Relationships between First Test Day Metrics of First Lactation Cows to Evaluate Transition Period

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Abstract. *The objective of this study was to apply principal component analysis (PCA) and multiple correspondence analysis (MCA) on Dairy Herd Improvement (DHI) data of animals on their first lactation to discover the most meaningful set of variables that describe the outcome on the first test day. Data collected over 4 years were obtained from 13 dairy herds located in Québec – Canada. The data set was filtered to contain only information from first test day of animals on their first lactation, resulting in 1637 observations and 35 variables. Eight additional variables were created from the existing DHI metrics. PCA was performed on numeric variables (n = 14) after they were standardized to mean = 0 and standard deviation = 1. MCA was performed on categorical variables (n = 20). Seven numerical variables and eight categorical variables were selected as meaningful to describe the variation on the first test day using PCA and MCA. These variables could be used to evaluate the outcome on the first test day of animals on their first lactation and assist in the evaluation of their transition period. Future work could focus on modeling the relationship between those variables.*

Keywords. *Dairy herd improvement data, precision dairy farming, principal component analysis, multiple correspondence analysis.*

Introduction

In precision dairy farming, Dairy Herd Improvement (DHI) metrics are important for decision-making. However, DHI databases are over-parameterized and it is necessary to apply multivariate statistical methods in order to get meaningful data insights. Principal component analysis (PCA) is useful in analyzing multivariate numeric data sets. The aim of the technique is to represent the data using a reduced number of axes (principal components) that represent the variation observed on the data set in decreasing order (Borcard et al. 2011). The results can be analysed visually through biplots of the principal components which in turn allow to select the most meaningful set of variables that describe the variation. Multiple correspondence analysis (MCA), on the other hand, is commonly used to analyze categorical variables. It is an extension of correspondence analysis and makes possible to investigate patterns among multiple qualitative variables (Abdi and Valentin 2007). The total variation in the data set is named inertia in MCA. The first dimension carries the most variation (inertia) followed by the second dimension and so on. The contribution of each categorical variable to the total inertia on each dimension are estimated and the variables that contribute the most are more? meaningful in explaining the variation.

One important usage of DHI databases would be to evaluate the transition period of dairy cows. The transition period is defined as the 3-week period before and after calving (Grummer 1995; Drackley 1999). The offset of a new lactation is likely to create a negative energy balance in dairy cows (Bell 1995), making them susceptible to poor productive and reproductive performance (Drackley 1999; Esposito et al. 2014). The Transition Cow Index (TCI) (Nordlund 2006) has been proposed as a tool to evaluate the success or failure of the transition period for multiparous dairy cows based on DHI measures from the first test of a new lactation and the last test of the previous lactation. However, no such tool is available for cows entering their first lactation. Therefore, the objective of this study was to apply principal component analysis (PCA) and multiple correspondence analysis (MCA) on DHI data of dairy cows on their first lactation to discover the most meaningful set of variables that describe the outcome on the first test day and could potentially be used to evaluate the transition period of primiparous dairy cows.

Materials and Methods

Valacta, which is the Québec and Atlantic Centre of Expertise on Milk Production, in Canada, provided the data used in the present study from a pre-existing dataset. Therefore, no approval was necessary from the Ethics Committee on the Use of Animals from the Federal University of Jequitinhonha and Mucuri Valleys in order to conduct this study. Data processing and modelling were performed in the statistical software R (R Core Team 2017).

Creating the Working Data Set

The data were collected between 2011 and 2014 from 13 dairy herds located in Québec, Canada. The data was initially filtered to contain only information of the first test of animals on their first lactation, which resulted on 1637 observations and 35 DHI variables. Eight additional variables were created based on existing information. They were fat to protein ratio (FPR) on the first test, fat to true protein ratio (FPRt), energy corrected milk, age at first calving, season of calving, month of calving, season of birth, and month of birth. FPRt was created by removing milk-urea nitrogen from milk protein before calculating its ratio with fat content. Energy-corrected milk was calculated using the following equation proposed by Tyrrell and Reid (1965):

$$\text{ECM (kg/d)} = 12.55 \times \text{fat (kg/d)} + 7.39 \times \text{protein (kg/d)} + 0.2595 \times \text{milk yield (kg/d)}$$

Numeric variables (n = 45) were then entered into a Pearson correlation matrix to check for linear correlations between them. Variables with a greater than 0.95 correlation coefficient were evaluated for exclusion based on biological relevance. Twenty numerical variables were kept for further PCA analysis.

Out of twenty-three categorical variables, three that indicated the breed of the animal, the dam, and the bull were excluded because more than 99.4, 99.5, and 99.5% respectively, were of Holstein breed. Therefore, 20 categorical variables were kept for further MCA analysis.

PCA and MCA

Prior to PCA and MCA, missing values were handled using the package *missMDA* (Josse and Husson 2016). The functions *estim_ncpPCA* and *estim_ncpMCA* were used to estimate the number of dimensions for PCA (numerical variables) and MCA (categorical variables), respectively, by cross-validation. The optimal number of dimensions are the one that leads to the smallest mean square error of prediction (Josse et al. 2012). Next, the functions *imputePCA* and *imputeMCA* also from the package *missMDA* (Josse and Husson 2016) were used to replace the missing values of quantitative and qualitative variables, respectively using the number of dimensions estimated.

The PCA was performed using the function *rda* from the package *vegan* (Oksanen et al. 2017) on numerical variables (n = 14) scaled to a uniform matrix of mean = 0 and standard deviation = 1. Eigenvalues were calculated to find out the proportion of variation explained by each principal component. Significant eigenvalues were determined by the Kaiser-Guttman criterion? (Borcard et al. 2011).

The MCA was performed on categorical variables (n = 20) using the function *MCA* from the package *FactoMineR* (Sebastien Le et al. 2008).

Results

PCA

The first 5 eigenvalue dimensions were significant based on Kaiser-Guttman criterion [eigenvalue dimension higher than the average of all eigenvalues dimensions (Borcard et al. 2011)] and are depicted on Figure 1. The first principal component (PC1) with an eigenvalue of 4.20 explained 30.0% of the total variation and the second principal component (PC2) with an eigenvalue of 3.20 explained 22.8% of the variation. Altogether, PC1 and PC2 explained 52.8% of the total variation (Figure 1). Variable contrast was evaluated on all significant eigenvalue dimensions, but many redundancies were found after the PC2. Therefore, PC1 and PC2 were enough for the purpose of this study.

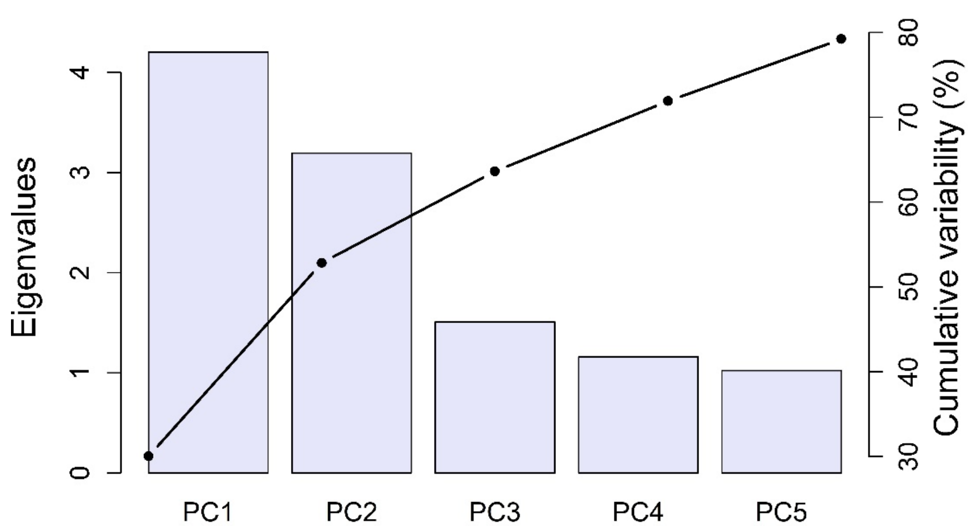

Figure 1. Cumulative variance plot and five significant eigenvalues according to kaiser-Guttman criterion (Borcard et al. 2011) extracted from principal components (PC) generated using principal component analysis (PCA).

The PCA vector ordination plot of PC1 and PC2 are depicted on Figure 2. Energy-corrected milk of the first test-day, standard fat yield for 150 days-in-milk (DIM), standard protein yield for 150 DIM, standard milk yield for 150 DIM, standard energy-corrected milk yield for 150 DIM, milk yield on first test day, and lactose yield on first test day explained more than average of the total variation. Therefore, they were considered the most meaningful set of variable to describe the variation on the first test day. Table 1 shows a Pearson correlation matrix of the 7 PCA-selected variables.

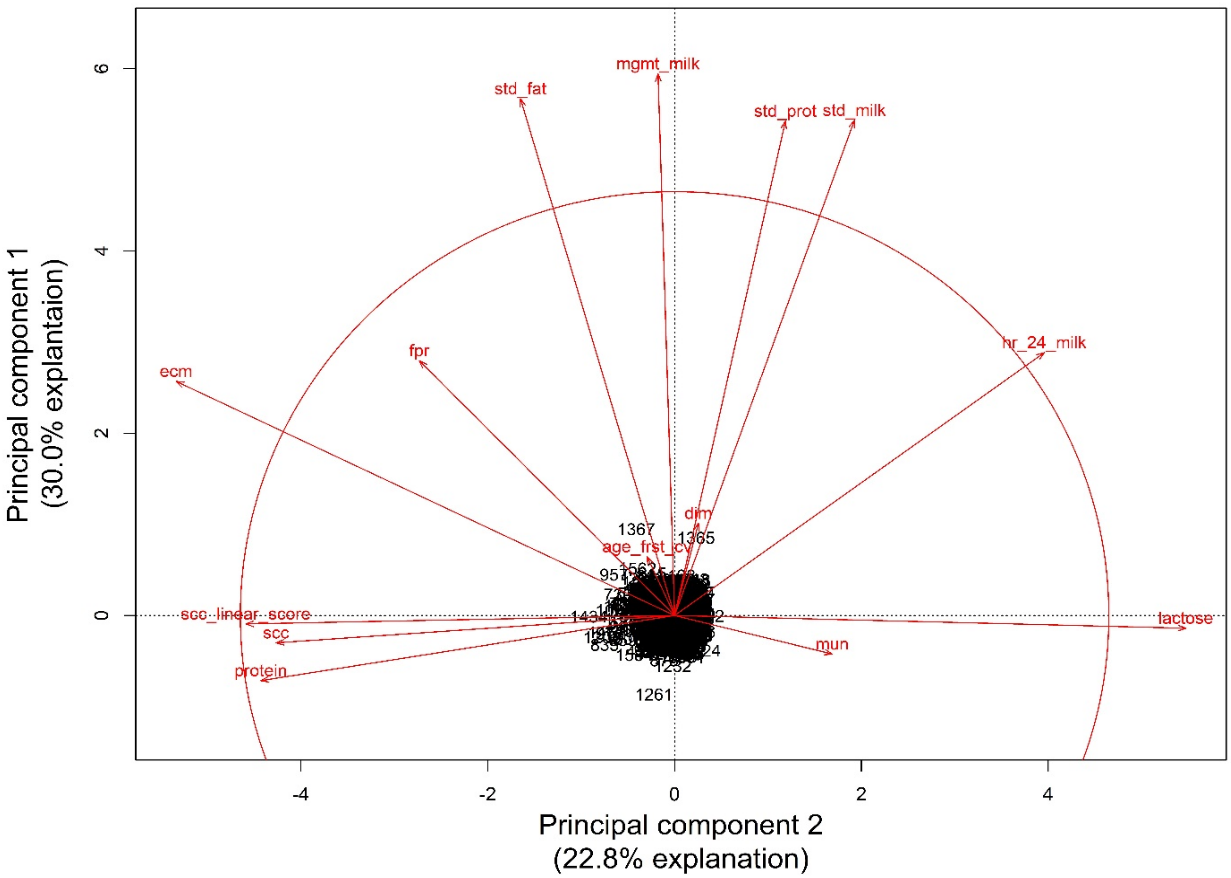

Figure 1. Biplot in the principal components 1 and 2 plane, depicting the directionality of variables and the amount of variation (arrow length) explained by each of them standardized to mean = 0 and standard deviation = 1 versus the mean of eigenvalues (○) for all standardized variables. Each dot in the center represents one animal. mun = milk urea nitrogen (mg/dl) on first test day, standardized; lactose = lactose yield (kg) on first test day, standardized; hr_24_milk = milk yield (kg) on first test day, standardized; std_milk = standard milk yield (kg) for 150 days-in-milk, standardized; std_prot = standard protein yield (kg) for 150 days-in-milk, standardized; dim = days in milk on first test day, standardized; mgmt_milk = standard energy-corrected milk (kg) for 150 days-in-milk, standardized; std_fat = standard fat yield (kg) for 150 days-in-milk, standardized; age_frst_cv = age at first calving (days), standardized; fpr = fat to protein ratio, standardized; ecm = energy-corrected milk (kg) on first test day, standardized; scc_linear_score = linear score of somatic cell count on first test day, standardized; scc = somatic cell count on first test day (104 cells ml-1), standardized; protein = protein yield (kg) on first test day, standardized.

Table 1. Pearson correlation between seven principal component analysis-selected variables from first test day of dairy cows on their first lactation.

Item[1]	hr_24_milk	lactose	std_milk	std_fat	std_prot	mgmt_milk	ecm
hr_24_milk	1.00						
lactose	0.41	1.00					
std_milk	0.54	0.14	1.00				
std_fat	0.29	-0.18	0.76	1.00			
std_prot	0.47	0.08	0.95	0.76	1.00		
mgmt_milk	0.41	-0.05	0.92	0.95	0.92	1.00	
ecm	-0.24	-0.54	0.07	0.62	0.17	0.41	1.00

[1]hr_24_milk = milk yield (kg) on first test day; lactose = lactose yield (kg) on first test day; std_milk = standard milk yield (kg) for 150 days-in-milk; std_fat = standard fat yield (kg) for 150 days-in-milk; std_prot = standard protein yield (kg) for 150 days-in-milk; mgmt_milk = standard energy-corrected milk (kg) for 150 days-in-milk; ecm = energy-corrected milk (kg) on first test day.

MCA

The first 32 dimensions were considered significant based on their eigenvalues. Analysis of variable contributions to each dimension showed that different levels of the variables month of birth and calving, season of birth and calving as well as information regarding the calving of the second calf were the most relevant variables. In addition, a map depicting only the first two dimensions was enough to represent the variables according to their overall relevance, even though the 1st and 2nd dimensions only explained 4.7 and 3.5% of the inertia, respectively (Figure 3).

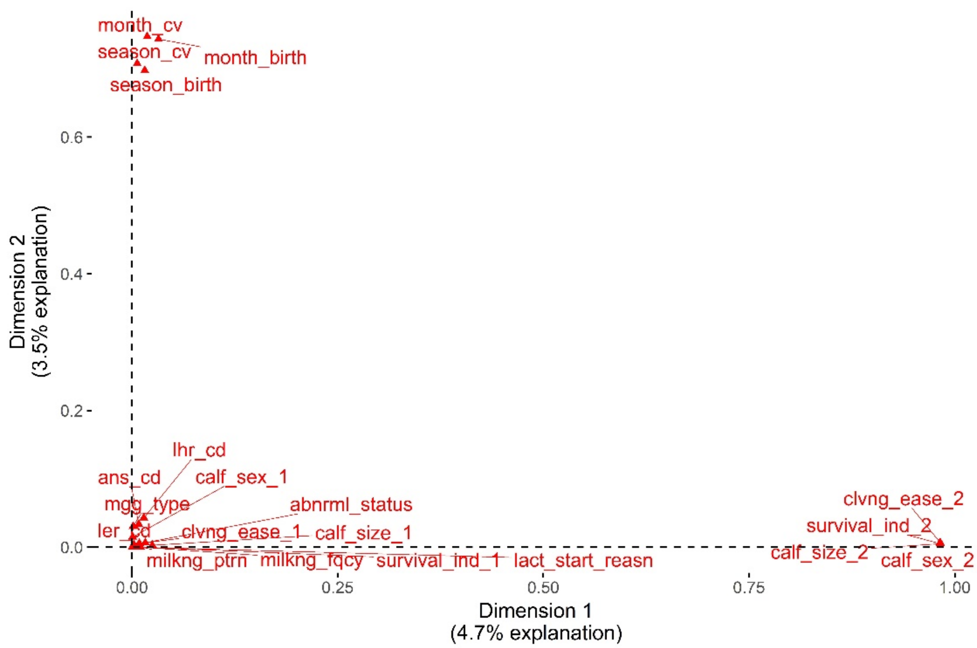

Figure 3. Multiple correspondence analysis map in two dimension axes of all categorical variables. month_cv = month of calving (1 – 12); month_birth = month of birth (1 – 12); season_cv = season of calving (summer, fall, winter, or spring); season_birth = season of birth (summer, fall, winter, or spring); clvng_ease_2 = calving ease of 2nd calf (unobserved, easy pull, hard pull, or mal-presentation); survival_ind_2 = survival of 2nd calf (yes or no); calf_size_2 = size of the 2nd calf (small, medium, or large); calf_sex_2 = sex of 2nd calf (female or male); clvng_ease_1 = calving ease of 1st calf (unobserved, easy pull, hard pull, or mal-presentation); survival_ind_1 = survival of 1st calf (yes or no); calf_size_1 = size of the 1st calf (small, medium or large); calf_sex_1 = sex of 1st calf (female or male); ans_cd = animal status (dry, milking, entered dry, entered milking, left herd, or lab only); mikng_ptrn = milking pattern (24-hour, am, or pm); milkng_fqcy = milking frequency (1 or 2 milking per day); mgg_type = management type (feed milking, feed dry, or feed prep); abnrml_status = abnormal status (initially accepted, questioned production, disallowed after questioning, allowed after questioning, or missing data); lact_start_reasn = lactation start reason (calving or abort); ler_cd = lactation end reason (dry-normal, dry-sick, died, sold, or terminated – off test); lhr_cd = left herd reason (dairy production, rented out, low milk production, bad temperament, slow milker, mastitis, udder breakdown, feet problems, sickness, accident, old age, milk fever, displaced abomasum, bloat, poison, transferred, reproductive problems, culled because of conformation, difficult calving, leucosis, peritonitis, pneumonia, injury on udder, arthritis, Staphylococcus aureus, Johne's disease, did not left the herd, unknown, or other).

Discussion

We have applied PCA and MCA to DHI dataset and successfully identified a subset of variables that best describe the variation observed on the first test day of dairy cows on their first calving. Some calculated variables were selected by PCA as more useful to describe the test day variation than the individual parameters themselves (Figure 2).

Dairy cows are susceptible to suffer from diseases and metabolic disorders during the transition period as a consequence of a negative energy balance (Drackley 1999). A direct approach in evaluating the transition period of dairy cows would be based on disease rates or metabolic disorder rates during this period. However, such approach has shown to be not very successful mainly because of inconsistencies regarding definition and recording of such events as well as low occurrence (Nordlund and Cook 2004). In addition, methods previously proposed such as cull rates by 60 days-in-milk (Roberts et al. 2012) lag between the offset of a new lactation and the evaluation results. Therefore, the transition period must be evaluated based on other variables such as DHI variables from the first test of a new lactation, since the test occur at the beginning of a new lactation which is when the incidence rate of metabolic disorders that are likely to affect the test results is the highest (Drackley 1999; Gantner et al. 2016).

Milk yield and its components were PCA-selected as important variables (Figure 2). Milk yield of first test is a better predictor of non-infectious disorders occurring during the transition period than body weight changes (Heuer et al. 1999), mainly because such disorders are likely to reduce milk yield during its occurrence (Gantner et al. 2016) as well as the entire lactation(Drackley 1999). Among those, subclinical ketoses is the main metabolic disorder with reported incidence rates reaching 43.2% (McArt et al. 2012). It is the risk factor for others diseases (Suthar et al. 2013; Gröhn et al. 1989) such as cystic ovarian and clinical endometritis (Shin et al. 2015). Dairy cows that suffered from ketosis during the transition period are 4.3 times more likely to not get pregnant on first insemination compared to cows that did not suffered from ketosis (Rutherford et al. 2016). In addition, the peak incidence of subclinical ketoses occurs at the beginning of the lactation (McArt et al. 2012) which is around the time when the first test day occurs.

Lactose is the main osmotic constituent of milk (Auldist et al. 1995). It is synthesized in the Golgi complex and stored in vesicles prior release on the alveoli (Sutton 1989). Its concentration 9in milk remains proportionally constant (Sutton 1989) following the total yield (Auldist et al. 1995). Therefore, the total amount measured on the first test day would be correlated to total milk yield of the test. Such correlation can be observed on Figure 2, since both vectors of lactose and milk yield are pointing to the same directions in the biplot. In addition, Buckley et al. (2003) have found that milk lactose content is a good tool to evaluate reproductive performance of dairy cows, which in turn is impaired if any disorders occurs during the postpartum transition period (Fonseca et al. 1983) mainly as a consequence of the negative energy balance (Drackley 1999).

Even though managerial practices are of great importance in ensuring a successful transition period, environmental conditions are also important. Cows calving on the coolest seasons has previously shown better productive (Stanton et al. 1992) and reproductive performance (Farin et al. 1994) compared to cows calving during the hottest seasons. The main reason for such result is the heat stress from which animals suffer during hot seasons. Shahzad et al. (2015) have shown that dairy cows calving during the summer with high temperature have altered liver fatty acid metabolization leading to lipidosis as well as induced inflammatory and intracellular response making the cow more susceptible to health disorders right after calving. In addition to calving season, birth season might also affects the transition period of first-calving dairy cows. Animals born during hotter months showed higher first test day (Van Eetvelde et al. 2017) and first-lactation 305-day (Chester-Jones et al. 2017) milk yield than cows born during the coolest months. In our study, MCA-selected variables account for time of year of calving and birth (Figure 3), which is in accordance to the result of other studies. Therefore, such variables would be of importance to evaluate the transition period of first-calving dairy cows.

Conclusion

Seven numerical variables and 8 categorical variables were selected as meaningful to describe the variation on the first test day using PCA and MCA, respectively. These variables could be used to evaluate the outcome on the first test day of animals on their first lactation and assist in the evaluation of their transition period. Future work could focus on modeling the relationship between those variables in order to evaluate the transition period of dairy cows, making possible to strategically handle the animals during such period and using DHI metrics in the contex of precision dairy farming.

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