Kohonen Networks Applied to Rincón del Toro Rock Art Site Analysis

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Abstract. This presentation describes a type of rock art analysis. The tool used in the analysis is a non-supervised unit network known as Kohonen network, which belongs to the learning paradigm called "regularity detector". It is almost exclusively used as pattern classifier and that fact led us to the idea of testing it with the data from Rincon del Toro, La Rioja, Argentina. The Kohonen network, a device sensible to pattern differences, is capable of organizing itself through executing calculations using pattern data. However, this device is not really classifying the group of patterns. The patterns are actually producing the device's auto-organization. In that context, the output yielded is a function of the data and any given "manual" classification hypothesis can be contrasted against it.

Introduction

This presentation is the second step in a project we introduced in Gotland (Sweden) during the CAA conference in 2001. We had developed a database system that records geographical and analytical information about rock art sites. One of its features is a supervised neural network or "units" network (to avoid biological meanings) applied to pattern recognition.

That system was developed in the context of a broader research project that analyzes the usage of computational research tools in social sciences. We cover, among other areas, the benefits of analytic and synthetic approaches and the improvement that represent the computer as a whole (data file, calculus device, transformational generator) (Reynoso, C. 48:1986) in social research. That includes the new paths in methodology made in PC, like neural networks, genetic algorithms, cellular automata, agent-based models, etc.

From an epistemological point of view, we believe that there is finite ways to model knowledge. Following Reynoso (278: 1998), four general models can be distinguished: mechanic, statistic, systemic and phenomenological. The mechanic model implies the linearity of the components; the statistical model implies the correlation of the elements that conforms the phenomena; the systemic model implies the no-linearity of the components to describe the phenomena; and at last, the phenomenological model implies the lack of generalization with an emphasis in particularity. These four model types are not mutually exclusive. A particular research project may lie in more than one category. Thus, none of the forms of organizing knowledge is better than others by itself. It depends on the research needs. None of these forms reflects the phenomena by itself; it is a researcher's choice where to apply the appropriate model. The complexity or simplicity attribute is function of the perspective and there is nothing in the phenomena that implies one or the other.

The computer brings a new perspective in the way that social scientists make science. A lot of things that are practically impossible with paper and pen are very simple for a computer. New techniques are arising like genetic algorithms, agent based models, cellular automata or neural networks. Even in social anthropology, the researchers are using computers to organize data like field notes or life histories.

In the context of our rock art database, we implemented one example of a statistical model, where the data is classified in arrange to pattern "prototypes" chosen by the researcher. With this units network, showed earlier in Gotland, the researcher can train the net to get his/her own classes, using the system to recognize the unclassified or new patterns. These patterns can be crossed with data in the database by queries, bringing contextual information. The unit of analysis used in the recognition is the element, a minimal unit of sense (this is again a *researcher's choice*) in a drawing.

The new approach that we are introducing here, the non-supervised Kohonen unit network, lets the net itself find the clusters configuration in which the elements are grouped. In that way, there is no predefined information about the pattern belonging to a class. The classification is the product of the interaction between the net and the data. This behavior makes the net a support tool for the researcher, but at the same time, it can introduce a classification hypothesis.

This type of tool started to be used in social research in the context of anthropology's cognitive theory. This school, also known as ethnoscience, put the emphasis in the native classification, embracing the emic paradigm. To reach their goal, in the early times, the anthropologist used a set of formal tools named componential analysis. A few anthropologists continue working on this theory, searching for new tools in other knowledge domains like classification statistics and prototype semantics (D'Andrade, 1995). The native capabilities to classify and understand classifications in particular situations promoted the development of some tools to emulate this situation. Neural networks was one these tools (Strauss and Quinn, 1997).

In our work, the researcher can test his/her own classification hypothesis with the one provided by Kohonen auto-organized map. The internal relation that produce the classification keeps blind, like in a black box, but the output may help the researcher to find new clustering hypotheses and contrast with his/her own. Nonetheless, the most interesting property of this procedure is that classification is a function of the data samples only and there is no subjective component once the samples are chosen.

Kohonen Network

Kohonen networks are also known in the literature as Learning Vector Quantifier. They belong to the learning paradigm called "regularity detector" (Rumelhart y Zipser 1986:160). They implement a type of learning called "competitive" in which the units composing the network compete to get all the weight change after each pattern is presented.

In Kohonen networks, there are no hidden layers that can produce nonlinearities. Thus, they have a lot of limitations regarding the type of work they can do. However, they are simpler and faster than most of other networks. They are almost exclusively used as pattern classifiers and that fact led us to the idea of testing them in the data from Rincón del Toro, La Rioja, Argentina. This site was extensively studied by Adriana Callegary, who provided the images information and helped us to ramp up the use of them in this analysis

The network's goal is to find the "winner" unit for each pattern. The patterns from which the same winner is obtained are classified as belonging to the same class.

The network processing can be divided in four stages.

- The elements composing the paintings are separated in elements. We did that manually using the end user level graphic tool. To separate the elements we followed the guidelines of Hernandez de Llosas et al (2001) that investigated a similar site in the same area. In that work, the elements are divided in zoomorphic, anthropomorphic and abstract. We maintained that classification a as goal and as a way to measure the network accuracy.
- Once the each element was saved as a bitmap, we resample them to 64x64 matrices.
- The next step is a normalization procedure where the black and white values are converted in -1 and 1, the values that the network consumes. In this case, normalization is not as relevant as in other ones, for our samples are always in the same sampling space, the range -1 and 1.
- The scaled patterns are computed with the network unit's weights. This computation is very simple from the mathematical point of view. The network input layer works as a retina having a unit for each matrix point.

At its time, each input unit has a link with each of the output units. This link is represented by a weight. The value that determines which is the winner unit is calculated in the following way:

$$out = \sum_{i}^{n} x_i w_i \qquad 1$$

Where n is the size of the input matrix, x is the input value from the matrix data point and w the weight of the link.

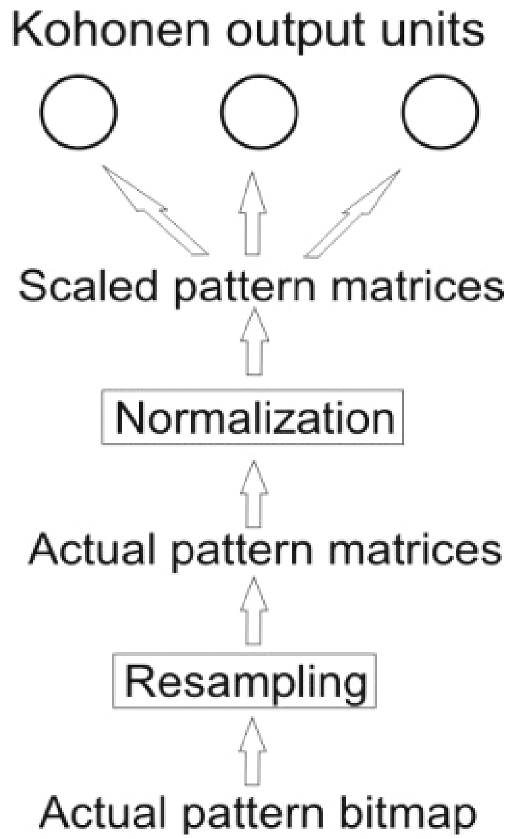


Fig. 1. Representation of the process of our Kohonen network program.

The other computation that the classification needs is the weight adjustment. The adjustment is done subtracting the weight to the data point and then adding that difference to the weight, but multiplying it by a learning rate, which is always a number bellow 1.

$$e = x - w^t \qquad 2$$

$$w^{t+1} = w^t + e\alpha \qquad 3$$

Where x is the input data, w is the weight, a is the learning rate and t is the time.

This type of learning has the disadvantage of leaning easily towards the one unit that first starts to win. And once it starts to win, it could win all the time, given that the rest of the training patterns might not to be strong enough to offset the trend. For that reason there is the concept of "neighbor" unit. Instead adjusting just the winner's weights, the adjustment it is applied also to certain number of other, contiguous units.

Working with Rincon Del Toro Petroglyphs

The elements that compose the motives from this site can be manually divided in the three mentioned categories: abstract, anthropomorphic and zoomorphic. Although there are elements that are very difficult to assign to one of these categories, it is possible to find a reduced group whose class membership is well defined. We started the processing with that group, which is presented in tables 1, 2 and 3. The goal of the network processing is to get to this manual classification.

To process this data with the network, we choose to work with 10 output units. The number of output units affects how many weight connections there will be between the output layer and

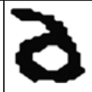
Reference Letter	a	b	c	o	g
Image Input to the Network					
Location (Petroglyph number)	1	1	1	1	1

Table 1. Abstract figures.

Reference Letter	k	1	m	n	**n**
Image Input to the Network					
Location (Petroglyph number)	2	2	11	11	1

Table 2. Zoomorphic figures.

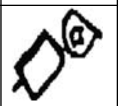
Reference Letter	h	d	e	f
Image Input to the Network				
Location (Petroglyph number)	1	1	1	1

Table 3. Anthropomorphic figures.

Figure	Class	neighbors =8	neighbors =8	neighbors =5	neighbors =5
D	Zoomorphic	10	1	1	1
E	Zoomorphic	10	1	1	1
F	Zoomorphic	1	10	10	10
H	Zoomorphic	10	1	1	1
O	Abstract	6	1	1	1
C	Abstract	6	10	6	6
B	Abstract	6	10	6	6
A	Abstract	6	10	6	6
G	Abstract	6	1	2	2
K	Anthropomorphic	4	9	10	10
L	Anthropomorphic	1	10	10	10
M	Anthropomorphic	1	10	10	10
N	Anthropomorphic	1	10	10	10
N	Anthropomorphic	1	9	10	10

Table 4. Results from runs.

the input data matrix, and thus, it affects the amount of information the network can hold at any given point of time. We tried with larger number of units and there was no classification improvement. We fixed the learning rate at 0.3. We made two runs with 5 neighbors and two with 8. The table 4 shows the results. Notice that we did not use the manual classification during the processing.

Considering the classes that we manually set in tables 1 to 3, the first run was the one with poorer accuracy: 64.28%. The other three had a 78.57% of successful class assignment, compared to the manual classification.

Even though that these results seem promising, the next step we made was not very encouraging. We included a big part of the site data, which consisted in 68 images from the site petroglyph 1, 2, 3, 7, 9 10, 11 and 12. The accuracy plummeted to below 50%.

This failure shows one feature that Kohonen networks shares with other forms of unsupervised statistical pattern classification and learning: the difficulty of handle large number of features. For example, let p, q, and r be patterns. What means to say that class c contains p, q and r? It means that p, q and r share a least one feature. For a Kohonen network, each data point is a feature. So, when the sample data covers a large spectrum of features, the quantity of relevant features is proportionally large and the decision regarding the pattern's class assignment is more difficult.

We made several test on the data, using more and less elements and changing the training parameters. Through this process we identified two big avenues of further improvement: reducing the elements batch size and abstract as many features as possible.

Reducing the batch size is to partition the training set using less data per batch. Let's suppose that working with x elements shows more accuracy than doing it with the whole set of n. In that case we could run all the combinations of n elements and group them according with the frequency that the network put them in the same class. If n is small enough, it could be done just in a few days of processing. Using our data, if we wanted to use batches of 3 elements, we would have to make 50,116 runs. If each runs lasted 2 seconds, we would need only a little more than 27 hours. This approach is very interesting because it rests on a cognitive proposition that would support the model: classification cannot be done from a very large set of features (Rosch, 1978, cited by D'Andrade, 1995). That means, in other words, that reducing the number of compared patterns reduces the number of classifying features.

Another set of improvements towards increasing the accuracy is abstracting features from the images. In Rincon del Toro's data, both the angle of inclination and the width of the tracing are variables that could be abstracted from the images. The first case is difficult to achieve because images position can change the class to which the image belongs. Anyway, we tired "straightening" image f. After that, the image started to belong to the same class than e and d. On the other hand, an abstract feature as the image's inclination angle could be treated before/after classification as a post/pre processing task.

Abstracting the line width is very interesting because it is easy to demonstrate how a wider trace can produce a quantity of relevant data points several folds larger than a narrower trace. Relevant means here that a data point represents an activated feature. In such cases, the divergences on the quantity of activated data points can easy lead to pattern assigned to different classes.

Nevertheless, what is the ultimate advantage of having such a classification device? It is clear this type of networks can be part of the database search engine. Of course, if the database has archeological data, certainly it would help archeologists to find the records they need if the search criterion is an image pattern.

Yet, as we say before, the scientist can use the network results as a way to contrast his/her classification hypothesis. But which is the benefit of doing that? One can compare the classification with that from a colleague or group of colleagues, for example. One can even make survey and find the most shared classification.

Conversely, there is a big difference between manual classifications and the one showed in this paper. The Kohonen network, a device sensible to pattern differences, is capable of organizing itself through executing calculations using the pattern data points. Therefore, it is the group of patterns what is causing the device's auto-organization rather than the device is classifying it. Hence, the output yielded is function of the data. Thus, a given "manual" classification hypothesis can be contrasted with a function of the data.

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