Continuous Data Quality Management for Machine Learning based Data-as-a-Service Architectures

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Abstract: Data-as-a-Service (DaaS) solutions make raw source data accessible in the form of processable information. Machine learning (ML) allows to produce meaningful information and knowledge based on raw data. Thus, quality is a major concern that applies to raw data as well as to information provided by ML-generated models. At the core of the solution is a conceptual framework that links input data quality and the machine learned data service quality, specifically inferring raw data problems as root causes from observed data service deficiency symptoms. This allows to deduce the hidden origins of quality problems observable by users of DaaS offerings. We analyse the quality framework through an extensive case study from an edge cloud and Internet-of-Things-based traffic application. We determine quality assessment mechanisms for symptom and cause analysis in different quality dimensions.

1 INTRODUCTION

Data-as-a-Service (DaaS) solutions make raw source data accessible in the form of information processable by the consumer of the service. A problem here is that quality concerns observed by the consumer of the service are caused by quality problems related to the raw source data or its processing, which are hidden from the consumer.

Continuous Data Quality Management (CDQM) is concerned with an ongoing process of continuously monitoring and improving the quality of data and derived information. In particular, in contexts dominated by high volume, velocity and veracity of data (generally referred to as big data), like the Data-as-a-Service (DaaS) context here, such a continuous quality management process is essential. Data processing through machine learning (ML) techniques is here an integral part of obtaining value out of the raw data, but require a dedicated CDQM solution for DaaS architectures.

While data quality models exist, there is a need to extend data quality to the ML model level. Furthermore, we need to close the loop by mapping quality problems (the symptoms) at ML level back to their origins (or root causes).

Our contribution is, firstly, a layered data architecture for data and ML function layers and, secondly, a root cause analysis based on a closed loop between data and ML layers. We determine quality assessment mechanisms for symptom and cause analysis in different dimensions, including situational analysis and timeseries, determination outcome, object, type and techniques. Our approach is suited to situations where raw data quality might not be directly observable or assessable, thus a new way of inferring quality is needed.

A case study is the mechanism through which we validate the quality framework. The context is set in public data services (DaaS), here at a regional level (more specifically, a regional IT and Data service provider). The application is traffic management, which is based on traffic and weather data collected locally in an edge cloud and IoT setting.

2 CONTINUOUS DATA QUALITY MANAGEMENT

Continuous Data Quality Management (CDQM) for *data services* is a continuous process of data quality (DQ) actions: prevention, detection and correction. The prevention of problems is, however, not always achievable. Thus, we focus here on the detection and correction of quality problems. We target specifically the quality of information models that are created from data using machine learning tech-

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niques. Data quality refers to how well data meets the requirements of its users. This includes for example accuracy, timeliness or completeness (Thatipamula, 2013). Quality frameworks for data and information have been investigated (O'Brien et al., 2013; Azimi and Pahl, 2020b; Azimi and Pahl, 2020a). There is also a commonly accepted classification of (big) data aspects that can help in organising and managing the quality concerns (Saha and Srivastava, 2014; Nguyen, 2018), often called the *4V model*: volume (scale, size), velocity (change rate/streaming/real-time), variety (form/format) and veracity (uncertainty, accuracy, applicability). Our chosen IoT application domain exhibits all of those characteristics. Note, that sometimes value is added as a fifth concern, but we focus on the technical aspects here.

In the *Edge Cloud* and *Internet-of-Things* (IoT), so-called things (such as sensors and actuators) produce and consume data, processed in a edge cloud, in order to provide data services (Pahl et al., 2019).

Here *data quality* concerns arise. In case the underlying data is inaccurate, any extracted information and also derived actions based on it are likely to be unreliable (Mahdavinejad et al., 2018). Furthermore, the edge cloud environment in which the data collection occurs is often rapidly changing in terms of architecture and data characteristics. In order to focus our investigation, we make the following assumptions: (i) all data is numerical (i.e., text or multimedia data and corresponding quality concerns regarding formatting and syntax are not considered) and (ii) data can be stateful or stateless. Thus, IoT is a 4V big data context with specific data types.

Two central questions and analysis steps shall be applied in our use case setting: *(1) Quality Value Analysis:* is based on quality goals and thresholds. Goals are defined in terms of quality dimensions such as accuracy or completeness. The reaching of goals is determined using predefined thresholds. *(2) Problem Cause Analysis and Prediction:* rely on pattern and anomaly detection to identify DaaS information model quality problems and map them the data layer, possibly including time series such as quality graphs over time (at DaaS and source data level). The questions is whether a problem source (at data layer) can be identified or predicted based on an analysis of the DaaS layer.

3 DaaS QUALITY ASSESSMENT & PROBLEM CAUSE ANALYSIS

An empirical study (Ehrlinger et al., 2019) identified different quality deficiencies such as accuracy or com-

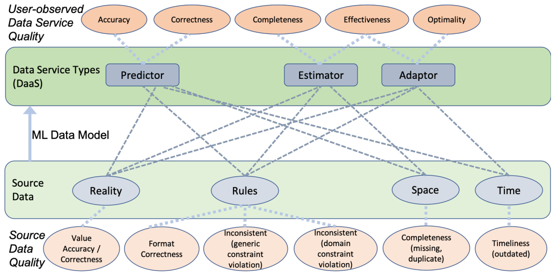


Figure 1: Layered DaaS Quality Management Architecture.

pleteness in ML data models. Our aim is to attribute these types of problems more systematically to different root causes for our use case. The differentiation can help to better identify IoT-level root causes for observed problems: *(1) Problems with IoT input data.* Assume a data table `'TrafficCount(Location, Date/Hour, Direction1, Direction2)'`. Two types of data quality problems are: (i) missing values (e.g., for one direction), which could result from a single sensor failure, and (ii) missing record (e.g., all data for a whole hour or from one location), which could result from communication failure. *(2) Problems with ML data model training.* Here unsuitable training sets (e.g., incomplete) could have been used.

3.1 Data and Service Quality Layers

The basis of the data quality framework is the raw data layer, see Fig. 1. We distinguish context-independent data qualities (complete, missing, duplicate, correct/accurate value, correct format, timely/outdated, inconsistent/violation of generic constraint) and context-dependent data quality (violation of domain constraints). Raw (or source) data is consumed to produce machine learning models. In order to better understand the processing purpose, we categorise these into DaaS function types: *predictor*, *estimator* (or calculator) and *adaptor*. For these functions, we define an information quality model. Input for function quality includes (i) structural model quality: accuracy, correctness, completeness, effectivess, optimality and (ii) function-specific quality: accuracy/correctness [predictor], complete/effective [estimator], effectiveness/optimality [adaptor].

The evaluation of our use case will shows that we can relate DaaS function quality to DaaS function types and techniques, see Fig. 1: Predictors are concerned with accuracy (regression) and correctness (classification). Estimator are concerned with effectiveness (clustering) and completeness (clustering). Adaptors are concerned with effectiveness (classification) and optimality (regression).

3.2 Closed Service Quality Loop

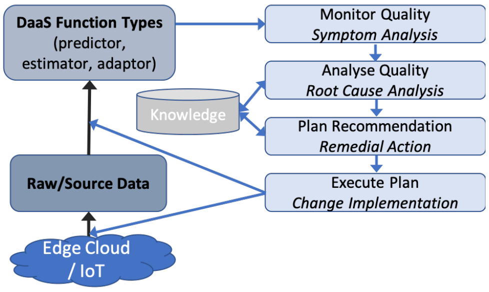


Figure 2: Closed Service Feedback Quality Loop.

Our DaaS Quality Management Architecture includes a feedback loop based on the MAPE-K adaptation pattern (with its Knowledge-based phases Monitor, Analyse, Plan and Execute) to control data and information quality, see Fig. 2. At the core is a mapping of DaaS model quality to source data quality, see Fig. 1.

Accuracy is considered the most important quality concern. High precision relates to a low false positive (FP) rate $TP/(TP+FP)$, i.e., correctly identified over incorrectly identified. High recall relates to a low false negative (FN) rate $TP/(TP+FN)$, i.e., correctly identified over not identified correct cases. High precision means that a DaaS function returns substantially more relevant results than irrelevant ones, while high recall means that it returns most of the relevant results.

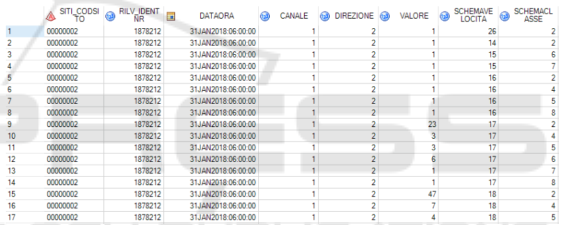
For example for *predictor accuracy*, influencing factors are data incomplete, data incorrect, data duplication, and outdated data. A concrete example is the count of road services per areas, which could suffer from outdated or duplicated data. For correctness, the same as above is the case. For *estimator effectiveness*, an example is outdated date, which applies to self-adaptive systems for traffic control that directly depend on the current situation. *Adaptor ineffectiveness* could be caused by an incorrect format in temperature measurements (Celsius vs Fahrenheit). Some of these conditions also depend on whether the application context is stateful or stateless as in the 'outdated' case.

The analysis of the underlying data quality problem of the observed ML quality problem could lead to remediation recommendations in two categories: *Source data:* recommendation to use other raw/source data, which could mean more, different, or less data. *ML training/testing data:* recommendation to use other ML training/testing data selected or to use even another ML technique.

4 USE CASE: IoT-EDGE TRAFFIC MANAGEMENT

4.1 Quality Assessment and Symptom Analysis

We start with quality assessment and symptom analysis activities. The different DaaS service functions shall be discussed in terms of (i) the quality dimension and its definition, (ii) a concrete example of a DaaS function and (iii) the determination of quality value. In a negative quality case, we talk about the symptom. These are based on a vehicle data set based on the 'TrafficCount', combined with 'WeatherData' for the respective location, see Fig. 3. The functions and expected qualities are as summarised in Table 1 with how the quality is measured and success is determined. We look at three function types and their quality goals:
(1) An **estimator** for traffic volume: effective and complete.



	SITI_CODSITO	RILV_IDENTNR	DATAORA	CANALE	DIREZIONE	VALORE	SCHEMAVELOCITA	SCHEMACLASSE
1	00000002	1878212	31JAN2018:06:00:00	1	2	1	26	2
2	00000002	1878212	31JAN2018:06:00:00	1	2	1	14	2
3	00000002	1878212	31JAN2018:06:00:00	1	2	1	15	6
4	00000002	1878212	31JAN2018:06:00:00	1	2	1	15	7
5	00000002	1878212	31JAN2018:06:00:00	1	2	1	16	2
6	00000002	1878212	31JAN2018:06:00:00	1	2	1	16	4
7	00000002	1878212	31JAN2018:06:00:00	1	2	1	16	5
8	00000002	1878212	31JAN2018:06:00:00	1	2	1	16	8
9	00000002	1878212	31JAN2018:06:00:00	1	2	23	17	2
10	00000002	1878212	31JAN2018:06:00:00	1	2	3	17	4
11	00000002	1878212	31JAN2018:06:00:00	1	2	3	17	5
12	00000002	1878212	31JAN2018:06:00:00	1	2	6	17	6
13	00000002	1878212	31JAN2018:06:00:00	1	2	1	17	7
14	00000002	1878212	31JAN2018:06:00:00	1	2	1	17	8
15	00000002	1878212	31JAN2018:06:00:00	1	2	47	18	2
16	00000002	1878212	31JAN2018:06:00:00	1	2	7	18	4
17	00000002	1878212	31JAN2018:06:00:00	1	2	4	18	5

Figure 3: Traffic Count Data Set - based on Regional Recordings https://mobility.api.opendatahub.bz.it/v2/swagger-ui.html.

Here the effectiveness can be defined as to what extend the estimation can be correct and effective for better performance. For example, to estimate the traffic volume for an August in general irrespective of concrete weather, we obtain the result by using supervised learning. To ensure the correctness of the estimation, the historic data should be checked, e.g., the results from earlier years $Y1$ and $Y2$ imply the estimation year $Y3$, i.e., $Y1, Y2 \rightarrow Y3$. Completeness for the estimator is easy to determine.

This function is used for *long-term road planning* for all roads, see Fig. 3.
(2) A **predictor** for traffic volume and level for a concrete future date.

For this purpose, the function calculates a volume V using $F(T,C,W) \rightarrow V : INT$ based on temperature, number of cars and weekday. For immediate assessment, we need to check observations in the current state and assume problems might have been there also in the past. Furthermore, we cannot predict the likelihood of any source of problem.

Figure 4: Public DaaS [Web Site] – Traffic Level Prediction – motivated by https://www.autobrennero.it/en/on-the-road/traffic-forecast/.

As another example, we can consider a predictor for car types: accurate and correct. In this situation correctness can be considered a special case of accuracy, i.e., 100% accuracy.

This function is used for *short/mid-term management* on major roads, see Fig. 4.

(3) An **adaptor** for traffic signs: effective and optimal.

Figure 5: Public DaaS [Road Sign] – Dynamic Traffic Signpost on the Motorway.

An adaptor proposes some actions after the calculation and evaluation of the situation. An adaptor function should be effective. For this function the calculations for speed are done based on car volume and emissions ($F(C,E) = Speed$). The optimal target is minimal emissions E_{min}, but this is constrained by traffic throughput (too restrictive speed limit might cause traffic stop and thus low emissions, but throughput is inadequate). If the quality is insufficient, the problem could be either the training data and sensors.

This is used for *immediate motorway management*, see Fig. 5.

4.2 Root Cause Analysis and Remedy Recommendation

We now look at cause analysis in more detail. The use cases are summarised in Table 2 for the data quality analysis and Table 3 for the problem root cause analysis and recommendation. The aim is now to determine a cause (either definitive or likely) from sources such as training data or source data. For all cases, we note (i) calculation of metric, (ii) assessment of problem situation, (iii) analysis of possible root causes (along the two categories or more fine-granular in terms of concrete data quality dimensions, and (iv) a strategy for better cause determination.

4.2.1 Steps 1 and 2: Metric Calculation and Problem Assessment

These steps are presented in Table 2. For the predictor accuracy, we analysed the accuracy input parameters: *TP:* if current state $OBS(currentstate)$ is correct and next state $V = OBS(nextstate)$ also results in correctness – indicates a given condition exists, when it really does. *FP:* if current state $OBS(currentstate)$ is incorrect and next state $V = OBS(nextstate)$ results in correctness – indicates a given condition exists, when it does not. *TN:* if current state $OBS(currentstate)$ is correct and next state $V \neq OBS(nextstate)$ results in incorrectness – indicates a condition does not hold, when it really does not. *FN:* if current state $OBS(currentstate)$ is incorrect and next state $V \neq OBS(nextstate)$ results in incorrectness – indicates that a condition does not hold, while in fact it does.

4.2.2 Step 3: Cause Analysis and Recommendation

The use case results are presented in Table 3. For Case 2 for example, false positive (FP) is an error in data reporting in which a result improperly indicates a problem, when in reality it is not present such as a vehicle that is not a car, but recognised as such. A false negative (FN) is an error in which a result wrongly indicates no quality problem (the result is negative), when actually it is present. Here, raw sensor data can be wrong. Consequently, FP problem causes are:

- raw data is wrong: e.g., sensors giving incomplete data such as too small dimensions given so that a van is recognised as a car,
- training data is wrong: e.g., not enough annotated/labelled cars in training set so that very large cars (SUV) are identified as vans/trucks.

We can also summarise the FN problem causes:

- raw data wrong: either sensors giving incomplete data (e.g., too big dimensions provided, so that its recognised as a van) or sensors giving incomplete data (e.g., too small dimensions given so that a van is recognised as a car),
- training (data) wrong: not enough annotated/labelled cars in training set so that very large cars (SUV) are identified as van/truck training (data) wrong (not enough annotated/labelled cars

Table 1: Use Cases – DaaS Functions and Quality.

	(1) Estimator	(2) Predictor	(3) Adaptor
Function & Quality	Estimator: effective, complete	Predictor: accurate, correct	Adaptor: effective
Sample Function	estimate the traffic volume for an August in general	car type categorisation	calculate traffic sign action (target: change speed limits to lower emissions)
Quality Value	*Calculation*: correctness of prediction for historic data (could use for training/validation data from past August or previous July). *Success*: degree of effectiveness for threshold T	*Calculation*: Precision, Recall based on *TP, FP, FP, FN*. *Success*: a threshold T on predefined degree of accuracy.	*Calculation*: observation after applying action $OBS_E(Apply(Action))$. *Success*: is effective, if $E_{i+1} < E_i$ for emissions E. The aim is the reach a target emission while not having too slow traffic.

Table 2: Use Cases – DaaS Quality Analysis.

	(1) Estimator	(2) Predictor	(3) Adaptor
Calculation of Metric	$F(C,P) \rightarrow Volume$ estimates volumes of traffic for general periods	$F(T,C,W) \rightarrow Volume$ predicts vehicle numbers based on temperature, counted cars, weekday	$F(C,E) = Speed$ adapts speed limits based on car volume and emission
Assessment of Problem Situation	Goal achievement: • the results from earlier years $Y1$ to $Y2$ imply the estimation $Y3$, i.e., $Y1,\ldots,Y2 \rightarrow Y3$	Goal achievement: • Four cases occur: (i) 100% accuracy, (ii) $<$ 100% accuracy, but within tolerance (threshold T), (iii) $< T$%, (iv) undefined. • Accuracy is defined using $Precision = \frac{TP}{TP+FP}$ and $Recall = \frac{TP}{TP+FN}$.	Goal achievement: • emissions (primary): $E_{new} \leq E_T$ for threshold T as ultimate goal; $E_{new} < E_{old}$ as just improvement, i.e. these are 100% effective, and x% effective. • throughput: $OBS_C(\ Apply(\ Speed)) = C_{new}$ • secondary: C_{new} as close as possible to C_{old}

Table 3: Use Cases – Cause Analysis and Recommended Target for Remedial Action.

	(1) Estimator	(2) Predictor	(3) Adaptor
Cause Analysis	Both *training and sensor data* can be a cause for quality problems	*Training data*: F is always fully defined *Sensor data*: possible problems include data integrity (violation of domain or integrity constraint) and data completeness, but generally all data quality dimensions are relevant	Both *training and sensor data* can be a cause for quality problems

in training set so that very small or very large cars are not covered.

Cause Analysis. In order to determine problems, we try to identify indicative patterns or anomalies. In pattern identification different situations can be distinguished. For example, a steep decrease in a quality graph over time (time series) could point to a sudden sensor failure. A gradual decrease of quality could point to problems within the data. In a flat effectiveness quality graph, the problem could be arising from the training data. Or in other cases, in a classification function, patterns in sequences of symbols can have different meanings in each situation, e.g., unexpected repeated symbols or unexpected increase in symbols.

Examples where *time series* can help are (i) outages, i.e., no data for a period (communications problem), and (ii) incorrect data, i.e., sensors faulty (e.g., giving to high measurements). Here, the Assessment is based on the detection of patterns or anomalies. A time series for a current assessment could for example be a normal series $CBTCBT$, changing into $CCTTCC$ as a sequence that shows an unusual pattern (here for vehicle categories car C, bike B and truck T). The cause analysis uses pattern/anomaly detection, with pattern mappings to the data level. Time series can be used for predictive maintenance (prediction of future problems, through the identification of changing patterns).

Remediation Recommendation. The general strategy used in all quality remediations is training data validation. Different DaaS functions F_i are created for different training data sets and then according to the result different options can be taken. One option is to compare functions themselves and another one is to compare input/output values. For instance, we could do majority vote on similarity (e.g., on 3 data sets). If one is different, this set has a specific property, e.g., more July data than others. The recommendation could be to check July data for completeness or accuracy. This might have to be done manually. If necessary, a different function needs to be constructed.

The primary remedial strategy is starting with training data changes and/or constructing different DaaS functions. An automated comparison can then be carried out, in relation to historic data or between different functions. This strategy has the pragmatic advantage of involving only the data science/engineering team.

5 RELATED WORK

The related work shall now be discussed by covering the data quality level, machine learning process perspective and DaaS model quality.

Data-level quality has been investigated in (O'Brien et al., 2013), (Casado-Vara et al., 2018), (Sicari et al., 2016). In (O'Brien et al., 2013), data quality problems where classified into two groups of context-independent and context-dependant from the data and user perspective. In (Casado-Vara et al., 2018), a new architecture based on Blockchain technology was proposed to improve data quality and false data detection. In (Sicari et al., 2016), a lightweight cross-domain prototype of a distributed architecture for IoT was also presented, providing supporting algorithms for the assessment of data quality and security. We adapted here (O'Brien et al., 2013) to our IoT application context.

The ML process perspective was discussed in (Amershi et al., 2019). A machine learning workflow with nine stages was presented in which the early stages are data oriented. Usually the workflows connected to machine learning are highly non-linear and often contain several feedback loops to previous stages. If the system contain multiple machine learning components, which interact together in complex and unexpected ways, this workflow can become more complex. We investigate here a broader loop from the later final ML function stages to the initial data and ML training configuration stages, which has not been comprehensively attempted yet.

Another aspect is the machine learning layer (Plewczynski et al., 2006), (Caruana and Niculescu-Mizil, 2006). Different supervised learning approaches were used. Specific quality metrics applied to ML-based data models have been investigated. (Kleiman and Page, 2019) discuss the area under the receiver operating characteristic curve (AUC) as an example of quality for classification models. In (Sridhar et al., 2018), a solution for model governance in production machine learning is presented where one can track and understand the provenance information of how an ML prediction solution came to be. Also the quality of data in ML has been investigated. An application use case was presented, but without a systematic coverage of quality aspects. Data quality is important in many ML-supported DaaS applications, such as scientific computing. In (Deja, 2019), the authors investigate high-energy physics experiments as an IoT-type setting that points out the need for a systematic, automated approach to achieve higher accuracy compared to training problems arising from manual data labelling. While the previous work looked at the DaaS side as root causes, in (De Hoog et al., 2019) another IoT and edge cloud setting is considered that highlights the uncertainty of sensory data as problem causes. The proposal is also to give data quality a prominent role in the process. (Ehrlinger et al., 2019) only covers IoT root causes in the analysis, but not ML training data problems. We aimed here to condense the different individual quality concerns in a joint data service quality model that takes in board lessons learned from (Deja, 2019; De Hoog et al., 2019; Ehrlinger et al., 2019), but provides a closed feedback loop.

6 DISCUSSION AND CONCLUSIONS

DaaS applications make data accessible that in its raw data format would not be usable. Machine learning is often used to process raw data in order to create meaningful information for a DaaS consumer. While typically accuracy is the key concern of the created data models, we aim at a broader categorisation of quality, covering the raw data as well as the DaaS model layer We investigated an integrated DaaS quality management framework. We provided a fine-granular model for a range of service quality concerns addressing common types of machine learning function types. The central technical advancement is the mapping of observable quality deficiencies of DaaS functions to underlying, possible hidden data quality problems, i.e., providing a root cause analysis for symptoms observed by the service consumer. In addition, remedial actions for the identified problems and causes can be recommended by the framework.

In the use cases, we considered the validation of both DaaS function types and related data quality types in symptom and root cause analysis. In our IoT and edge cloud case study, quality data regarding current situations have been used as well as time series,

Table 4: DaaS Quality Assessment Dimensions.

	DaaS Quality Value			DaaS Quality Time Series		
quality value	accuracy	correct/ effective:	optimal	accuracy	correct/ effective	optimal
metric & measurement	mostly done manual, maybe automated with other sensors, e.g., optical issues (dust) or loss of connectivity can be detected	historic data – can be mostly automated	can be automated, but needs waiting for the next state; can either be ML data or raw data	determine source by mapping time series to underlying raw data sequences (e.g., car type series)	temperature prediction series (jump > 20 degrees is sensor fault)	time series could be difficult to interpret (if heating switched on or cloud workload is suddenly high), the adaptor will struggle

as indicated in the table[1]. The main observations for both situational and time series-based quality analysis are summarised in Table 4 that covers the different quality concerns and how they are determined.

Some open problems remain, however. We provided informal definitions for the function and data quality concepts, but all aspects beyond accuracy need to be fully formalised.

From an architectural perspective, we also plan to address more complex architectures with multiple clusters of data producers to be coordinated (Fowley et al., 2018; Scolati et al., 2019; von Leon et al., 2019; von Leon et al., 2018), which would allow us to generalise the results to multiple edge-centric DaaS (Pahl et al., 2018).

We considered traffic management and weather so far. Another application domain is mobile learning that equally includes heavy use of data being collected from and delivered to mobile learners and their devices (Kenny and Pahl, 2005; Pahl et al., 2004; Murray et al., 2003; Melia and Pahl, 2009). These systems also rely on close interaction with semantic processing of interactions in order to support cognitive learning processes (Fang et al., 2016; Javed et al., 2013), which would help to increase the understandability of the DaaS offering provided.

The ultimate aim is to to automate the problem cause identification, e.g., through the analysis of ML techniques such as regression, classification or clustering or through the use of statistical (probabilistic) models, e.g., to use Hidden Markov Models HMM to map observable DaaS function quality to hidden data quality via reason-based probability assignment. The automation of assessment and analyses is a further concern that we aim to address in the future.

[1] In addition to time series, *aggregation* is a mechanism based on location or time. However, this has not been covered in the use cases.

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