# A Measure Data Catalog for Dashboard Management and Validation

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Abstract: The amount and diversity of data that organizations have to deal with, intensify the importance and challenges associated with data management. In this context, data catalogs play a significant role, as they are used as a tool to find and understand data. With the emergence of new approaches to storing and exploring data, such as Data Lake or Data Lakehouse, the requirements associated with building and maintaining the data catalog have evolved and represent an opportunity for organizations to develop their decision-making processes. This work explores a metric data catalog for analytical systems to support building, validating, and maintaining dashboards in a Business Intelligence system.

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## 1 INTRODUCTION

Analytical systems are an essential asset for analysing business activities. The ability to analyse data and understand its meaning, context, and outcomes, represents a powerful tool that can be used to support decision-making processes (in the most diverse areas such as sales, marketing, product development, and business-to-business partnerships). Without support from one of the most important elements of any business: the data itself, managers must base their decisions on assumptions and/or intuition.

Nowadays, there is an increasing awareness that it is necessary to understand the organizational reality and map it with the reality external to the organization. Managers want to understand market behaviors and anticipate changes, which often translate into strategic tactics and changes. This is a premise that has always supported the development of Business Intelligence (BI) systems. However, decision-making processes are increasingly influenced by the amount of existing data, its heterogeneity in terms of structure, and by the time window available to make decisions.

One of the ways to analyse data is through the creation of reports/dashboards. Visuals are usually framed within a report/dashboard context and are used to present relevant information to decision-makers. To develop the visuals, it is necessary to link previously prepared data (typically stored in a Data Warehouse) and create measures that are based on the business processes, perspectives, and events that need to be analysed. Measures can be represented by a simple numeric attribute, can be derived, or composed by several attributes, or even from other metrics. They can also be additive, semi-additive, or non-additive (Kimball & Ross, 2013) and can have

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different format representations considering the context in which they are used. Additionally, some tools allow for the creation of measures used only for producing reports, providing a way to reuse previous calculations to create a new measure. Several reports/dashboards are developed and used across all organization departments in real-world scenarios. In such cases, maintaining and using metrics with consistency is a difficult task since each measure can be used by other measures in different reports to support different business activities. This means the same metrics can appear in different fact tables. Conformed facts should be used, ensuring the metrics that are compared or computed together have the same technical definition. If they conform, they should have the same name, otherwise should be named differently to alert business users. We believe the naming conventions are not enough and are potentially error-prone.

A Data Catalog (DC) supports the documentation of data used in the analytical system, preserving the metadata in which definitions of the objects used, their relationship, exploration paths, and quality evaluation are stored. A DC helps to understand the meaning of the data from a business glossary, consult information from the data dictionary in a contextualized way, and to visualize, analyze and monitor the different data sources (Wells, 2019). A Measure Data Catalogue (MDC) for an analytical system can be seen as a specialized DC, storing a collection of specific business metrics, maintained by the data engineers/governance team, which can be used in several data sources, reports, and dashboards.

This paper explores an MDC implementation to support metrics management and its use. In practice, the MDC is presented to semantically describe the metrics composition, relationship, lineage, and visual representation according to specific contexts. After the presentation of the related work in section 2, the concept of MCD is presented in section 3, demonstrating how the use of metrics metadata can improve the development of dashboards and reports. Section 4 presents a case study that exemplifies the MDC application for a specific scenario. Finally, the main conclusions and future work directions are presented in section 5.

## 2 RELATED WORK

In recent years, the complexity and amount of data have increased considerably, which has contributed to the emergence of new techniques to enrich and represent data, enhancing the extraction of knowledge to add business value. As a result, Data Lakes (DL) emerged as a possible solution to deal with these new requirements. With DL popularization, Data Catalogs (DC) have been increasingly used for metadata management. Atalion Data Catalog[8], Azure Data Catalog[9], and Google Cloud Data Catalog[10] are just a few examples of proprietary DCs that use technology and specific vocabularies. Currently, the DC technological offer is also strongly associated with proprietary technology platforms and integrated as an integral part of "full-stack" data platforms.

Recently (Guido De Simoni, 2021), Gartner presented a new approach based on the concept of active metadata for handling metadata in modern data applications. The main idea is to replace the traditional metadata approach in which data is statically stored (and accessed manually as a separated tool) in a repository (DC), with an active metadata management approach that considers metadata as a part of a data platform, which means that it can be embedded across analytical and transformation procedures to provide context. With these new trends in mind, this section presents the most relevant and disruptive approaches for representing and exploring metadata in a DC context.

In (Dibowski et al., 2020), the authors present a semantic layer incorporating a semantic DC built with standard technologies. The semantic layer consists of an ontology and a knowledge graph, providing a semantic description of all DL resources. Resources include a heterogeneous set of documents, datasets, and databases. The semantic description of these resources includes information about the content, its origin, and access control permissions. The access control component is supported by the Open Digital Rights Language (ODRL) ontology, allowing the description of access to DL resources, mapping resources, users, and allowed actions. The use of knowledge graphs for the representation of metadata is also explored in (Dibowski & Schmid, 2021). This work shows the application of knowledge graphs for semantic description and data management in a DL, improving the ability to reuse data and enhancing automatic data processing by specialized algorithms. The authors argue that data without a description of

[8] https://www.alation.com
[9] https://azure.microsoft.com/en-us/products/data-catalog
[10] https://cloud.google.com/dataplex

its meaning and schema has a reduced value and that semantic enrichment is the key for data to be used more intelligently by different applications.

There are still some interesting works that use metadata to support the data presentation layer that typically translates into reports and/or dashboards. In (Blomqvist et al., 2017), the authors present a knowledge graph (an ontology that supports indicator discovery and data visualization) and an application capable of performing metadata analysis to build and present dashboards according to the identified indicators. In (Lavalle et al., 2021), the authors propose a methodology that collects user needs and creates appropriate visualizations in a semi-automatic way. The proposal covers the entire process, from the definition of requirements to the implementation of visualizations. Another work that explores personalized data exploration is presented in (Bianchini et al., 2019), where the authors propose an ontology for the semantic representation of key indicators. In addition to the ontology and user characterization, a semantic layer is presented that supports personalized access to urban data.

A DC exposing an architecture incorporating a semantic layer, built with standard semantic technologies, enhances the use of data in areas such as Machine Learning and Artificial Intelligence, see (Dibowski & Schmid, 2021). Furthermore, the growing importance of using semantic layers in analytical systems is increasingly evident, see (Zaidi et al., 2017). Its level of applicability is directly associated with the type of enrichment performed on the data. Several authors have used DC to support access control mechanisms and data quality control and allow exploring data in a personalized way and framed with the main indicators of a given domain. These are recent research topics with practical applicability in several business domains, which translates into an ever-increasing potential for application. For the interested reader, we refer to the following publications on the subject (Eichler et al., 2021; Megdiche Imen and Ravat, 2021; Ravat Franck and Zhao, 2019; Sawadogo & Darmont, 2021; Scholly et al., 2021).

# 3 THE COMPLEXITY BEYOND MEASURES DEFINITION

From marketing to sales, BI can be applied everywhere. It is already common practice in companies to support daily decisions with BI analyses. This process enables decision-makers to gain a more comprehensive and informed overview of what is happening at the corporate level. For this purpose, decision-makers are usually presented with reports and charts based on existing business data in data warehouses. The most common method for building these data warehouses is the dimensional model proposed by (Kimball & Ross, 2013). In this approach, business-relevant measures are stored in fact tables so that they can be grouped according to different dimensions that represent various ways of analysing the data.

For example, “SalesQuantity” can be one of the measures used in a fact table that allows analysing of sales levels from different angles, such as the number of sales per day or per store. Since in this case, it is a measure that can be summed in all dimensions (facts can be summarized by adding them together), it is called an additive measure. On the other hand, measures that can only be summed in some dimensions are considered semi-additive. “Stock” is one of these examples, because if we consider the dimensions “Product”, “Store” and “Calendar”, we can add the stock of several products and several stores, but we cannot add it over the dimension “Calendar”. Finally, when facts cannot be added in any of their dimensions, as is the case with ratios, they are called non-additive measures. Since the goal of Kimball's dimensional modelling is to facilitate queries and analysis, it is preferable to include numerical and additive measures in the fact table (Kimball & Ross, 2016).

To make data useful for decision-makers and enable an assessment of business performance, it is necessary to use measures that serve as a basis for creating charts and reports. These metrics can be divided into three types: elementary, aggregated, or derived. An elementary metric corresponds to a fact (fact table measure) with the lowest level of detail. An aggregated metric shows the result of an aggregation function (such as SUM, COUNT, or MAX) applied to an elementary metric. Finally, a metric is “derived” if it has been created using formulas that consider other metrics. As an example, let us assume that a company uses a data warehouse consisting of the fact table “Sales” including the measures for each sales line:

1. Quantity: the number of units sold
2. Value: total value in dollars
3. Cost: value in dollars
4. Margin: value in dollars

Measures 1, 2 and 3 are elementary measures corresponding to the sales line grain, i.e., the more granular detail level. Measure 4 can be computed by subtracting the “Cost” from the “Value” measure. For


Figure 1: Sales schema.

that reason, it is classified as a derived metric since it is calculated from other metrics. All these metrics are additive (or fully additive) since they may be summed up across any dimension, producing a meaningful result from a business perspective.

Additionally, several measures that can be identified from business requirements, are not placed directly in the fact table but created in the BI tool for supporting the development of reports and charts. Nonadditive measures are not typically stored in fact tables. Instead, they are broken down into additive measures that can be used to calculate them. Ratios represent a typical example of a nonadditive measure that represents a critical measurement for business processes that is posteriorly computed by the BI tool to support data presentation:

1. “Total Sales”
2. “Sales Current Month” and “Sales Previous Month”
3. “Sales Variance” represents the total sales value from the current month minus the total sales value from the last month
4. “Sales Variance %” represents the ratio between the total sales value from the current month and the total sales value from the previous month
5. “Total Units Sold”

In this case, measures 1, and 5 are aggregate measures. These measures consider the sum of the “Value” and “Quantity”, respectively, along any dimension of the star schema, such as the ‘Calendar’ dimension. Measures in 2 are also aggregate measures obtained from the elementary measure “Value” aggregated for the current and last month. Measure 3 is a derived metric that calculates the sales variance as the difference between the sales value from the current month and the sales value from the previous month (Eq. 1). Measure 4 is also a derived measure, is non-additive and corresponds to the ratio between the “Sales Current Month” and the “Sales Previous Month” (Eq. 2).

$$SalesV = Sales\ CM - Sales\ PM \tag{1}$$

$$SalesV(\%) = \frac{SalesV}{Sales\ PM} \times 100 \tag{2}$$

Considering these measures, the company can use data analysis software such as Power BI[11] to create reports and charts to help with business data analysis. When defining metrics, it is important to ensure that they cover all intended analysis requirements and that they are valid and error-free. For example, it should be ensured that there are no metrics that are calculated by summing non-additive measures. Based on the defined metrics, it might be useful for the company to create a chart showing the sales variance values for each product (measure 3) and a second chart showing the evolution of the percentage of sales variance associated with each product on each day (measure

[11] https://powerbi.microsoft.com

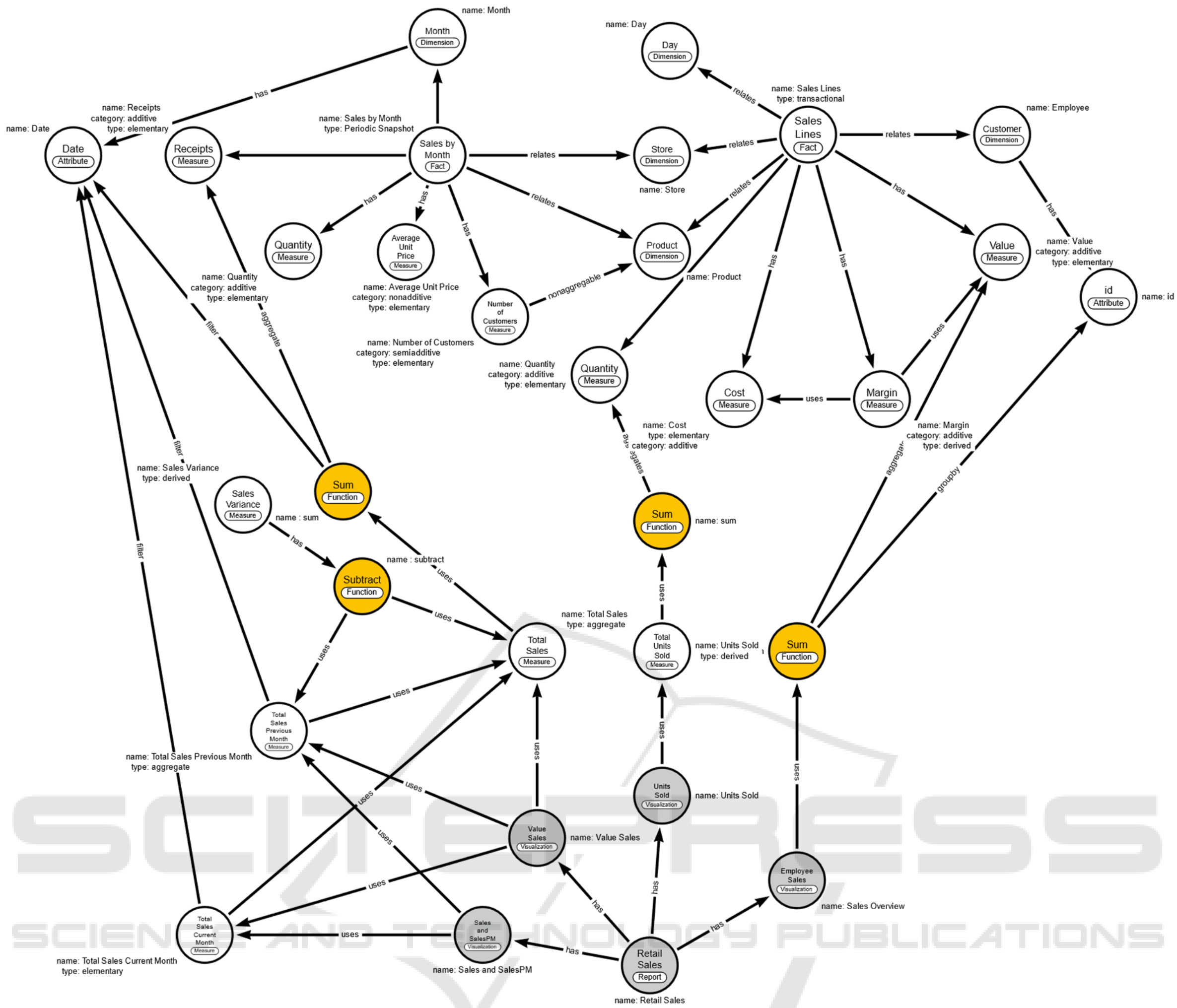


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Figure 2: Property graph for representing the described use case domain.

4). Note that in this case the value of this measure is directly linked to the value of measure 3. This dependency requires special care because any change in the formula used to calculate measure 3 affects the values of measure 4. Suppose that for some reason the company has understood that from a visual point of view, it is better to report sales variance in thousands of euros and starts to use the calculation formula of Eq. 3. This change means that Eq. 2. must also be changed, otherwise the chart will show incorrect values.

$$SalesV = (Sales\ CM - Sales\ PM)/1000 \quad (3)$$

Therefore, when analysing data with hundreds of measures covering different business areas and with many derived measures, it is important to know the relationships between them and to identify the reports/charts in which they are used to avoid errors of this kind. In these cases, it is important to ensure that changes to any of the metrics do not lead to incorrect metrics in the areas that depend on them.

## 4 CONNECTING MEASURES

Reports and dashboards are two common tools to visualize data. Typically, these tools provide several visualizations to fulfil analytic needs. Bar, Pie, and gauge charts are just examples of visualizations that can compose reports and dashboards. Reports and dashboards can have different meanings depending on the tool or scope used. For example, Microsoft Power BI sets the dashboard on the hierarchy top, i.e., they are built from the developed reports, representing a story through visualizations. In this case, reports embody the complexity related to managing and presenting summarized data. The reports are made up of pages which in turn are composed of visuals configured to present data from a specific dataset. Visuals are in turn composed of data objects holding data (dimension and fact tables) and the respective measures used in aggregation procedures.

Measures calculate a result using a mathematical expression. Associated with visuals, page, and report filters, data aggregation changes according to the user's interaction with the reports, allowing faster and more dynamic data exploration. Business changes can imply changes in the measure's composition, and those measures can be shared not only by multiple visualizations/reports but also can be used to create other measures. Maintaining visualization's correctness in large reports can be difficult to handle since one simple change can require multiple adaptations, which is time-consuming and prone to error. Additionally, when dealing with several measures and complex dimensional schemas, errors can occur and compromise the results presented in the visualizations. For example, applying a SUM aggregate function to a non-additive measure can result in unexpected results.

The data representation is another important consideration since the same measure can be represented in different formats considering the context in which is used. There are also business rules that affect not only measurement calculation but also the presentation of dimension attributes. These considerations are studied and evaluated in the early development phases. For example, in the dimensional modelling development process (included in the four-step Kimball method (Kimball & Ross, 2016)), the measure identification and categorization are done when fact tables are planned. Typically, the data mart profiles are identified and based on their needs, a set of queries are analysed to identify the requirements that need to be fulfilled by the system. Based on these query requirements, the measures are identified and evaluated. The findings are documented alongside the categorization of each measure and from the identified measures, a subset (the elementary measures) is used for implementation in the dimensional schema. Even if measures are not included in the final schema, they will be used posteriorly when aggregate schemas are developed or when reports or dashboards are implemented. This documentation is an important asset for building an analytical system and we believe it should be integrated within the system, i.e., it should play an active role in the development of dashboards, instead of being stored in some repository in a nonstructured way.

These resources are identified using a semantic approach. Semantic technologies involve the use of structured vocabularies to define and organize meaningful data, easier to understand for both domain experts and computers. Metadata is stored in a machine-readable format that can be easily processed and interpreted by other system components. This allows for more advanced capabilities, providing mechanisms to categorize and contextualize data, and enabling validations and data discovery capabilities about measures and their context.

Figure 1 presents a data mart schema composed of two stars each one supporting the same business process in different grains. The transaction "FACT_sales_lines" fact table stores the individual sales lines information, which includes the set of elementary measures described in section 3, and the derived measure 'Margin', defined for the same atomic level of detail . It serves as a granular repository of atomic data for this business process. The snapshot "FACT_sales_by_month" fact table periodically samples the "FACT_sales_lines" data. While "FACT_sales_lines" is considered an elementary schema (preserves the more granular version of data), the "FACT_sales_by_month" is an derived schema since it stores data aggregated from individual transactions in a periodic snapshot. In the "FACT_sales_by_month" fact table the following measures are represented:

1. number of customers
2. average unit price
3. receipts
4. quantity

Metric 1 represents the number of customers that purchase for a given month and is not aggregable across product (DIM_product) or calendar dimensions. Metric 2 is non-additive, however the MIN or MAX operator can be used to aggregate it. Receipts and quantity are additive metrics for the "FACT_sales_by_month" schema. These schemas are used for supporting Power BI reports and dashboards developed to support sales analysis.

Figure 2 presents a property graph model for supporting measures representation and the related context in the analytical system. In a property graph model, both the relationships and their connecting nodes of data are named, and capable of storing properties(Fensel et al., 2020). The represented knowledge model describes interlinked entities, properties, and relationships. It consists of the following:

- Nodes represent entities in the domain subset: several labels are declared to represent the node's purpose in the graph. The data artefacts such as dimension ("Dimension" label) and fact ("Fact label") tables are represented. Additionally, their attributes ("Attribute" label) and in particular the measures ("Measure" label) are represented. Measures can be attached to the fact table or can represent measures created in the BI tool concept. Aggregation functions ("Function" labels) and expressions ("Expression" labels) are also represented using specific nodes since they are fundamental to understanding how measures are calculated and used. Additionally, concepts related to the data visualization used by BI tools are represented. There were identified reports ("Report") and their visualizations ("Visualization"). The relationships between these concepts allow for the identification of the reports and respective visualizations that are using specific measures (allowing for measures traceability).

- Relationships represent how entities interrelate: they have a type, direction, and properties. The "Relates" label is used to associate "Fact" nodes with "Dimension" nodes, and the "has" label provides a way to describe a stronger relationship between concepts. For example, data artefacts (Facts and Dimension) and their parts, i.e., fields and more specifically, measures. The "has" label is also used to associate visualizations with reports and specific functions or expressions with measures or visualizations to describe specific calculations. The "uses" label describes a weaker dependency between nodes and it is useful to describe how nodes depend on one another. It can be used to describe the dependency of a given measure on other measures (for derived measures), the dependency of visualizations on specific measures or the dependency of some functions/expressions in specific fields or measures. There are also represented some specific labels used to describe measures can or attributes that can be used in a specific calculation: "aggregation" for describing data aggregation, "groupby" for describing grouping constraints or "filter" for describing some selection applied to data that will be used in a specific calculation.
- Properties represent key-value pairs used in both nodes and relationships to store additional data. For example, they are used to describe measures type ("elementary", "aggregated", or "derived"), category ("additive", "nonadditive" or "semi-additive"), name and description (omitted in the graph from Figure 2).

The graph from Figure 2 describes a subset of the concepts related to the case study described in Figure 1. It focuses on measures and how they can be represented in the graph data model. There are measures created in the context of fact tables (the "has" relationship with "Fact" nodes allows for their identification) and measures created in the context of a specific BI tool, in this case, the Power BI.

Additivity is expressed for measures, i.e. allowing for the identification of measures that cannot be used in the SUM operator for an aggregation operation. This is particularly useful if some report is using them for data aggregation, allowing for the identification of errors that can compromise analytics perception. The graph can also represent the limitations in the aggregation through the "nonaggregable" relationship, providing another validation aspect to the measures used in reports.

Each measure is classified into the following types: i) "elementary" represent granular facts, ii) "aggregate" represent an aggregation of facts, and iii) "derived" when the measures is calculated from other measures. These definitions are helpful for identifying dependencies between measures if something changes as described in section 3. This is in fact a real problem today for Power BI developers since the same measure can be used in several visualizations and can be the origin for dozens of other measures. In complex scenarios it can be difficult to manage all these dependencies and anticipate the impact of a simple change in a measure formula. The dependency is also preserved using functions and expressions, describing measures, and manipulating calculations, revealing important dependencies not only between measures but also between dimensional attributes (for example, involving filtering). These calculations can be expressed between measures and visualizations.

Considering a Power BI specific scenario, source data is ingested, transformed, and enriched to serve specific analytic purposes. A Power BI project can have specific visualizations and filters, and metrics over the data. Power BI metrics, i.e., measures, can be created based on calculations that are needed to be analysed. Metrics can be used to summarize, aggregate, or calculate specific values, as explained in section 4. Measures implementation is supported by DAX (Data Analysis Expressions) language that covers a wide range of operators and functions for filtering, aggregation, and calculations. For example, the following expression in DAX:

```
Total Sales PM = CALCULATE([Sales], PREVIOUSMONTH('Calendar'[Date]))
```

is used to calculate the total sales for the previous month. The expression is organized as follows:

- `Total Sales PM` is the name of the measure being created;
- `=CALCULATE([Sales], PREVIOUSMONTH('Calendar'[Date]))` represents the calculation being performed. The `CALCULATE` function is used to modify the filter context of the calculation. In this case, it's being used to filter the sales data to the previous month.
- The `[Sales]` measure is being used as the expression to be filtered by the `PREVIOUSMONTH` function;
- The `PREVIOUSMONTH` function is a time intelligence function that returns the previous month of the date provided in the argument. In this case, `'Calendar'[Date]` is the date column being used as the argument.

After the creation, the metrics `Total Sales PM` can be used to analyze and visualize the total sales for the previous month.

All the artefacts developed in a Power BI project are stored inside the *pbit* file, which is used as a template file that contains the data model and queries from the Power BI report. Measures and schema models can be extracted, parsed and linked as in the graph model presented in Figure 2. For testing purposes, a Neo4j[12] database was used. A set of validation rules written in Cypher - the query language used in Neo4j - allows the identification of wrong aggregations either by identifying non-aggregable measures across some dimensions or wrong aggregations (such as the use of the SUM function in non-additive measures). For example, the measure `Sales Variance` cannot be used with the SUM operator since it doesn't make sense to add percentile values across records. Additionally, the graph allows traceability, which is in fact a pressing problem for Power BI users. It is possible to understand the impact of measure changes, for example in related measures or in the visualizations and associated reports. The following Cypher expression:

```
MATCH(m:Measure{name:'Total Sales'}) <-[:uses*]-(o:Measure) return m,o
```

can be used to find the measures that are connected to the measure denoted as `Total Sales` through the relationship denoted as `uses`.

# 5 CONCLUSIONS

In recent years, organizations are dealing with more and more data that need to be processed and analyzed to support their decision-making processes. In addition to the organizational data typically supported by a centralized data architecture, there is an increasing need to consume external data that complement and contextualize the organizational reality.

Data cataloguing and semantic layers can be used to provide context and control, providing meaning to the data so that it can be correctly explored by users. Therefore, we believe that its use in the particular context of reports/dashboards will help to facilitate the design and implementation process, as well as the process of maintenance and control of the entire process of visualization and data exploration. In this paper, a Data Catalog sub-component for analytical systems was presented, describing how measures can be documented and connected with their underlying context: Fact/dimension tables and reports/visualizations, preserving important properties that constrain its use for providing business insights. A property graph was implemented serving as a metadatabase for supporting the reports/dashboards development, helping to ensure data correction, and allowing for data control and traceability.

As future work, the research presented in this paper can be extended in several ways. For example, expanding the coverage areas for metadata, which can help data scientists in searching and discovery data, providing access control and privacy rules to data, data lineage useful for ETL pipelines, explanation and reproducibility for Machine Learning techniques applied to data and data quality thought data statistics, preservation business rules and identification of outliers. All this can be connected to powerful knowledge graphs that can be extended with taxonomies and ontologies, bringing new capabilities related to data representation and exploration (using, for example, inference mechanisms).

[12] https://neo4j.com/developer/graph-database

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