Visual Analysis of Time-dependent Multivariate Data from Dairy Farming Industry

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Abstract: This paper addresses the problem of analyzing data collected by the dairy industry with the aim of optimizing the cattle-breeding management and maximizing profit in the production of milk. The amount of multivariate data from daily records constantly increases due to the employment of modern systems in farm management, requiring a method to show trends and insights in data for a rapid analysis. We have designed a visual analytics system to analyze time-varying data. Well-known visualization techniques for multivariate data are used next to novel methods that show the intrinsic multiple timeline nature of these data as well as the linear and cyclic time behavior. Seasonal and monthly effects on production of milk are displayed by aggregating data values on a cow-relative timeline. Basic statistics on data values are dynamically calculated and a density plot is used to quantify the reliability of a dataset. A qualitative expert user study conducted with animal researchers shows that the system is an important means to identify anomalies in data collected and to understand dominant data patterns, such as clusters of samples and outliers. The evaluation is complemented by a case study with two datasets from the field of dairy science.

1 INTRODUCTION

To increase the competitiveness of the dairy sector in the national economy, the dairy industry focuses on improving farm management. The information on farm productivity to support management on dairy farms is often collected by Dairy Herd Improvements agencies. Dairy farmers are usually visited once per month, during a day called *test-day*. Information on the herd such as breeding events, gender, and weight of new-born calves is collected. In addition, the milk production of each cow is measured and a milk sample is gathered to determine the fat and protein content, as well as somatic cell count.

Test-day records represent a valuable resource for animal researchers, but as data sources become larger, the analysis and exploration of patterns in data becomes more complex, representing a critical bottleneck in analytic reasoning. To address these problems, a visual analytics approach can be used to let users explore their data and interact with them with the aim to find interesting insights and eventually data anomalies and formulate hypotheses. Techniques that support the production and dissemination of analysis results may help researchers communicate to a variety of audiences.

In this paper, we present an interactive system to analyze time-dependent multivariate data. A suite of visual analytics tools is designed for animal researchers, allowing them to perform an in-depth study of data in order to develop and explore their hypotheses. Since test-day records are multivariate data with an intrinsic time-varying nature, we devise techniques that are capable of representing linear and cyclic time behavior simultaneously, for example, by showing seasonal and monthly effects. Furthermore, a density plot is included to let the user evaluate the reliability of each dataset. Our system design is characterized by its conceptual simplicity that intends to be an easy-to-use tool for researchers with no background in visual analytics.

The utility of our system and its visualization methods are evaluated by a qualitative user study with domain experts and demonstrated in a case study. Two datasets from the dairy industry in Sicily (Italy) are used. In Sicily, approximately 125,000 dairy cat-

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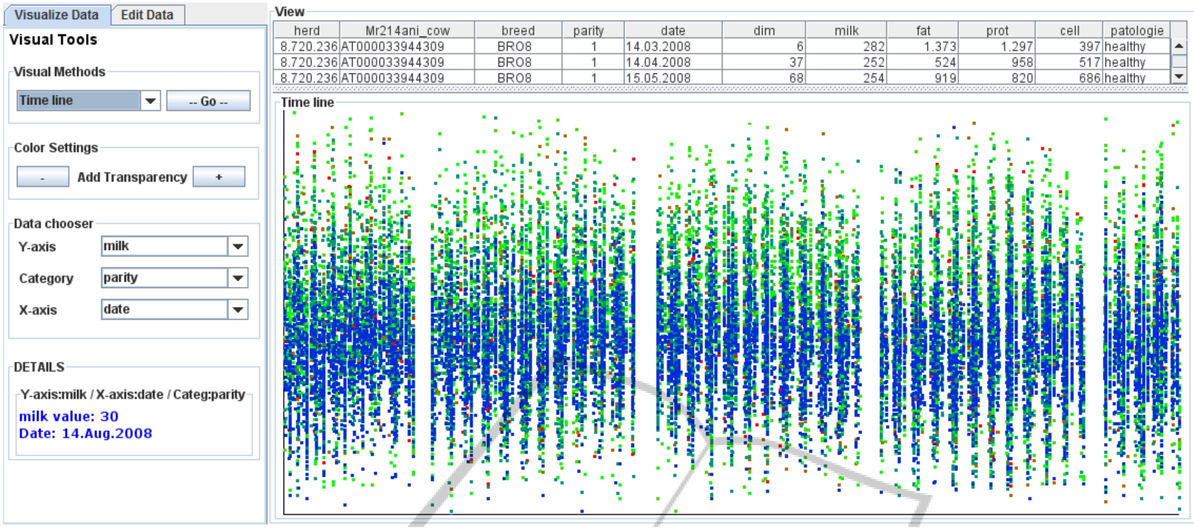


Figure 1: System overview. Raw data are shown in tabular form. In the bottom part, the view shows a scatter plot of selected data. The production of milk is shown for each day (absolute timeline). In this example, the *parity* value (number of lactations) is used as category. During the first parity, milk production is lower than in the next and the data value range is narrower. Missing data points follow a regular pattern (recurring blank vertical stripes) that reflects the lack of data samples collected during summer vacation (August).

tle are raised. Compared to other regions such as those in Northern Italy, smaller traditional and less modernized farms are present that have to deal with hot climate, higher costs of feed and energy. Around 62% of Sicilian milk is produced in Ragusa province, representing therefore the most important production center for the dairy sector in Sicily. In 1996, the dairy research center CorFiLaC was established to support the development of the dairy sector in Ragusa (Caccamo, 2012). The datasets provided by CorFiLaC and used for our case study cover the typical range of (varying) sample rate and time span in which data are collected.

2 RELATED WORK

As our system was designed to analyze different aspects of the same dataset, it merges visualization methods from several application domains. In this section, relevant topics from several areas will be covered, according to the different aspect of data analysis on which the user wants to focus.

2.1 Animal Research and Dairy Industry Domain

One of the main topics investigated by animal researchers is the study of movement of individual organisms or groups of animals. There is an increasing interest in movement ecology. Accordingly, there are a few examples of visualization and visual analytics research geared toward data from movement ecology. Grundy et al. (2009) exploit data obtained through tri-axial accelerometers to trace movement of wild animals. They make use of interactive spherical scatterplots and spherical histograms instead of the 2D time-series plots commonly used to study acceleration data.

Visual analytics is also used to study and model epidemic spread in herds. Afzal et al. (2011) present a suite of predictive visual analytics tools to model the spread of Rift Valley Fever through a simulated mosquito and cattle population in Texas.

However, we see only very little previous visualization work on animal research related to the dairy industry. In fact, there is almost no previous paper in which visualization tools and visual analytics methods would be used on milk production records or other data from dairy industry. The only exception known to us is the work of Galligan, who created *Cowpad* (Galligan, 2007), a suite of web tools to present analytical problems commonly occurring on dairy herds. Simple interfaces let the user evaluate the effect of changing variables in the process of dairy farm management. However, these tools do not use any advanced visualization or interaction technique to represent data involved in the simulation, only curve diagrams and gauge metaphors are proposed.

With this paper, we want to fill this gap in the literature, adopting visual analytics methods for this particular application domain.

2.2 Time-Varying Data Visualization

For animal researchers, it is important to investigate how various factors on dairy production change over time. Data used for this contribution have a temporal dimension that makes it possible to highlight monthly, seasonal, and annual trends.

For time-dependent data, there is a large collection of different visualization techniques for different purposes of data exploration and depending on the characteristics of the temporal structure. Following the taxonomy by Aigner et al. (2011), dairy production datasets exhibit a quite specific structure: they show a dual structure of time, both linear and cyclic.

Van Wijk and Van Selow (1999) present a system to identify patterns and trends on multiple time scales simultaneously. It allows the visualization of univariate time-series on different levels of aggregation by clustering similar daily data patterns. We use different levels of aggregation to visualize two different timelines at once. Spiral approaches are a way to visualize large datasets and to support the identification of periodic structures in data. Previous solutions (Carlis and Konstan, 1998; Weber et al., 2001), however, are not suitable in cases in which the cyclic trends of data are not perfectly periodic, or the period is not known but subject to specific seasonal effects.

To the best of our knowledge, no previous work addresses the problem of visualizing linear and cyclic time data simultaneously.

3 APPLICATION BACKGROUND

Data on farm productivity is often collected by Dairy Herd Improvements (DHI) agencies. Milk production of each cow is measured and a milk sample is analyzed to determine fat and protein content, and somatic cell count. These records are then processed and analyzed centrally (i.e., on DHI computers) by taking into account information generated during previous test-days at both herd and individual cow level. A few days after the test-day, the farmer receives a report containing information collected during the test-day. This report may also contain management information on individual cows and the herd as a whole. The information from the report can then be used by the farmer (or milk and cheese producer) for making decisions focusing on the improvement of farm management practices (Caccamo, 2012).

Although DHI data and information can contribute to improve management practices, the benefits only come about if the farm managers and/or the animal researchers that work as advisors at DHI spend considerable effort for analyzing the incoming information. This process can be time-consuming and complex due to the large amount of data.

3.1 305-Days Lactation Yield and Test-Day Models

Milk recording is recognized as a valuable means for breeding and herd management worldwide. Furthermore, these records are also used to perform a *genetic evaluation* for dairy production traits. The genetic evaluation of dairy sires and cows has been based on the analysis of the 305-day lactation yield for many years. It uses the total amount of milk produced during a lactation (or milking) period. Usually, a dairy cow lactates for about 10 months ($\sim$305 days) each year before it dries up prior to giving birth to its next calf. The ideal method to estimate the 305-days lactation yield is to measure the amount of milk and milk components of each cow on a daily basis for 10 months after calving. However, one sample of milk is usually taken monthly for each cow. As stated by Schaeffer and Burnside (1976), a common method of predicting 305-days yield is to compute the average production between two tests, multiply by the number of days between tests, and accumulate this quantity after each report. If the interval between two tests is much longer than 30 days, erroneous predictions of this value could result. Several methods have been developed to improve the prediction of 305-day lactation yield. The term lactation curve is used to refer to the curve representing the rate of milk secretion with advance in lactation.

After two decades, animal researchers started to use test-day yields for genetic evaluation rather than 305-days yield. By definition, a test-day (TD) model is a method of evaluating daily production of milk, fat, protein and somatic cell count considering effects for each test-day instead of one set of fixed effects over the lactation. The TD model estimates lactation curves and their changes.

In the early 1990's, Ptak and Schaeffer (1993) identified some drawback in the new approach, such as the need to store all of the individual test-day yields on every cow, or the higher computational time needed to calculate a genetic evaluation by using more values per cow instead of only one.

Within less than a decade, test-day models have been adopted in several countries. Test-day models are often used to perform national genetic evaluations for dairy cattle. Estimation of genetic, environmental, and herd effects can be used to predict future productions on individual cows. Deviation between predicted and actual production could be used to detect a disease at an early stage, i.e., before the cow shows clinical signs. Therefore, animal researchers need a system to identify abnormalities in lactation curves.

Nowadays, the storage of big amounts of data or the computational resources needed to handle these data do not represent a problem anymore. It is possible to use the complete set of test-day records collected over the years. Researchers can work directly on those data with no use of statistical or mathematical models that could lead to loss of precision or erroneous predictions.

3.2 Multiple Timelines

The challenge for dairy producers is to interpret and utilize data from dairy production properly to improve decision making. Milk production data have an intrinsic dual timeline nature. Usually, lactation is represented according to a "cow-related" timeline: a curve shows the quantity of produced milk changing over time, from the day of calving to the moment in which the cow is *dried off*, and milking ceases. About sixty days later, one year after the birth of her previous calf, a cow will calve again, starting a new parity (period of lactation).

Since the "cow-relative" behavior is most important for temporal analysis, that *relative time*—represented as day-in-milk—is of highest relevance for analysis. Parities represent *cyclic time* characteristics in the data because the parities progress similarly. If one analyzes a single parity, there is *linear time* behavior within that parity. However, there is another temporal aspect that needs to be taken into account: the *absolute time* of the yearly calendar. Possible seasonal effects on production of milk and milk components ratio are due to yearly *cyclic* effects. However, within the year, we consider calendar dates as *linear time* because there are no weekly or daily effects on milk production data.

In this paper, a method to show and analyze the dual nature of time, with respect to the linear and cyclic time behavior is presented.

4 SYSTEM OVERVIEW

In our system, several visualization methods are used. Well-known approaches are used besides some new techniques for visualizing two coexisting timelines simultaneously. The aim of the tool is to assist animal researchers in all the phases of their analysis process. A preliminary analysis could be performed for a data cleaning phase; then a deeper exploration lets the user study different aspects of the data, comparing different views. To address multivariate and time-dependent data visualization, we designed our system to support several, complementary views. The user can choose from a list of four different views (see below for details).

It is possible to load and handle any kind of multivariate dataset with the constraint that a field containing a date (or time) must be included. Data are loaded and shown in a tabular form similar to spreadsheets and application programs that animal researchers are used to work with.

4.1 Scatter Plots

One of the visualization methods in the system is based on scatter plots. In this way, multivariate data can be shown, such as the attributes milk production, fat contents, protein values, and their time dependency. Any data field can be used as x-axis and y-axis. A third data field can be used as a *category* to accordingly color each data point in the scatter plot. In this way, the colored scatter plot can show three data dimensions. If the *category* field chosen contains labels that assign classes (categorical data), the user is asked to select a color for each label. Otherwise data points are colored automatically using a color scheme selected by the user from a suggested list. Furthermore, it is possible to filter data by *category* values. When a burst of aggregated data points overlaps making the scatter plot difficult to understand, transparency can be used to reduce visual clutter. Moving the mouse pointer over the plot, details on data points are displayed next to the view. Figure 1 shows the scatter plot, and the side panel. This panel is used for choosing data to plot, and environment settings.

4.2 Statistic Metrics and Density Plots

A line chart of mean values as well as standard deviation can be superimposed on the scatter plot diagram, showing aggregated statistical quantities. Moreover, the density of data samples in the dataset for each y-axis value is calculated and shown as a histogram. The histogram allows the user to assess the quality of the original data indirectly; less density is related to higher variability of the data samples in that region. Therefore, the combination of density diagram with other diagrams allows us to include a measure of uncertainty in the overall visualization.

A low-pass filter can be used to smooth the line plots and density plots. The user can increase or decrease width of the low-pass filter interactively. In Figure 2, a dataset is displayed in which the density

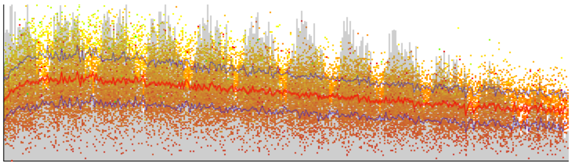


Figure 2: Statistics on time-varying multivariate data. The value of produced milk for each day-in-milk is shown. Scatter plot points are colored according to the value of fat contained in the sample of milk. The curve of density of samples in the dataset is represented in gray. The red line indicates the mean value of quantity of milk and the blue lines the standard deviation.

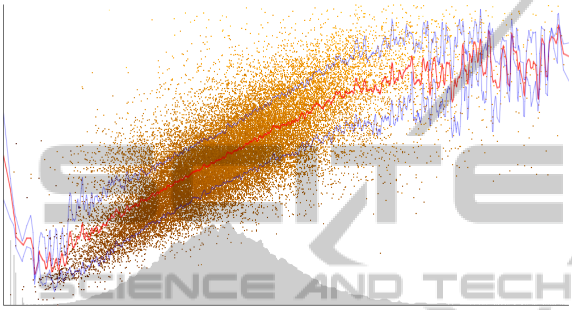


Figure 3: Relation between the quantity of milk (x-axis) and the percentage of protein (y-axis). Data points are colored according to the percentage of fat in milk samples (lighter color for higher values). The density plot shows that the number of samples for milk quantity follows a normal distribution.

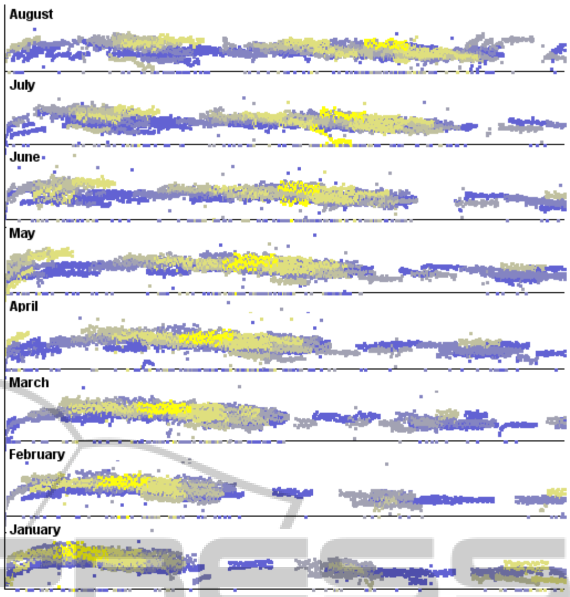


Figure 4: The value of produced milk for each day-in-milk (relative timeline). The absolute timeline (date) is shown by aggregating monthly data. Data points are colored from blue to yellow according to the parity. In first parities milk production is lower. Stacked scatter plots highlight differences in milk production and in data sampling: a (shifting) gap in data points for a certain period in day-in-milk is visible.

of data samples varies over time following a regular pattern: more samples are collected in certain days of the month. As shown in Figure 3, the density plot can be used to recognize that samples are normally distributed for a certain random variable (milk in this example).

4.3 Multiple Timelines View

We present two methods for showing multiple timelines simultaneously. As discussed in Section 3.2, the different temporal data characteristics make it difficult to analyze the temporal effects. In particular, depending on the focal point of analysis, cyclic and linear as well as relative and absolute time play a role. For analysts, it is useful to highlight cyclic data patterns as well as to point out differences between different periods of time. The first method aggregates data points for different periods of time over the relative timeline. Multiple scatter plots share the same x-axis that represents the relative timeline. A plot is shown for each period of the absolute timeline. The user can choose the time period to use from a list to aggregate data and build up a stacked view of several plots. It is possible to create a plot for each season, month, or year. In Figure 4, stacked scatter plots are shown for different months. This method helps identify frequent patterns in data points or highlight cyclic behavior, but it is difficult to draw a comparison between data values at the same relative time point in different plots.

The second method uses a single plot: different line charts are drawn, representing the mean value curve for aggregated data on different time intervals. In this view, each plot shares the same coordinate system, so that the line charts are aligned. Thus, it is simpler to identify differences in the curve of values for different time periods.

5 CASE STUDY

We demonstrate the usefulness of our approach for two datasets with different features from the same application area. Data used for our study was provided by CoRFiLaC dairy research center.

The analysis was conducted with an expert that was familiar with the datasets. During our study, hypotheses made by the domain expert were confirmed with the visual analytics approach, and the implementation of new features was suggested in the sense of a formative process.

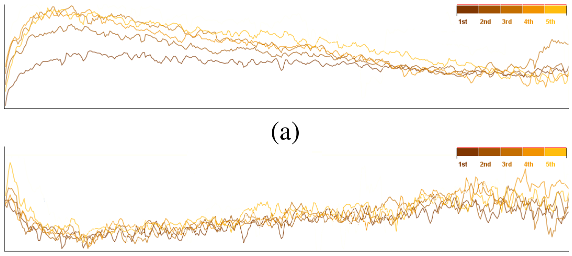
Data used for our study were collected and used by animal researchers to assist farmers in the management of dairy herds. The first dataset (*Dataset 1*) contains 175,689 records on 6,468 cows from over 40 herds. Samples were taken monthly at the test-day, for over 10 years. Each record provides the following information: identification number of the herd and the cow, breed of the cow, number of lactation (also called parity), date of the test-day, days-in-milk (i.e., the number of days between the calving of the current parity and the test-day), yield of milk, fat and protein contents, detected pathology associated with the test-day.

The second dataset (*Dataset 2*) used contains data collected from one farm only, i.e., one herd. At this farm, production data are collected in autonomy, without the support of a DHI agency. It is a modern farm in which data are collected almost daily. Data records regard a single herd of 90 *high production cows* that continue to produce a sufficient quantity of milk for 11 months after calving (5 to 395 days-in-milk).

5.1 Analysis Process

The analysis started by showing an overview of data contained in *Dataset 1* (see Figure 1). By using the absolute timeline (date of test-day), a recurring gap is evident in data sampling. This gap can be explained by the period of vacation that was observed in the farm during years prior to 2010 in Sicily.

Colors were used to mark data points according to the detected pathology associated with the test-day. Different views allowed us to spot significant changes in the overall shape of curves, from which we could derive some insights. A slight loss in milk production was recognized for cows suffering from mastitis, when using the relative timeline (days-in-milk). When using the absolute timeline, we noticed a lack of registered sick cows before 2005. The density plot revealed evident changes in number of data samples over time. In the dataset, an increase in data collected in the last years could be recognized, which we attributed to the employment of modern systems in farm management. By showing data according to the days-in-milk (see Figure 2), a regular pattern in the density plot could be highlighted. Usually, the same group of agents from the DHI agency visits all the farms in the same area, scheduling one visit per month for each one. Thus, each peak in the density plot corresponds to the recording day (test-day) in the biggest farm of the area.



(a)

(b)

Figure 5: Multiple line plots highlight differences in lactation curve (a) and fat contents (b) for five parities. The quantity of fat decreases during the peak of milk production. The shape of the fat curve is equal for different parities, whereas the shape of the lactation curve changes over parities.

During the first analysis phase, the system turned out to be a useful and fast means for data cleaning—on top of direct visual analysis.

The multiple timeline views were used to find differences in milk production for different seasons. In winter, cows generally produce more milk than in spring, but no evident differences could be identified for different months. By plotting stacked data points for each month, some data points in the August plot are shown, which is an anomaly in data recording that could be confirmed after the session.

During the analysis process, some new features were suggested by the domain expert. The possibility to aggregate data and to visualize different plots according to the breed and the parity number were added in response to the expert's comments. By showing different curves for breeds, it is possible to find out which cow variety is more productive and how milk composition between different stocks differs. Different lactation curves for each parity confirm well-known theories. Figure 5 shows different curves for the first 5 parities in the data from *Dataset 2*. The domain expert also asked to re-align data according to the beginning of the lactation period, so that it is possible to find differences in the lactation curve depending on the moment of calving.

6 EXPERT EVALUATION

The analysis of the feedback by potential target users describes preferences concerning views and features of the tool, and helps us improve the software to meet users' needs. We were mostly interested in following the natural process of hypothesis building and problem-solving adopted by the animal researchers. To achieve this goal, it is fundamental to let the domain experts operate in their workplace as explained

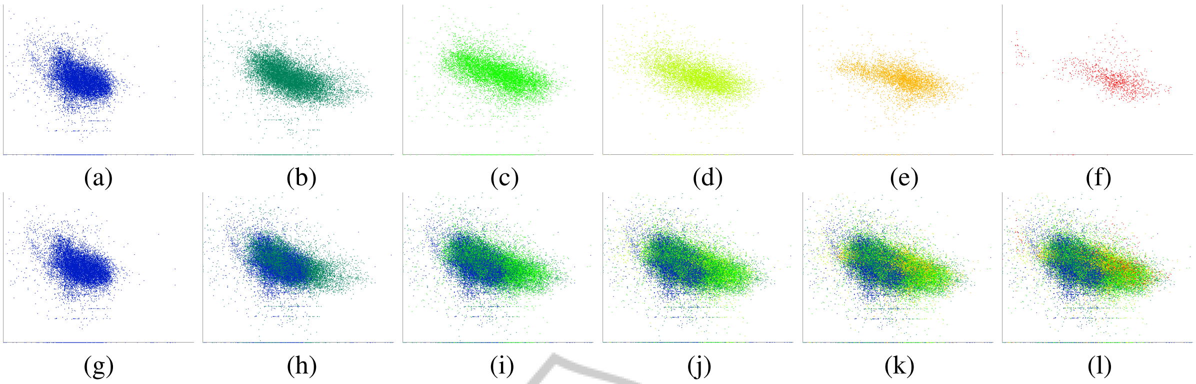


Figure 6: Scatter plots show the relation between quantity of milk (x-axis) and percentage of fat (y-axis). Data points are colored according to the parity. These image series shows different uses of the interactive filter. Figures (a)–(f) show data for different parities (1 to 6). In Figures (g)–(l), the first endpoint is constantly set to parity 1 and the width of the interval is sequentially increased, to add data points from the next parity to the plot. Milk-fat correlation is different between the first two parities and the next ones. From the third parity, the percentage of fat decreases, while the production of milk increases. The number of data points falls off in last parities because most of the cows became less productive, removed from the dairy herd, and marketed for beef, around the age of four.

by Dunbar and Dunbar (1999) proposing in-vivo studies. For our study, we adopted the pair analytics approach. This method generates verbal data about thought processes in a naturalistic human-to-human interaction with visual analytic tools. It requires two participants, a Subject Matter Expert and a Visual Analytics Expert (Arias-Hernandez et al., 2011).

Every study session was performed by using a VoIP software for communication and each audio session was recorded. An application for remote desktop control was used to operate on a computer in the IT laboratory at CorFiLaC. The three volunteers worked directly on the computer used for the user study.

During a preliminary group session, the participants were informed about the procedure and the voluntary nature of the experiment. Afterwards, a private study session was performed with each of the participants left alone in the IT laboratory. For each session, the remote desktop was video recorded. Each session was performed in conjunction with a Visual Analytics Expert that was able to control the remote computer by using mouse and keyboard. He was disheartened to control remotely the system and let the Subject Matter Expert use it. The Visual Analytics Expert was instead encouraged to talk with the animal researcher and ask for comments and the motivation behind every choice made to perform the requested tasks.

At the beginning of the private session, the volunteer was asked to inspect the overview of a subset of records from *Dataset 1* (in Figure 1). The analysis performed by the domain expert during the case study was used as ground truth to evaluate the correctness of the volunteers' answers. The first task was to explain the missing value pattern in the scatter plot. The second task was to freely comment the data points cloud according to the color coding used to produce the plot.

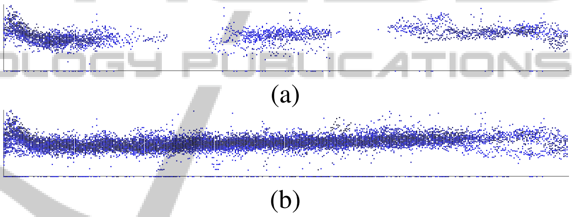


Figure 7: (a) Fat content for day-in-milk during fall. (b) Fat content for day-in-milk for parity started in fall. Data points are colored from black to blue for the first three parities. Missing samples visible in (a) that can affect the analysis task are avoided by aligning data points on the season of calving, as shown in (b).

Then, the participant was asked to freely use the visual analytics approach on *Dataset 2*.

Each study session took about 90 minutes for each participant. During the session, the experimenter annotated the user's behavior, preferred view, and interaction methods to complement audio and video recording that were analyzed afterwards for the qualitative analysis of the system usage sessions.

For the qualitative user study, three domain experts from CorFiLaC (Sicily), i.e., potential target users, were asked to use our system.

The simple tasks assigned were used to evaluate the effort required to understand the plots. Two of the participants readily explained the lack of data points and the regular pattern followed.

The second task involved the comprehension of the color coding used to mark data points according to the parity. None of the participants had any difficulties working with this task. Their comments revealed that they took advantage of using color to highlight different data behaviors. Initial difficulties to correctly interpret the scatter plot were overcome with the help of the Visual Analytics Expert.

User opinions on ease of use and utility of our system were collected by the questionnaires sent to the domain expert after the user study sessions. The answers show that the overall user experience with the system was positive. The participants identified the multiple timelines view as the most useful when line charts are used. They also found the possibility to use the same view to highlight differences for different parity or breed interesting, referring to the features suggested by the domain expert involved in the case study. In particular, they indicated as an important means for analysis the possibility to re-align data on the day of calving. This method helps obtain information on the shape of complete curves, not considering gaps in data sampling as shown in Figure 7.

Each of them preferred to use line plots to compare the lactation curve shape, but they used scatter plots to identify anomalies in the data, such as gaps in data sampling of artificial data values. They recognized the system as a means for simple graph creation, in order to show analysis results to farmers.

In the free comments section of the questionnaires, each of them asked to filter data interactively, without recurring to the editing interface of the system. An interactive filter was later implemented and the usage is shown in Figure 6.

7 CONCLUSION AND FUTURE WORK

We used a visual analytics approach to support animal researchers in analyzing multivariate time-varying data. The system is designed to address the needs of the domain experts. By using real-world data from the dairy industry, we could prove the utility of the system as a means of identifying anomalies for a data cleaning phase, and as a tool for hypothesis building. Besides, an expert user study showed that researchers without background knowledge of visual analytics methods are able to adopt the system quickly.

For proper interpretation of lactation curves, milk production information has to be related to management practices and environmental conditions that might affect lactation curves. The individual cow level data have to be analyzed besides herd level data. The possibility to handle this kind of data could be added to our system in future work. Also, different case studies could be conducted on datasets from other domains. The multiple timeline nature of the data from dairy science might be present in other data as well, and the system might be applicable there, too. Finally, the expert user study could be extended by including a larger group of domain experts.

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