Modeling Pig Rearing as a Digital Shadow

Tobias Zimpel[1]

Abstract: Pig rearing and animal welfare are increasingly in the interest of society. To enhance animal welfare using data-driven analyses, modeling the pig rearing process is essential to create corresponding data sets. Pig rearing is a complex process for increasing pigs' weight (from approx. five to 25 kilograms) involving various actors (e. g. farmers, veterinarians) to provide goods (e.g., food, water) and services (e.g., medical care). Thereby, pigs live in pens equipped with condition-measuring sensors, like the pen's temperature or pigs' activity. Manual measurements (e.g., weights) are also conducted, resulting in various data sources. For analyzing these data, measured in different contexts, a digital shadow appears as an approach for modeling these data traces. Therefore, we report on a digital shadow for pig rearing, including the assets pen and pig, sensor sources, data traces (e.g., pens' temperature), and the purpose of analyzing causes of necrosis (dead tissue) with association rules.

Keywords: digital shadow, pig farming, process modelling.

1 Motivation

Pig rearing pursues the complex task of raising pigs (increasing pig's weight from approx. five to 25 kilograms) over several weeks while maintaining animal welfare. Animal welfare can be defined by using the five freedoms, including the freedom from hunger, stress, pain, and injury [Fa09]. To achieve this goal, various actors work together to provide goods (e.g., food, water) and take care of the pigs. Farmers, veterinarians, craftspeople, and food suppliers can represent such actors. Each actor can collect data, resulting in potentially different data sources (e.g., different sensors in a pen) [Ri20]. Therefore, data may differ in their structure, meaning or aggregation level. Data is combined into a dataset using extract, transform, and load processes. Then further data analysis is based on this entire data [Ne20]. In pig rearing, we analyze pig and pen data to suggest causes for necrosis (dead tissue) using association rule mining. Therefore, contextual information is required.

The concept of digital shadows (DS) may be able to support this analysis of necrosis in pig rearing. A DS is a set of data traces with corresponding aggregation or abstraction functions collected for a specific purpose [Bi20]. Therefore, a DS provides a view of assets (like pig and pen), including contextual information [Be21]. Elements in DS are data traces, data sources, data points, metadata, model, and purpose [Be21]. Data traces corresponds to a set of data points (e.g., temperature) recorded by a source (e.g.,

[1] University of Hohenheim, Department of Information Systems 2, Schwerzstraße 35, Stuttgart, 70599, tobias.zimpel@uni-hohenheim.de

temperature sensor) and linked to a DS and metadata [Be21]. Metadata describes relevant contextual data for the DS, like the pen's target temperature or sensor precision. [Be21]. The model adds relevant information about the asset, like data structure, to the DS [Be21]. Purpose describes the objective of the DS, such as analyzing pig and pen data for causes of necrosis [Be21]. Against this backdrop, we address the following question: *How to design a digital shadow for the analysis of necrosis in pig rearing?*

This paper is structured as follows: In Section 2 describes the use case of pig rearing. In Section 3, we present digital shadows for the assets pen and pig. Finally, Section 4 discusses the potential implications and challenges of the digital shadow and concludes the paper.

2 Use case description

The use case describes the pig rearing process based on processes at the Boxberg Teaching and Research Centre (LSZ) in Germany. The LSZ is the central educational, experimental, and testing facility of the state of Baden-Wurttemberg in the field of pig farming. Pig rearing is part of a supply chain for the production of pork. Such a supply chain is shown in Figure 1, based on the supply chain reference model (SCOR) version 12 (see [AP17]) and according to [LS13]. The supply chain in Figure 1 includes the SCOR level-1 processes source (sS), make (sM), and deliver (sD) and is limited to one actor per stage. The lowercase "s" in sS, sM, and sD stand for SCOR [AP17]. End customer describes various types of customers, like butchers or restaurants.

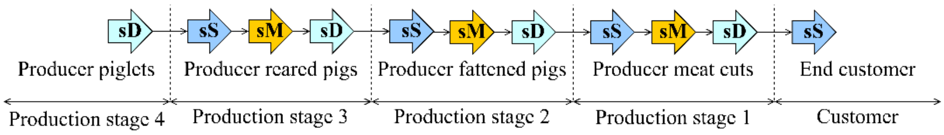

Fig. 1: Supply chain production of pork (SCOR diagram, level-1 processes)

The pig rearing process is located in production stage three, resulting in corresponding effects for the subsequent stages. Such an effect can originate from pigs' necrosis (e.g., medical care or loss), which can occur in the rearing process (as well as in production stages four and two) [Re20].

Figure 2 shows a pig farming supply chain, including one upstream production stage and a selection of producers for production stage two. Missing producers include, for example, producers of manipulable material and lightning. We are aware of potential inconsistencies in the distinction between internal and external actors. However, Figure 2 presents the complexity of the rearing process and potential data traces along with each good flow between the production stages.

We also assume that potential necrosis causes are in pig's environment (the pen) and thus in the production stage two. [FS81, FU79, KFS82]. For example, such causes could be failures in the ventilation system (producer air), or water system (producer water), resulting in a factor supporting necrosis (e.g., stress due to hot air). To analyze such potential causes of necrosis using association rules, we generated a dataset containing data from production stages one and two.

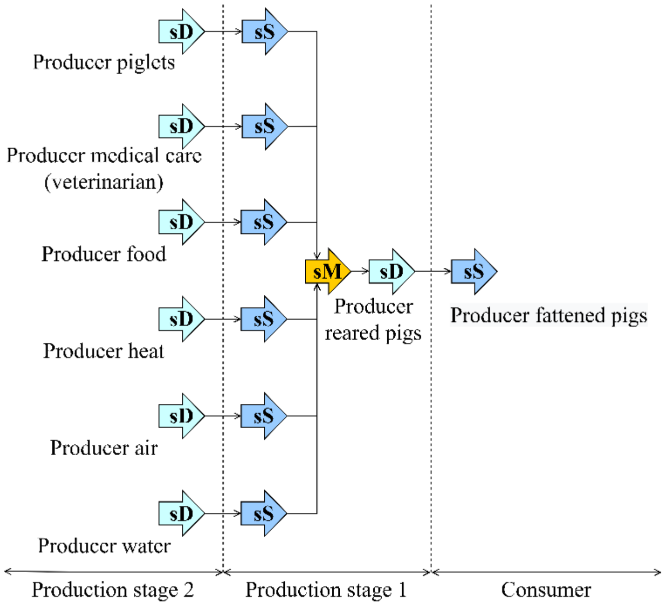

Fig. 2: Supply chain pig rearing (SCOR diagram, level-1 processes)

3 The Digital Shadow

We identified two assets for the purpose of data-driven proposals for necrosis causes in pig rearing: pen and pig. While Figure 3 presents the pen's digital shadow, the pig's digital shadow is shown in Figure 4.

The asset pen in the corresponding digital shadow contains a name and an identifier. The pen is also connected to the asset pig to access the pig's data. The digital shadow should contain data traces for each property or state that may be relevant to necrosis analysis. Therefore, the pen’s digital shadow should include information about each actor in production stage two (see Figure 2) as a data trace (e.g., temperature history provided by the heat producer). Due to the number of actors in Figure 2 and the corresponding amount of data traces, we only included data traces for temperature and food. However, the temperature data is similar to water and humidity data (provided by air and heat producers). Therefore, analogous to temperature, a data trace for water and humidity can be added into the digital shadow. The data trace for medical data is ignored due to the underlying complexity. Metadata for temperature data traces should consist of information about data quality and data collection to understand and analyze underlying data (e.g., handling missing data). Another relevant information in the metadata is the target temperature to enable the comparison with the actual temperature. Each temperature data point reports the actual temperature in Celsius at a given point in time for the pen. The food trace is measured and integrated similarly to temperature, with changes in labeling and unit of measurement. Different sensors record temperature and food data. The pen's model is a Unified Modeling Language (UML) class diagram.

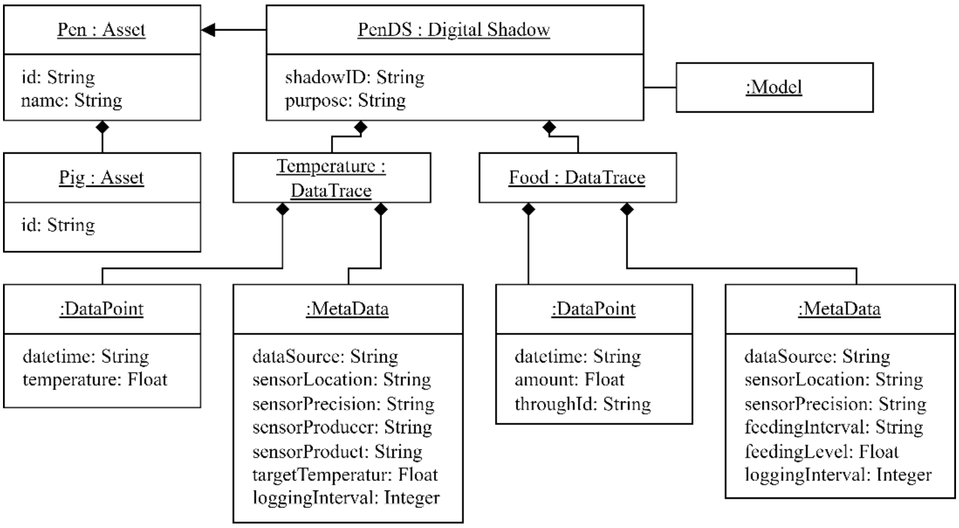

Fig. 3: Pen's digital shadow (UML class diagram)

The asset pig in the digital shadow of the pig has the attributes identifier, birthday, gender, and breed. Furthermore, the asset pig is linked to the asset pen to access pen data. The data trace consists of pigs' assessments regarding the presence of necrosis at different dates during the rearing. An employee decides at each assessment on the presence or absence of necrosis according to a uniform scheme. One assessment corresponds to one data point. Therefore, the employee who performed the rating and the rating scheme constitute necessary information in the metadata to consider these factors in the analysis (e.g., to compare assessments). Another data trace could be the pigs' weight, which can be integrated similarly to the pen's temperature in the corresponding digital shadow. Similar to the pen's model, a UML class diagram is a model for the digital shadows of pigs.

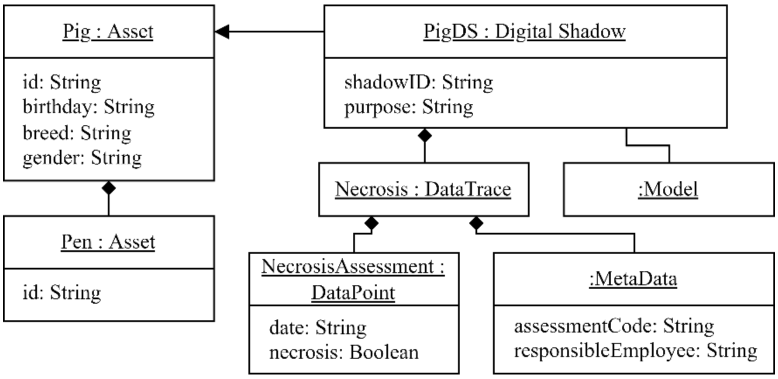

Fig. 4: Pig's digital shadow (UML class diagram)

4 Discussion and Conclusion

In this work, we presented pig rearing and corresponding data-driven analysis as a use case for digital shadows. We proposed two interconnected digital shadows for pens and pigs. Both digital shadows consist of selected data traces, like pens' temperature or pig's presence of necrosis. Further data traces can be integrated similarly in the future.

The digital shadow supports the data-driven analysis of necrosis in two ways. Firstly, the digital shadow includes context information resulting in an increased understanding and another way of presenting this information. Increased understanding of context information is justified by the otherwise necessary manual search and analysis of context information. We assume reduced time for data understanding by providing contextual information in the digital shadow metadata. There is often separate documentation for each data-trace. In addition, sometimes, no or only partial documentation is directly available. Secondly, we assume that the digital shadow can simplify the combination of relevant data into an asset due to the prior defined data structures. Thus, we assume that an increased data understanding of data and prior defined data structures accelerate the analysis process concerning the required time. Therefore, improvements in data analysis can benefit the underlying process – in this use case, pig rearing. However, analyzing the actual implications and challenges in practice is future work.

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