level of generalization/compression per category.

5.4 Knowledge profile in details

Learn_RBF, Minif=2, Maxif=16384

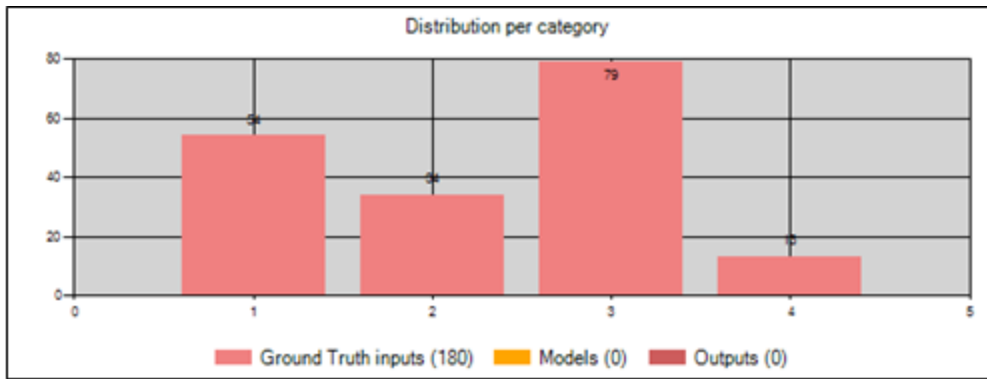
Neurons	Total	Cat0	Cat1	Cat2	Cat3	Cat4	Cat5	Cat6	Cat7	Cat8	Cat9	Cat10	Cat11
Percentage	100	0	25.64	7.69	2.56	10.26	7.69	2.56	2.56	10.26	5.13	5.13	20.51
Count	39	0	10	3	1	4	3	1	1	4	2	2	8
Max AIFs	6005	0	4904	5458	5254	5031	5133	6005	5133	5205	5445	5637	5404
Neurons/Inputs	8.88	n/a	11.76	5.77	3.33	16.67	10.34	3.03	14.29	11.11	5.41	3.64	15.69

5.5 Corrective Actions and Improvements:

- Verify accuracy of the GT categories in the dataset
- Learn additional training set
- Re-consider the relevancy of the dataset (i.e. feature vectors) to classify and discriminate the intended population of objects or events

6 Classify the training set in RBF mode

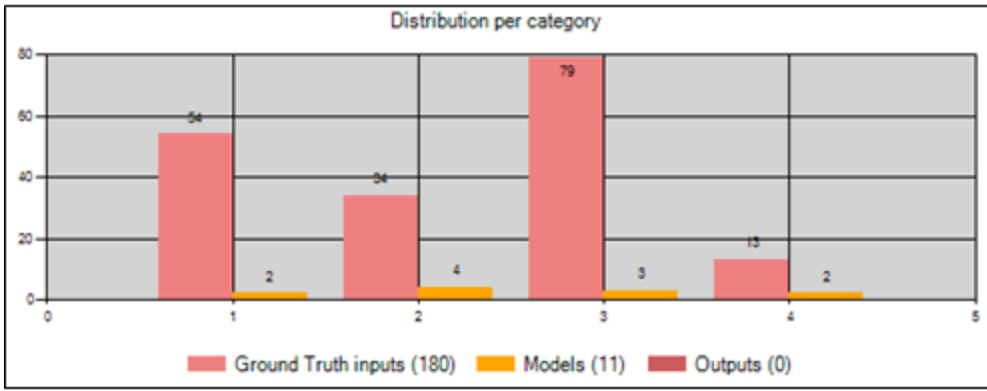
Click the Classify button and verify that the committed neurons recognize the entire training set correctly. This operation is very important to comprehend the consistency and relevancy of the training dataset and consequently the validity of the knowledge base it can generate.



Inputs:
Vectors, with a
Ground Truth c

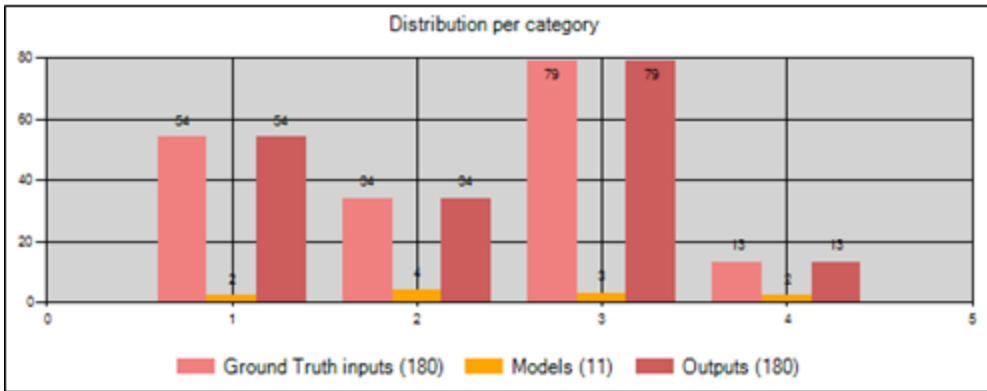
Learn

Models:
Inputs retained
to describe the



Classify

Outputs:
Vectors and the
categories



6.1 Definitions

6.1.1 Accuracy code

The Accuracy is based on the comparison of the Category Out (CatOut) and the Ground Truth category (CatGT).

Since the Category Out is a function of the selected consolidation rule (best match, dominant, unanimity, minimum consensus), changing the rule can change the accuracy.

- Correct CatOut == CatGT
- Incorrect CatOut != CatGT
- NA Case of a non-existent Ground Truth Category

6.1.2 Status code

The Status code is based on the responses of the top N firing neurons. In the case of a KNN classification, the value N is equal to the select K value. In the case of an RBF classification, N can be less than K.


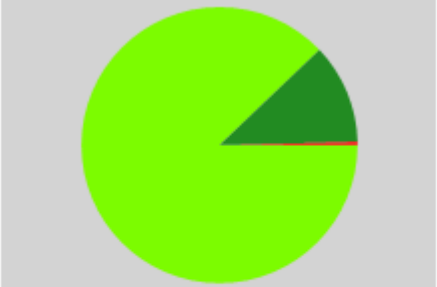
- ID, Identified All firing neurons recognize the same category
- UNC, Uncertain All firing neurons do not recognize the same category
- UNK, Unknown CatOut is equal to zero

6.2 Observations:

Accuracy should be 100% since the neurons have learned the entire training set.

A certain level of uncertainty is acceptable.

Unknown are unacceptable

Ideal	Acceptable	Exceptional (**)
<p data-bbox="266 1232 613 1260">% Accuracy per Recognition Status</p>  <p data-bbox="306 1667 561 1694">Correct_ID 100.00%</p>		<p data-bbox="1018 1232 1365 1260">% Accuracy per Recognition Status</p>  <p data-bbox="1050 1581 1321 1688"> Correct_ID 87.87% Correct_UNC 11.75% Incorrect_UNC 0.34% NA_UNK 0.03% </p>

The histograms of the Ground Truth and Output categories should be identical. If not, go to Corrective Actions.

If uncertainties exist in moderate amount, you can identify the categories which are close to one another and may introduce confusion in future classifications:

- Check "Confusion matrix"
- Open the View\Details\Uncertain and observe the recognized categories

If uncertainties exist in significant amount, consider corrective actions:

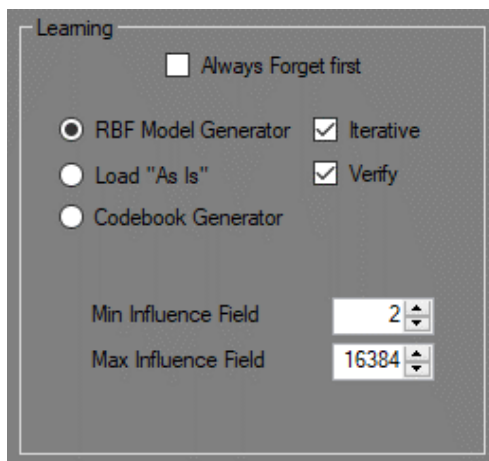
- Verify accuracy of the GT categories in the dataset
- Learn additional training set
- Re-consider the relevancy of the dataset (i.e. feature vectors) to classify and discriminate the intended population of objects or events

(**) Unknown recognition of vectors from the training set should not occur except if the consolidation rule requires a minimum number of consensus.

In KNN mode, it is possible to observe incorrect recognition if a pattern falls within the influence field of the correct neuron but is at a closer distance from another neuron with a different category.

7 Continue or Learn differently

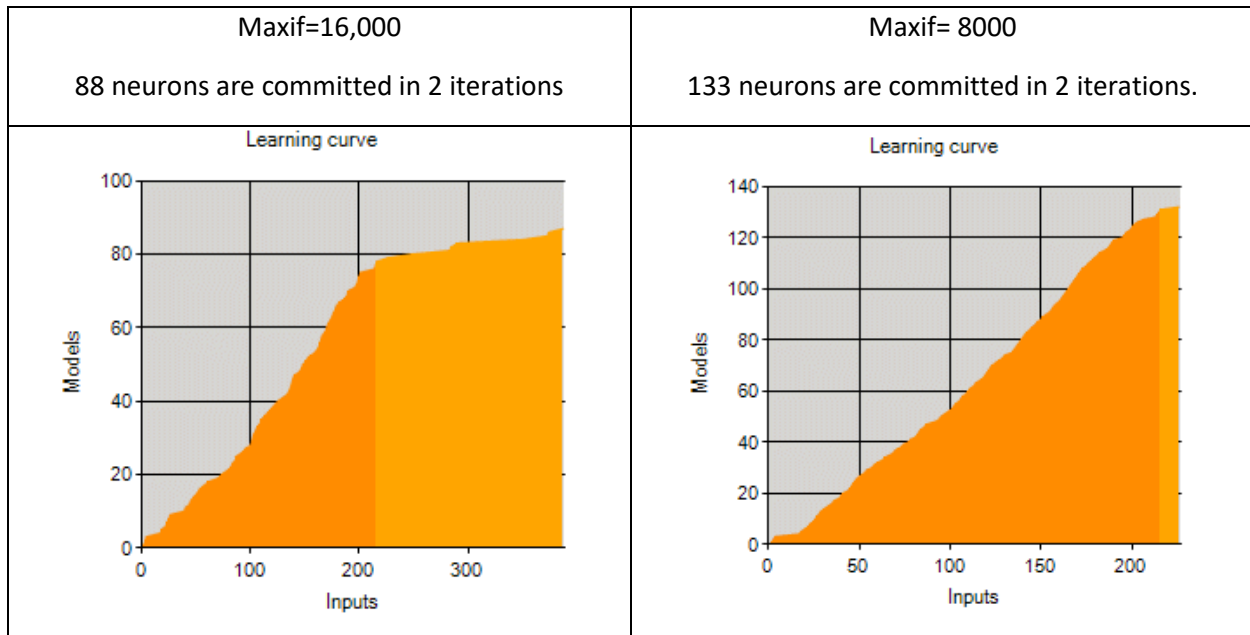
In order to improve the accuracy of the recognition, the NeuroMem Knowledge Builder makes it easy to rebuild a new knowledge from scratch using different settings described below:



If the checkbox “Always Forget First” is not marked, make sure to click the Forget button prior to re-learning the same training set with the new settings.

7.1 Maximum Influence Field

- The higher, the more liberalism and over-generalization. Tendency to model the decision space with few neurons with large influence fields.
- The lower the more conservatism. Tendency to model the decision space with more neurons, but with smaller influence fields.



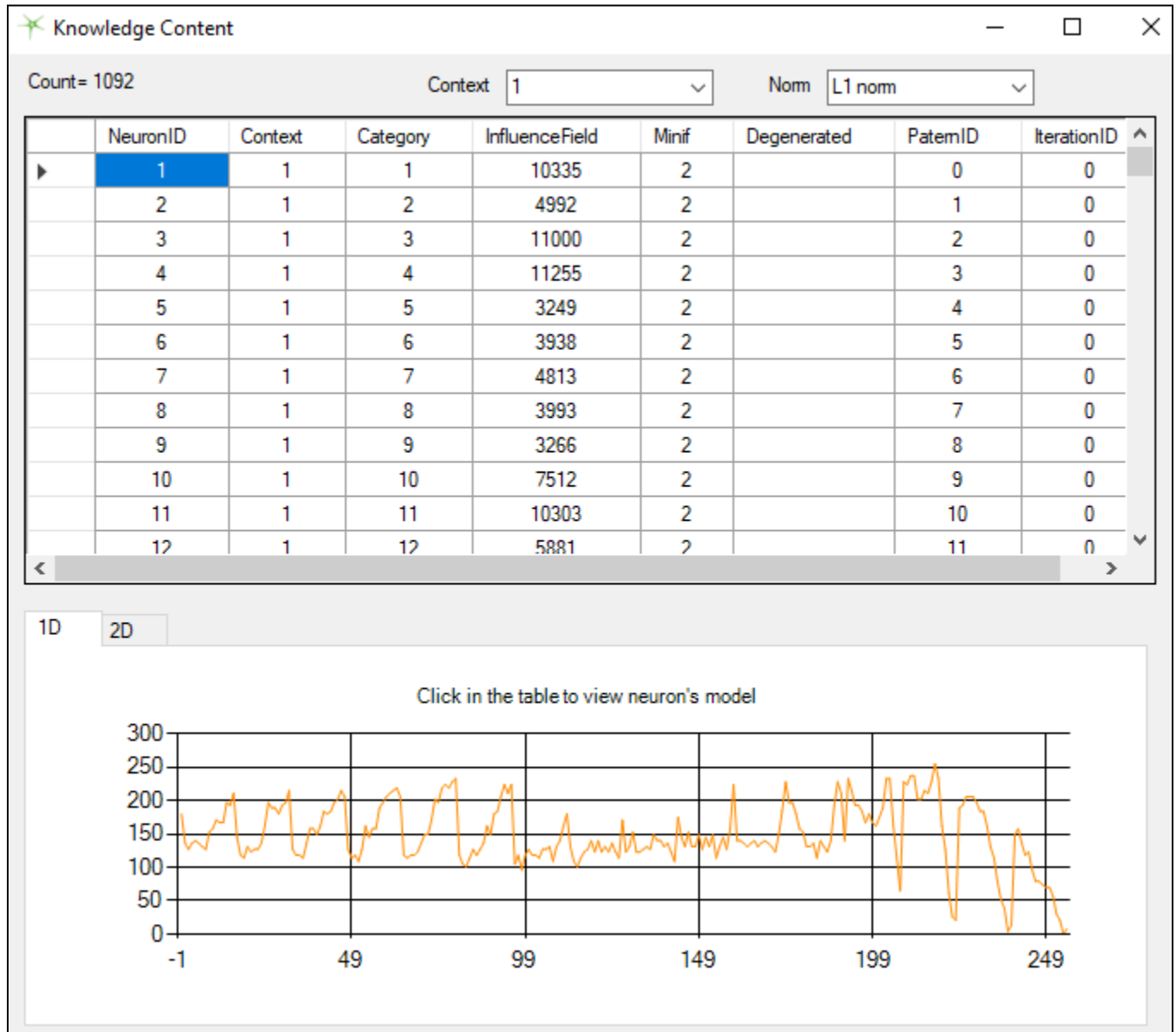
7.2 Minimum Influence Field

- The higher, the more uncertainties since the neurons are prevented to shrink their influence field under this Min value
- Increasing the Minif helps separate the categories with and without confusion, flag outliers and reveal non discriminating features
- The categories with possible confusion may later be handled differently by introducing the use of a different datasets representing different feature in order to waive uncertainties

7.3 L1 versus LSup norm

- The norm defines how to calculate the distance between the input patterns and the models stored in the neurons.

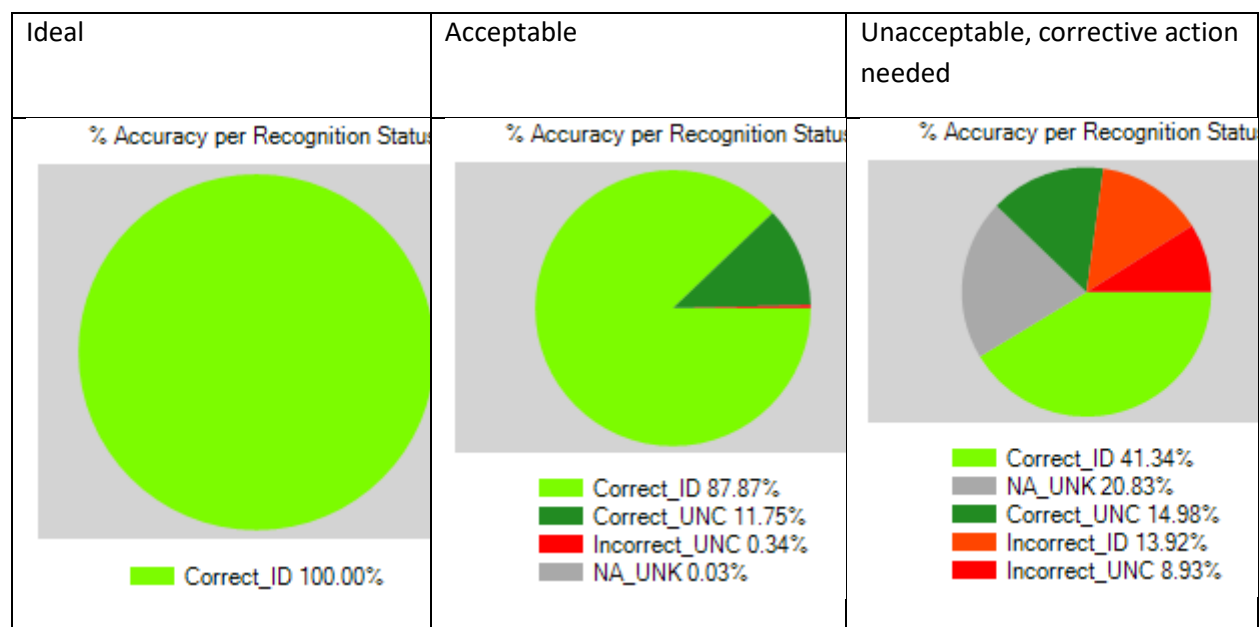
8 Review knowledge



9 Classify a new testing set and observe

9.1 Results at a glance

The true accuracy of a knowledge is rated by observing its classification of examples never seen before. It is realistic to expect false classifications at first, but NeuroMem can easily correct these inaccuracies by learning new examples. Multiple iterations between learning and validation might be necessary to obtain a robust knowledge which can adapt to the variations of your objects.

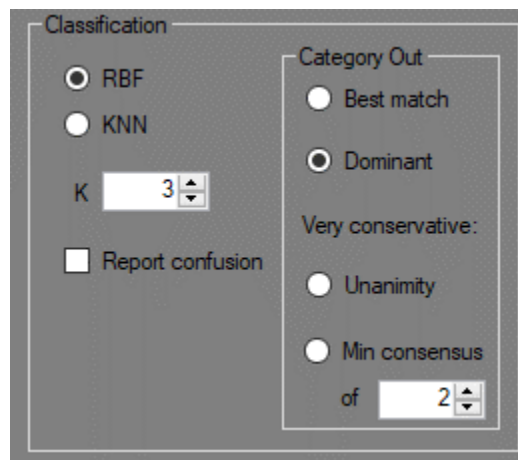


- The ideal case is 100% Correct with 100% Identified.
- The worst case is to have any Identified Incorrect.
- A remedy to minimize the ID_Incorrect consists of turning them into UNC (correct or incorrect) so they can be isolated and processed differently.

9.2 Change consolidation rules

Multiple neurons can recognize a same input vector and be in agreement with its classification, or not. In such case, the consolidation rule is applied to output a single category value, Cat Out.

Cat Out is the value used to determine if the recognition is accurate or not by comparing it to the Ground Truth category. Changing the decision rule can affect the percentages of correct and incorrect.



9.2.1 K best responses

The recognition of a vector will return up to K triplet values (Cat, Dist, Nid) in the case of an RBF classification, and exactly K triplet values (Cat, Dist, Nid) in the case of a KNN classification. Typical values are 1, 3 or 5.

9.2.2 Single Category Out

Out of the K best responses, the global response or category Out can be defined as

- Best Match: The category of the first firing neuron (Cat1)
- Dominant: The dominant category among the K firing neurons
- Unanimous: The category unanimously recognized by the K firing neurons; category Unknown otherwise
- Min consensus: The dominant category if it has a minimum count; category Unknown otherwise

	Cat GT	Length	Status	Accuracy	CatOut	Cat 1	Dist 1	Nid 1	Cat 2	Dist 2	Nid 2	Cat 3
	1	192	UNC	Incorrect	2	1	1017	6	2	1740	10	2
	1	192	UNC	Incorrect	2	1	1475	6	2	1986	10	2
	1	192	UNC	Incorrect	2	1	479	6	2	1966	10	2
	1	192	UNC	Incorrect	2	1	435	6	2	2018	10	2
	1	192	UNC	Incorrect	2	1	337	6	2	2416	7	2
	1	192	UNC	Incorrect	2	1	302	6	2	2485	7	2
	2	192	UNC	Incorrect	1	1	2003	6	2	11519	2	
	1	192	UNC	Incorrect	2	1	1348	6	2	1857	10	2
	1	192	UNC	Incorrect	2	1	495	6	2	1746	10	2
	2	192	UNC	Incorrect	1	1	2016	6	2	11520	2	
	2	192	UNC	Incorrect	1	1	1924	6	2	11570	2	

In the above example, the selected vector has a Ground Truth category of 1 and the first 3 firing neurons recognize respectively the categories 1, 2 and 2

With Dominant Category rule, CatOut=2, → Accuracy Status = Incorrect

With Closest Category rule, CatOut=1 → Accuracy Status = Correct

9.3 Details per category

Accuracy	Total	Cat0	Cat1	Cat2	Cat3	Cat4	Cat5	Cat6	Cat7	Cat8	Cat9	Cat10
Correct	80.36%	0%	9.77%	11.85%	7.18%	8.22%	6.88%	6.88%	9.16%	7.99%	5.23%	7.18%
> ID	65.13%	0%	8.25%	9.39%	6.40%	6.45%	5.63%	5.66%	7.92%	5.69%	4.77%	4.97%
> UNC	15.23%	0%	1.52%	2.46%	0.79%	1.78%	1.24%	1.22%	1.24%	2.31%	0.46%	2.21%
Incorrect	10.94%	0%	0.58%	0.23%	1.14%	1.40%	1.45%	1.24%	0.81%	1.24%	0.74%	2.11%
> ID	5.43%	0%	0.30%	0.05%	0.69%	0.53%	0.71%	0.58%	0.51%	0.66%	0.56%	0.84%

> UNC	5.51%	0%	0.28%	0.18%	0.46%	0.86%	0.74%	0.66%	0.30%	0.58%	0.18%	1.27%
NA	8.71%	0%	0.66%	0.18%	1.83%	0.81%	0.86%	1.04%	0.46%	0.81%	1.27%	0.79%
> UNK	8.71%	0%	0.66%	0.18%	1.83%	0.81%	0.86%	1.04%	0.46%	0.81%	1.27%	0.79%

9.4 Details per vector

Global response 1st firing neuron 2nd firing neuron → K neur

	Cat GT	Length	Status	Accuracy	CatOut	Cat 1	Dist 1	Nid 1	Cat 2	Dist 2	Nid 2	Cat 3
	1	192	UNC	Incorrect	2	1	1017	6	2	1740	10	2
	1	192	UNC	Incorrect	2	1	1475	6	2	1986	10	2
	1	192	UNC	Incorrect	2	1	479	6	2	1966	10	2
	1	192	UNC	Incorrect	2	1	435	6	2	2018	10	2
	1	192	UNC	Incorrect	2	1	337	6	2	2416	7	2
	1	192	UNC	Incorrect	2	1	302	6	2	2485	7	2
	2	192	UNC	Incorrect	1	1	2003	6	2	11519	2	
	1	192	UNC	Incorrect	2	1	1348	6	2	1857	10	2
▶	1	192	UNC	Incorrect	2	1	495	6	2	1746	10	2
	2	192	UNC	Incorrect	1	1	2016	6	2	11520	2	
<												

9.5 Corrective Actions and Improvements

- Try different values for K and different consolidation rules (see below)
- Verify accuracy of the GT categories in the dataset
- Learn additional training set
- Re-consider the relevancy of the dataset (i.e. feature vectors) to classify and discriminate the intended population of objects or events

10 Change between RBF and KNN

10.1 RBF

The number of firing neurons is variable. The program reads the response of the closest firing neurons stopping after K of them.

In the report below, each row corresponds to an input pattern and you can observe that some vectors are recognized by a single firing neuron (Cat 1, Dist 1, Nid 1), others by two or three firing neurons.

Accuracy	CatOut	Cat 1	Dist 1	Nid 1	Cat 2	Dist 2	Nid 2	Cat 3	Dist 3	Nid 3
Correct	2	2	3212	2						
Correct	2	2	3518	2						
Correct	2	2	4519	2						
Correct	2	2	7510	2						
Correct	1	1	1865	6	2	1956	10			
Correct	1	1	1930	6						
Correct	1	1	1758	6	2	1765	10			
Correct	1	1	1543	6	2	1952	10	1	3828	1
Correct	1	1	1540	6	1	3651	1			
Correct	1	1	1492	6	1	3701	1			
Correct	1	1	1401	6	1	3700	1			

10.2 KNN

All neurons always fire. The program reads the response of the K closest firing neurons.

The Status code can never be Unknown. Note that the amount of incorrect classifications can considerably increase since the accuracy is ranked by comparing the Ground Truth category to the Category of the closest match regardless of its distance value.

Accuracy	CatOut	Cat 1	Dist 1	Nid 1	Cat 2	Dist 2	Nid 2	Cat 3	Dist 3	Nid 3
Correct	1	1	2056	6	2	2271	10	2	2961	7
Correct	1	1	2096	6	2	2273	10	2	2997	7
Correct	1	1	2200	6	2	2323	10	1	2989	1
Incorrect	2	2	2332	10	1	2347	6	1	2842	1
Incorrect	2	2	2350	10	1	2433	6	1	2756	1
Incorrect	2	2	2363	10	1	2434	6	1	2755	1
Incorrect	2	2	2364	10	1	2393	6	1	2796	1
Incorrect	2	2	2342	10	1	2383	6	1	2806	1
Correct	1	1	2334	6	2	2335	10	1	2855	1
Correct	1	1	2282	6	2	2327	10	1	2907	1
Correct	1	1	2188	6	2	2347	10	2	2858	7

10.2.1 The Confusion Matrix

Each row corresponds to a Ground Truth category and the columns report the counts per recognized category. For example $\text{Confusion}[A,B]=K$ means that K patterns assigned with the Ground Truth category A are actually recognized a category B. The numbers along the diagonal ($\text{Confusion}[A,A]$) are the numbers of correct responses. Any other number reports uncertainties between the category A and B ($\text{Confusion}[A,B]$).

In the following example, the highest confusion resides between the categories [3 and 8], [3 and 5], [4 and 9].

GT	Unknown	Cat 0	Cat 1	Cat 2	Cat 3	Cat 4	Cat 5	Cat 6	Cat 7	Cat 8	Cat 9
Cat 0:	38	926	0	1	4	0	2	6	0	3	0
Cat 1:	32	2	945	2	0	1	0	4	8	4	2
Cat 2:	99	3	0	871	9	1	1	0	8	7	1
Cat 3:	109	2	0	6	835	0	19	0	3	20	6
Cat 4:	76	1	2	0	0	861	0	6	2	6	28
Cat 5:	107	2	1	0	28	0	737	5	0	11	1
Cat 6:	50	2	3	2	0	11	7	881	1	0	1
Cat 7:	83	0	11	5	8	3	0	1	866	1	22
Cat 8:	134	6	4	5	21	4	12	2	3	775	8
Cat 9:	103	1	3	2	4	30	6	0	17	8	826

11 Load testing set and observe

To be completed...

12 Classify batches and export results

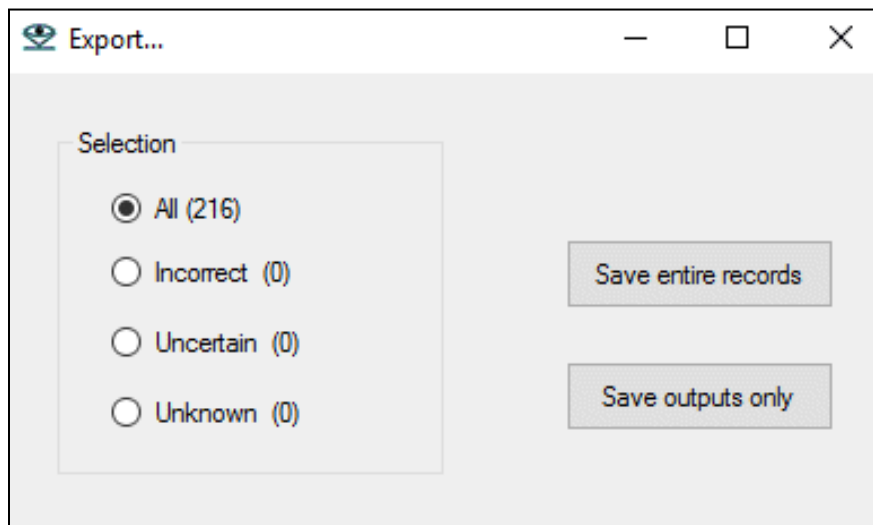
The results generated by the Classify command are appended to the input dataset in the format described below.

12.1 Output format

The results generated by the Classify command are appended to the input dataset in the format described below. The value K is defined in the Preferences menu (default is 3) and determines the length of the output record.

Status code	Accuracy code	CatOut	Cat 1	Dist 1	Nid1	Cat2	Dist2	Nid2	...	CatK	DistK	NidK
UNK=unknown	Correct	Global response of the firing neurons Choice of BestMatch or Dominant category	Response of the 1st firing neuron including its distance, category and identifier.			Response of the 2nd firing neuron			Response of the K th firing neuron			
ID=identified	Incorrect											
UNC=uncertain	N/A		In KNN mode, there are always K firing neurons			In RBF mode, K is a maximum applicable						

The results can be exported in two formats and for the entire set of vectors or with the filters listed in the panel below:



13 Save and export the knowledge

A validated knowledge can be saved for export to other hardware platforms featuring a NeuroMem network and programmed to generate the same type of vectors as the ones used for the training of the knowledge.