

Categorization of Birth Weight Phenotypes for Inclusion in Genetic Evaluations Using a Deep Neural Network

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Summary with Implications

Birth weight serves as a valuable indicator of the economically relevant trait calving ease. However, the method used to collect birth weight data can impact the amount of phenotypic variation within a contemporary group and could impact subsequent genetic predictions of both birth weight and calving ease. The aim of this project was to investigate the use of a Deep Neural Network to categorize birth weight contemporary groups based on data quality and to determine the impact on the ranking of animals for calving ease Expected Progeny Differences (EPD). Although most birth weight contemporary groups were classified as real, some contemporary groups were classified as having been generated from a hoof tape or as fabricated. Across the entire population, the removal of contemporary groups where birth weights were clearly classified as fabricated did not impact the genetic prediction for calving ease, however, for animals with higher accuracy associated with their calving ease Expected Progeny Differences, the impact was greater leading to a change of 1 to 2 units in Expected Progeny Differences. Results suggest that a well-trained Deep Neural Network can be effectively used to classify data based on quality metrics prior to inclusion in routine genetic evaluation.

Introduction

Birth weight (BW) serves as a valuable indicator of the economically relevant trait calving ease (CE). More germane to the issue of birth weight data collection is the fact that many bull buyers rely on actual birth weight values as a primary selection criterion. This, in conjunction with a real or per-

ceived obligation to record a birth weight even if birth weight recording did not occur, could potentially lead to fabricated birth weight phenotypes. Even with a desire to contribute valuable data to genetic evaluations, producers may not have the labor required to physically weigh every calf born and thus might use hoof tapes or simply guess weights. The process used to generate birth weight data impacts phenotypic variation and could impact subsequent genetic predictions of both BW and CE. The aim of this project was to investigate the use of an Artificial Intelligence algorithm called a Deep Neural Network (DNN) to categorize contemporary groups based on data quality and to determine the impact on the ranking of animals for CE EPD.

Procedure

Contemporary groups (CG; n=1,200,000) were simulated including individual animal birth weight, sex and age of dam. Twelve possible classifications for CG were assumed that could impact CG phenotypic variance, including weights recorded with a digital scale (REAL), hoof tape (TAPE), those that were fabricated (FAB), and those that were generated with a mixture of methods (DIRTY; e.g., some real weights but missing values were fabricated). Within these four broad categories, CG were further delineated based on variation in age of dam, and the increments of birth weight phenotypes (e.g., 2 or 5-lb increments). These twelve types were later combined to make 4 CG types that would ultimately be used in genetic evaluations (Table 1). Contemporary groups had a minimum of 10 and a maximum of 500 animals. The simulated CG information were used as input variables for the training (80% of the CG) and testing (20% of the CG) of a Deep Neural Network with the goal of accurately and consistently predicting the CG type. This process was replicated 10 times. Multiple parameters of the DNN were tested and compared using both accuracy and precision (consistency) in the simulated data and

the final model was chosen based on these two criteria. The final DNN model was used in the prediction of the CG types for birth weight from the American Hereford Association (n=46,177 CG).

The final prediction of the type of each CG was based on the mode of the 10 replicates. Agreement scores were calculated and defined by the proportion of replicates that led to the final CG type prediction. For example, if nine of the ten DNN replicates predicted a CG to be REAL, then the agreement score was 90%.

The impact of removing records from CG classified as FAB from the four categories on resulting CE EPD was investigated. Calving ease direct (CED) and calving ease total maternal (CEM) EPD were calculated using a multi-trait animal model including birth weight and calving score data and implemented using the BOLT software.

Results

The majority of CG were classified as REAL or TAPE (70.66% and 16.27% of the total CG; Table 1). As expected, the lowest phenotypic variance was for FAB CG (12.87 lb²), while REAL and TAPE CG had the highest and intermediate variances (76.94 lb² and 33.27 lb²), respectively. From these results, approximately 80% of the predictions were classified as "Excellent", meaning that of the 10 replicates, the DNN classified the CG the same at least nine times showing a high degree of confidence in the prediction.

A high correlation was observed for CED and CEM EPD (0.91 and 0.86, respectively) between the case when no corrective action was taken (all records used) and when BW and CE records of animals from CG predicted as being FAB were removed. Only records from CG with agreement of 90% or greater were removed. However, Table 2 shows the distribution of animals by change in CE EPD between the two cases mentioned above. Animals with moderate to higher accuracy (Beef Improvement Federation scale) for CE EPD appear to be

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Table 1. Summary statistics of real birth weight (BW) for combined predicted contemporary group (CG) types and the percentage of CG by agreement categories (Excellent= >=90%; Good >=70% and < 90%; Moderate= >=50% and < 70%;Poor= <50%).

| Type ¹ | % CG | % Animal | Mean BW | Var BW | Mean CG Size | Var AOD ² | Agreement ³ | | | |
|-------------------|------|----------|---------|--------|--------------|----------------------|------------------------|-------|----------|------|
| | | | | | | | Excellent | Good | Moderate | Poor |
| REAL | 70.7 | 73.8 | 84.2 | 76.9 | 29.4 | 3.2 | 87.8% | 7.5% | 4.5% | 0.2% |
| TAPE | 16.3 | 13.7 | 79.3 | 33.3 | 23.7 | 3.0 | 52.1% | 25.4% | 21.0% | 1.4% |
| FAB | 7.0 | 6.0 | 78.7 | 12.9 | 23.9 | 2.9 | 60.7% | 20.2% | 17.4% | 1.7% |
| DIRTY | 6.0 | 6.5 | 81.4 | 63.3 | 30.5 | 3.5 | 83.9% | 9.1% | 6.4% | 0.6% |
| Mean | | | 82.8 | 59.5 | 28.2 | 3.15 | 79.9% | 11.4% | 8.2% | 0.5% |

¹ REAL=real groups collected with a digital scale; TAPE=groups collected with a hoof tape; FAB=Fabricated weights; DIRTY= A mixture of types.

² AOD=Age of dam

³ Agreement refers to the proportion of replicates that produced the same prediction.

Table 2. Percentage of animals by calving ease direct (CED) EPD change and CE EPD accuracy level.

| CED EPD units | Levels of CED EPD accuracy using all records | | | | |
|----------------|--|-------------------|-------------------|-------------------|--------|
| | =<0.10 | >0.10 & <=0.25 | >0.25 & <=0.35 | >0.35 & <=0.55 | =>0.55 |
| <=1 unit | 78.0% | 48.7% | 34.7% | 32.7% | 34.7% |
| > 1 & <=2 unit | 19.9% | 28.5% | 32.4% | 31.9% | 31.9% |
| > 2 & <=3 unit | 1.3% | 12.0% | 17.4% | 20.2% | 22.7% |
| > 3 & <=4 unit | 0.4% | 5.3% | 8.2% | 9.2% | 5.6% |
| > 4 & <=5 unit | 0.2% | 2.6% | 3.9% | 3.7% | 3.5% |
| >5 unit | 0.3% | 2.9% | 3.3% | 2.2% | 1.4% |
| No. Animals | 12,596 | 2,770,882 | 508,658 | 12,820 | 141 |

impacted the most. This is due to the fact that they have the greatest number of progeny and, consequently, are the most at risk of having records of descendants removed.

Conclusions

Given these results, it is recommended to remove birth weight and calving ease phenotypes from the genetic evaluation for animals belonging to contemporary groups predicted as FAB with a consistency of classification of 90% or greater.

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