Automated anomaly detection for milk components and diagnostics in dairy herds

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Abstract

Changes in the bulk tank milk component profiles (e.g., basic components, MUN and specific fatty acids) often indicate some positive or negative effects of nutrition, management, and environmental factors. Generally, producers and their advisors detect abnormal trends by visual inspection of components on a report, which is tedious and requires skills due to large volume of information. Our interim goal is to develop analytical tools to assist in the identification of unwanted, abnormal trends. Our broad goal is to develop tools that can propose plausible diagnostics and possible actions to re-establish the desired situation.

To achieve the interim goal, identification of anomalies is based on three numerical indicators (deviation, variation, and gradient) and breed-specific population ranking. Deviation is the difference between component values and population benchmarks, while variation and gradient indicate short-term (e.g., 4 days) and longer-term (e.g., 10 days) changes, respectively. We developed a python package which is executed daily to generate indicator values for all milk components, calculate the herd rank for each indicator, and create a series of reports for validation purpose. Among all possibilities that were investigated to trigger alerts and attention messages, an approach based on extreme gradients of the three main groups of fatty acids was adopted to start with.

With respect to the broad goal, we explore a rule-based expert system approach for diagnosing and recognizing potential issues regarding herd or rumen health management. Currently, we are at the stage of eliciting, implementing, and validating diagnostic IF-THEN rules with the collaboration of domain experts and computer scientists. The rules are based on the anomaly indicators and ranks. In parallel, we are exploring the use of ontology and symbolic artificial intelligence to develop a more complete diagnostic and recommendation system.

Keywords: Bulk tank milk component, anomaly detection, time series analysis, rule-based system, diagnostic rule, ontology.

Introduction

Changes in the value of indicators such as bulk tank milk components generally indicate some positive or negative effects of management and environmental factors such as feed quality, feeding behaviour, or ambient conditions. The data provided on milk profiles keeps expanding with the recent addition of fatty acids (e.g., de novo, mixed, preformed, polyunsaturated) to more standard components (e.g., fat, protein, MUN). Abnormal and unwanted trends can be detected in this data, which is generally done by producers and their advisors through visual inspection of components on a report.

Routine bulk tank analysis of milk fatty acids allows early detection of pattern changes which can provide early information on potential future problems. For example, a sudden and unplanned drop in de novo fatty acids concomitant with an increase in preformed fatty acids will often result in impaired rumen function, and eventually a drop in fat and protein yields, which will have an impact on milk revenue.

Trend anomaly detection on a report is tedious and requires skills, especially when simultaneously considering many complex variables such as specific fatty acids. Indeed, changes in trends often are not so obvious to detect by visual inspection, especially if they happen gradually over many days. In addition, there are many complex variables which are moving simultaneously in different directions. Also, experienced experts are not always available for consulting. One possible solution is to use robust analytics to provide insights to producers and their advisors, to help them reacting more rapidly and making more informed decisions.

This project aims to

1. assist in identification of anomalies in bulk tank milk components using basic statistical techniques;
2. inform/alert a producer and advisors that an abnormal trend is happening.

Complementarily, the use of a rule-based artificial intelligence (AI) approach is explored to help diagnosing and recognizing potential issues with respect to herd or rumen health management.

Our anomaly detection approach is based on the transformation of raw milk component values into features which we believe better represent an anomaly. These features, or indicators, are some basic statistical measures extracted from milk component values, and subsequently, a series of reports are produced for validation purposes on a daily basis. For running the aforementioned tasks, we developed a python package. However, the software should get enhanced to be capable of triggering messages and alerts based on extreme values in the new features. In parallel, we will continue to work with domain experts on the development of diagnostics rules.

Material and methods

Data

The lab analysis is performed on a bulk tank milk sample of a typical herd every two days for extracting the profile of its components, including fat, protein, MUN, and fatty acids such as de novo, mixed, preformed, and polyunsaturated. In this project, there are seven time series that are considered for each herd. Having such data for about 1300 herds over 3 years, we calculate daily a moving average per breed for each component and use it as time series benchmark. All components are on a milk basis for this analysis (kg/hL for fat and protein, mg N/dL for MUN and g/100g milk for fatty acids).

Anomaly detection method

Our anomaly detection approach consists of two major steps: (1) Calculating statistical measures for all components of all herds, and (2) Ranking the herds, each component separately, within the same predominant breed. Specifically, in the first step, three measures are calculated for all components of each herd, as illustrated in Figure 1:

- *Deviation* is the difference between the component value and population benchmarks (see the chart lines of the de novo which show that herd values are lower than benchmarks). The advantage of using deviation measure is removing

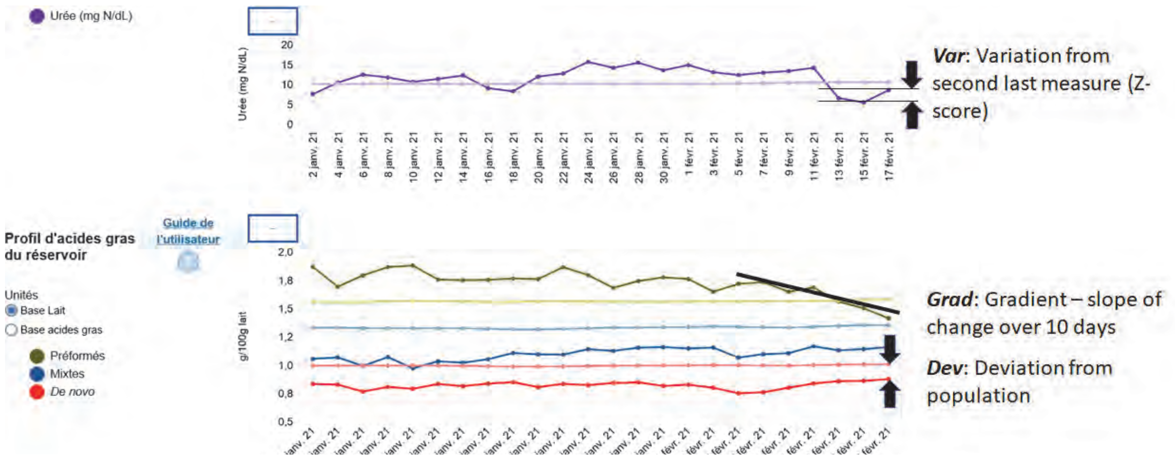

Figure 1. Calculating deviation, variation, and gradient. Component profiles and their corresponding benchmarks are shown by dark and light colours, respectively.

trend or seasonality, and population reaction effects, such as thermal stress, in the original time series.

Variation is defined as the difference of the current component value from the second last measures (see the line chart of the MUN). We also calculate the z-score of the variation values for each herd to make results comparable with each other herd. Variations specify short-term changes.

- *Gradient* is defined as the rate of change in 10 days (see the line chart of the preformed which indicates a decreasing trend). Gradients represent trends or long-term changes.

It must be noted that the number of lags in variation and the number of days in gradient are considered as parameters which can be regulated based on expert opinion and on-going calibration.

After obtaining the measurements, we can rank the herds, each component separately, in the second phase. Rank, or more precisely, percentile rank, is a common metric for scoring that maps a quantity to a value between 0 and 100. For instance, if rank of the fat deviation for a herd is 20th, it means 20% of the herds are below that herd. Having three measures and seven milk components, we will end up to 42 indicators (21 raw values + 21 rank values) for each herd. It is worth mentioning that ranking is done within the same predominant breed. However, it also can be done without considering the breed, if the number of herds with specific predominant breed is scarce.

Transformation of the deviation, variation (z-score), and gradient raw values for each herd into percentile ranks has some advantages:

1. It is unitless.
2. We can easily select thresholds and extract data (e.g., top 10%).
3. It can be used as a proxy for probability, likelihood, or degree of confidence.

Diagnostic method

Our basic approach toward finding problematic herds is to assess component ranks in extreme cases, for each measure, separately, while user-defined thresholds define low and high extremes, where both are considered anomalies. Based on an inventive formula, we assign a confidence level to each measure/component of a herd, and consequently, a total confidence level to the herd, along with the number of confidence levels. For instance, consider gradient ranks for a herd are 4 in fat, 9 in protein, 1 in de novo, 0 in mixed, 89 in preformed, 98 in polyunsaturated, and 5 in MUN. If we set low and high thresholds to 10% and 90%, respectively, then the preformed value is filtered out and the confidence level for a component is calculated using the following relation:

$$conf = \begin{cases} 100 - rank & if\ rank \leq Low \\ rank & if\ rank \geq High \end{cases} \quad (1)$$

This leads to a confidence level greater than the high threshold for a component, i.e., 96 in fat, 91 in protein, 99 in de novo, 100 in mixed, 98 in polyunsaturated, and 95 MUN. Then, we report the average of the confidence levels over the six confidence levels as overall confidence level for the herd, which in this example equals to 97.

Although our basic approach recognizes problematic herds, it leaves the interpretation of anomalies and diagnosis to farm advisors or producers, which can be challenging. To assist producers and their advisors in diagnostics and selection of corrective actions, the use of a rule-based expert system approach is being explored. Currently, we are at the stage of eliciting, implementing, and validating diagnostic IF-THEN rules with the collaboration of domain experts and computer scientists. The rules are based on the anomaly indicators and ranks. In parallel, a prototype ontology-based diagnostic and action recommendation system was developed to explore the convenience of a symbolic AI approach in terms of experts' knowledge maintenance and automated reasoning capabilities,

Results and discussion

A python package was developed for trend anomalies and diagnostic. Using the package, daily anomaly reports for advisors can be produced. One report consists of the statistical measures by component and herd ranks. We also create symbolic rank reports to highlight the herds with the lowest or highest percentile scores, applying user-defined thresholds over the ranks. These results are intended to trigger alerts for producers and advisors in extreme cases.

Extreme value analysis

Currently, we have come up with two extreme cases which relate to the existence of severe problems in herds. However, these cases are not associated with a specific diagnostic. Interpretation of extreme cases remains with the observant:

- Extreme Case I: *De novo* is decreasing (i.e., the rank of the gradient is less than 10%) and preformed is increasing (i.e., the rank of the gradient is greater than 90%). See, for example, Figure 2. This case usually reflects a sudden body mobilization. Documented examples would include important stress affecting a great proportion of cows in the herd (e.g., diarrheal episode through the herd, feed delivery issue impacting ration composition for a few meals/hours), an expected but sudden change in ration composition (e.g., cows going out on pasture in early summer, addition of an oil-containing feed as home-roasted soybeans or potato chips) or an important proportion of cows freshly calved.
- Extreme Case II: *De novo* is decreasing, mixed decreasing, and preformed decreasing. See, for instance, Figure 3. Our experience shows that these cases are often related to an overall decrease in dry matter intake in the herd: Preformed fatty acids decrease because of the lower fatty acid intake directly; and de novo and mixed fatty acids decrease because of the decreased rumen precursor availability due to reduced rumen fermentation, therefore affecting mammary gland synthesis of these fatty acid groups. It is important to note that this change could also be due to an increase in milk yield (i.e., dilution effect on fatty acid concentrations on a milk basis), therefore a generally positive outcome for the producer.

It should be noted that we are developing a mechanism which not only recognizes severe problems, but also display attention messages on reports accordingly, and suitably sends alerts to the producers at a reasonable frequency (not too high to be unnecessarily bothering, and not too low to leave severe cases unrecognized). To find out if the above extreme cases can be considered as the base of the alert/attention system, we analysed the data over a 3-month period (February to April 2022), which contains 52,483 observations on 1271 herds. Table 1 shows a summary of the analysis: For instance, if only the trend of the de novo fatty acid is investigated, we see that about 90 percent of herds had at least one observation of negative trend in these

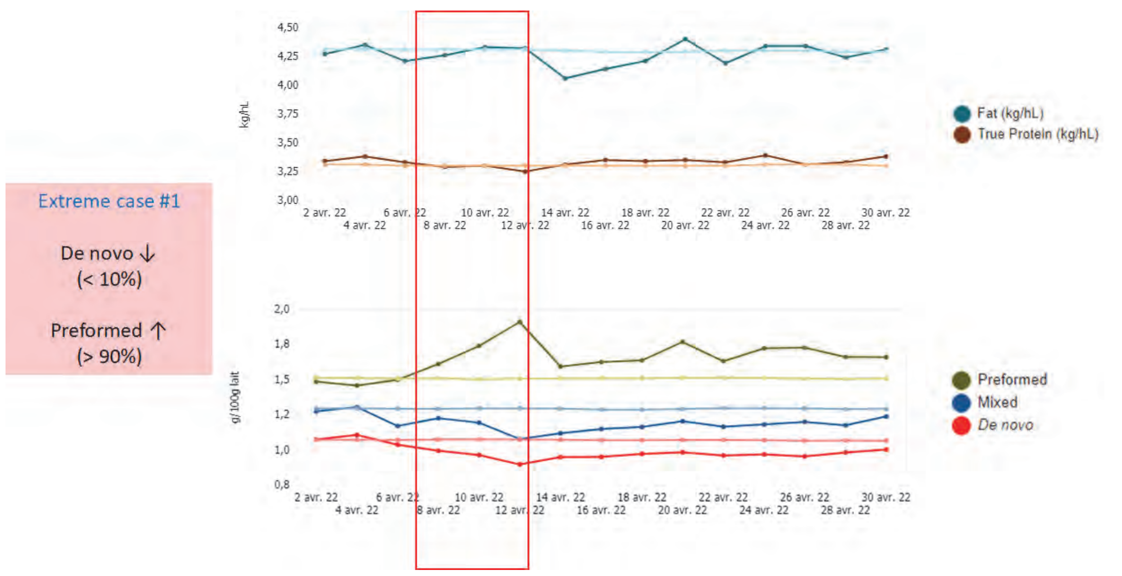

Figure 2. An example of the component profile of a herd in Extreme Case I.

Table 1. Analysis of extreme cases.

	% Observations	% Episodes	% Herds
All records	100%	100%	100%
De novo is decreasing	9.6%	5.5%	90.4%
Extreme Case I	1.7%	1.2%	36.%
Extreme Case II	0.7%	0.5%	18.6%

3 months. Or, equivalently, 9.6 percent of the records had an occurrence of decreased de novo (which corresponds to the fixed thresholds of 10%), among which 5.5 percent of records indicate episodes of decreased de novo, considering an episode is defined as a series of consecutive drops or increases. The average length of episodes in this case is equal to $\frac{9.6}{5.5} \approx 2$. Interestingly, the number of observations and episodes in both Extreme Case I and II is very low. Thus, both cases look qualified enough to trigger alerts along with proper messages on reports for producers at the beginning of an episode with an average length of 1.4 observations. Without triggering new alerts, attention messages can remain on reports during an episode.

With the help of domain experts in collaboration with computer scientists, we developed a rule-based system with seven diagnostic profiles and corresponding sets of corrective

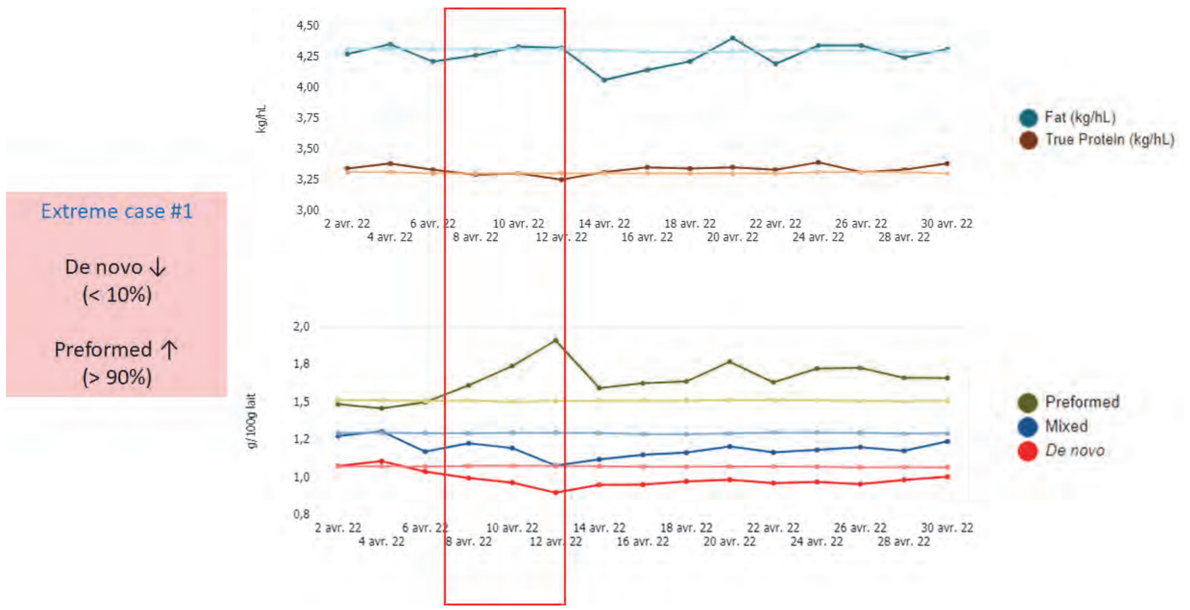

Figure 2. An example of the component profile of a herd in Extreme Case I.

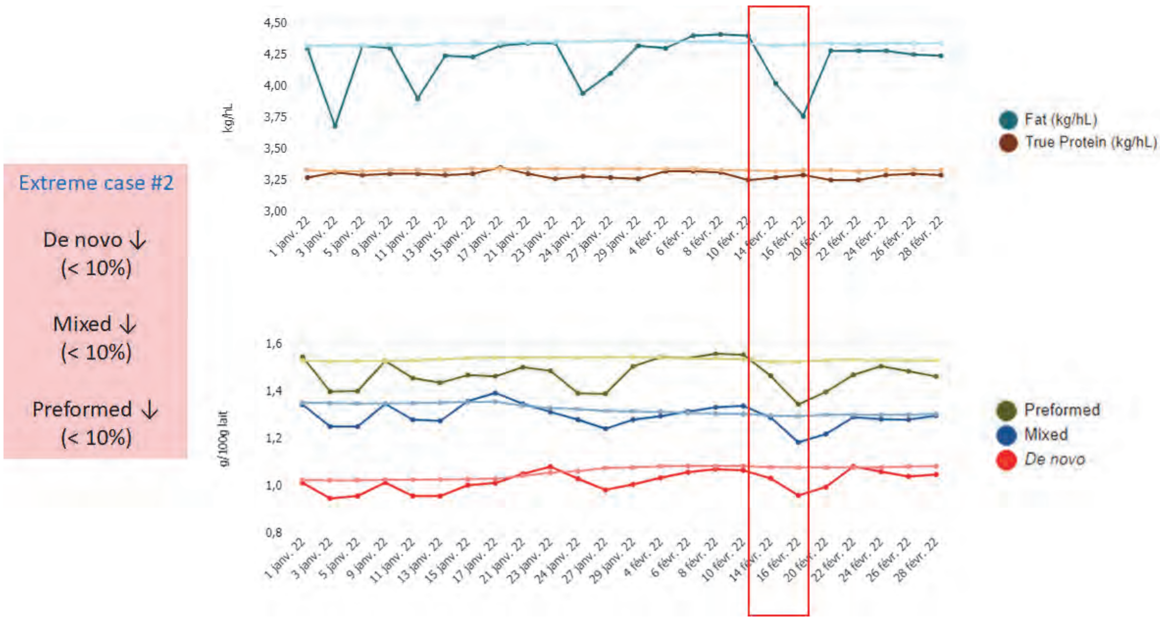

Figure 3. An example of the component profile of a herd in Extreme Case II.

Diagnostic rules

actions. Examples of profiles are risk of acidosis (Figure 4) and lack of consumption. One rule was developed for each profile, with each rule antecedent consisting of terms evaluating the value of selected deviations and gradients of milk components. A level of confidence in a diagnostic can be calculated through the ranks of the antecedents, similar to the previously presented extreme gradient rules. The rules were implemented in the anomaly detector program that runs every day. All rules are checked against all herds, and firing results are circulated for validation purposes.

Without surprises, this prototyping exercise has shown what has been known for years: there are challenges in the development, adjustment and maintenance of rule-based systems, and this approach leads to knowledge bases that tend to be static and limited in scope. For example, the possible corrective actions that were identified could individually be associated with different profiles, actions could be revised, and new actions could be frequently added, edited, or removed. Such knowledge could be embedded and handled more efficiently through an ontology, as we explored that avenue by implementing the seven rules and diagnostic profiles together with possible corrective action in a prototype. In this prototype, the ontology is stored in an OWL (Ontology-Web-Language) format and accessed by a python script. This script populates the ontology with the bulk tank data for each herd, which triggers an embedded reasoner and produces the corresponding diagnostics. Queries on the ontology can be done to retrieve possible corrective actions. Although, this prototype ontology was very limited, it could be expanded to make more complete recommendations, like suggestions about how to implement some corrective actions. In addition, such an ontology could be coupled to other existing ones, to expand the scope of recommendations of additional specific information.

In this project, we are developing a software application for recognizing anomalies in dairy herds, having bulk tank milk component profiles, such as fat, protein, MUN, and

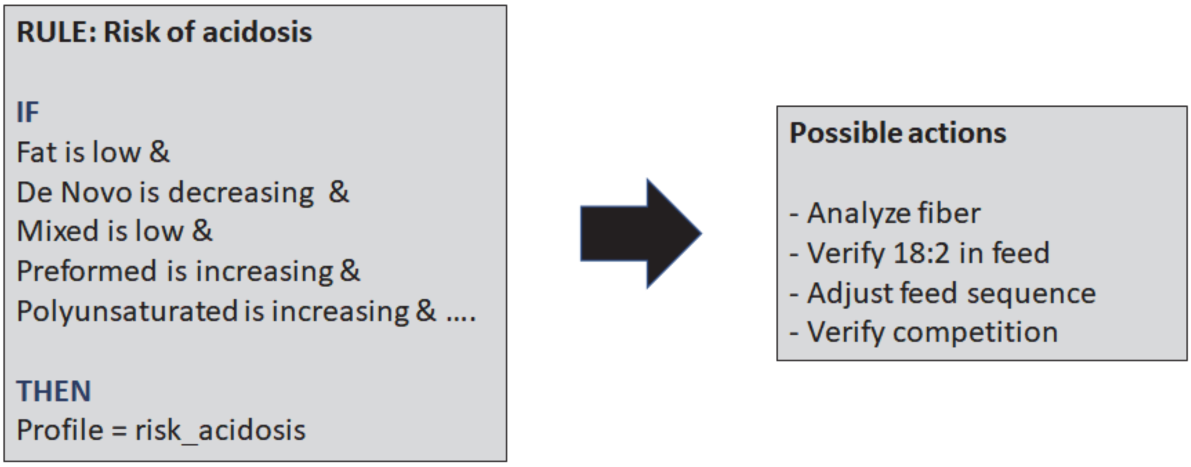

Figure 4. An example of a diagnostic rule and possible actions.

Conclusion

some specific fatty acids. This system will be equipped with an alert/attention system for producers and their advisors.

In the first phase of the project, we developed a python package to transform raw milk data to three statistical indicators (deviation, variation, gradient) that can represent anomalies, rank the herds based on the values of the indicators, and build daily reports which can be interpreted by experts to recognize anomalies. Based on such reports, we also investigated two extreme cases situations that can be related to severe problems (without implying a specific diagnosis) in herds, so that can be used for triggering alerts for producers and advisors. The extreme cases are identified from extreme fatty acids trends.

The second phase was focused on the development of a rule-based expert system. Currently, we are at the stage of building a knowledge base that consists of IF-THEN diagnostic rules for diagnosing issues such as risk of acidosis and lack of consumption. These rules are created based on indicator profiles obtained from the first phase, with the help of domain experts in collaboration with computer scientists. However, because of the challenges in updating and improving rule-based systems, we explored the use of ontology and symbolic artificial intelligence to develop a more complete diagnostic and recommendation system. Such an ontology can be expanded to cover additional dairy management areas in future.

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