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Neural networks for animal science applications: Two case studies

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Abstract

Artificial neural networks have shown to be a powerful tool for system modelling in a wide range of applications. In this paper, we focus on neural network applications to intelligent data analysis in the field of animal science. Two classical applications of neural networks are proposed: time series prediction and clustering. The first task is related to the prediction of weekly milk production in goat flocks, which includes a knowledge discovery stage in order to analyse the relative relevance of the different variables. The second task is the clustering of goat flocks; it is used to analyse different livestock surveys by using self-organizing maps and the adaptive resonance theory, thus obtaining a qualitative knowledge from these surveys. Achieved results show the usefulness of neural networks in two animal science applications.

Keywords: Neural networks; Multilayer perceptron; Self-organizing map; Animal science

1. Introduction

Artificial neural networks (ANNs) have been applied to a huge amount of fields during last years (Arbib, 2003; Hu, 2003). However, there are some fields in which the use of ANNs is still scarce; animal science is one of these fields. This lack of ANN applications in animal science is quite paradoxical, as data analyses are usually carried out in this field, and ANNs have shown to be more powerful than classical statistical methods to carry out this kind of tasks (Arbib, 2003; Bishop, 1995; Ripley, 1996).

Two examples are used in this work in order to show the ability of ANNs to solve animal science problems: a time series prediction (Makridakis, 1997; Weigend, 1993) and a clustering application (Theodoridis, 1999). The multilayer perceptron (MLP) (Bishop, 1995) is the neural model used for time series prediction, whereas the neural models used for clustering are the Kononen's self-organizing map (SOM) (Kohonen, 2000) and a network based on the adaptive resonance theory (ART), the ART2 network (Fausset, 1994; Jang, 1996).

The first problem tackled in this paper is related to milk yield (MY) weekly prediction by using current animal factors (body weight, diet, litter size, number of lactation, etc.), as well as the current MY prediction (an autoregressive model). MY weekly prediction becomes more useful for management purposes than the analysis of the different factors which can affect MY at the end of lactation.

The clustering application is completely different since a qualitative model is desired in order to extract useful knowledge from data. Goat production in Murcia Region (Spain) requires a deeper knowledge of their farming characteristics and practices. Knowledge of MY prediction is important because is the main income for farmers, but without a good feeding program is difficult to achieve their goals. The nature and availability of biomass of semiarid Spanish lands may limit the animal welfare and productivity, and thus, lower milk production may be achieved, as well as a decrease in kid survives and income for selling milk. Supplementation during the year with forages, by-product, concentrates and/or total mixed ration (TMR), is a common practice when pasture is scarce, as happens in Murcia Region. Ninety-four flocks from Murcia Region are used to analyse the relationship between food management practices. The herd food management practise is obtained by surveys to farmers.

The remainder of the paper is outlined as follows. Section 2 shows the neural methods used in this study. Results achieved in different applications are presented in Section 3, ending up the paper with some conclusions in Section 4.

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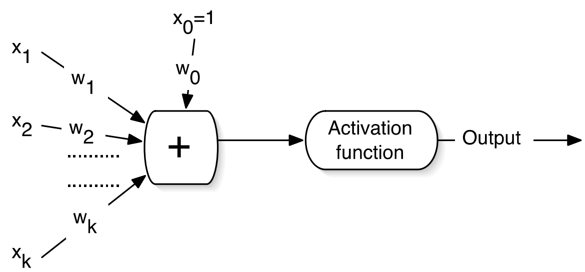

Fig. 1. Schematic of a neuron model.

2. Neural models

2.1. Multilayer perceptron

A multilayer perceptron (MLP), is an ANN, formed by elementary processing units, the so-called neurons. A typical neuron model is shown in Fig. 1 (Haykin, 1999).

The main components of the model are:

Sum function. It carries out a linear combination of the neuron inputs through the use of a set of coefficients, known as synaptic weights. Being $\mathbf{w} = [w_0, w_1, \ldots, w_k]$ the vector of coefficients, and $\mathbf{x} = [1, x_1, \ldots, x_k]$ the input vector, the sum function is given by the scalar product of both vectors. When using a neural model, the goal is to find the optimal synaptic weights to solve the problem. The process of searching the optimal weights is known as network learning.

Activation function. It is a non-linear function which gives the network its non-linear nature. The most used activation functions are the sigmoid function (its values ranging between 0 and 1) and the hyperbolic tangent, which ranges between -1 and $+1$.

As it can be inferred from Fig. 1, a neuron without an activation function is equivalent to a multi-variant analysis. Therefore, a non-linear combination should be more powerful than a multi-variant analysis (Ripley, 1996).

Neurons are arranged in layers to form an MLP. The first layer is known as input layer, and the last one is called output layer. All the other layers are called hidden layers (Arbib, 2003). This kind of arrangement enables the neuron outputs to be used as inputs to neurons of following layers (non-recurrent network) and/or previous layers (recurrent networks). Fig. 2 shows a typical MLP structure.

Several remarks should be made regarding the learning process (Arbib, 2003; Bishop, 1995; Haykin,1999):

The learning rate must be chosen appropriately. The learning algorithm is based on finding the closest minimum, being this learning rate a parameter which measures the speed of approaching the minimum.

The network architecture must also be chosen appropriately. While the number of neurons in the input layer and the output layer is given by the problem, the number of hidden layers, and the quantity of neurons in each hidden layer must be chosen depending on the particular problem.

Due to the iterative nature of the learning process, it is necessary to choose the initial values of the synaptic weights. Different initial values are usually tested in order to achieve an optimal model.

In order to obtain a model with validation capabilities, data is split into two data sets: a training set used to obtain the neural model, and a validation set used to test the behaviour of the model with data different from the training set used to obtain the model.

Two different approaches can be carried out to train the network. The first approach is based on updating the synaptic weights for each pattern of the data set (on-line approach) whereas the other approach is based on updating the synaptic weights once for all the training data set (batch approach).

2.2. Self-organizing map (SOM)

The self-organizing map is a neural network proposed by Teuvo Kohonen in 1984 (Haykin, 1999; Kohonen, 2000). Neurons are arranged in two layers: an input layer, formed by n neurons (one neuron for each input variable) in Fig. 3 and an output layer in which information is processed; this second layer is usually arranged in a two-dimensional structure.

Neurons of the output layer are characterised by a weight vector with the same dimension as the input vector. For instance, neuron i,j (i-th row, j-th column) is characterised by the weight vector $\mathrm{w}_{ij} = [\mathrm{w}_{ij}^1 \mathrm{w}_{ij}^2 \ldots\ldots\ldots \mathrm{w}_{ij}^n]$. Similar input patterns are mapped close each other in the output layer (Kohonen,

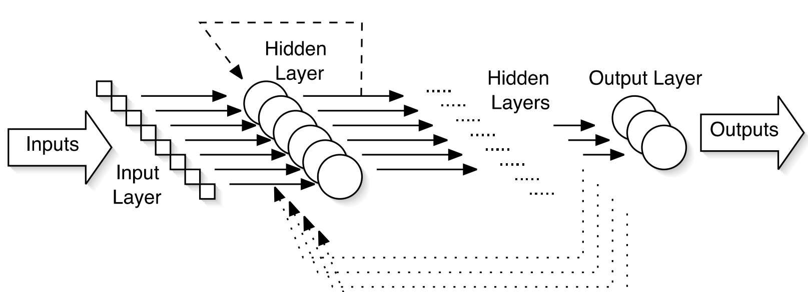

Fig. 2. Multilayer perceptron. Dotted lines stand for recurrent neural systems.

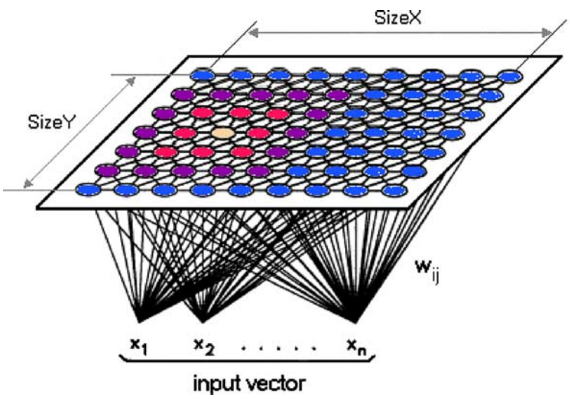

Fig. 3. SOM architecture with n-dimensional inputs.

2000). Algorithm procedure can be summarized, as follows (Haykin, 1999; Kohonen, 2000):

Weight initialisation.
Choice of an input pattern $x=\left[\mathrm{x}_1\ \mathrm{x}_2.........\mathrm{x}_n\right]$.
Measurement of the similarity between weights and inputs. If the Euclidean distance is taken into account, then the similarity measure is given by $d(\mathbf{w}_{ij},\mathbf{x})=\sum_{k=1}^{M}(w_{ij}^{k}-x_k)^2$
The most similar neuron to the input pattern is called best matching unit (BMU).
Synaptic weights are updated as $\mathbf{w}_{st}(n+1)=\mathbf{w}_{st}(n)+\alpha\cdot h(\mathrm{BMU},\mathbf{w}_{st})\cdot(\mathbf{x}-\mathbf{w}_{st})$, where $\alpha(n)$ is the learning rate and $h(n)$ is known as neighbourhood function. The value of this function depends on the distance between the BMU and the neuron to be updated, the closer the two neurons the higher the value of this function. Moreover, this function is the responsible of preserving the topological relationships among input patterns (Kohonen, 2000).
The previous steps are performed a predetermined number of iterations. When this number is reached, the learning algorithm is stopped. While the number of iterations is lower than the predetermined value, go to step 2.

Once the map training is finished, the visualisation of the two-dimensional map provides a qualitative information about how the input variables are related each other for the data set used to train the map. SOM is a visualisation tool rather than a clustering tool, although it is possible to obtain clusters of similar patterns from the two-dimensional map. Nevertheless, another model is proposed in order to carry out this clustering task, namely, the adaptive resonance theory (ART).

2.3. Adaptive resonance theory (ART)

This model is based on analysing the similarity between input patterns and cluster prototypes. If a pattern is similar enough to a certain cluster prototype, then the prototype is updated in order to incorporate information from this pattern. If the similarity is not sufficient, then a new cluster is formed, whose prototype is given by this pattern. This model solves a usual problem of other neural models, namely, the corruption of the information already learnt by the contribution of new patterns (Arbib, 2003). In particular, we used the ART2 network which allows to use this theory with continuous-valued input vector (Fausset, 1994). Cluster prototypes have the same dimension as input vectors. ART2 procedure can be stated as follows (Kung, 1993):

Weight initialisation.
Given an input pattern $\mathbf{x}$, the Euclidean distance between this pattern and every neuron is computed. Therefore, the distance between the j-th neuron and the input pattern is given by $d_j=||\mathbf{w}_j-\mathbf{x}||$.
The most similar neuron to the input pattern is selected in order to analyse whether it is a good-enough representation of the input pattern. This neuron is denoted as v.
A vigilance test is performed in order to test whether the prototype is a good enough representation of the pattern: $||\mathbf{w}_\mathrm{v}\cdot\mathbf{x}||>p$ where ρ is the vigilance parameter ($0<\rho<1$).
If the vigilance test is not accomplished, then a new neuron is created, whose weights are given by the input pattern.
If the vigilance test is accomplished, then the weight vector of the winner neuron is updated:

$$\mathbf{w}_v=\frac{\mathbf{x}+\mathbf{w}_v\cdot N_v}{N_v+1}$$

where N_v is the number of data points in the winner node v so far. This means that if there are many points in the neighbourhood of the winner, then it is hard to move the winner. The vigilance parameter controls the desired degree of similarity between the weight vector and the input pattern; low values involve that a low similarity is needed, and therefore, a low number of clusters is produced. On the contrary, high values involve a high number of prototypes.

3. Practical applications

3.1. Milk yield prediction

Milk yield (MY) is a key factor in the management of goat livestock since it becomes the main farmer income. MY is important to identify which goats are the best milk producers, and also to analyse the current state of a certain livestock. Therefore, MY prediction is very helpful as it enables the farmer to make decisions about livestock management before the end of lactation, when decisions are usually made.

A homogenous group of dairy goats within a commercial farm (Excamur, S.L.) was selected in this trial. This farm is a member of ACRIMUR (Murciano-Granadina Goat Breeder Association—*Asociación Española de Criadores de la Cabra Murciano-Granadina*). The selected farm is a representative sample of these kinds of farms in the south-eastern Spain.

The data set used in this work was formed by 36 goats. They were split into two data sets: a training set (26 goats) to obtain the prediction model, and a validation set (10 goats) in order to guarantee the generalisation capabilities of the network. Both data sets were similar with regard to the diet followed by goats

Table 1
Mean values and standard deviations of the input variables for both training and validation sets

	Lactation number (*)	Number of kids	Control number	Metabolic weight (kg3/4)	Milk yield (kg)
Training					
Mean	4.94	1.82	8.13	16.91	2.20
Std	1.37	0.58	3.52	1.25	0.80
Validation					
Mean	4.80	2.10	9.10	17.36	2.06
Std	1.25	0.54	3.42	1.63	0.64

* Lactation number indicates lactation period.

Table 2
Root mean-square error (RMSE) obtained by the simple models as well as by the best neural models in MY prediction. Net(1) has an architecture 6×3×1 and *online* learning, Net(2) 6×3×1 and *batch*, Net(3) 6×3×3×1 and *batch*, and finally, Net(4) 6×4×4×1 and *online*

	Training set (kg)	Validation set (kg)
Model_1	0.47	0.42
AR(1)	0.44	0.39
AR(2)	0.44	0.40
Net(1)	0.37	0.31
Net(2)	0.37	0.31
Net(3)	0.37	0.31
Net(4)	0.36	0.31

in order to avoid biased models. A weekly follow-up was carried out for every goat, being the study period of 22 weeks.

The most important variables that could affect MY were taken into account (Gipson & Grossman, 1990). These variables can be easily obtained in a flock which is subject to a milk control process. The used variables were the following: number of lactation, number of kids, time between parturition and the first milk control, type of diet[1], metabolic weight (Klieber, 1961), and current MY. Table 1 shows the mean values and the standard deviations values of the input variables; similar values for both data sets show the suitability of the data-splitting criterion, which guarantees unbiased models.

Three simple models were proposed in order to have a fair reference for model comparison:

A trivial model (Model_1) which uses the following prediction rule: $m(t+1)=m(t)$, being $m(k)$ the variable to be predicted (MY).
Two autoregressive models: AR(1) which takes into account the previous value of the prediction variable, and AR(2), which considers the two previous values of this variable.

With regard to neural models, different architectures and weight initialisations were proposed. This procedure is due to the learning algorithm used, the Levenberg-Marquardt algorithm, which is based on finding the closest minimum to the initial weights, so that, if this is a local minimum, then a non-optimal solution is achieved (Luenberger, 1984). This algorithm shows a better performance than other more widely used algorithms, such as, the classical backpropagation algorithm (BP). With regard to hidden nodes, if only one hidden layer was taken into account, the number of neurons ranged between 2 and 15, whereas if the two hidden layers were taken into account, the number of neurons in each layer ranged between 2 and 6, in order to avoid overfitting (Haykin, 1999). Moreover, the stopping criterion was based on cross-validation (Bishop, 1995; Haykin, 1999).

A comparison of the results achieved by the different models is shown in Table 2.

[1] In this work, two diets were used to fulfil nutritive requirements during lactation, being the difference between these two diets the ingredients of each one.

Fig. 4 shows the MY predicted by the neural model Net(4) compared to the desired signal, for both training and validation sets. An accurate prediction is achieved in a global point of view. Nevertheless, it is also important to analyse whether the prediction is accurate for every particular goat; therefore, results for individual goats are also shown in Fig. 5.

Fig. 5 shows that the prediction achieved by Net(4) is also accurate for individual goats, except for a small amount of goats; for instance, goat #24 in the training set and goat #7 in the validation set.

3.2. Qualitative analysis of goat farms by SOM

Section 3.1 carries out a quantitative analysis to predict MY in goat farms. Nevertheless, qualitative analyses are also important since they are very helpful to understand how the models work, and thus, they can be used for knowledge discovery. Sections 3.2 and 3.3 show the use of clustering techniques for analysing the relevance of variables involved in this problem as well as to identify characteristic behaviours in the management of goat farms.

Feeding becomes the most important factor to take into account when a new stockbreeding activity is initiated since it typically involves more than half of farming expenses (Haenlein, 2001). This is the reason why farmers filled in a survey on their feeding procedures in order to study feeding management. The usefulness of this information stems from the fact that it allows an overall estimation of farms, thus trying to amend mistakes for improving farm development and competitivity.

Data used in this study are referred to 1999 and were obtained between 2001 and 2002 from surveys returned by 94 farm owners dedicated to goat production. The surveyed farms comprised approximately 15% of the total official census of Murciano-Granadina breed farms in Murcia Region. Eleven variables were studied. The first two variables were related to the geographical location in Murcia Region (6 counties (V1): 1-Altiplano, 2-Campos de Cartagena, 3-Noroeste, 4-Río Mula, 5-Valle del Guadalentín, 6-Vega del Segura) and herd size (V2: number of goats). The other nine variables were related to nutrition management and milk income. Three variables were obtained asking farmers whether they supplement the diet for different physiological stages (replacement feeding V3: No(0) /Yes(1); lactation feeding V4: No(0)/Yes(1); gestation feeding

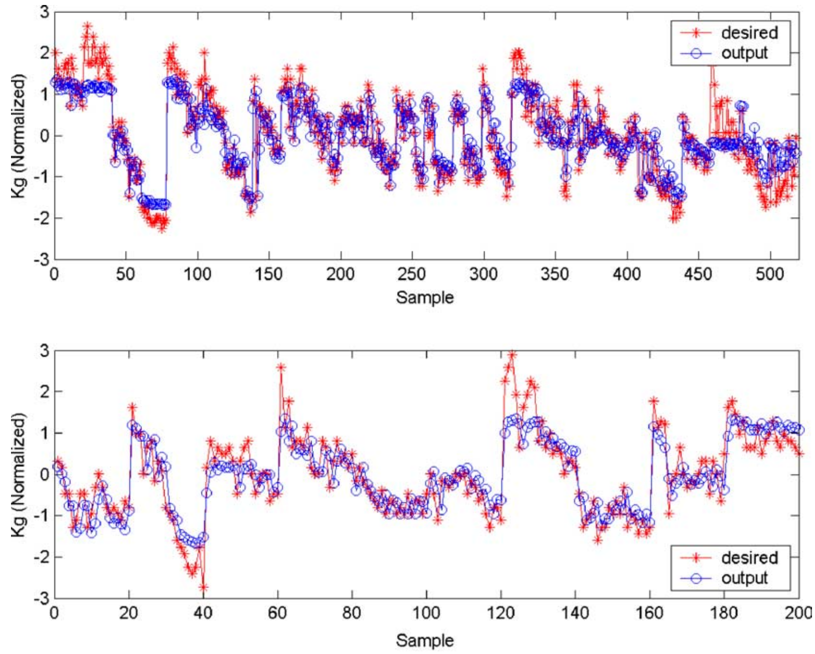

Fig. 4. MY predicted by Net(4) and desired signal for both training and validation sets.

V5: No(0)/Yes(1)). The sixth variable was obtained by asking farmers whether they have any nutrition support by external personnel (V6: No(0)/Yes(1)). The variable type of feeding (V7) has three possible answers; diet elaborated by farmers (coded as 0), farmers who buy compound feed (coded as 1) and farmers who buy total mixed ration (coded as 2). The variable peak lactation feeding (V8) has three options as well; No (coded as 0), Yes (coded as 1) and animal for meat production (coded as 2). Body condition score (V9) is a subjective measurement that farmers tend to use in order to evaluate whether nutrient supplementation appears to be necessary (No(0)/Yes(1)). Milk income (V10) (€/ goat) was evaluated for each farm, and finally the last variable taken into account was the use of Byproduct (V11: No(0)/Yes(1)) to feed animals.

Our aim was to extract knowledge from these variables. SOM was applied to carry out this task since it preserves topological relationships among data while mapping data into a two-dimensional map. An SOM formed by 8×6 neurons with

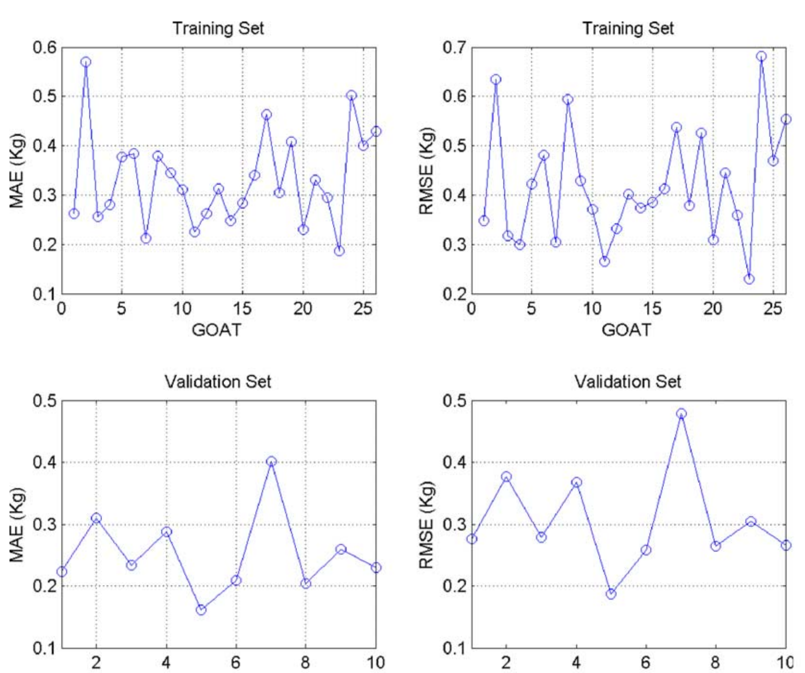

Fig. 5. MY prediction for the individual goats which form the training set and the validation set. The root-mean-square error (RMSE) and the Mean Absolute Error (MAE) are used as accuracy measures.

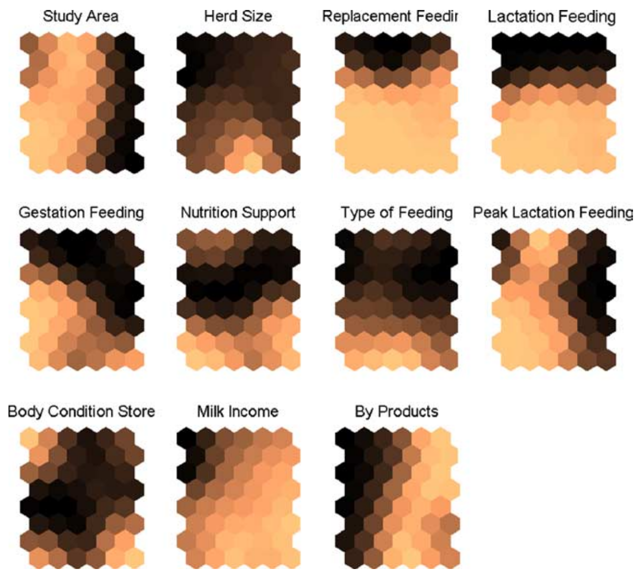

Fig. 6. Grey-scale representation of the components of the vectors which represent each neuron in the map. The darker the colour the lower the values of the components.

hexagonal architecture (each neuron has six neighbours) was used. Data was normalised (mean zero and variance unity) in order to avoid unbiased models due to the different range of values of the variables. The batch mode was used to train the network and a Gaussian neighbourhood function was chosen.

Fig. 6 shows the components of the vectors which represent each neuron in the map. There are several zones of the map that should be highlighted. For instance, those variables in which both 'replacement feeding' and 'lactation feeding' appear to be relevant, are mapped into the lower parts of the map in light colour. These zones of the maps also correspond, within variable 'type of feeding', to those farms using compound feed (grey colour and intermediate part of the map) and total mixed ration (light colour and lower part of the map). On the contrary, the dark area in the upper part of the map represents farmers who make their own diet. To sum up, the lower part of the map with light colour represents farmers which consider groups of goats within their herds, and these groups are fed according to the physiological stage (mainly replacement and lactation). Moreover, these farmers tend to buy to food companies. The light area is also present in the variable 'nutrition support', i.e., farmers who buy to food companies, are also supported about their technical decisions; moreover, it can also be appreciated that 'milk income' also shows light colours, which indicates more income from milk yield. The use of feeding sub-products (variable 'byproducts') is biased to the right map of the map, including both farmers who buy to food companies and those who make their own rations. The analysis of variable 'gestation feeding' shows that this topic is still in an early development, even though its physiological relevance. In spite of farmers do carry out an individualised feeding of animals which are being milked, they do not take into account individual factors such as the four weeks of the 'peak lactation feeding' (maximum milk yield). Moreover, only a few farmers take into account the 'body condition score'.

3.3. ART clustering of goat farms

The main advantage of ART over other clustering algorithms stems from the fact that it does not need to know the number of clusters in advance, but it can find the natural number of clusters once chosen the vigilance parameter ρ (Theodoridis, 1999). ART2 models were trained, finding an optimal value of $\rho = 0.98$. Six clusters were found by the algorithm, whose prototypes are shown in Table 3.

Table 3 shows that three clusters include almost all the patterns, namely, clusters #1, 2 and #4. Cluster #1 include 35% of the patterns which belong to the county *Campos de Cartagena*. Farms of this cluster show a medium size and also medium income from MY (308 € per goat and lactation). Some farmers produce their own feeding whereas others buy to food companies, thus taking advantage of the technical support provided by companies. They carry out a management by groups of goats, depending on their MY capabilities.

Cluster #2 include 32% of the patterns which belong to the north-western area. This cluster includes smaller farms and their income is also lower than Cluster #1. These farms do not receive technical support, but they produce their own food and their management is the same for all the goats. Therefore, this cluster shows a management quite poorer than that of cluster #1, thus suggesting that an improvement should be taken into account for a considerable percentage of farms in Murcia Region.

Cluster #4 is located in the county *Valle del Guadalentín* and it includes small farms. They do not show any income from milk sale because these farms are focused on meat instead of milk. Their management does not consider differences among goats, and therefore, this cluster represents the poorest management among farms of Murcia Region.

Table 3
ART2 clustering. Cluster prototypes and percentage of patterns assigned to each cluster

Cluster	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	% Data
1	2.12	185.85	0.97	0.79	0.33	0.52	1.48	0.12	0.48	308.48	0.67	**35.11**
2	3.43	124.07	0.13	0	0.13	0.33	1.27	0.33	0.47	141.8	0.3	**31.92**
3	4.85	251.58	1	1	0.81	0.69	2.12	1	0.27	267.27	0.35	**1.06**
4	5	53	0.33	0	0.33	0.33	1.33	2	0	0	0.33	**27.66**
5	1	1450	1	1	1	0	3	0	0	0	1	**3.19**
6	4	800	1	1	0	0	3	1	1	355	1	**1.06**

The other clusters are not representative enough since they involve a very small percentage of data.

4. Conclusions

Neural networks have been used in two animal science applications. Results have shown their suitability to be used in this field, in which the quality and accuracy of the models is essential to increase farm returns.

With regard to MLP, achieved results have been better than those obtained with classical easy models in terms of accuracy (prediction improvement: 0.11 kg/goat/lactation). This involves a prediction improvement of 22 kg/lactation for a medium size herd formed by 200 goats, which may improve herd management. Moreover, neural networks have provided an estimation of farm locations, which could be used to avoid mistakes and improve their development and competitivity.

With regard to SOM, maps have shown that farmers tend to carry out a management based on groups of goats, which has shown that feeding management of farms focused on dairy produce is more adequate than that of farms focused on meat production. This adequate management has also included technical support and it has involved an income increase from MY. These conclusions are similar to those obtained in previous works, which studied goat herds from other Spanish regions, such as Andalusia (Castel, Mena, Delgado-Pertiñez, Carmuñez, Basalto & Caravaca et al., 2003; Delgado-Pertiñez, Alcalde, Guzmán-Guerrero, Castel, Mena & Caravaca, 2003) or Catalonia (Milán, Arnalte, & Caja, 2003).

With regard to ART, it has produced three relevant clusters which showed three kinds of herd management's practices in Murcia Region. Basically, these clusters represented farms which were characterised by a policy based on dairy goats with supplementary feeding, dairy goats without supplementary feeding, and finally, meat production. The relevance of supplementary feeding has turned out to be very importance since profits were raised (between 140 € and 310 € per goat)

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