A preliminary evaluation of the use of on-animal sensor data to predict metabolizable energy intake of sheep using Deep Belief Networks

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Abstract

The use of digital technologies in livestock businesses can improve the efficiency of farmers managing welfare and productivity of their animals. One opportunity is to use high resolution livestock behaviour information to inform decision making. Livestock behaviour recorded by sensors such as GPS or accelerometers, can be analysed to capture activities that can inform farm management. In this paper, our focus was on livestock grazing behaviour in relation to the feed supply in extensive grazing systems. We investigated the use of a Deep Belief Network (DBN) to predict the Metabolizable Energy Intake (MEI) of sheep directly using sensors. With the complexity and the availability of more data forms especially in the sensor data, the use of DBN was evaluated as an analytical method that could be applied to improve farmer's understanding of livestock grazing behaviour and feedbase management by the prediction of MEI values daily. Based on a field experiment, results generated from the DBN achieved with the MSE result of 5.6 to the training dataset and the testing dataset of 11.6. This demonstrated that the DBN method can be undertaken to predict the MEI for sheep using sensor data. Furthermore, by finding out which factors influenced grazing behaviour this study can be used to better interpret biological interactions in grazing systems, and potentially be extended to develop sensor technologies and new analytical methods in other agricultural domains.

Keywords: deep belief networks, livestock behaviour, energy intake, machine learning, predictions, on-animal sensor data

Background

Regular monitoring of livestock that are managed in extensive grazing systems is essential for the animal's welfare and productivity, and in some countries, is mandated by law (Lindgren 2016). However, inspecting livestock is a costly and onerous task for farmers managing large herds across extensive agricultural landscapes. New sensor technologies have created an opportunity for farmers to use behavioural information in the day-to-day management of flocks with greater efficiency than has previously been possible. The key to this is the development of new analytical approaches to process large volumes of sensor data into information that enables management. In this paper, we explore the application of Deep Belief Network (DBN) to predict the energy intake of sheep grazing crop stubbles in Western Australia directly from the sensor data.

It is widely accepted that relationships exist between grazing behaviour and feed supply. However, factors affecting these behaviours are still poorly understood, and relationships may be influenced by the characteristics of the paddock environment, flock structure and type of livestock (Prache and Peyraud 2001). Sheep have been found to respond to decreased sward biomass by increasing grazing time, reducing time idling, increasing distance walked and reduced time spent and number of bites taken at each feeding station (e.g. Allden and Whittaker 1970; Penning et al. 1994; Roguet et al. 1998; Prache et al. 2006). Distance sheep separate from their cohorts is also affected by feed supply (Dudzinski, 1969; (Dumont and Boissy 2000). Prache and Peyraud (2001) suggest that at some point sheep can determine that there is a net energetic cost in further increasing grazing time and found that although feeding time increased with feed depletion in a pasture, up to a point, it then decreased when feed supply was further depleted. So, behavioural response to feeding supply is complex, and our understanding and use of this information are likely to benefit greatly from developments in sensor technologies and new analytical methods.

Deep Belief Network (DBN) was first introduced by Hinton et.al. (Hinton et al. 2006). It was intended to solve three problems that occur when a back-propagation algorithm is applied to deep layer Neural Network i.e. a slow learning time, a poor parameter selection technique that leads to poor local optima and necessity of substantially labelled data set for training (Arel, Rose et al. 2010). The architecture of DBN was formed by a stacked Restricted Boltzmann Machine (RBM), and its purpose is to initialize a learning process in DBN. Input provided to DBN passes through a series of stacked RBM that builds the layers of the network. The word “restricted” points to the fact that there are no connections between the units in the same layers. Salakhutdinov and Hinton (Salakhutdinov and Hinton 2009) in their study claimed that using RBM, learning would be more efficient and effective because there is no connection between the hidden unit in the same layer. The advantage of RBM in the pre-training process of DBN has been evaluated in some researches. Since the pre-training process (initialization) uses RBM instead of random weight, the performance of DBN has been shown in many papers to be better than any conventional NN. Bengio et al. (Bengio, Lamblin et al. 2007) have stated that the performance of DBN when applied to MNIST handwritten digits dataset show a significant improvement over feed-forward networks. Moreover, in NLP and vision classification tasks (Larochelle, Erhan et al. 2007) there are many factors of variation that interact in nonlinear ways and make learning more difficult. However, in facing such complex structure problems, DBN has also shown its resilience. As DBN has not been used widely in this area, it is one of the purpose of this paper to investigate the possibility of using DBN for such prediction.

In this paper, we test the hypothesis that DBN analytics can predict the energy intake of sheep grazing a wheat crop residue, and provide a signature as to when the feed supply from the paddock becomes depleted. If estimates of pasture quality and the animal’s energy intake could be identified through individual animal monitoring from sensor data, this could be used to develop decision support systems for livestock farmers.

Methods

Data for this study was from a previous field trial, where a group of 174 Merino sheep (62 kg and aged 4.5 years at the commencement of the study) were sourced from a commercial flock in the central Wheatbelt of Western Australia. The sheep were grazed in an 88 ha paddock containing wheat crop stubble for 55 days, and four sheep were selected randomly and fitted with GPS tracking collars which recorded their position and activities (roll and pitch angle) at 5 minute intervals. A subset of 20 sheep was identified and weighed weekly, including those with tracking collars. At all times, the sheep had access to water ad libitum from a single dam located in the paddock. The CSIRO Floreat Laboratory Animal Ethics Committee approved the protocol for the experimental work undertaken and monitored the welfare of the animals (organisational approval reference 0715).

Two sets of data are used in this study, namely sheep weight and sheep monitoring datasets (i.e. sensor dataset). The first dataset (sheep weight) included eight weeks of the weight measurements of the sheep recorded on a weekly basis. The second dataset (sheep monitoring) included data collected from the GPS collars (i.e. sensors) on the three sheep (monitoring data of the fourth sheep was not suitable to be used due to a high proportion of missing data). The second dataset has 27 attributes and includes data that link to the sheep’s behaviour.

The first step in this study was to use the sheep weight information to calculate the energy intake of the sheep over the duration of the grazing trial. The daily Metabolizable Energy Intake (MEI) of the sheep was calculated based on weekly live weight gain or loss, using the equations from Thomas et al. (2009). The calculated MEI was then matched with the sheep tracking data. Instead of using all the available attributes in the monitoring data, in this study, we selected the Temperature, Δ Pitch, Δ Roll, Distance and Speed attributes as the predictors (independent variables), which were considered to have the greatest biological relevance. Furthermore, we also calculated the grazing time as a predictor for MEI.

For training of the DBN, we needed MEI data at a daily resolution to match the aggregated daily resolution of the sheep monitoring dataset. To obtain the MEI daily basis data, we applied the polynomial interpolation approach. We assume that we need to nearly fit a polynomial curve that passes all the calculated weekly MEI. After some experiments, we found that the 2nd order polynomial interpolation provided the best trend line for most of the calculated weekly ME. The 2nd polynomial curve is then used to interpolate the daily MEI values.

To establish the DBN prediction model, we use the independent variables (the predictors) from the sheep monitoring dataset; Temperature, ∆ Pitch, ∆ Roll, Distance, Speed, and Grazing time. In this analysis, we only included day-time activity from sunrise to sunset local-time as early morning and late afternoon were identified as the periods when a large majority of grazing occurs. For the temperature and the speed, we average the temperature and the speed of the sheep movement for the whole day-time period (data available in 5 minute intervals) to represent the temperature of the day and the daily speed movement. As for ∆ Pitch, ∆ Roll, and Distance, the daily sum of each of these variables was used for the day-time period as the value for the day.

The dependent variable of the model, was the interpolated daily MEI value from the calculated weekly MEI value. Using the above independent variables and the dependent variable, the DBN was trained using data from two animals. After the DBN training (establishing the prediction model), it was used to predict the MEI for the third animal that was not included in the model training.

The parameters of the DBN were selected and adjusted to obtain the good performance for training the dataset and generating the prediction model.

Table 1. DBN parameters

Parameters	Values
Hidden layers	20-18-8-6
Activation function	Tanh
Learning rate	0.1
Learning rate scale	1
Momentum	0.4
Number of epochs	3000
Output function	Linear
Batchsize	10
Hidden dropout	0.2
Visible dropout	0.1
CD	1

Results

In this study, we used Deep Belief Network (DBN), one of the machine learning techniques, to establish the prediction model. DBN was used to predict the MEI values. We utilised the mean squared error (MSE) to find the difference between the estimator and what is estimated. The MSE is calculated using the following formula:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\check{Y}_i - Y_i)^2 \qquad (1)$$

Where $\check{Y}$ is a vector of n prediction and Y is the vector of observed values corresponding to the input to the function which generated the predictions. Y_i is the i*th* value of the vector.

The results show that by using the 2nd polynomial interpolation, the combination data of animal ID280 and animal ID285 provides the best MSE value result for predicting data of animal ID291.

MSE training data = 5.6	MSE testing data = 11.6

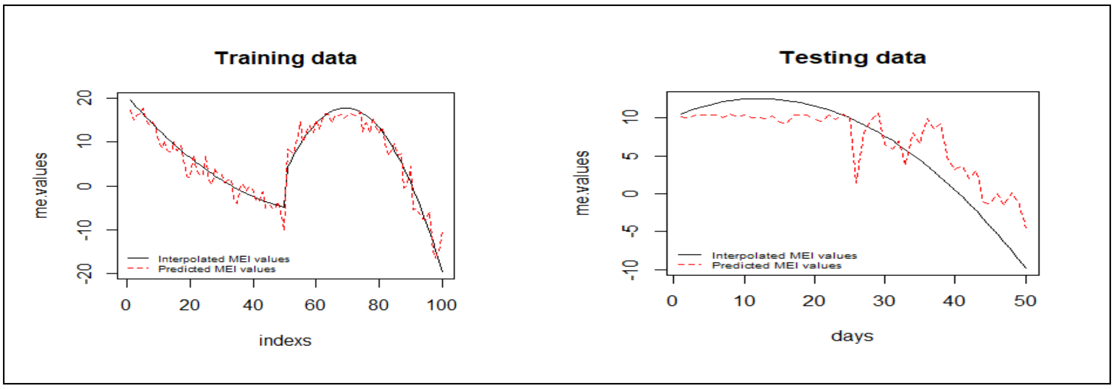

Figure 1. The MSE result values and the graph of the training and testing data

Conclusion

The DBN method has been applied to predict the energy intake of sheep grazing. The result shows that this technique can predict the MEI value with a more sensible data trend line using sensor data directly. In the testing data, the prediction values show that in the first four weeks the MEI increases then it decreases in the following weeks. In this preliminary study, only three animals' data were available to be used so there are a number of limitations in our analysis. First, only two animals were available for training and testing the established model was conducted on the third animal. We also have a limited number of data available for MEI as it was derived from weekly weighing of sheep in the field and only eight weeks of data points are available to interpolate to daily data. Finally, the capacity of the model to predict MEI of sheep grazing other crop stubbles was not determined. So, subsequent research should be focused on methods to aggregate and test a broader range of behavioural data that is derived from livestock grazing in other stubble paddocks under similar conditions.

Based on this study, it is possible to establish a good prediction model using DBN techniques to predict MEI from sensor data. However, the limitation of available data and the noise in the data could affect the model. Other grazing environments are needed to test the model. A different environment such as capturing data from the different paddocks at two or three different seasons and the different type of livestock should be considered. The selection predictor variables and an assessment on which provide more influence in the prediction of MEI can be used to inform the development of new sensor technologies with improved scope and reliability.

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