The 29th ILP conference, 3–5 Sep 2019, Plovdiv, Bulgaria.

Estimating Productivity of Dairy Cows by Inductive Logic Programming

Shun Sasaki[1], Ryo Hatano, Hayato Ohwada, and Hiroyuki Nishiyama

Faculty of Science and Technology, Tokyo University of Science, 2641 Yamazaki, Noda-shi, Chiba 278-8510, Japan
7418512@ed.tus.ac.jp

Abstract. In this study, we attempt deriving rules to estimate the productivity of dairy cows using inductive logic programming (ILP) for dairy farming. The milk yield of dairy cows is economically important and, of course, should be large. Accordingly, we selected data using the total milk yield in a lifetime as a threshold, and our ILP algorithm learned about positive and negative cases. As a result, 42 rules in positive, and 11 rules in negative were derived. ILP is also applicable for dairy farming and can provide useful information for farmers.

Keywords: Inductive Logic Programming · Prediction · Dairy Cow · Productivity.

1 Introduction

Till date, inductive logic programming (ILP) approaches have been applied to a wide range of pattern matching tasks, as the ordinary ILP algorithm can produce a set of interpretable rules in terms of logic programming based on first-order logic as a (supervised) machine learning model [1]. In contrast to ordinary machine learning models such as deep neural networks, the resultant rule set produced by an ILP algorithm directly explains the hidden patterns in a given training set. In some cases, applying the resulting rules to the desired applications directly is possible.In this study, we apply an ILP approach to the field of dairy farming. Our aim is to provide helpful feedback to dairy farmers using an ILP system. To achieve this, this short paper focuses on deriving hidden rules to describe the productivity of dairy cows at an early stage of rearing.

From 2009 to 2018, the number of dairy farmers in Japan decreased by 4% every year, i.e., 32% in total [2]. However, as the number of breeding cows per dairy farm increases, many farmers face heavier workloads. To overcome this issue, some dairy farmers have started automating tasks such as milking, employing *robots*, e.g. the DeLaval Voluntary Milking System (DeLaval VMS). Using such milking robots, we can effectively collect data from the dairy cows: milking yield, milking time, feed intake, hormone content of the yield milk, among others. In this study, we propose an ILP-based method to find hidden rules of highly (or lowly) productive dairy cows by combining various data from the aforementioned milking robot and medical histories recorded by a veterinarian.

2 Related Work

It is known that the productivity of dairy cows is linked to their pregnancy status. Hence, relevant studies for modeling the productivity of dairy cows have focused on the pregnancy status in terms of success or failure of artificial insemination. In 2014 , Shahinfar et al. proposed a method to predict, via machine learning, the chances of successful pregnancy in cows at the time of artificial insemination based on the data of the cow's medical history including production/reproduction [3]. They trained and compared five machine learning models: decision tree, bagging, random forest, naive Bayes, and Bayesian network. From the results it was found that the best model was the random forest, with an accuracy of 70%. As for ILP approaches, Matsumoto et al. proposed a method to find the hidden rules of optimal conditions for successful artificial insemination of dairy cows [4]. They obtained rules that explain possible optimal artificial insemination timings and conditions based on progesterone value, feed intake, activity amount, and parity.

3 Outline of Our Method

To obtain a set of rules to suit our purpose, we follow the usual ILP preprocessing techniques. That is, we select data such as milk yield, feed intake and hormones levels etc. from our raw dataset, extracting features by calculating the mean and variance of the obtained subset and converting them into logic programming form. Afterwards, we label such features in terms of the logic program and obtain a set of rules using the learning algorithm of ILP.

3.1 Data Set

As mentioned in our introduction, we use information on milk yield, feed intake and hormones levels in the milk collected from dairy cows by the DeLaval VMS milking robot. A cow enters the apparatus and the robot begins to locate its udder with a three-dimensional scanner. After detecting the appropriate position of the udder, it attaches a vacuum cup to milk the udder and starts automatically. During milking, the robot also records data such as milking time, milk yield and hormones levels in the milk, to be saved in a management database. For the purpose of our study, we collected the data of 9011 cows in 29 Japanese farms from 2015 to 2019. Our raw dataset consists of almost 2 million rows and 11 columns.

3.2 Preprocessing

In this study, if the raw data entry does not contain any missing columns, and matches at least one of the following conditions, we use it to extract features: (1) The status of a cow is 'retired' (2) The status of the cow is both 'active' and over 3 parities (3) The milking period of a cow exceeds 300 days. From the obtained subset of our dataset, we extract 25 types of features, including parity, number of failed inseminations and before/after of milking peak at each parity. Then, we convert the extracted features into logic programming form. In this study, we use the following definitions of 13 predicates in terms of the logic program to represent both features and rules, where the arguments of every predicate are a cow number and entry value :

1. Parity of cow
2. Number of times insemination failed
3. Average milk yield of cow
4. Average feed intake of cow
5. Average beta-hydroxybutyric acid content of milk
6. Average lactate dehydrogenase content of milk
7. Average progesterone content of milk
8. Standard deviation of milk yield of cow
9. Standard deviation of feed intake of cow
10. Standard deviation of beta-hydroxybutyric acid content of milk
11. Standard deviation of lactate dehydrogenase content of milk
12. Standard deviation of progesterone content of milk
13. Days until milking peak
14. Days after milking peak
15. Milking days in this parity

To calculate milk yield peak, we use an exponential moving average, which is a moving average that gives a positive weighting to the most recent data:

$$\mathrm{EMA} = \begin{cases} 0 & (k < n) \\ (\sum_{i \in k} i^{th} \text{ day's value}) \div k & (k = n) \\ (\text{Value on the day} - \text{Previous day's EMA}) \times \alpha & \\ \qquad\qquad\qquad\qquad + \text{Previous day's EMA} & (k > n) \end{cases} \tag{1}$$

This measure has a smaller amplitude and faster response than a simple moving average, so the turning point is recognized faster. In this study, we set the parameters as $n = 3$ and $\alpha = \frac{2}{(n+1)}$.

We divide the data of 663 cows into a 1:1 positive or negative group. The threshold in this case is about 18300 kg of milk yield in a lifetime. Afterward, we use Parallel GKS, developed by Nishiyama et al. [5] to obtain a set of rules as a model of ILP. In order to use Parallel GKS, we need to specify parameters called Plimit and Nlimit. Here, Plimit and Nlimit indicate the minimum number of positive cases that must be included and the maximum number of negative cases that can be tolerated, respectively. We set the parameters at 30 for Plimit, which corresponds to approximately 9% of the learning target, and 10 for Nlimit, which corresponds to approximately 3% of the learning target.

4 Result and Discussion

As a result, we obtained 42 rules from the positive group whose total milk yield is more than average, and 11 rules from negative group. The classification accuracy is 71.43% for positive cases and 79.56% for negative cases. As an example, we focus on two rules for the positive group in what follows. Here {T, F} denotes the number of positive examples (T) and the number of negative example (F) the rule covers.

```
{96, 10} class(A) :-
            aveBHB_2_before(A, smallLow(0.05:0.07)),
            aveBHB_3_after(A, smallHigh(-0.03:0.01))          .
{60, 10} class(A) :-
            aveBHB_1_after(A, smallHigh(-0.03:0.00)),
            aveBHB_2_after(A, smallHigh(-0.02:0.01)),
            aveLDH_2_after(A, smallLow(21.85:31.78)),
             aveLDH_2_all(A, smallLow(23.65:32.06))
```

This rule indicates the following: the BHB average before milking peak at 2 parities was slightly smaller, and the BHB average after milking peak at 3 parities was considerably smaller. The second rule indicates that the BHB average after milking peak at 1 parity was considerably smaller, the BHB average after milking peak at 2 parities was considerably smaller, the LDH average after milking peak at 2 parities was slightly smaller, and the LDH average at 3 parities was slightly smaller. From the above examples, the rules related to BHB can be seen. It is known that dairy cows with high BHB concentrations might be malnourished. However, it is understood that the generated rules are appropriate because they showed that the BHB value is smaller than average. On the other hand, cows must give birth to at least two calves to meet generated rules. In further studies, we want to derive rules that can be applied to dairy cows at an earlier period than these results were. In addition, we want to provide a helpful implementation that allows dairy farmers to utilize these results using touchscreen devices, e.g., tablets.

Acknowledgement

This study is supported by Livestock Promotional Subsidy from the Japan Racing Association. The first and fourth authors are also supported by JSPS KAKENHI Grant Number JP19K12105.

References

1. Muggleton, S., de Raedt, L.: Inductive logic programming: Theory and methods. The Journal of Logic Programming **19-20**, 629–679 (1994), special Issue: Ten Years of Logic Programming
2. Ministry of Agriculture, Forestry and Fisheries: Livestock statistics (2018), `https://www.e-stat.go.jp/stat-search/files/data?sinfid=000031761476&ext=pdf`
3. Shahinfar, S., Page, D., Guenther, J., Cabrera, V., Fricke, P., Weigel, K.: Prediction of insemination outcomes in holstein dairy cattle using alternative machine learning algorithms. Journal of dairy science **97**(2), 731–742 (2014)
4. Matsumoto, A., Kubota, C., Ohwada, H.: Extracting rules for successful conditions for artificial insemination in dairy cattle using inductive logic programming. In: Proceedings of the 9th International Conference on Machine Learning and Computing. pp. 6–10. ICMLC 2017, ACM, New York, NY, USA (2017)
5. Nishiyama, H., Ohwada, H.: Parallel inductive logic programming system for superlinear speedup. In: Lachiche, N., Vrain, C. (eds.) Inductive Logic Programming. pp. 112–123. Springer International Publishing, Cham (2018)