Computers and Electronics in Agriculture 110 (2015) 36–41

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Improved estimation of bovine weight trajectories using Support Vector Machine Classification

Jaime Alonso [a,*], Alfonso Villa [b], Antonio Bahamonde [a]

[a] *Artificial Intelligence Center, University of Oviedo at Gijón, Asturias, Spain*
[b] *Association of Breeders of Asturiana de los Valles (ASEAVA), Abarrio, N° 24, E-33424 Llanera, Asturias, Spain*

ARTICLE INFO

Article history:
Received 16 May 2014
Received in revised form 2 September 2014
Accepted 2 October 2014

Keywords:
Support Vector Machines (SVM)
Weight prediction
Growth curves
Beef cattle

ABSTRACT

The benefits of livestock breeders are usually closely related to the weight of their animals. In this paper we present a method to anticipate the weight of each animal provided we know the past evolution of the herd. Our approach exploits the geometrical relationships of the trajectories of weights along the time. Starting from a collection of data from a set of animals, we learn a family of parallel functions that fits the whole data set, instead of having one regression function for each individual. In this way, our method enables animals with only one or a few weights to have an accurate estimation of their future evolution. Thus, we learn a function F defined on the space of weights and time that separates the trajectories in such a way that F has constant values on each trajectory. The key point is that the specification of F can be done in terms of ordering constraints, in the same way as preference functions or ordinal regressors. Therefore, F can be obtained from a classification *SVM* (Support Vector Machines). To evaluate the method, we have used a collection of real world data sets of bovines of different breeds and ages. We will show that our method outperforms the separate regression of each animal when there are only a few weights available and we need medium or long term predictions.

1. Introduction

The estimation of the weight of bovines, and other livestock, as a function of time is very important for breeders. The efficiency of growth determines the economic benefits not only in beef cattle, but also in dairy bovines (Arango and Van Vleck, 2002).

There are different approaches to study weight evolutions in the literature. In (West et al., 2001), the biological fundamental principles of the growth of many diverse species are emphasized. They show that it is possible to fit the same sigmoid for cows, pigs, guppies or shrimps, provided that it is performed a transformation of time and weight data to a common *dimensionless* scale. The estimation of the weight of bovines has been studied since a long time ago; see, for instance (Enevoldsen and Kristensen, 1997). The use of Artificial Intelligence tools to predict beef cattle scores is not new. In (González-Velasco et al., 2011; Alonso et al., 2007) assessment functions for beef cattle are presented. Moreover, to estimate live weights of bovines in (Stajnko et al., 2008; Tasdemir et al., 2011a; Tasdemir et al., 2011b) the authors used digital image processing procedures.

A different point of view is used when the objective is the selection of stud bulls. In this case, the bulls are housed together in central evaluation stations; they stay there for several months, depending of the management policies of breeds and beef markets requirements. During that time each bull is weighted approximately every 15 or 30 days; at the end of the testing period, bulls are ranked according to their genetic merits. The methods used to compute this ranking include the use of a pedigree tree in order to consider not only the observed rate of weight gain, but mainly the capability of bulls to transmit genetically that gain to their progeny (Meyer, 2002; Meyer, 2002; Meyer, 2005; Schenkel et al., 2002; Freetly et al., 2011). A comparison of different genetics methods can be seen at (Jaffrézic and Pletcher, 2000).

In this paper we are concerned with finding accurate predictions of weights of beef cattle, neither for the whole specie nor for the expectations of the progeny. We want to anticipate the weight of each single animal in order to improve the incomes of breeders (Diez et al., 2003; Alonso et al., 2007; Alonso et al., 2013), given that market prices follow a well known annual cycle.

The approach proposed in this paper exploits the geometrical relationships of the trajectories of weights along the time. Starting from a collection of data from a set of animals, we learn a family of parallel functions that fits the whole data set, instead of having one regression function for each individual. In this way, our method

* Corresponding author. Tel.: +34 985 182 032.
E-mail addresses: jalonso@aic.uniovi.es (J. Alonso), avilla@aseava.com (A. Villa), antonio@aic.uniovi.es (A. Bahamonde).

http://dx.doi.org/10.1016/j.compag.2014.10.001
0168-1699/

enables animals with only one or a few weights to have an accurate estimation of their future evolution. To learn this family of functions, in the next section, we describe how to build a classification data set. The idea is to deal with an ordering of the trajectories in the same way used to learn ordinal regression (Herbrich et al., 2000; Herbrich, 2002; Alonso et al., 2008) or to learn preferences (Joachims, 2002; Bahamonde et al., 2004); see also (Schultz and Joachims, 2003).

To evaluate the performance of the method, we have used real world data sets of bulls and cows of different breeds and ages. Of special interest are the results achieved with young bulls of *Asturiana de los Valles*, a beef breed of the North of Spain. We will show that, in all cases, our method outperforms the individual regression of each animal, in special when there are only a few weights available and we need reliable medium or long term (more than 100 days) predictions.

2. Material and methods

2.1. Data

In the research reported in this paper we used several real world data sets of bovines of different breeds and ages. A data set of 351 Angus bulls from the Indiana Beef Evaluation Program (IBEP). All animals have 6 weights recorded taken at ages 180–509 days.

A second data set of 822 bulls of *Asturiana de los Valles* with more than 5 weights after the adjustment period. They have from 5 to 11 weights (after the adjustment period), but most of them (557 animals) have 6. The ages of the animals range from 241 to 508 days.

Finally, a third data set obtained from Meyers program to compute the relative genetic merits (Meyer, 2002). The data includes the weights of a group of cows from the Wokalup Selection Experiment in Western Australia. We only considered the records of the animals (358) with at least 2 weights; the maximum number of weights is 6 recorded between 19 and 82 months.

2.2. The method of weight trajectories

Let us consider a set B of bovines. For each animal we have recorded a number of weights. The whole data available can be represented by a set of pairs (w_{ai}, d_{ai}) where w_{ai} is the ith weight of the animal a taken when it was d_{ai} days old.

A first attempt to generalize these data consists in computing one regression function f_a for each animal trying to optimize the loss produced by the differences

$$w_{an} - f_a(d_{an}), \forall\ a \in B \tag{1}$$

Provided that for each animal $a \in B$ we want to predict its weight w_{an} at day d_{an}.

However, if we want to be able to estimate the weight of a new animal (not in B), we have two options. If we have obtained reasonably good approximations with the family $(f_a : a \in B)$, and these family of functions belong to the same class, say linear for instance, then we can try to induce a new regressor of the same class for the new animal. Unfortunately, faithful regressors need a large collection of observations, and in this case this requires time, what it is contradictory with our intention of anticipating the weight in future days. Additionally, the acquisition of data is costly and in general a risky task both for people and for the animals that become stressed during weighting sessions (Goyache et al., 2001).

The second option consists in trying to generalize somehow the set $(f_a : a \in B)$ to obtain a kind of universal function able to estimate the weight of any animal at any time. It is not clear how to do this; and, on the other hand, it is necessary to consider individual differences: in some cases they are really important. But if we were able to devise a method to take advantage of all pairs (w_{ai}, d_{ai}) at the same time, we can wait an improved generalization performance, since the number of such pairs in practice is usually high.

The method that we are proposing in this paper emphasizes the role of the trajectories followed in the space of weights and days (W x D) by the successive weights of the animals. Thus, we first look for a function $F : W \text{ x } D \to \Re$ able to separate the trajectories considered as subsets of W x D. In other words, a function F such that

$$F(w, d) = constant \tag{2}$$

defines implicitly all reasonable trajectory for the weights of the animal (see Fig. 1).

Then, given a set of measurements of an animal $a, \{(w_{ak}, d_{ak}) : k = 1, \ldots, n-1)\}$, we define the constant for its trajectory as the average of F values obtained on each point. In symbols,

$$constant_a = \frac{1}{n-1}\sum_{k=1}^{n-1} F(w_{ak}, d_{ak}) \tag{3}$$

Therefore, to estimate w_{an}, the weight of the animal at day d_{an}, we only need to obtain from (2) the explicit version of the function relating w and d.

Returning to the optimization problem of (1), to express it in terms of F, we need to constraint the form of this function. So, let us assume that $F(w, d)$ is a linear combination of the first argument and a general function of d, say $g(d)$; that is,

$$F(w, d) = \alpha\ w + g(d), \alpha \in \Re \tag{4}$$

Then, we have that the explicit version of the function that predicts the weights of the animal a, f_a, is given by

$$f_a(d) = \frac{1}{\alpha}\left(\frac{1}{n-1}\sum_{k=1}^{n-1} F(w_{ak}, d_{ak}) - g(d)\right) \tag{5}$$

Therefore,

$$\begin{aligned} w_{an} - f_a(d_{an}) &= w_{an} - \frac{1}{\alpha}\left(\frac{1}{n-1}\sum_{k=1}^{n-1} F(w_{ak}, d_{ak}) - g(d_{an})\right) \\ &= \frac{1}{\alpha}\left(F(w_{an}, d_{an}) - \frac{1}{n-1}\sum_{k=1}^{n-1} F(w_{ak}, d_{ak})\right) \end{aligned} \tag{6}$$

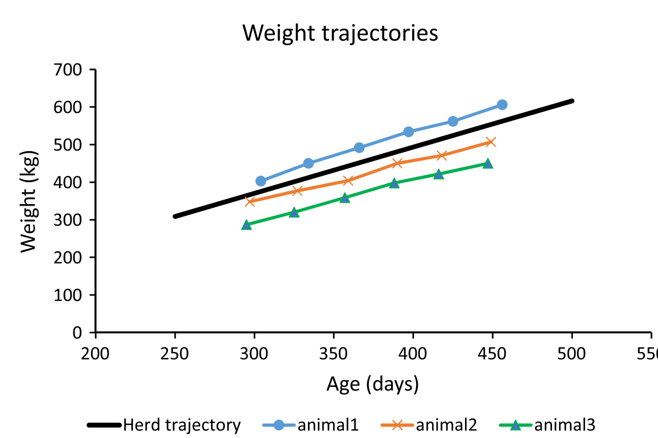

Fig. 1. Herd trajectory found for *Asturiana de los Valles*; comparison with three sample animals. Trajectories of each animal can be obtained from herd trajectory and a constant value.