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Data Integration and Data Engineering Techniques

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Abstract

Data integration and data engineering techniques play a crucial role in the modern data landscape, facilitating the seamless amalgamation of diverse data sources to derive meaningful insights. As organizations increasingly rely on big data analytics, the need for efficient and robust data integration methodologies becomes paramount. This paper explores various techniques for data integration, including Extract, Transform, Load (ETL), data virtualization, and data federation, emphasizing their applicability across different domains. Additionally, we discuss data engineering practices that ensure the quality, scalability, and accessibility of integrated data, such as data modeling, pipeline architecture, and real-time data processing. By examining case studies and emerging trends, this work highlights the significance of these techniques in enabling organizations to harness the full potential of their data, ultimately driving informed decision-making and fostering innovation in an increasingly data-driven world.

Keywords: Data Integration and Data Engineering, Industry 4.0, Internet of Things (IoT), Smart Manufacturing (SM),Computer Science, Data Science,

1. Introduction

The last several years have been quite active in the data integration and data engineering domain. With the birth of big data, the graph of data has been rapidly growing higher and higher. Companies, institutions, and people are producing data at unprecedented paces. Data-driven decisions have become an inescapable path. Big data, however, has meant data variety, another key feature of the new data era. Data is structurally diverse. Of course, the tabular format is still a huge majority, but do not underestimate other types like semistructured (XML, JSON), graph, log, and text. Data integration and data engineering have the challenging task of restructuring this data graph into something useful to human intelligence. Data systems are no longer merely a tube of bytes between the input keyboard and the output monitor, but rather a filter that has to extract useful knowledge out of these digital residues. Then all the big data cycles can be activated, producing clues that are not available otherwise.According to Pyke's Model of Data Management, data integration and engineering are associated concepts but they cannot be confused. Data engineering has a broader meaning. It is a branch of engineering dealing with the techniques and methodologies for harnessing data in support of the life cycles of the devices. As such, data engineering techniques, rules, and methodologies should be context-independent. Otherwise, that needs to be mentioned. On the contrary, data integration focuses on proactive organization skills of corporate data systems that could be inspired by plural disciplines. Development of a data integration model could be assisted by a divergent knowledge base and by cognitive fit and perspective

of diverse actors (e.g., managers, technicians, external partners) whose viewpoints occur as distinct accuracy levels of models.

1.1. Background and Significance

As a discipline, data integration techniques have been well established now for some time and are motivated by the simple idea that in a modern enterprise, there is a profusion of different database management systems, flat files, and XML files that are distributed throughout the enterprise and across organizational boundaries. Some of these database systems are proprietary, with no published API available. PHP and JDBC provide some interoperability but lack vendor neutrality. Add to this mix the complexity introduced by the use of many different publishing technologies such as HTML, RSS, ATOM, or Open Standard API to help clients access and use a provider's application. Furthermore, the increase to near real-time and real-time interaction with the diverse, autonomous entities of different enterprises, including transaction handling, and data exchange in B2C, B2B, moral surfing, client services, etc. grows every day. What has become clear is that data integration is an enabling technology that is required whenever there are applications that cut across these organizational boundaries. - Written Permissions by Catherine H. Little, 2017. Data Interaction and Data Integration Techniques in 2017. Computer Science and Software Engineering, 2017, 1-28.

2. Foundations of Data Integration

Data integration (DI) in computing deals with combining data residing at different sources and providing the user with a unified view of this combined data. Examples of such sources that DI allows to integrate data from are relational databases, XML databases, RDF-stores, or CSS stylesheets. The user who sees these different stores as if they comprise one single unit may want to carry out complex queries over the combined set of data and want to receive the results quickly and satisfactorily. Merging data in such a way that the user can extract new information efficiently is the heart of data integration.The seamless handling of irrelevant or conflicting data during the data integration process is called applicability. The focus on the applicability of data integration is a special feature of the data integration approach we present in the thesis and forms a part of the thesis by itself. Our definition of data integration therefore makes the part of the data integration problem that we deal with explicit by mentioning "applicability". By considering the applicability of data within the data integration process, data can stay independent and thus be of a limitless kind. The applicability mechanism applies to independent data as it addresses the interests of the querying users as they browse around over the integrated data. Such browsing users that consult the integrated data are part of the data themselves since they adapt data. Also, changing the applicability mechanism data themselves originates from the external business environment.

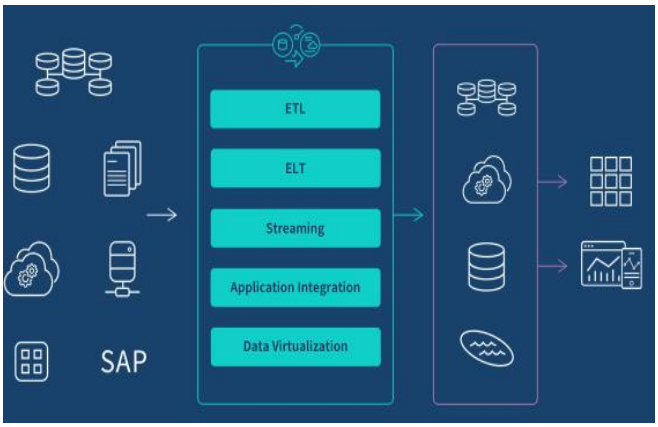

Fig 1: Data Integration

2.1. Definition and Concepts

The term data integration refers to the capability of combining data residing at different sources and providing the user with a unified, transparent view of these data. A wide range of data integration techniques and technologies is available, including extraction, transformation, loading (ETL), enterprise information integration (EII), enterprise application integration (EAI), message-oriented

middleware (MOM), database link/three-schema architectures, federated database systems. A recent survey on data integration solutions and techniques shows a few main issues of importance that have to be addressed in this area including but not limited to ad-hoc data, complex analytical queries, large-size databases, meta descriptions, integrated system evolution, transparency, and privacy, security policy integrability.Data engineering is data-centric engineering that relates to data aggregation, data modeling, storage, distribution, transformation, integration, discovery, analysis, protection, and visualization in specific business processes. Data engineering is performed in different contexts mainly data warehouses (DWs), data marts (DMs), and online operational analytical processing (OLAP) in support of the decision-making process, which is usually also referred to as data warehousing. Several data engineering techniques and technologies are available, including extract-transform-load, data warehousing, data mining, knowledge management, data preprocessing, quality web data analysis and integration, online analytical processing (OLAP), and decision support systems (DSS). Data warehousing has been widely applied in various information organizations (e.g., healthcare organizations) as a well-focused business model approach to coordinate data analysis, access, and reporting.

3. Key Data Integration Techniques in 2017

We anticipate seeing significant growth of unified access and data integration platforms offering solutions to the challenges of managing and accessing on-premises and cloud data sources. These platforms will include data contextualization, time-based lineage, and annotations to address the self-service data preparation and data quality aspects. A consolidated metadata repository, smart schema updates, and data semantics will become an important part of the data integration process. The emergence and adoption of container technologies like Docker or Apache Mesos will drive easier migration of data services throughout the private and public clouds. Consequently, technology providers in the data integration field will focus on offering comprehensive solutions with containers throughout the entire data lifecycle, thus addressing enterprises' needs for IT services deployment on demand in a more agile operational manner.

The current investment in new microservices, Docker containers, Apache Mesos, and Kubernetes with system integration accelerates the requirements for reliable and robust connections with various data sources. These sources include agile databases, big data warehouses, distributed data storage, legacy systems, proprietary data sources, SAAS systems, and various trading partners' systems. Hence, the requirement to build available, trustworthy, and reusable data flow components and related data connector integrations. Data services focused on integrating microservices-enabled data components with new system integration capabilities embedding reusable data services, real-time orchestration, and regulatory compliance functionalities.

3.1. ETL (Extract, Transform, Load)

ETLs are moving a bulk of data - once a day, once an hour, or in smaller batches, e.g. incoming purchases from a mobile game to the Magnus system. The focus of the teams working with ETLs is to plumb as many sources as they need, guarantee data quality, make all the necessary transformations, schedule the ETLs to not interfere with the running game, and overall maintain them error-free.Challenges of game data ETLs are the large volume of data, changing data schemas (as a game is a live product, data comes in real-time), and validation of processed data between different time levels.

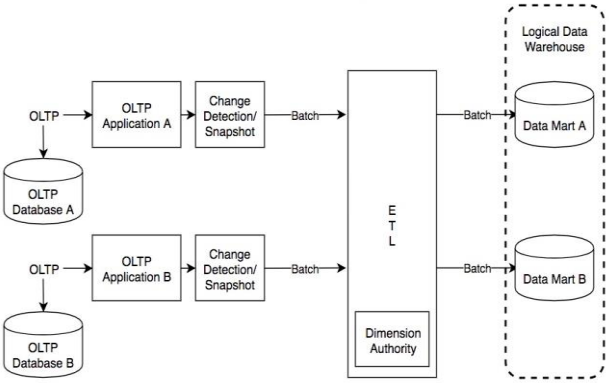

Fig 2 : Conventional ETL Diagram

ETL engineering is a well-known field with a great presence of tools that are required to function at scale in any company that generates a large amount of structured data. Commercial options are an easy option with reasonable pricing, but one must carefully calculate the possible reserves. If self-hosting will be the choice, choosing a fast pipeline in at least one language from the data warehouse and having the data somewhere hot accessible is a must. In this scenario, we are more than happy to rely on Apache Spark and our internal libraries that sit on top of Spark with Python API.

4. Data Engineering in 2017

With the use of Apache Beam, you can write your data transformation, joining, aggregating, etc. processes in Java, Python, and Go, and you do not have to worry about the underlying infrastructure. Apache Beam has the following connectors to different execution frameworks. Note that Apache Beam APIs are already stable and will not change as they are used by various Google Cloud users, so you can start using them without fear of any major changes. Apache Beam has the following execution engine connectors:- DirectRunner - Bare Metal Runner, running in single-threaded mode, useful for simple unit testing or running on a single machine without the need for a cluster. - Apache Flink - Apache Flink is a data processing system that runs programs in distributed mode across a cluster. - Apache Spark - Apache Spark is another powerful framework that provides APIs for building big data applications. With the use of Apache Beam, you can now also write Spark programs using the Beam API. - Apache Gearpump - Apache Gearpump is another distributed streaming engine for general data processing. With Beam capability, you can write your data processing using the Beam API and run it on Apache Gearpump with very minimal changes. Since Beam is an Apache incubating project, we expect it to provide more ecosystem integration with other execution engines in future months.Since Apache Beam manages the lifecycle of the program on behalf of the user by its portability framework and runs on multiple execution engines (Direct mode to start and test and other distributed processing engines), it helps programmers to forget about the underlying infrastructure that their program will execute.

4.1. Data Modeling and Design

This section addresses approaches for developing clean and efficient data models, logical architecture of storage systems, and the mapping of specific data entities into storage. Fielded solutions are often not crisp enough in the definition of the internal schema of databases, the specific storage, indexing, and other performance-related features for each data entity such as tables, networks, or documents. This section presents several potential solution approaches for improved data engineering.The early decision to use a centralized data model can make many future data integration problems much easier. The use of a single conceptual schema yields several advantages: constancy of meaning, standards for data exchange and query interfaces, shared understanding, and economies of scale in data design, storage, and handling. However, practicality trumps elegance in many scenarios, and this simple model may not apply to federations, distributed systems, or multi-enterprise consortia. Ongoing data standards and industry consolidation leverage the investments in the centralized schema at a minimal cost. Still, a shared model is of great value if the data is conceptually unified. Then

semantic links that cross time, fussily enforced by databases and applications, are far simpler.

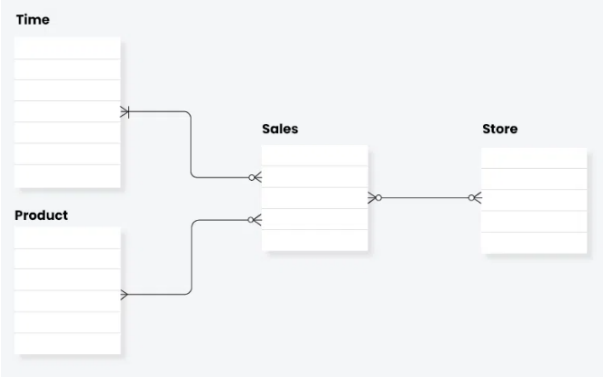

Fig 3 : Conceptual Data Models

5. Conclusion

Data integration and engineering have been around for decades. Especially after Philip Russom coined the term "Data Engineering" in 2011, we started seeing more and more interest from data practitioners on the subject. The main reason is the variety, velocity, and veracity of data that we have been witnessing since the last decade, which required us to ramp up the methodology and best practices for data engineering. Apart from building a ubiquitous data lake or a hub-and-spoke model in terms of data integration, organizations have realized that they need a similar set of attention concerning data engineering to get these systems running correctly.In this chapter, we briefly walked through the concepts, methodologies, and techniques used in data engineering both with a classical perspective and with products coming with Hadoop and Big Data space. We hope this chapter will be a good introduction to data engineering and a stepping stone for practitioners who aim to further explore the depth of the field.

5.1. Future Trends

These five research areas provide a short-term vision of future data integration research activity. However, in the long term, data integration challenges are expected to involve even more advanced techniques. The fusion of multiple data allows for analyzing existing relationships and then improving the results of prediction and discovery algorithms, which currently do not take this feature into account. Other possible long-term questions of data integration involve obtaining larger and more credible public databases, which are one key issue in the information enhancement context. This facility would enable more effective transparency of the decision-making process. In addition to these new wire issues, the same issues are formulated in the future trends section.The next challenge would be building applications based on existing or future data integration tools in a rapid, cheap, and reliable manner. This challenge fully removes the requirements for data integration. An additional problem is the so-called private data, for example, when data that entities are not willing to share must be shared between several entities to carry out a joint analysis. The reason for this is the data ethics issue, that is, there are serious concerns about what can be inferred when sharing. Similarly, in the long run, several conclusions emerge from the principles and data integration techniques for multimodal network extraction.

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