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Original Article

Unlocking Data Potential: How Data Modelling Enhances Visualization Readiness

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Abstract: *In the day and age of exponential data, not only has volume increased, but so has demand for meaningful aggregation, processing and representation of information. Data modelling can be recognised as a basic process for improving data preparedness for visualisation. In data modelling, data requirements of a specific domain are depicted based on a structure that can be implemented in a way that is neutral to the implementation scheme. Data modelling formalisms define the elements of the model that have to be developed. With logical data modelling, you have a data model. Data modelling is one of the key procedures in data management as it helps to build up ideas about data items and their relationships. This paper focuses on three distinct stages of data modelling: conceptual, logical, and physical data models and their integration. Furthermore, the paper analyses how data modelling supports and improves data visualisation as it organises data correctly to produce accurate representations and meaningful visualisations. By integrating data models, it becomes possible to convert large datasets into informative visualisations, thus facilitating better understanding and decision-making. The challenges of data modelling, such as data quality and integration from multiple sources, are also discussed, along with their impact on data visualisation readiness.*

Keywords: *Overview of Data Modelling, Data Modelling Enhances Visualization, How Data Modeling Prepares Data for Visualization and Challenges.*

I. INTRODUCTION

In introduction the data organisations are constantly bombarded by information that they have never seen before and yet still not able to derive meaning from it. Determining trends, patterns, and relationships in data often enables good decisions to be made. However, this journey often begins with perhaps one of the most important processes: data modelling. The data model forms the base structure of the organisation, structuring and preparation of the data-accurate, reliable, and ready for visualisation tools to interpret and communicate effectively. In this article, learn how proper, robust data modelling practices unlock the full potential of data, making the creation of visualisations used in actionable insights and insight-based business strategies. It is well knowledge that ML tasks involving data preparation need a lot of processing time. Training sets are ultimately created via data preparation [1]. A strong network architecture, safe data handling practices, data accessibility, and industry backing are all essential elements of a successful data mining project. Thus, at each step of the data preparation process, this article provides ideas for maximising the performance of data collecting [2].

Three data models—the conceptual, logical, and physical data models—that are described at various degrees of abstraction may be developed as part of the data modelling process. Conceptual, logical, and physical data models are used in this context to describe three entities (Person, Student, and Professor) and their primary connections[3]. In summary, it is crucial to understand the data entities and their interactions using a conceptual data model at a higher degree of abstraction since the richness and intricacy rise from a conceptual to a physical data model. Using a Logical Data Model, the emphasis then shifts to describing those entities without concern for implementation specifics. Finally, the ability to depict the data supported by a certain DBMS is provided by a Physical Data Model[4][5]. Figure 1 shows the various area of data modeling.

Figure 1: Usage of Data Modelling

The graphic depiction of the importance of data is known as data visualisation. Providing the data in an understandable and appealing manner is the aim of data visualisation. That is, aiding in the process of interpreting data is the main goal of data visualisation [6]. It is crucial as it is easier to discover and handle information when it is presented visually. Data cleansing, data structure exploration, outlier and odd group detection, trend and cluster identification, local pattern detection, modelling output evaluation, and result presentation are all made easier by data visualisation. Data visualisation may make it easier and faster to spot patterns, correlations, and trends in datasets that might otherwise be hard to see in plain text and numbers [7][8].

Integrating disparate data sets from various sources into a single, coherent whole is known as data integration. This process is essential in many fields, such as business, government, and healthcare, where stricter information quality standards have necessitated the creation of more efficient data integration tools in order to gather data in a variety of formats and with a wide range of characteristics relevant to spatial data logic and physics. [9]. To create an integrated system for the gathering and administration of data from several sources, the data integration system should handle basic urban data, thematic characteristics data, spatial technologies, and consistent geographical and temporal reference[10].

Many academics believe that big data has high standards for consistency, integrity, and usefulness in its data quality evaluation since it encompasses numerous aspects. Currently, data quality assessments concerning electrical power primarily define the evaluation object, evaluation indication, rule, and weight before computing a score to build a model for the data quality assessment. Data quality evaluation with actual power businesses, which include massive amounts of data, diverse equipment, and complicated business systems, is one method that some scholars use to evaluate data quality issues[11].

This paper provides a comprehensive analysis of the different stages of data modelling—conceptual, logical, and physical—and highlights how each stage contributes to a more profound understanding of data structures and relationships. The following contributions as:

- The paper demonstrates how data modelling directly impacts data visualisation by ensuring data is organised and structured in a way that facilitates the creation of accurate and meaningful visual representations, leading to better data-driven decision-making.
- By discussing data modelling as a tool to enhance data quality, this paper contributes to the development of methods that ensure data accuracy, consistency, and reliability, which are essential for effective data visualisation.
- The paper identifies challenges in data modelling, such as integrating data from multiple sources and maintaining scalability, while also proposing potential approaches to address these challenges for better data readiness.

The following paper is structured as follows: Section I provide the topic overview with paper structure; Section II provides the overview of data modelling and enhancing visualisation with data modelling discussed in Section III, how data modelling prepares data for visualisation given in Section IV; challenges of data modelling discussed in Section V. Section VI and VII provide the literature review on this topic, and conclusion with future work.

II. OVERVIEW OF DATA MODELLING

The process of conceptually representing data items and their connections to one another is called data modelling. Gathering requirements, conceptual, logical, physical, and implementation designs are some of the phases that are usually included in the data modelling process. Data modellers collaborate with stakeholders to gain an understanding of data requirements[12], then define entities and attributes, create relationships between data objects, and finally build a model that accurately depicts the data in a method that database administrators, application developers, and others can use. As a result, it promotes more uniformity in security, semantics, rules, and names. Consequently, data analytics is enhanced. Regardless of how the data is used, the importance of its organisation and accessibility is emphasised. Figure 2 shows the models of data modeling.

A. Types of data models:

Data models are essential for structuring and organising data effectively. It can be categorised into several types, each serving specific purposes and scenarios. Here are the primary types of data models:

a) Conceptual Data Model:

This is an overview visual representation of the analytics or business operations that a system facilitates. It delineates the types of data required, the relationships between various business entities, and the corresponding business rules. Conceptual data models are mostly used by corporate leaders to understand how a system operates and make sure it satisfies their demands. Conceptual models are independent of particular application technologies or databases.

b) Logical Data Model:

A logical data model describes the specifics of the database implementation, delves deeply into the data structure, and gives each object properties. The physical data model is based on this data model [13]. The only distinction lies in the fact that logical data models are not exclusive to any one database, unlike physical data models that are created for a single database management system such as Oracle or MySQL. Database agnosticism persists in this data model. Vertabelo transforms the abstract data types of the characteristics into database-specific data types in order to create a physical data model. The logical modelling method takes the semantic structure that was constructed during the conceptual stage and uses it to try to impose order by putting important values, relationships, and discrete entities in a logical structure that is brought into at least 4th normal form (4NF).

c) Physical Data Model:

The data is broken down into the actual tables, clusters, and indexes needed for the data store at the physical level, where the technical details of the data storage, such as data types and indexes, are defined (using "logical" twice would be confusing). An organisation's database's internal structure, including its tables, columns, and connections, may be planned with the use of physical data models.

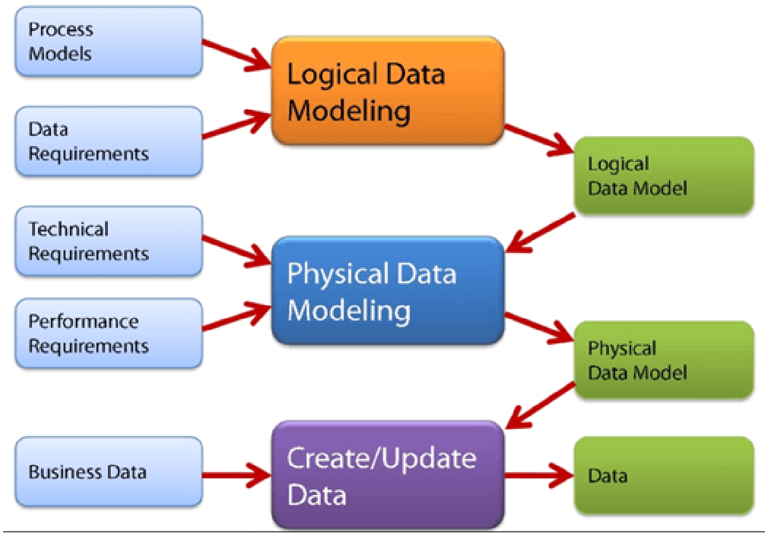

Figure 2: Models of Data Modeling

III. DATA MODELLING FOR ENHANCING VISUALIZATION

Data modelling is essential for better data visualisation because it provides a consistent framework for organising and comprehending dataset interactions. As a result, stakeholders will have an easier time interpreting and gaining insights from data visualisations that are both useful and accurate [14]. Data visualisation, or more accurately, visualisation management, presents complex needs to stakeholders in a clear and concise manner, allowing them to better grasp their significance and interdependencies. Any organisation may benefit greatly from data visualisation since it facilitates the making of choices in real-time. By keeping things simple, pertinent, and easy to understand, it helps consumers avoid information overload by visualising extracted data into logical and useful segments. The following are a few data visualisation tools:

- Python: Its huge and vibrant scientific computing community, together with its various libraries that provide more flexibility, make it one of the best programming languages for data visualisation.
- R is a free and open-source software environment that focuses on graphics creation. R was developed to analyse data.
- Data visualisation creation and execution were facilitated using Tableau, a business intelligence presentation tool.
- Power BI can handle Microsoft's own products and also get data from a wide range of other sources [15].

A. Visualization Based on Integration of Data Models

- Practically, integration of the data models is carried out according to the choice of the system of the transformers that performs settling one model to another. The character and the order of transformations are determined by the metadata characterising the data of the particular model analysis. The same approach can be used for the data visualisation task.
- The alignment of one data model to another one or even class of the models makes essential functions used for the model management, so functions used to determine the data required for the data passing from the one model into the another or its management. Functions needed for transition in fact, may not use all functions of the source model

but some. The set of functions used for access to the model or its management will be referred to as the Behaviour of the model.

- The definition of the required data converters is based on what subset of data elements is selected for visualisation and how it should be presented. In particular, in the applicative environment, it is possible to determine a slow data conversion, in which actual data is calculated (converted) as needed. This is convenient, for example, when visualising a part of a large collection of data.
- When defining a set of transformations and then actually performing the transformations, some constraints are distinguished: they are imposed both on the transformation as a whole and on the set of data obtained as a result of the transformation. Such constraints can be associated with an incorrect description of the data in the format of the model adopted for them (for example, support to relational tables that are not in the first normal form).
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- There may be some constraints in the data converters themselves (for example, constraints on the size of the data schema, on the selection of the transformer system that settles one model to another determines how data models are practically integrated. Meta data defining the data of the specific model analysis determines the character and sequence of changes. The data visualisation challenge may be approached in the same way. A data model's alignment with another model, or even with a class of models, is crucial for model maintenance and the functions used to identify what data is needed for data transfer across models[16]. Data modelling is useful for:
- Designing Databases: Data modelling aids in the creation of schemas, which specify how various data pieces are connected to one another, how data is organised in a database, and what kinds of data may be stored. This provides the framework for effective data storage and retrieval, which is necessary for data analytics.

- Understanding Data Relationships: Data modelling entails establishing connections between different data elements. Understanding these interactions is critical in data analytics because it may uncover patterns and dependencies that would otherwise be missed.
- Integrating Data: Data modelling assists data integration from different databases since data from several databases may be combined and analysed systematically. It is very important when analysing large datasets or performing complex analyses with many databases involved.
- Predictive Modeling: The analytic workflow often involves data models, especially in the use of predictive modelling. These models help generate future trends from past data and patterns to find danger and opportunity.
- Ensuring Data Consistency: A key attribute of data modelling is, therefore ensuring that the rules for data are sets and established, leading to the provision of good data quality as well as consistency. It can increase the quality of data analysis and reduce the risk of errors in the final results of data analysis.

IV. HOW DATA MODELING PREPARES DATA FOR VISUALIZATION

Data visualisation should be an important component of the data pre-processing and analysis phases of a machine learning algorithm as it offers the means to explore, review and describe the patterns within the data easily and succinctly. In order to make better cleaning and preprocessing decisions, visualisation is useful during data preparation for spotting problems such as distribution skewness, missing values, and outliers [17]. During analysis it is essential for finding improvement features that can be considered in a model, the structure of data and the interconnections between the variables. Data visualisation aids ML since it makes aligned prefab data sets more comprehensible in a more simplified format so as to enable a better choice of fit approaches to modelling. This is true because stakeholders can understand diverse concepts involved in their business and make decisions based on data and information derived from the raw data. Figure 3 shows the data visualisation areas.

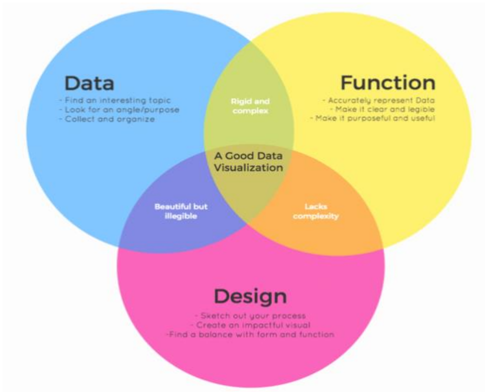

Figure 3: Data Visualisation

Commonly utilised techniques are listed below:

- Histograms: Helpful for making numerical data distributions more visually appealing.
- Scatter plots: This tool is helpful when used to determine the correspondence between two quantitative variables with a view to establishing a relationship.
- Box plots: Enables one to search for outliers and also shows how data has been distributed through the use of quartiles.
- Heatmaps: Good for finding correlations and trends in feature sets and useful for depicting matrix data where colours stand for values.
- Pair plots: A great way to start exploring data is to have a way to see the distribution of individual variables as well as the relationships between them.
- Line charts: Crucial for displaying patterns in data across time.
- Bar charts: Useful for comparing amounts across several categories. 8. Correlation matrices: Examine the relationship between numerous factors graphically, frequently depicted as heatmaps.

The development of insightful visualisations relies heavily on data modelling. Here's how:

- Structured and Organized Data: Logically and coherently organised data is what makes up a well-structured data model. This structure makes it simpler to extract and show data in a variety of visualisation formats, which aids in comprehension and interpretation.
- Ensuring Data Integrity: Data modelling contributes to data integrity by defining connections between various data pieces. As a result of the visualisations' reliance on dependable and accurate data, this integrity guarantees the consistency and accuracy of the data.

- Improves Efficiency: A well-designed data model streamlines data processing, facilitating the easy and rapid retrieval of visualization-related data. It may be especially useful when working with complicated data sets or massive amounts of data.
- Facilitates Data Analysis: If data modelling can show the connections and organisation of data in a clear and detailed way, it can help with more in-depth data analysis.
- Supports Interactivity: The interactive aspects of many modern data visualisation tools rely on the data being formatted in a specific way.

A. Role of Data Modelling in Enhancing Data Quality

Data quality is defined as the absence of unacceptable flaws. It isn't the lack of flaws. Every company will have them. The lack of those flaws causes us to fall short of a benchmark that would have real, measurable negative commercial consequences. Those bad consequences could include mistreating customers, incorrectly stocking shelves, launching dumb promotions, or passing up opportunities for expansion. Proper data quality management is also a value proposition that, while never flawless, provides more value than it costs. Improved data entry system modelling is a useful but frequently disregarded solution for poor data quality issues. A multitude of methods allow data to enter environments [18] [19]. If data is to be used effectively by the business, it must be appropriately modelled, whether it be data that is entered, received, or calculated.

The following are the main data modelling constructs that are associated with the data quality fault categories that are pertinent to data entering data quality:

- Uniqueness – guaranteeing that each column will have distinct values.
- Check – assures that the value of a column will be within a set of predetermined parameters
- Key – compelling the desired references among entities to remain intact, such as the customer's existence prior to placing an order.
- Mandatory – ensures that a column is filled with a valid value
- Default – assigning a value in the absence of input
- Null – letting a column use null (no value) rather than requiring a value.

V. CHALLENGES OF DATA MODELLING ENHANCES VISUALIZATION

Unlocking the full potential of data for effective visualisation requires well-thought-out data modelling. Data modelling provides a structured framework for managing and organising data, making it more accessible and comprehensible for visualisation tools. However, there are several challenges that come with ensuring that data modelling enhances visualisation readiness:

- Data Quality and Consistency: One of the biggest hurdles in data modelling is ensuring that the data is accurate, clean, and consistent. If care is not taken the source data can contain errors which will be displayed in the visualisation.
- Data Integration from Multiple Sources: Data in an organisation context can be gathered from various systems, platforms and even in different forms. Unifying these sources into a cohesive model is complex and can hinder visualisation readiness.
- Complexity of Data Relationships: Real-life data is rarely about many-to-many relationships, nested structures, and alike, quite often, it contains these complications. Inability to correctly model these relationships leads to suboptimal visualisation.
- Scalability Issues: When data increases then it brings the issue of how to manage the increased volume by refining the data model. Inaccurate models can skew information output and presentation hence decelerate the decision-making process due to delays.
- Modeling for Real-Time Data: A number of visualisations, particularly in the financial or IoT sectors, demand real or near real-time data. Inherent data models can be limited in dealing with the requirements of a stream data.
- Balancing Detail and Simplicity: Although it is necessary to reflect all the peculiarities of the data, model overcomplication can lead to difficulty in making and analysing the visualisations. Simplify the model as much as possible given that the details have to be included.
- Ensuring Metadata Management: Lack of proper metadata can lead to confusion about what the data represents, how it’s structured, or its limitations. This ambiguity can hinder data visualisations by misinterpreting or mislabeling the data.
- Selecting the Right Tools: Not all data modelling tools and frameworks are equally suited for visualisation. Some may not provide the necessary flexibility, integration, or features that visualisation platforms require.

VI. LITERATURE REVIEW

This section provides a literature review on data modelling with visualisation techniques existing work. Some studies are discussed below:

In, Nie et al., (2021) the suggests a hybrid hierarchy-based big data integration platform that employs the data warehouse as the middle-tier data source and classifies the underlying multi-source heterogeneous data sources based on themes. Experiments demonstrate that our data integration platform enhances query performance when compared to the conventional approach of directly linking the underlying data source[20].

In, Hanson, (2007) a thorough method for designing an architecture that attempts to be as scale-neutral as feasible while addressing this visualisation challenge throughout the entire universe. A fundamental component is the power scaled coordinate (PSC) representation of model-rendering processes, and the range of PSC-based methods we have developed to extend and refine the traditional graphics framework to the scale domains of astronomical visualisation[21].

In, Biagi and Russo, (2022) offered assistance in addressing the identified gaps in the literature by lending a hand in the creation of a DWH data model integrated with a BI system. Executives in charge of operations and governance stand to gain the most from the application prototype in terms of monitoring risks, communicating effectively, sharing knowledge about the company's strategic areas, and optimising and improving performance [22].

In, Schulz et al., (2016) proposed an incremental visualisation paradigm that adds support for partitioned data and visualization operators to enable updates to intermediate visualizations to the already-established Data State Reference paradigm. Partitioned data and operators can be utilised alone or in tandem to achieve specific trade-offs in output quality, displayed data quantity, and responsiveness (frame rates) [23].

In, Alexandre, (2016) investigate how data visualisation might be enhanced by including interactive approaches. They analysed Portuguese news media case studies to find ways to improve visualisation storytelling and offer more insightful interactions [24].

In, Pourabbas and Shoshani, (2015) blend the features of three core data models to provide a shared framework for representing their semantics. Basic data models incorporate well-known ideas such (1) modelling object classes (or entities), their characteristics (properties), and interactions among them, (2) modelling multidimensional objects and attributes that may be summarised over their dimensions, and (3) modelling hierarchical structures [25]. The following Table 1 provides a summary of the related work for data visualization in data modeling with different tools and techniques.

Table 1: Summary of the Related Work for Data Visualisation in Data Modelling

References	Objective	Key Findings/Contributions	Strengths	Limitations	Future Work
[20]	To propose a big data integration platform for managing multi-source heterogeneous data.	Improved query performance by abstracting complex, multi-source data into manageable layers and using a data warehouse as a middle-tier for more efficient data access.	Significantly enhances query efficiency and reduces complexity in data access.	May struggle with very complex data environments; limited testing beyond initial scenarios.	Test scalability in more complex, real-world data environments and explore advanced optimisation strategies for larger datasets.
[21]	To address the visualisation challenges of the entire Universe, using a scale-neutral architecture.	PSC-based techniques offer a scalable solution for universe-wide visualisations, ensuring consistency across varying astronomical scales.	Provides a comprehensive, scalable framework for handling astronomical visualisation at multiple levels of detail.	Limited to astronomical datasets and requires adaptation for broader usage.	Extend PSC techniques to larger and more complex datasets; optimise real-time rendering in other large-scale domains.
[22]	To design and develop a DWH data model integrated with a BI system for top management.	Demonstrated benefits for top management in terms of governance and performance monitoring, providing an intuitive tool for strategic analysis and decision-making.	Strong practical application for top management, particularly for governance and compliance.	Prototype-focused may need further scalability and adaptability for different business	Refine the model to adapt to various industries and expand integration with more comprehensive BI

				environments.	tools for broader use.
[23]	To propose an incremental visualisation model that supports partitioned data and intermediate updates.	Provides a flexible and efficient model for incremental visualisation, balancing data quantity, output quality, and responsiveness	Enables dynamic updates, which are crucial for real-time visualisation scenarios.	Limited to partitioned data and specific visualisation operators, potentially restrictive for larger-scale systems.	Investigate further real-time data applications and extend the model to handle even larger, non-partitioned datasets for broader use.
[24]	To enhance storytelling and insight generation in data visualisation through interactivity.	Identified successful interaction techniques that improve storytelling, resulting in deeper engagement and better insights.	Enhances storytelling through interactivity, improving user engagement with data visualisations.	Focused on a specific domain (news media), and results may not generalise to other domains.	Explore more diverse domains (e.g., journalism, education, business) and test additional interaction techniques to broaden usability.
[25]	To create a unified framework for representing semantics in data models.	Provides a versatile and comprehensive framework to represent various data types and their relationships, improving data interpretation.	Unified approach simplifies complex data modeling tasks, making the system more versatile across contexts.	The framework may require further adaptation for extremely complex or specialised data types	Continue to refine and extend the framework for real-world applications, focusing on complex data models and further scalability.

VII. CONCLUSION

Data modelling plays an important role in the effective visualisation of data by ensuring that data is well-structured, organised, and consistent. It provides a robust framework for designing databases, understanding data relationships, and integrating multiple data sources, all of which are crucial for creating insightful and actionable visualisations. Proper data modeling helps in the enhancement of data quality, leading to more reliable analytics and improved decision-making. While challenges like data integration and scalability remain, a well-thought-out approach to data modelling can overcome these issues and contribute to effective data visualisation. Ultimately, a solid data modelling strategy not only supports but significantly enhances the ability to derive insights from data through visualisation.

The limitations of this study include a lack of focus on domain-specific challenges in data modelling and the potential difficulty in generalising the findings to all types of data environments. Additionally, the study does not address the computational complexities associated with large-scale datasets and real-time data integration. For future work, we propose expanding the research to include industry-specific case studies and exploring automated methods for model optimisation. Investigating scalable and adaptive approaches for real-time data modelling, particularly for big data environments, would also be a valuable direction for further research.

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