AI-DRIVEN DATA ENGINEERING

TRANSFORMING BIG DATA INTO ACTIONABLE INSIGHT

Eswar Prasad Galla

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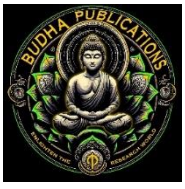
Hemanth Kumar Gollangi

Janardhana Rao Sunkara

Chandrakanth Rao Madhavaram



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Janardhana Rao Sunkara

Janardhana Rao Sunkara is an accomplished Oracle Database Administrator with over 9 years of experience, specializing in database management, optimization, and security across industries such as Pharmacy Retail and Manufacturing. His expertise spans Oracle technologies (19c, 12c, 11g, 10g) on platforms like Red Hat Linux, Solaris, and IBM-AIX, with a proven track record in large-scale database migrations and cloud integration on AWS and Azure.

In addition to his database skills, Janardhan has a strong background in Big Data, AI, Machine Learning, and DevOps. He has successfully applied AI and ML techniques to enhance database performance and predictive analytics, while his DevOps experience with tools like Jenkins, GIT, and Ansible has enabled efficient automation of database operations.

Janardhan's ability to integrate advanced technologies with Oracle RAC, Dataguard, Exadata, and GoldenGate has made him a key contributor to high-availability and secure database environments. His innovative approach has significantly benefited organizations like CVS Health and Hewlett Packard Enterprise, reflecting his commitment to excellence and continuous improvement in the field of data management and technology.

Holding a master's degree in Electrical Engineering, Janardhan has made significant contributions to organizations like CVS Health, Hewlett Packard Enterprise, and Ciena Corporation. His role in solving critical database issues, optimizing performance, and integrating cutting-edge technologies like Big Data, AI, ML, and DevOps into the database management lifecycle has earned him recognition as a forward-thinking leader in the field. Janardhan's career reflects a commitment to innovation, excellence, and continuous learning in the ever-evolving landscape of data management and technology.

Chandrakanth Rao Madhavaram

Chandrakanth Rao Madhavaram is an accomplished IT professional with over 9 years of experience in designing, developing, and deploying scalable cloud-based applications. He has a proven track record of delivering high-quality software solutions using .NET technologies, including ASP.NET, C#, and MVC. His expertise extends to Azure services such as Azure Functions, Azure DevOps, Azure Storage accounts and Azure SQL Database enabling him to build robust and efficient cloud-native applications.

Throughout his career, Chandrakanth has worked on various projects across different industries including finance, healthcare and Product based companies. He is adept at collaborating with cross-functional teams to ensure seamless integration and delivery of software products.

Chandrakanth is passionate about continuous learning and stays updated with the latest advancements in cloud computing and .NET development. In addition to his technical skills, he is known for his attention to detail and strong communication skills. He is committed to delivering innovative solutions that meet client requirements and drive business success.

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INTRODUCTION TO AI-DRIVEN DATA ENGINEERING: REVOLUTIONIZING BIG DATA

1.1. Introduction to Big Data

Big Data is a highly complex and still-developing abstract concept. Universally accepted definitions and taxonomies do not yet exist. Nonetheless, Big Data refers to the analysis of large amounts of data in a relatively short period, enabling models that were impossible to build previously. The study of this data must involve new tools and technologies and should provide novel insights into the phenomena being monitored. Because the insights are often obtained in "real-time" (or very shortly after the "real-time" event) and by very large amounts of data, the monitoring systems are commonly referred to as real-time and social network analysis systems.

Beyond the challenges, Big Data also offers great opportunities. These massive amounts of data can be mined to help understand human behavior, develop smarter applications and infrastructures, increase business revenues, and develop predictive analytics methods. However, making sense of Big Data requires developing new tools, systems, and data models, combined with the knowledge necessary to take advantage of them. To this end, the design of a new course on Big Data Engineering for Computer Science and Engineering undergraduate-level students is described and presented. After an analysis of how Big Data course creation is approached in European organizations of higher education and research, the course is structured into six theoretical topics and six laboratory practices. The contribution of the tutorial dataset and laboratory practices to understanding Big Data technology is highlighted.

In recent years, the term "Big Data" has become increasingly popular in both business and academic literature. Big Data refers to vast amounts of data that cannot be stored, managed, or analyzed using traditional processes. Although the name implies large volumes of data, it refers to four primary dimensions, known as the 4Vs: Volume, Variety, Velocity, and Veracity. Over the last decade, the data captured in the dimensions of Big Data have rapidly increased. Every day, billions of mobile phones are generating torrents of text data and images

through social media. Online platforms are continuously generating data in the form of characters recorded in scrolls and clicks. In addition, an increasing number of sensors, smart cards, and RFID readers are capturing data in the form of positions, movements, and frequencies. This data deluge poses significant challenges to traditional tools and technologies for collecting, storing, processing, analyzing, and visualizing data.

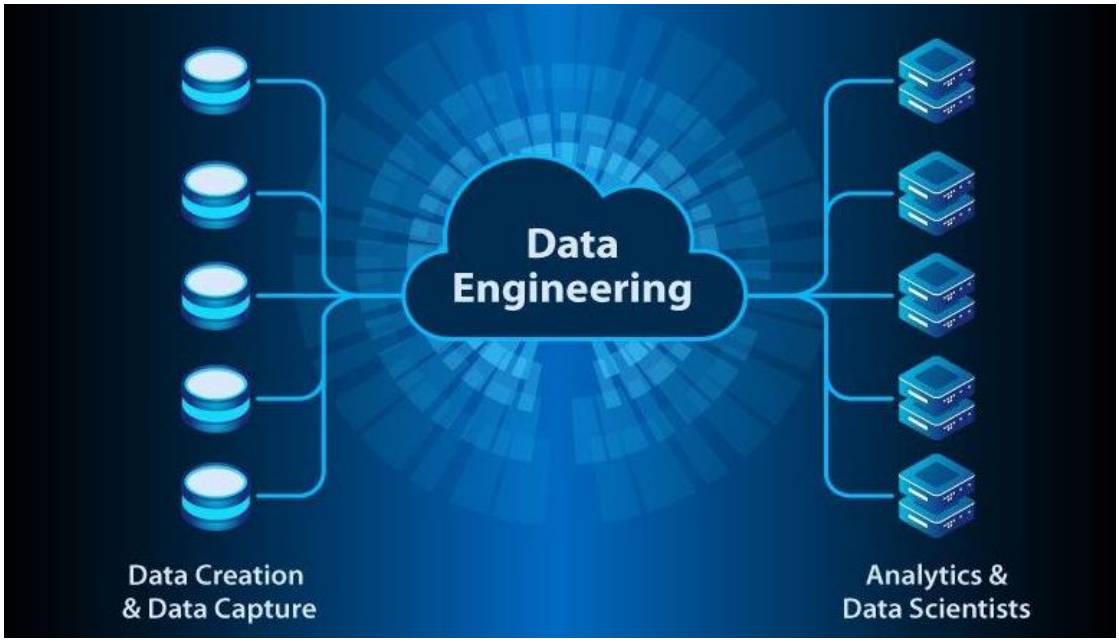

Fig 1.1: Role of AI in Data Engineering

1.1.1. Definition and Characteristics

Consequently, these properties stress the limits of existing technologies. Mesh and ring networks exhibiting varying bounded delays extend the challenge. Growth outpacing improvement further complicates the big data situation. Consequently, core big data components, including representation, cost-effective storage, real-time processing, and exploitation of hidden knowledge, must be rethought. These properties have led to new approaches and high-profile big data projects at leading institutions. Previous efforts concentrated on the development of big data across different databases, languages, industries, and other semantic entities. However, a composite view of big data remains conspicuously missing.

Real-time data streams generated from online and Web-enabled devices add a second dimension to the dilemma of all too complex datasets. These collections of data objects are

naturally formed as ordered continuous sequences. They grow rapidly as the world changes, produce streams of different, often never-before-seen data objects, and do so at high, often unpredictable, arrival rates. Simple aggregations over fixed time intervals lead to an avalanche of swarming knowledge. Similar types of items can pass by simultaneously in groups, with intervals between group arrivals magnitudes greater than the continuous flow. These batches of data items, called bursts, are important in decision-making, but complex and costly to detect.

The term big data refers to datasets that are so large, fast, or complex that they're impossible to process using traditional methods. Big data is often defined according to the following 5V characteristics: Volume, Variety, Velocity, Veracity, and Value. In recent years, the number of datasets significantly larger than the number usually handled by traditional systems has increased dramatically. For example, the storage capacity of hard disk drives, along with the portions of these devices installed in machines doing business on the Web, has increased geometrically (10^6 factor) between 1956 and 2008. World data were stored in amounts approaching 10^27 bytes in 2008. Still more alarming is the rapid growth rate of data. The improvement brought by subsequent generations of technology is astonishing. The amount of data in 2008 peaked near 10^15 USD which was often considered the annual budget of the Research Division of a healthcare company. By a rough estimate, 75% of the datasets stored exceeded the data processed.

1.1.2. Importance and Applications

The phrase "big data" refers not only to the immense volume of data but also to its importance and applicability in real-life situations. Big data holds tremendous potential in many fields including earth sciences, health sciences, social sciences, and engineering to improve accuracy and accelerate speed exponentially in achieving reliable simulation, prediction, analysis, and understanding of complicated/multiscale processes and between high-dimensional parameters. An abundance of data allows mining the underlying complex patterns/structures that cannot be observed from a small amount of data and formulating the wide applicability (the so-called big data effect) of the data-driven approaches. Data-driven approaches utilizing empirical data alone to extract basic features of underlying processes/systems are emerging as a new paradigm for scientific discovery complementing the model-based approach such as that mentioned above.

The importance of big data can be gauged from the tremendous growth in the volume of data that is being generated and processed by various sources. Advances in computers, sensors, data storage, and technologies have made it possible for an increase in data collection/integration in various forms (text, images, videos, etc.) at a fast pace and lower cost. Consequently, big data has become an indispensable part of the world and a pillar of modern advanced science and engineering. In the last two decades, big data has captured much attention from different disciplines including the fields of finance, earth sciences, social sciences, medicine, biosciences, and engineering because of its importance in broadening the research landscape, enabling new scientific inquiry, and achieving unprecedented discovery in key areas of academia, industry, and national labs.Big data encompasses not just the sheer volume of information but also its profound significance and practical application across various fields. This vast array of data holds transformative potential in domains such as earth sciences, health sciences, social sciences, and engineering by exponentially enhancing accuracy and accelerating the speed of simulations, predictions, and analyses. The ability to discern intricate patterns and structures that are obscured in smaller datasets underscores the "big data effect," which highlights the power of data-driven approaches in complementing traditional model-based methodologies. The exponential growth in data generation, driven by advances in computing, sensors, and storage technologies, has made it possible to collect and integrate diverse forms of data—text, images, videos—more rapidly and cost-effectively. As a result, big data has become a cornerstone of modern science and engineering, revolutionizing research and discovery across numerous disciplines including finance, social sciences, medicine, and biosciences, and establishing itself as a critical component of contemporary academic, industrial, and national research endeavors.

1.2. Evolution of Data Engineering

The above makes data engineering and its underlying architectures look difficult and obscure. Some cloud providers—such as Amazon—offer solutions for a classical on-premise structure and make tensions for their languages available on the cloud. These solutions might be appealing for firms that are used to that kind of system, but the conditions of use are drastically different. Within that type of architecture, if a query becomes too expensive, it is far too late to intervene: the only feasible option is to either stop running the query or upgrade the entire DB machine. Embedded solutions provided for big data on cloud databases focus almost exclusively on relational solutions, hence projecting wrong assumptions about the data processing environment. It is commonplace for the industry to take for granted the knowledge

of several technologies that are necessary for data engineering. Ironically, talented analytics professionals understand how to process data using SQL, but they do not understand Hadoop or Hive. As a result, most scientific publications on data processing economize on Hadoop and Hive assumptions but dive into high-level technologies. It may very well be that this technological scattering is to some extent limiting the adoption of cloud computing in the field.
Data engineering is one of the fastest-growing job positions in technology. However, the above description does not reflect the necessities and challenges of such a position anymore. First of all, the majority of distributed systems for data storage and processing are open-sourced, but it is no longer necessary or efficient for a data engineer to know how they work internally. The growing popularity of the cloud computing industry led to a great number of firms providing on-demand data storage and processing services. It makes sense to leave the design of low-level systems for professionals in that industry and to focus instead on the selection of services and the design of workflows on top of those services. This might seem trivial, but leads to very complicated architectures that only a handful of professionals can comprehend.
The term "data engineering" was coined by Jeff Dean in a blog post. In that post, Dean argued that the data growth at Google required the deployment of a class of employees that were not only software engineers, but also data analysts and specialists in the design of systems for data processing. That is, an individual involved with data engineering is responsible for the same things that someone working in software engineering is, but also uses statistics (e.g. distinct or sum count statistics, averages, etc.) and is skilled in the deployment of systems for storing, processing, and analyzing data—such as distributed file systems, data caching systems, streaming data pipelines. However, the design of these systems is very difficult, because they should be fault-tolerant, resilient, efficient, and scalable more than in an order of magnitude. The same post contains detailed descriptions of the internal workings of the above systems.
In recent years, the volume of data generated by organizations and individuals has increased exponentially. Consequently, how data is processed, stored, and analyzed has transformed. The task of collecting, processing, and storing large datasets often seems Herculean, especially for small and medium-sized organizations. This is where data engineering comes in. Data engineering involves building and maintaining infrastructure for collecting, storing, and analyzing datasets. To do all the above satisfying quality and performance requirements, the application of artificial intelligence in this task can be particularly beneficial.

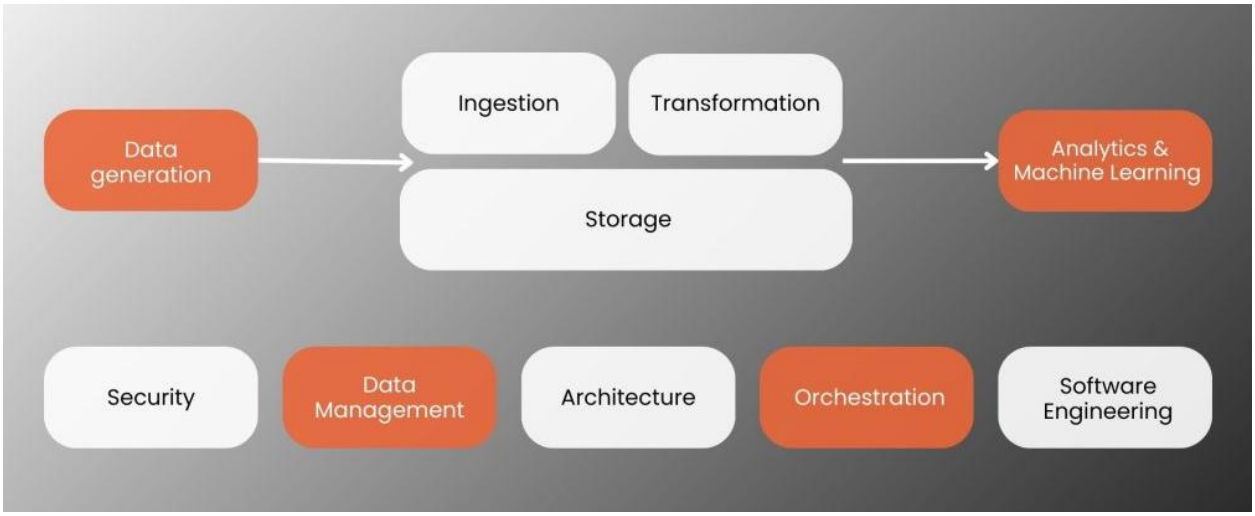

Fig 1.2: The Evolution of Data Engineering

1.2.1. Traditional Data Engineering Approaches

With the advent of the cloud and big data technologies, early big data open-source systems rapidly grew in popularity. The prevailing industry-winged tools and utilities became these engines on top of raw big data systems, notably utilizing the Hadoop ecosystem. Complex data consumption, processing, and storage pipelines could be easily set up, with the variety, volume, and velocity of data considered. However, this approach has numerous limitations as requiring developers of the above systems is a daunting task for any firm. Tool development for setting data engineering pipelines in this ad hoc manner is hampered due to the complexity and rapid evolution of these big data systems. The big data utilities became less effective with the explosion of data science needs involving data fusion, cleaning, and analytic feature construction from raw tables, social media, and temporal data streams for monitoring/sensing tasks.

Since then, with the availability of low-cost massively parallel processing (MPP) platforms and SQL-based engines, warehousing approaches gained popularity. A data engineering leg was created for users developing data warehouses to allow analytical applications using SQL queries with aggregated, integrated, domain-specific data as input. However, with the boom of the IoT (Internet of Things) and data from non-relational sources like social media, video/image repositories, complex networks, and scientific computing, this approach also became inadequate. The explosion of unstructured or semi-structured and heterogeneous data outstripped the capability of traditional database systems to accommodate this complexity as scientific computing and social media analysis were not meant to fit in 'DB tables.'

Data is primarily generated from transactions conducted by individuals or machines in web-based applications and sensor networks. Once accumulated, the data needs to be transformed, cleaned, integrated, and aggregated, enabling analytical applications like data mining and predictive modeling. Traditional data engineering approaches can be classified into desktop, data warehousing, and data lake approaches. Initially, as commercial DBMS (Database Management Systems) became available in the '80s, desktop approaches emerged, allowing users to view data in tabular form and create simple queries in SQL. While users became acquainted with the technicalities of 'form' or 'table' based display, users of spreadsheets formulated views as collections of data tables and built queries involving sets and set operations. However, with the explosion of web-based applications and their transactional and sensor data, heavy data accumulation outstripped the existing approaches' capability for clean handling.

Data engineering, a crucial discipline in the realm of data management and analytics, has traditionally been approached through various methodologies. From the rudimentary handling of data in the early computing days, it has evolved into a sophisticated field necessitating specialized skills and knowledge. However, in the face of voluminous, heterogeneous, and rapidly changing data influx, traditional approaches exhibit considerable limitations.

1.2.2. Emergence of AI-Driven Data Engineering

Limitations of traditional data engineering approaches and the synergy of upcoming data engineering challenges with unprecedented advancements in AI techniques, which ultimately led to the rise of AI-Driven Data Engineering, are discussed. The current state and key innovations of this emerging field are provided, along with an overview of the emerging industrial response. As a foundation for the exploration of AI-driven data Engineering, recent trends in data growth, architecture evolution, and investments in data processing and storage technologies that lead to unprecedented big data engineering challenges are discussed.

AI-Driven Data Engineering refers to leveraging AI technologies, primarily machine learning and deep learning techniques, to enhance the efficiency and effectiveness of data engineering processes. This comprehensive definition encompasses four focal points in the data engineering pipeline: (1) automatically building an efficient feature engineering pipeline from raw data, (2) optimizing the process of training machine learning models and their monitoring in production, (3) automatically determining an optimal version of a data flow, and (4) finding

an optimal data replication and partitioning scheme on a multi-database distributed infrastructure. For all of these points, there is a rapid growth of research works that utilize AI techniques to assist data engineering.

In recent years, a paradigm shift has occurred in the data engineering landscape, driven by exponential growth in data, increased demand for real-time analytics, and the rapid advancement of artificial intelligence (AI) technologies. Traditional data engineering approaches, which heavily rely on manual coding and configuration, have become increasingly inadequate. As a result, there is a growing need for innovative solutions capable of automating the complexity of big data engineering processes. Simultaneously, significant advancements in AI techniques, including machine learning and deep learning, have provided novel opportunities for addressing these challenges. Consequently, a new trend termed AI-Driven Data Engineering has emerged.

1.3. Role of Artificial Intelligence in Data Engineering

This essay outlines key AI-driven solutions to improve basic steps in the data pipeline, present achievements in the application of AI techniques to the field of analytics, and contextualize them as challenges that need to be adequately addressed by the research community. With the democratization of data science through self-service platforms, there is an increasing demand for data-driven analytics that needs to be addressed with solutions that ensure the accessibility of the technological basis to non-experts, the reliability and correctness of results, and compliance with regulations and policies.

Machine learning (ML) and deep learning (DL) techniques can be leveraged to improve the core data engineering processes of data extraction, data transformation, and data loading. Meanwhile, AI-driven data engineering involves the use of natural language processing (NLP) techniques to identify relevant datasets, along with metadata considering information with search history and query terms as part of the query understanding, to facilitate the identification of candidates for download. Similarly, metadata is employed to define an NLP framework for the identification of actionable datasets regarding quality and type after candidate datasets have been downloaded. NLP is also used to analyze the content of candidate datasets to be analyzed and the content of analysis scripts to identify relevant data definitions.

In recent years, the amount of data generated has increased exponentially, thanks to an increasing number of connected devices and storage units. Traditional ETL processes are time-consuming and often fail to keep up with the rapid growth of big data. This has led to the need

for AI-driven demand-based ETL, wherein data characteristics such as freshness, frequency, volume, and declining freshness are learned, and a series of ETL operations are triggered automatically based on learned knowledge.

Artificial Intelligence (AI) has emerged as a transformative force, revolutionizing various industries, and the field of data engineering is no exception. Data engineering encompasses the process of acquiring, managing, and transforming raw data into a usable state to generate insights and build analytical models. It involves a series of basic steps, including data extraction, data transformation, and data loading (ETL).

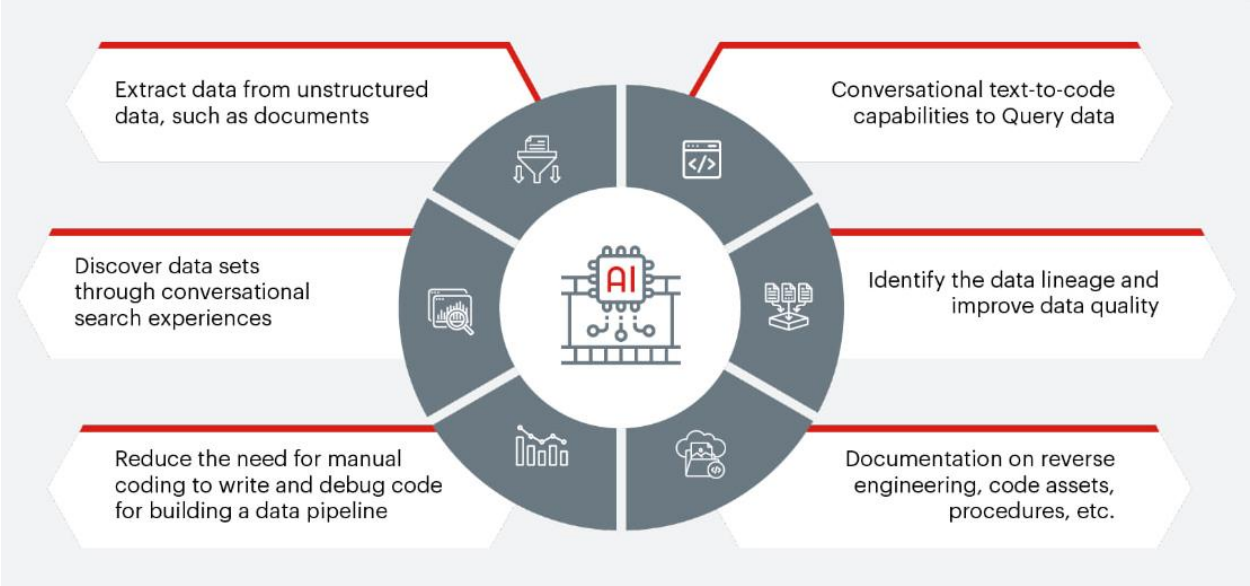

Fig 1.3: AI in Data Engineering

1.3.1. Machine Learning and Deep Learning Techniques

Early data cleansing techniques focused on checking the integrity of data based on defined rules. ML techniques classify data inaccuracies into seven classes: missing values, wrong data type, outliers, spelling errors, redundant data, data transformations, and wrong time stamps. Each of these classes can be tackled with a different type of ML technique. Data profiling is a step in which significant characteristics of data are extracted; based on these characteristics, interesting data patterns can be inferred. Statistical tests are informative techniques to describe a single variable (univariate tests). On the other hand, Chi-square tests

are informative techniques for studying the relationship between two variables (bivariate tests).

Machine learning (ML) and deep learning (DL) are based on similar concepts; both are artificial intelligence (AI) techniques. Regarding this, AI is defined as teaching a machine to perform specific tasks that generally require human knowledge and intellect. In this scenario, both ML and DL literature have focused on how to extract, select, transform, and aggregate knowledge from high volumes of data. These approaches can be subdivided into seven different classes: one-class training, unsupervised training, supervised training, deep unsupervised training, deep supervised training, semi-supervised training, and transfer training. The complete ingestion, transformation, and aggregation of knowledge from raw data to numeric features are processes in which EM can be applied. Here, ML or DL models are trained around the ingestion of raw data. This data pre-processing step works as a filter to select relevant or interesting information that is subsequently provided to knowledge aggregation stages.

The emergence of large data sets has necessitated the creation of automated techniques to ingest, comprehend, and utilize the underlying knowledge stored within these unstructured data sets. In this view, the inclusion of artificial intelligence (AI) is positioned as one of the mainstays for the evolution of data engineering techniques. Data engineering has been traditionally focused on the ingestion and transfer of large amounts of data to storage architectures where subsequent data transformation and aggregation workflows are executed. The rapid increase in data volume has made it difficult to gain insight from this data using traditional data engineering techniques; consequently, additional transformation steps have been fed downstream data processing analytics.

1.3.2. Natural Language Processing (NLP)

An internal strategy to review adherence to data quality standards can be implemented through the scheduling of automated checks and reports. Dashboards can be created to visualize statistics and track the evolution of data quality indicators over time.

Beyond textual data, NLP technologies can also be utilized to assess the quality of generated data through checks on textual field anomalies such as misspellings, abusive language, white spaces, or a large number of unique characters. Integrating pipelines that explore large language models enables error-checking methodologies without the necessity of requiring

training skills. Such methodologies can identify fields that need validation or cleaning through a semantic analysis of their contents.

State-of-the-art NLP currently employs pre-trained Transformer-based architectures. These models have been extensively trained on large corpora of documents, acquiring the ability to process diverse text representations and their contextual relationships. Consequently, they can be fine-tuned on a particular dataset containing a reduced number of labeled examples to accomplish various downstream NLP tasks. Thus, data engineers and scientists need to curate a clean and representative training dataset of specific NLP tasks to ensure the proper application of large pre-trained models.

Fundamental NLP techniques encompass tasks such as Named Entity Recognition (NER), Part of Speech (POS) tagging, Keyword extraction, Topic Modelling, and Sentiment Analysis. NER identifies and classifies key entities in a text, while POS tagging links each word in a sentence to its corresponding grammatical classification. Keyword extraction seeks to identify representative terms that summarize a document, and Topic Modelling identifies the main topics of various documents. Finally, Sentiment Analysis extracts subjective information from textual data to conclude the expressed opinion's polarity (positive, negative, or neutral).

Natural Language Processing (NLP) involves the application of AI technologies to comprehend and interpret human language. Its significance derives from the vast amount of unstructured textual data generated daily. NLP systems facilitate the conversion of this raw data into structured formats that allow organizations to extract valuable insights. Data engineers can utilize pre-existing NLP models and Natural Language Understanding (NLU) APIs to effectively process diverse client needs. Additionally, NLP technologies can be adopted to improve internal customer interactions through chatbots.

1.4. AI-Driven Data Engineering in Practice

Indisputably, companies such as Amazon and Netflix have successfully implemented ML in their ETL processes. However, architectural choices at a different degree of granularity do not seem to apply to other companies as they depend on the data engineering pipeline and are still highly reliant on human design. For example, AWS Glue and Data Warehouse-on-demand do offer AI-driven pipeline components focusing on data transformation, however, all of them still require further engineering for ingestion, storage, monitoring, orchestration, and data governance.

Social media giant Twitter recently released an AI-driven data engineering tool on its open-source platform, called "Data Pipeline." The tool is capable of designing ingestion and transformation pipelines at scale without the need for domain knowledge out of, out-of-the-box. It showcased state-of-the-art data quality forecasting mechanisms and autonomous project planning, including the intelligently evaluated choice of programming languages, frameworks, or systems for executing pipelines. It is trained on a problem-solution space design of previously implemented data engineering projects at Twitter. Thus, the framework is fully aligned with the company's data-handling objectives, incorporating expert knowledge and best practices. Even so, all techniques proposed seem hard to transfer to other companies or adapt to different problem statements. For instance, the language Llama2, with an input_df as one of its parameters, seems fine-tuned for a Spark Dataframe, which is Twitter's data pipeline framework.

The SOCS Foundation believes that AI will revolutionize data engineering. There is still a great deal of discussion around this topic within the data engineering community. AI implementations in real-world data engineering pipelines often fall short of grand expectations or are applied in restrictive areas, such as feature recommendations to ensure optimal data quality. In most cases, ML acts merely as an extension of the current framework, driven by the company's data and executed in batches. Furthermore, AI-driven data engineering often lacks a common language between data engineers, scientists, and researchers, with differing understandings of the term.

Artificial intelligence (AI) is revolutionizing big data. This book's introduction aims to provide readers, especially data engineers, with a structured overview of AI-driven data engineering. Data engineering, the process of transforming and organizing raw data for analysis and visualization, faces challenges in handling large and rapidly changing data streams. AI, particularly machine learning (ML), has the potential to automate complex data engineering tasks driven by patterns in the company's data in real time, efficiently incorporating innovation. Given the growing importance of data engineering, there is a pressing need to better understand how AI can be harnessed to drive the future of this field.

1.4.1. Use Cases and Case Studies

In retail, the organization uses AI systems to enhance demand forecasting, campaign management, and user recommendation engines. Enhancing demand forecast accuracy delivers a competitive edge for organizations in their planning process and high throughput of demand data. AI-powered systems conduct demand forecast automation tasks (data ingestion, cleaning, feature extraction, model selection, training, metadata storage, and score propagation) at a daily rate for 60k cases in 39 countries of Europe, Asia, and North America. The organization's data engines aggregate up to 500 demand-related data sources from several internal and external systems (POS, orders, shipments, ethnic groups, holidays, weather, promotional activities, and prices). The use case of a campaign in the retail domain has been studied where data engineering supports individuals to make campaigning-related decisions such as participant selection, offer design, campaign timing, and campaign performance evaluation. The AI-powered systems have an impressive campaign automation capability of automatically designing campaigns for 90% of weekly campaigns across 51 countries.

Some high-level use cases of AI-powered data engineering are found across several industries such as finance, retail, banking, healthcare, and telecommunications. In finance, the use cases of AI in data ingestion, data discovery, data preparation, and data monitoring have been found. The AI-powered data pipelines help streamline data ingestion by enabling organizations to connect with different data sources (cloud, on-premise, semi-structured, and unstructured), identify relevant data, a process known as data discovery, and selective ingestion of important data that has business value. AI systems assist in metadata collection from data sources, the generation of data models of data sources, and building natural language processing-based data catalogs on top of these models for easy search, access, and usage of data. In terms of data preparation, AI has helped with data quality enhancement, data transformation, and feature selection. AI-based tools and customized algorithms estimate some common metrics (completeness, consistency, validity, uniqueness, and timeliness) associated with data quality. Automated data transformation involves automation of data cleansing and joining, splitting, windowing, mapping, and datatype conversion tasks, where AI models build knowledge graphs of data sources and usage patterns for building transformation rules. In the financial domain, AI models supplement data engineering tasks by providing automated solutions from dozens of existing transformation projects. In terms of feature selection, the AI systems conduct supervised feature selection and filtering knowledge graphs to reduce the set of features.

The advent of artificial intelligence (AI) and its associated technologies, including big data and cloud computing, is set to have a profound impact on the data engineering landscape. This chapter takes a close look at some of the common use cases and case studies to help data engineers understand the impact of their role on the evolution of future data pipelines.

1.4.2. Challenges and Opportunities

Every novel technology brings new opportunities and possibilities, but also challenges that need to be addressed and tackled. Luckily, globally and through partnerships, strategies are already being developed and growing to tackle these challenges in the examples provided. These challenges will be further discussed in a workshop with all project partners to come up with project-specific and partner-specific strategies. Building on these strategies, the next step could be to assess to what extent these challenges are prohibitive for the project cases define a strategy to address the challenges, and set up projects to further develop these strategies. AI-driven data engineering (or autonomous data engineering) is seen as a potentially transformational and disruptive technology for the future.

While this chapter has presented a comprehensive overview of AI-driven data engineering, including various use cases, opportunities, and valuable case studies, it is important to discuss the challenges that come with this new technology. AI-driven data engineering is a complex technology that replaces a major aspect of advanced analytics and data science with machine learning and has various challenges. First, there is the data integration challenge, as it is often hard to integrate new data sources into advanced analytics and decision-making workflows. Second, there is the data-driven and black-box challenge. Buildings are complex and highly dynamic systems, and creating physics-based models is challenging, even for human experts, and even more so for machines. Third, there is the domain knowledge challenge. AI-driven data engineering does not only deal with complex models but also with complex environments and systems (such as buildings and energy grids), which typically require semi-expert knowledge of a wider set of skills. Finally, there is the combining opportunity. By combining different methods (e.g., machine learning and knowledge-based systems), it can overcome various limitations of either approach taken individually and can leverage most strengths.The advent of AI-driven data engineering heralds significant opportunities and transformative potential, yet it also introduces a set of complex challenges that must be addressed. This technology, which integrates machine learning into advanced analytics, faces several hurdles, starting with data integration—where incorporating new data sources into existing workflows

can be cumbersome. Additionally, the black-box nature of AI presents difficulties, particularly in dynamic systems like buildings, where creating accurate, physics-based models is inherently challenging. The domain knowledge challenge further complicates matters, as effective AI-driven data engineering requires expertise in diverse and intricate systems, such as energy grids. Despite these obstacles, there is promising potential in combining methods—such as integrating machine learning with knowledge-based systems—to leverage their respective strengths and mitigate individual limitations. Strategies to navigate these challenges will be discussed and refined in upcoming workshops with project partners, aiming to develop tailored approaches and project-specific solutions that advance the field of AI-driven data engineering.

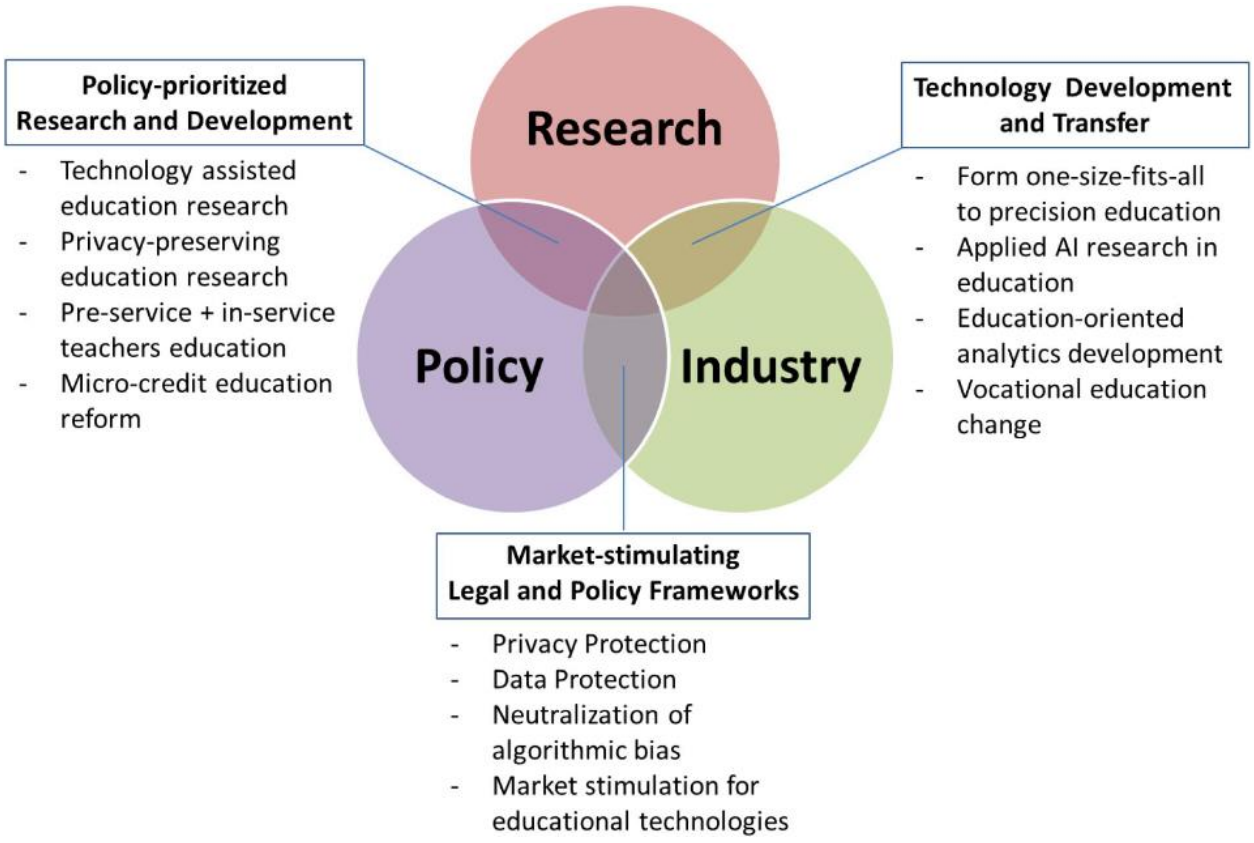

Fig 1.4: Challenges of AI-Driven Data Engineering

1.5. Future Trends and Implications

Another anticipated trend is the AI-assisted industrialization of data preparation and data analysis processes. Integrating new systems (hardware and software) in the existing environment always tremendously increases the complexity and unpredictability of the entire environment. The existing monitoring and help tools become inadequate or obsolete, and the

risk of hardware and software systems coming from different vendors not being compatible is very high. Early warning systems are needed to capture transient anomalies before they develop into unmanageable states, efficient experimentation designs to set up a new data flow/configuration of a data engineering tool, and diagnostic methods to trace the chain of causes of the failure and identify competent systems/components. Since this kind of processing is beyond the capabilities of narrow AI and needs complex thinking involving human expertise, it is predicted that intelligent AI systems will be developed and employed to improve performance and avoid disasters in highly complex environments (nuclear power plants, oil/gas/platforms, big cities, etc.). The development of such advanced AI systems for industrial application, perhaps at the scale of entire countries (like the US and China currently trying to gain technological supremacy), is comparable to the Moon race between the US and USSR in the '60s of the last century, a credible trigger and condition for the breakthrough in intelligent AI development.

The next inevitable trend is data engineering self-service, analytics service, and visualization service. The future AI-driven solutions will provide cloud-based data engineering services enabling non-technical users (such as product owners) to directly upload data sets (structured and unstructured), configure data collection/ingestion/preparation/transformation processes, and perform data analysis and visualization without seeking help from data engineers. It is predicted that over 50% of all data analysis/visualization currently performed by data professionals will be done by non-technical users. The eventual stage of data engineering self-service will be developing decades-long expertise encapsulated in AI agents replicating clients' data engineering modes of operation and providing data engineering services free of charge to the end-users. This will mimic the situation with robots used today by auto production companies to manufacture cars instead of semi-manual operations performed by hundreds of employees a century ago.

AI-driven data engineering holds great promise for the future of big data technologies, and several trends can be anticipated. The dominant trend over the next 5 years will be the advent of specialized data engineering solutions that integrate data collection, ingestion, preparation, transformation, and analysis/visualization seamlessly. Such end-to-end solutions will eliminate the need for separate tools for data collection and ingestion, storage, transformation, analysis, and visualization, and will be able to handle different data formats (structured and unstructured) concurrently. This will also necessitate more powerful and sophisticated data analysis, prediction, and visualization modules capable of analytics processing at multi-level (real-time and non-real-time). Coarse data collection/ingestion and preparation will be

followed by fine-grained preparation/processing/transformation, and multiple data flows undergoing concurrent processing will be managed automatically. All processing will be done at optimum cost without manual intervention, and the entire environment will be managed from the cloud and be accessible on any browser. Additionally, a set of powerful and intuitive visualization tools will be integrated into such solutions.Anticipated trends in AI-driven data engineering signal a profound shift toward the industrialization of data preparation and analysis. As new hardware and software systems are integrated into existing environments, the complexity and unpredictability of these systems increase, rendering traditional monitoring tools inadequate and heightening the risk of incompatibility between components from different vendors. To address these challenges, early warning systems, efficient experimental designs, and advanced diagnostic methods are essential for managing transient anomalies and tracing failures. The development of sophisticated AI systems, capable of complex reasoning beyond narrow AI's scope, is expected to enhance performance and mitigate risks in high-stakes environments like nuclear plants and large cities. This evolution in AI technology mirrors the historical context of the Moon race, highlighting a significant leap in intelligent AI capabilities. Another significant trend is the rise of data engineering self-service solutions, which will empower non-technical users to handle data collection, preparation, analysis, and visualization independently. As AI-driven platforms advance, over 50% of data analysis tasks currently performed by professionals may shift to end-users. The ultimate vision is to create self-service systems that encapsulate decades of expertise, similar to the role of robots in auto manufacturing. In the coming years, specialized end-to-end data engineering solutions will seamlessly integrate data collection, ingestion, transformation, and analysis, managing diverse data formats and processing needs with minimal manual intervention. These solutions will leverage powerful analytics and visualization modules, all managed from the cloud and accessible via any browser, streamlining data processes and enabling intuitive user interactions.

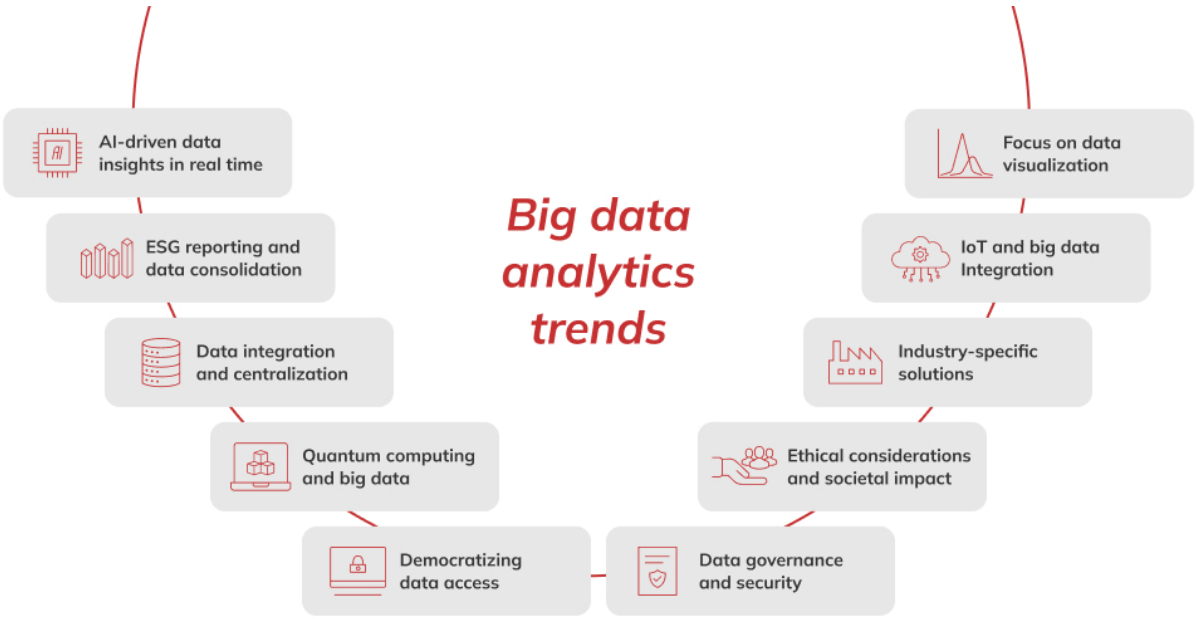

Fig 1.5: Trend AI-driven data insights in real time

1.6. Conclusion

Two pipelines have been shown as examples of the art of the possible: a simple ETL pipeline where a scraping tool is combined with a batch extraction of the victim's SMS pipeline, and a monthly update of a historical data mart where uplifts through Kafka, Spark, and DBT tools are combined. Just as Python democratized access to data engineering with DBT, Airflow, and Dragster, the proposed PartiQL NLP approach democratizes the discipline further, removing the low-level knowledge requirement for the pipeline nodes.

This work introduced the AI-driven approach to data engineering for the growing big data problem and took the first steps toward its use. A token-spilling pipeline leveraging PartiQL's string-based syntax is proposed to create a bridge from free modern interfaces such as ChatGPT to classical SQL- and programmatic-based pipelines. Using black-box tools in combination, reuse has been amplified, and productivity achieved. While the exploration focused on data engineering, it could readily be extended to data operations and modeling.

The rapid evolution of artificial intelligence tools such as ChatGPT and Co-Pilot has drawn attention to their potential in areas such as data science and analysis. However, while these tools can be powerful assistants for certain tasks, they struggle with others. The combination of NLP and deep learning with data pipelines, databases, and the cloud environment is a natural fit, and PartiQL is an interesting vehicle.

1.6.1. Future Trends

Although natural language processing will be ubiquitous shortly, the approach being proposed will permit a smooth transition period, that is initially without the introduction of any major disruptive paradigm shift in big data architectures, data engineering processes, and AI development methodologies. The expanding volume and variety of diverse data sources that must be consumed, engineered, and exploited to the benefit of enterprises' datification and (AI-driven) digital transformation initiatives must be enabled through the major continuous evolvement of big data ecosystems, architectures, solutions, and engineering practices, surrounding DEs in a high degree of complexity in datascape understanding and exploration.
Future trends in AI-driven data engineering are analyzed regarding the challenges of advancing the engineering practices of large-scale data-intensive AI and machine learning applications in complex ecosystems of high-quality, diverse data sources that must continuously adapt to rapidly evolving business requirements and surrounding conditions. Supported by an extensive analysis of the pros and cons, advantages, and limitations of the trends considered concerning the economic exploitation of AI technology and talent, an AI-driven data engineering macro framework is proposed, along with the components' technology stack to support its effective implementation. Following a description of the macro framework and the technology stack's components, an assessment of how the components address the challenges specified in terms of standardization, methodological framework, technology/environment independence, toolchain support, degree of AI autonomy, and level of human DEs involvement is provided.
The team of authors has endeavored to provide a comprehensive overview of the emerging discipline of AI-driven data engineering across multiple disciplines, exploring its critical importance and impact in the modern era of big data analytics and AI. The focus, in particular, is on professional communities of data engineers (DEs), software architects (SAs), developers, and data scientists (DSs) who are directly concerned with this specialization within their daily work, in particular, as a result of a broad paradigm change regarding how big data is being engineered, processed, and consumed.As natural language processing becomes increasingly pervasive, the proposed approach aims to facilitate a smooth transition without causing major disruptions in big data architectures, data engineering processes, or AI development methodologies. To accommodate the growing volume and diversity of data essential for enterprises' datification and AI-driven digital transformation, it is crucial to continuously evolve big data ecosystems, architectures, solutions, and engineering practices. Future trends

in AI-driven data engineering highlight the need to advance engineering practices for large-scale, data-intensive AI and machine learning applications within complex, high-quality, and diverse data environments. Analyzing these trends reveals the pros and cons, advantages, and limitations of various approaches concerning the economic exploitation of AI technology and talent. This leads to the proposal of a comprehensive AI-driven data engineering macro framework, supported by a technology stack designed for effective implementation. The framework addresses challenges related to standardization, methodological consistency, technology independence, toolchain support, AI autonomy, and the role of human data engineers. The authors provide a detailed overview of this emerging discipline, emphasizing its significance for data engineers, software architects, developers, and data scientists who are navigating the evolving landscape of big data engineering and AI.

CHAPTER 2

CORE CONCEPTS OF AI AND MACHINE LEARNING IN DATA ENGINEERING

2.1. Introduction

Different AI or machine learning techniques can be used for data engineering. Data engineering involves the use of large datasets for intelligent tasks such as interpretation and mining. In some cases, data is interpreted by human experts, while in other cases, it is automatically interpreted using AI techniques, for example, improving the quality of images using convolutional neural networks (CNNs). Data mining is a systematic, automated search for knowledge in a large collection of data. It seeks to develop a compact description of a data collection that highlights its general properties. Typical data-mining tasks include classification, clustering, and probabilistic modeling. Data engineering using AI or machine learning techniques places more emphasis on the latter, that is, on the automated interpretation of data using computer algorithms. The use of a high-level programming language such as Python is assumed, and computational issues are not considered significantly.

Machine learning (ML) is a branch of AI. It deals with the development of computer programs or algorithms that can learn and adapt. These programs use different ideas, such as neural networks and data mining, and require large datasets for training. Machine learning is now used in almost every industry for various purposes. In healthcare, for example, machine learning is used for disease diagnosis, monitoring patient records, and developing robotic prosthetics. In finance, it is used for algorithmic high-frequency trading. In data engineering, it is used for batch or real-time computing, for example, in filtering spam.

Artificial Intelligence (AI) is a branch of computer science. It deals with creating smart machines or computer programs capable of performing tasks usually requiring human intelligence. These tasks include problem-solving, understanding natural language, visual perception, speech recognition, decision-making, and learning. While automation has existed for thousands of years, AI is distinct from any previous technology. The development of the PC, microprocessor, and the Internet has made it possible to use AI and machine learning in various fields today.Data engineering leverages various AI and machine learning techniques

to handle and interpret large datasets for intelligent tasks. While human experts traditionally interpreted data, AI techniques now automate this process, enhancing tasks such as image quality improvement through convolutional neural networks (CNNs). Data mining, a key aspect of data engineering, involves systematically searching for knowledge within vast data collections to develop compact, descriptive models highlighting general properties. Machine learning (ML), a subset of AI, focuses on creating algorithms that learn and adapt from large datasets, employing methods like neural networks and data mining for tasks across different industries. In healthcare, ML aids in disease diagnosis and robotic prosthetics, while in finance, it drives algorithmic trading. AI, broader in scope, encompasses the creation of smart systems capable of performing tasks that typically require human intelligence, such as problem-solving and natural language understanding. The evolution of technology, including the personal computer, microprocessor, and the Internet, has made the application of AI and machine learning widespread, marking a significant advancement from previous automation technologies.

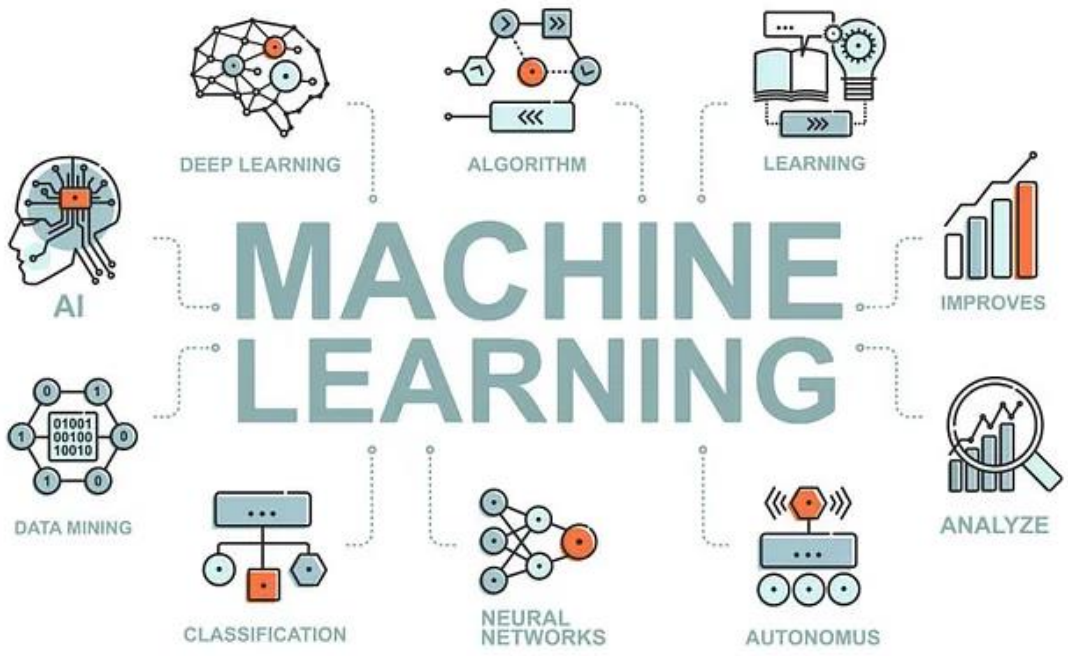

Fig 2.1: Core concepts of Machine Learning

2.1.1. Overview of AI and Machine Learning

Machine Learning refers to supervised learning description models starting with parameters set to random values. With every new event, which contains information on some parameters, there is an attempt to improve the model by changing its parameters to lessen its inefficacy. The number of parameters is significant, and it becomes a question about optimization. This system-free parameter search represents a new intelligent behavior that appears in the system. As a spinoff, the input data, which were just parameters, are translated into this intelligent behavior. Therefore, AI is not only described as a model/representation of behavior but represents embedded intelligent behavior within the system.

AI utilizes data, with algorithms as processing tools, to attempt to make the best decisions. Statistics is a type of data analysis where events are considered at a macroscopic level, using aggregates and averages over a large number of occurrences. This technique produces reasonably accurate results for smooth systems, such as those encountered in meteorology. However, for specific systems with a low number of events, statistical approaches are inefficient as the average number of occurrences is not enough to construct a relevant description. AI demonstrates that a specific approach can give satisfactory outcomes for particular systems. In this case, events evolve at a discrete time scale corresponding to the number of individual occurrences, leading to a great inequality in time scales.

In recent years, the field of AI and ML has witnessed significant growth, advancement, and evolution. Innovative concepts are proliferating almost daily, made feasible by the increasing availability of data. The arrival of Big Data gives rise to myriad challenges, including data generation at a phenomenal rate, the need for data storage and retrieval, in-depth analysis of data streams (internally and externally), and the execution of various processes at different time scales according to intelligent rules, as well as the translation of analysis outcomes into decisions.

Artificial Intelligence (AI) and Machine Learning (ML), concepts that were once relegated to the realm of science fiction, are rapidly evolving into transformative capabilities that provide businesses with a competitive edge. The development of problem-solving systems that exhibit reasoning, learning, or knowledge-retention characteristics is the focus of AI as a branch of computer science. Machine Learning, a subset of Artificial Intelligence, is concerned with the creation and use of data-conducive algorithms for automation. Whereas AI concentrates on the implementation of intelligent behavior and thinking, Machine Learning seeks to achieve

this through the development of intelligent programs that arise from self-learning intrinsic behavior.

2.1.2. Significance of AI and Machine Learning in Data Engineering

Most of these advancements heavily rely on the masterful design and tuning of datasets. In supervised learning problems, the datasets used to train and evaluate the machine learning models will ultimately determine the performance of the task. This data engineering process comprises a myriad of activities, including the identification of potential data sources, the design of different sampling strategies, the identification of potentially beneficial feature transformations, the construction of downstream datasets from daily-refreshing raw datasets, and the definition of train/test splits that minimize the possibility of label leakage while maximizing the predictive power of the models. All these tasks can be automated, allowing the researcher or developer to spend far less time on them and, hence, accelerate the development of relevant and validated solutions.

The exponential growth of data has resulted in the demand for highly skilled professionals and researchers in the areas of AI, machine learning, big data, and data engineering. Many initiatives have been taken on this front, to provide tools and techniques to facilitate the speedy development of applications that can extract a wealth of value from the data. These include API-based smart services; enhanced tools for identifying and training machine learning models on previously unavailable big data; pipelines that automate manual observations on big datasets; connected hardware and machine learning models that allow the identification of interesting datasets on the fly; and low-code solutions that cover the entire data engineering pipeline.

The transformative power of artificial intelligence (AI) and machine learning in the realm of data has been the driving force behind many emerging ideas and smart applications. This includes areas such as predictive analytics, smart surveillance, smart cars, recommendation systems, and smart cities. These innovations have made a tremendous impact on businesses to gain an advantage over their competition and simplify/automate complex and time-consuming tasks. In this regard, the rise of big data presents an unparalleled opportunity for businesses to gain insight into and harness this information to boost productivity and profitability. Data engineering, comprising a wide range of disciplines, tools, and frameworks, is the key to tapping the value of this newly available data.

2.2. Foundations of AI and Machine Learning

Machine learning. Machine learning is the discipline in computer science focused on providing computers with the ability to learn from data. Typically, machine learning models are fed a huge amount of data and are periodically adjusted (via incremental learning) so that their prediction ability becomes better according to some quantitative measure. Data learning distinguishes supervised, unsupervised, and reinforcement learning models.

Artificial Intelligence. AI mimics cognitive functions and implements them consistently, reliably, and accurately in a software environment. One of the most accurate, influential, and widely applied approaches to AI is the use of machine learning. This is a diverse family of algorithms that improves model accuracy with training data and comes in many flavors, including supervised, unsupervised, data generation, reinforcement learning, and others.

The computer science discipline related to data engineering has a few overall concepts that are essential to know before delving into a more technical discussion of the distributed MLOps framework being considered.

However, it is not enough for a machine to advance automatically; it also has to do so in a manner that is smart as well as humane. AI's rationale should be comparable to ethics, and its task should be akin to social responsibility. Beyond the technical challenges, a major pitfall for AI engineers would be to be non-sociable when designing humanity's 'digital twins', as virtual agents will manage such crucial aspects of modern life as banking and healthcare.Artificial intelligence (AI) is the intelligence demonstrated by machines, as opposed to the natural intelligence displayed by humans and animals. The applications of AI include expert systems, speech recognition, facial recognition, artificial creativity, and robots. More specifically, machine learning is a field of computer science that enables the design of algorithms that monitor data and, through progressive learning, improve a machine's performance concerning the task.

2.2.1. Key Terminologies and Definitions

AI, ML, DL, MLops, Automation, and DataOps are key term definitions for AI and ML in data engineering. The federal government is motivated and focuses on areas, driving needs, and otherwise constraints explored. This investigation ultimately explores the definition of AI and ML key terms, the feasibility of AI and ML tool development concerning data

engineering automation and the design of such tools in a time-efficient and resource-efficient manner.

With an understanding of the basic concepts of AI and ML, the feasibility of developing tools in these domains can be gauged. Strong variables driving the need for DataOps and AI tools in particular are also in focus. The federal government is largely a producer and gatherer of data, and the systems and domains have remaining constraints on the type of DataOps and AI tools that can be explored. Key term definitions include AI, ML, Deep Learning (DL), ML Operations (MLops), Automation, and Data Operations (DataOps). AI refers to the simulating of human behavior in machines programmed to think like humans and mimic actions. ML refers to the study of computer algorithms that can learn from data and identify patterns in data. DL is a type of ML representing the latest generation of ML techniques and neural networks with a depth forming the basis of the network that can have a large number of nodes in one layer transacting to another layer. DataOps is a set of processes, practices, and technologies to improve the quality, speed, and reliability of data analytics systems. Finally, MLops is a framework in which data scientists monitor and maintain machine learning systems in production environments. The application of these definitions in a federal government data engineering scenario is also elucidated.

As a precursor to the domain of AI and machine learning, it is evident that the basic terminologies and respective definitions are the premise that shall be explored first. The federal government is motivated to explore how Artificial Intelligence (AI) and Machine Learning (ML) can impact the development of data engineering automation tools. This includes the identification of AI and ML terms that apply to data engineering and big data domains. Data preparation, trenchant application of ML models, and examination of candidate models must happen as data warehouses are populated. The premise of automation of these tasks is in the domains of Natural Language Processing (NLP), MLops, and DataOps.To effectively advance in the domain of AI and machine learning, it is essential to first establish a clear understanding of fundamental terminologies and definitions. The federal government is particularly focused on exploring how AI and ML can revolutionize data engineering automation tools, emphasizing the need to identify and define key terms relevant to these technologies within the context of data engineering and big data. As data warehouses are populated, critical tasks such as data preparation, the application of ML models, and the evaluation of candidate models become central. The automation of these processes is closely tied to advancements in Natural Language Processing (NLP), MLops, and DataOps. These domains collectively contribute to streamlining data workflows, enhancing model efficiency,

and ensuring robust data management practices, paving the way for more effective and scalable data engineering solutions.

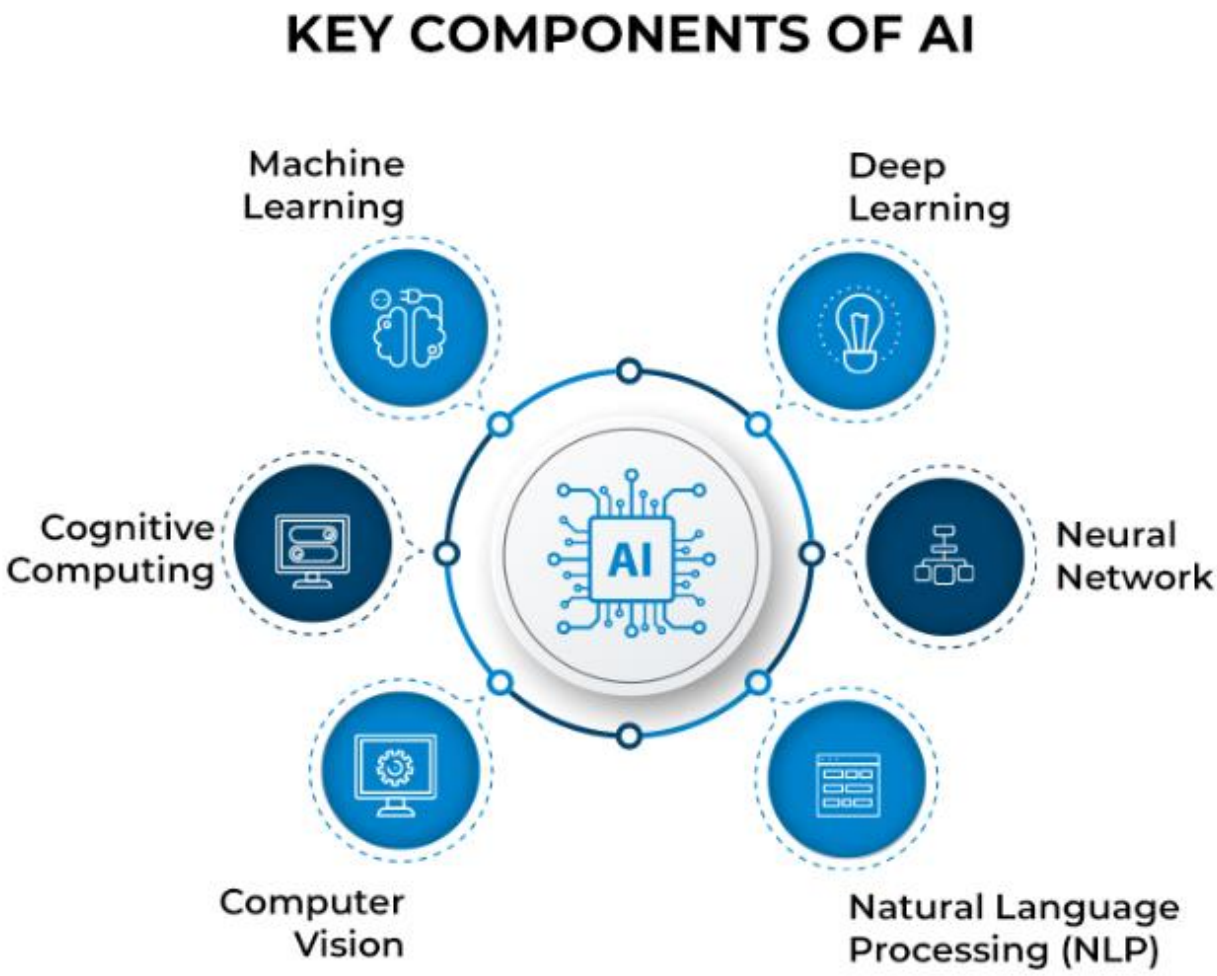

Fig 2.2: Key Components of AI

2.2.2. Types of Machine Learning Algorithms

Reinforcement learning provides a different mode of learning that involves a feedback mechanism, where an agent interacts with an environment in pursuit of a goal. In this learning paradigm, the agent is not provided with input-output pairs; rather, it tries different actions to attain certain objectives. The decisions taken by an intelligent agent can lead to two options: winning rewards or penalties. Accordingly, the agent needs to adjust its actions to maximize cumulative future rewards from several time steps. Thus, reinforcement learning focuses on learning what actions to take in states to maximize a reward signal.

Unsupervised learning algorithms work exclusively with input data without any corresponding output data, where the task is to find hidden patterns or intrinsic structures in the data. Unsupervised algorithms delve into the inherent properties of data to locate unique patterns. Some commonly used unsupervised learning algorithms include k-means clustering, hierarchical clustering, and other clustering algorithms.

Supervised learning algorithms work with labeled input and output data, where the algorithm learns patterns from the training data to generate correct outputs. A model is deemed successful when it can accurately predict unlabeled output data, following its prior learning from initially labeled training data. Examples of commonly used supervised learning algorithms include linear regression, logistic regression, decision trees, support vector machines, random forests, neural networks, and deep learning.

In the context of AI and machine learning (ML), algorithms serve as a set of rules or instructions designed to perform specific tasks or solve certain problems. Machine learning algorithms, heavily utilized in data engineering, manipulate data to uncover patterns that are instrumental for future predictions, decisions, and actions. Thus, ML algorithms represent a mechanized or digitalized alternative to human intuition or cognitive abilities. These algorithms can be classified based on various criteria, one of the common classifications categorizing them according to how data is fed into the algorithm. There are three broad categories of algorithms based on this classification: supervised, unsupervised, and reinforcement learning.

2.3. Data Engineering Fundamentals

In case the quality of provided data needs to be assessed, it is often a waste to pursue any kind of advanced cleaning before this filtering step. Possible flaws in coherence requirements as well as the effect of these flaws on a downstream processing pipeline may be estimated from subsets of the data. Inferences from the cleaning pipeline should be regularly gathered and promptly considered when tuning the data collection and preprocessing strategies. A fault in the data-generating infrastructure may propagate unnoticed as a lack of cleaning effort in the preprocessing infrastructure. Unfortunately, a single flaw can compromise the decision of an otherwise well-performing intelligent system.

Regardless of the data source, it is usually required to be converted to a coherent format before using it for training or inference. This usually means transforming the file type, encoding, aspect ratio, or other parameters. Data cleaning is the step of the preprocessing pipeline that attempts to remedy both the shortcomings caused by the data generation process and the

coherence requirements. Automation is key to effective data preprocessing and cleaning pipelines, as they usually have to tackle petabytes of data and require constant tuning when data characteristics change. Moreover, the pipeline should automatically be re-deployable in case of failures resulting from the changed environment.

Data is the fuel for any intelligent system, be it simple heuristics or complex deep-discriminative networks. Gathering and preparing the right data is arguably the most crucial and resource-expending part of building any AI system. An intelligent system can be envisioned as a pipeline with three major components: a data provider pipeline bringing raw information, an inference pipeline calculating a decision using the intelligence with the supplied data, and a feedback pipeline collecting the decision and possible outcomes to adapt the system's efforts. The data provider is often overlooked, as it does not represent the intelligence of the system. Careful design is necessary for it to provide the right amount and quality of raw data to feed into the intelligent component.

Fulfilling the vision of AI and automated decision-making requires the careful architecting of an intelligent system with machine learning at its core. In turn, each of these components must be integrated with data collection, storage, preprocessing, and cleaning systems – the focus of this chapter.

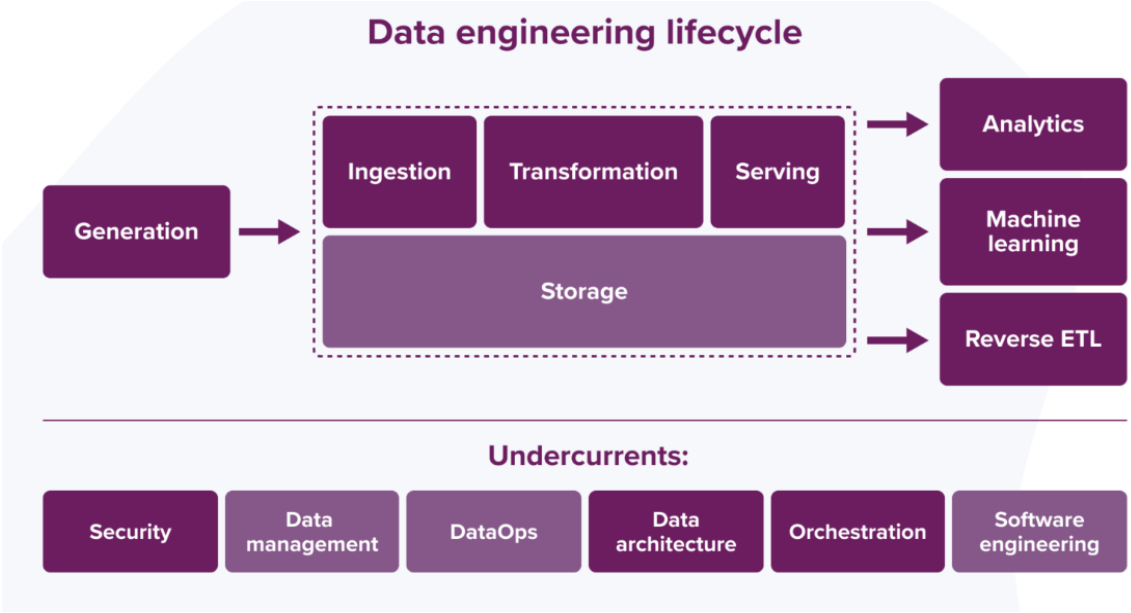

Fig 2.3: Fundamentals of Data Engineering

2.3.1. Data Collection and Storage

Once the data is collected, it needs to be stored properly for further processing and analysis. To process the data, it has to be stored on a physical medium that can be easily

accessed. Data can be stored in several ways such as hard disks, optical disks, solid-state drive (SSD), USB flash memory, and storage in the cloud. Unlike earlier days, a significantly greater amount of data is available today. The growth of this data in terms of quantity, complexity, and diversity is astonishing. Furthermore, the data is being collected at an exponential pace, leading to the concept of "Big Data". Big Data can be defined as extremely large and complex datasets. However, analyzing large datasets is difficult with the help of usual data processing application software like Excel, SQL, etc. Data engineers play an important role in creating pipelines for the collection and aggregation of big datasets, cleaning them, and transforming them into a format that allows the application of machine learning techniques. They also prepare datasets for machine learning and statistical modeling, and can also be involved in the direct application of machine learning techniques to solve business use cases.

In the data engineering process, data collection involves the retrieval of data from one or more sources for further processing or storage. Data is needed for different purposes, such as building machine models, and can come in different formats such as text, audio, video, streams, or images. One of the most important aspects of data collection is ensuring that the data is collected from a reliable and reputable source. Different companies and individuals make decisions based on data that may not be valid, and it is crucial to ensure that the right decisions are made based on the right data. A variety of tools have been developed for the data collection of text documents (web crawling), video, images (image acquisition), and audio (recording).

2.3.2. Data Preprocessing and Cleaning

Common methods for data cleaning include identifying and removing missing, duplicated, or outlier values, as well as resolving attribute inconsistencies. Incomplete data, for instance, can be handled by removing the elements containing incomplete values, replacing them with certain values, or using appropriate data mining techniques.

Data mistrust is one of the main problems related to data quality, as many data sets lack trustful sources or event histories. This may come from data sources such as crowd-sourcing, monitoring new sources in social networks, or sensing devices. These data sources may lead to technology and social biases. In some crowd-sourcing processes, certain groups may dominate the process, while people from different profiles may have different influences on the events the data record. As a result, the data set can be not only untrustful but also misleading. In the case of a temporal aspect, certain events or information may be lost and

undercounted. Data located outside a range, data duplicities, data being or not being in the right format, data becoming normally impossible or very unlikely to happen, or data providing a divergence in the data set context are also common patterns of mistrustful data. Mistrustful data may lead to garbage in garbage out (GIGO) scenarios, thus affecting further data processing, interpretation, analysis, visualization, and final decisions.

Different types of data preprocessing techniques are used in machine learning algorithms to prepare input data for the model. Data normalization and standardization techniques are commonly used to scale numerical attributes to a similar range and have a zero mean and unit variance. Encoding techniques are applied to categorical attributes to convert them into numerical format. Variable selection techniques are used to eliminate irrelevant or redundant data. Data transformation techniques are employed to format common attributes such as date and time.

Data preprocessing and cleaning are essential steps in the data engineering process, which involves transforming and preparing raw data for analysis and modeling. Data preprocessing involves transforming the data into a suitable format or structure using various techniques and methods, while data cleaning focuses on detecting and correcting inconsistencies, errors, and inaccuracies in the data. Both processes are crucial for ensuring the quality and reliability of the data, which is a critical factor in the success of any data-driven project or application.

2.4. Integration of AI and Machine Learning in Data Engineering

There are common concepts in modeling algorithms—the definition of a model and its hyperparameters—and different model definitions and hyperparameters depending on the algorithm used. A set of common hyperparameters (e.g., the number of trees, the maximum depth, and the learning rate) allow one machine learning algorithm to be interchanged with another and therefore train several algorithms. Hyperparameter tuning effectively entails searching for the optimal hyperparameter set, which can be conducted using manual searches or more sophisticated methods (e.g., grid and random searches, Bayesian optimization, and evolution strategies). These tuning techniques come with incredible execution times, exacerbated by the necessity of validating each hyperparameter set using a separate validation dataset.

The second major component of data engineering used in AI and machine learning applications is model training and evaluation. After finishing the data preparation pipeline, everything is ready to train machine learning algorithms on the datasets. Simple machine

learning algorithms can be trained using plain programming or scripting languages. Still, GPU-accelerated deep learning algorithms require specialized deep learning libraries and frameworks (such as TensorFlow, Keras, and PyTorch) that facilitate inserting the training pipeline into applications.

Data processing, transformation, and augmentation techniques change the contents of an existing data set, in turn changing the features of the data. Dealing with missing values, interpolation, and outlier detection and handling all assist in transforming the data into optimal features for algorithms. Data augmentation techniques such as synthetic data generation, adding jitters to values, time series expansions, and image transformations (e.g., rotation, zoom, and noise addition) are popular techniques that enhance the performance of algorithms. Feature engineering begins with exploratory data analysis, followed by the selection, extraction, and transformation of features. Feature selection removes irrelevant and redundant features from the data set, whereas feature extraction creates new features based on the existing ones. Transformation prepares features for the algorithm and may include encoding categorical features and discretizing continuous features. Domain knowledge and creativity are essential for successful feature engineering. For projects requiring nonstandard analysis, hiring domain experts is highly recommended.

Feature engineering transforms raw data into the format required by machine learning algorithms. It plays a crucial role in the success of any machine learning application. The right set of features can make a simple algorithm outperform complex algorithms and vice versa. Scikit-learn, TensorFlow's TFRecords API, and PyTorch's TorchVision library provide functionality for data preprocessing, transformation, and augmentation in Python.

Data engineering lays the foundation for successful AI and machine learning applications. Critical tools and techniques designed for data preparation are key components of the infrastructure supporting AI and machine learning endeavors. These core concepts of data engineering that facilitate AI and machine learning applications are as follows.

2.4.1. Feature Engineering

Feature engineering specializes in selecting or constructing the proper features for machine learning models. The feature space carefully designs or selects a load of features from the input data before being used by a specific machine-learning model. The trained classification model is only valid in the space covered by the chosen features and the model

architecture. Thus, chosen features determine the capabilities of the models. Feature selection aims to find a subset of features that retains the most relevant information to the model. Another alternative is feature extraction, which means constructing new features from the original ones and projecting them into a lower-dimensional feature space. This new feature space is called a feature space representation. It is important to note that in some cases, the word embedding is used to refer to the feature space representation in the understanding of deep learning models.

The fundamental aspects of feature engineering are described, providing insights into understanding the feature space of machine learning models. The choices made for feature engineering, matched with the applicable machine learning models, significantly determine the success or failure of a machine learning analysis. Nevertheless, knowledge about the nature of the feature space and the influence of the design choices is rare outside of the domain of machine learning experts. First, the vision and the purpose of every design choice, including the underlying philosophy, notions, and properties, have to be covered. Second, guidelines should be stated to help make the appropriate design choices matched to the intended applications. Finally, a certain degree of other knowledge is necessary for understanding the consequences of the design choices.

Feature engineering refers to the process of selecting, modifying, or creating features to improve the performance of a machine-learning model. Malfunctions in machine learning models usually arise from poor feature representation. Consequently, a strong feature representation will, in most cases, outperform sophisticated models. Nonetheless, machine learning practitioners often concentrate on modifying the model architecture instead of the proper feature presentation.Feature engineering is a crucial aspect of developing effective machine learning models, focusing on selecting, modifying, or creating features to enhance model performance. The process involves designing or selecting a subset of features from the input data, which defines the feature space that the model operates within. The quality and relevance of these features directly impact the model's capabilities and effectiveness. Feature selection aims to identify the most informative subset of features, while feature extraction involves constructing new features from existing ones to create a more compact, lower-dimensional representation of the data. This new feature space, sometimes referred to as word embeddings in deep learning, plays a pivotal role in determining the success of machine learning analyses. Despite its importance, the intricacies of feature engineering and the influence of design choices are often overlooked by those outside the machine learning field. Effective feature engineering requires a deep understanding of the underlying principles and

guidelines for selecting and designing features, as well as an awareness of how these choices impact model performance. Strong feature representation can frequently achieve better results than complex model architectures, yet practitioners often focus more on modifying model structures rather than optimizing feature presentation.

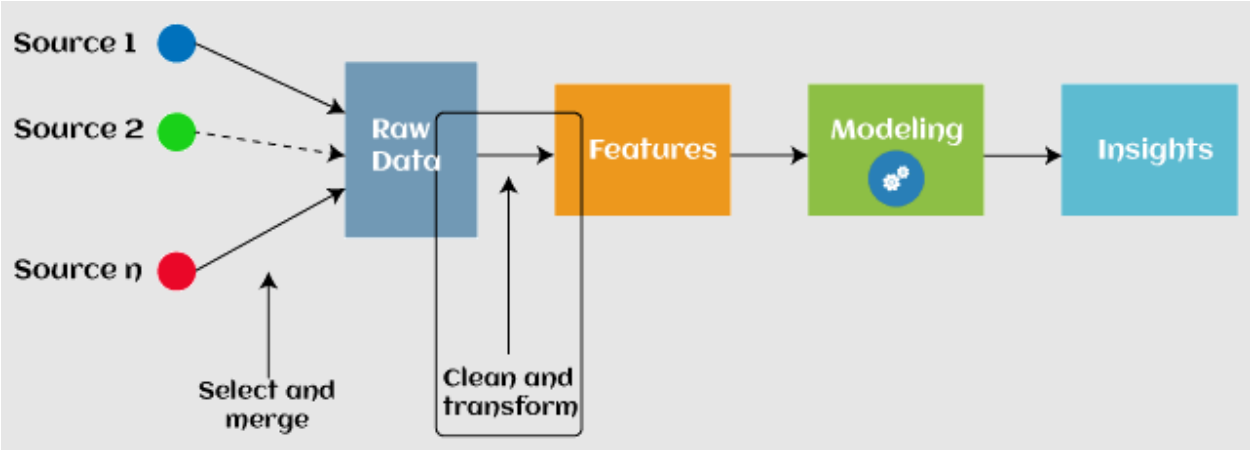

Fig 2.4: Feature Engineering for Machine Learning

2.4.2. Model Training and Evaluation

Once a model is chosen and trained, the next step is to evaluate it in light of the selection of candidates trained in parallel. Model evaluation consists of determining just how successfully a trained model translates inputs to targets for data that has not been provided for training purposes, including the training data itself. This process is widely implemented through what is known as cross-validation, where the original dataset is split into mutually exclusive subsets of data, ensuring that all data from the original set is accounted for. In the most basic form of cross-validation known as k-fold cross-validation, the dataset is split into k subsets of data, k models are trained, and for each model, one of the splits is used for testing purposes while the remaining k-1 splits are used for training. The performance of the model on the test fold is then recorded. This process is then repeated k times, ensuring that each fold has been used for testing purposes and that all have been used for training purposes k-1 times. The k resulting evaluation scores from the model are then combined, typically by averaging them, to produce a single evaluation score on the entire dataset. Since the performance on each cross-validation fold is independent of one another, this has the effect of shielding the evaluation process from data leakage.

For example, in the case of regression, commonly used losses include the Mean Squared Error (MSE), which is the average square error of the predicted vs actual values of the training data, and the Huber loss, which is a variant of the MSE that limits the influence of outlier samples. In the case of binary classification, commonly used losses include Binary Cross-Entropy Loss (or Log Loss), a widely used loss function for a binary classification model built with logistic regression, and the Hinge loss, primarily used with Support Vector Machines (SVM). In the case of multiclass classification, commonly used losses include Categorical Cross-Entropy (for mutually exclusive classes) and Hinge Loss variants (for non-mutually exclusive classes).
Model training is the process of fitting a machine learning model to a dataset to uncover the underlying relationships between specific independent variables and the target-dependent variable. This process is defined by the choice of model type, which alongside the choice of model features determines the actual model that will be trained. The model is trained by iteratively updating the model parameters (e.g., weights in a neural network) to minimize the difference between the predicted and actual target values of the training data. This difference is expressed through a loss function (or cost function), which generates a value representing how poorly the model predicts the training data and can be one of several possible variations depending on the machine learning approach of choice.
With the features determined, the next stage of the machine learning pipeline is model training and evaluation. At a high level, there are two aspects to this: one being the technical inner workings of how to fit a model to the data provided and how to determine if this has been done successfully; the other being the engineering of actual model training and evaluation tools in a manner that allows adequate usage of data engineering pipeline tools to target reliability and efficiency.

2.5. Challenges and Future Directions

The vast availability of data, combined with increased computing power and the emergence of advanced algorithms, has sparked the attention of multiple stakeholders towards the implementation of advanced analytics in a firm's technology-oriented decision-making processes. Despite the advantages associated with the implementation of advanced analytics, firms are hitting various roadblocks when trying to adopt them in their operations. The most common barriers preventing firms from implementing advanced analytics are uncertain returns, lack of understanding/cultural readiness, uncertainty regarding costs and risks, and lack of know-how.

AI systems lack the moral standing out of which humans act. AI can make judgments that lie outside of the law or intensive qualitative analysis like a human would. However, AI models must be governed similarly to how humanity is governed: the attempt to harmonize a system of relations based on shared moral values. How to approach the consideration of morals for AI systems is by far one of the most intriguing challenges regarding AI and machine learning models now pursued by society, academia, and the private sector alike. Very novel methods are necessary to create a structure like the law for AI, and the intellectual property and knowledge specially acknowledged.

Machine learning models are being improved upon, effectively leading to the development of their models. For now, the models remain generative, and thus creative, based on assets provided by a potential creator. There's an ongoing debate on whether those assets should only include free-to-use content. However, should the assets contain derivative works, is it right for AI to make a new creation without compensating the original creator? If all content remains by right the original creator's intellectual property, an AI model being able to deviate from the style, substance, and manner of said creation must raise concern. All things considered, should AI have all knowledge at its disposal? And how to patent it? As now envisioned, future advancements in AI would lead not only to creative capability surpassing that of humanity but also to moral ambiguity.

There are still several aspects regarding the core concepts of AI and machine learning in data engineering that require attention. All things considered, a powerful AI and machine learning model could lead to outperforming humans in several areas. Scientists are trying to improve AI's various perspectives on aspects such as graphics, vision, and language, but could it lead to moral degradation for AI systems? Ways around distinguishing and minimizing or

preventing unwanted actions from AI must be fully reevaluated now more than ever due to rapid advancements.

2.5.1. Ethical Considerations in AI and Machine Learning

The pros and cons of AI technologies must be identified to create new possible applications to advance ethical AI and ML capabilities and knowledge. Possible future work includes but is not limited to, countering toxic comments, developing classifiers for determining the toxicity of data and classifiers addressing fairness concerns, creating applications for predicting various animal behaviors using AI and ML models and data and addressing the impact of addressing consciousness and intents of individuals and objects.

As data and data engineering capabilities are used more often, ethical considerations become a part of the decision-making process. The consequences of data usage are increasingly apparent, with the impact of observations made for and using data, models, and applications on entities, including governments, organizations, and people. The emergence of ethical concerns can be attributed to the rapid adoption of data engineering capabilities and tools. Such ethical concerns must be addressed by data engineering in new applications.

AI and ML are being rapidly adopted by users for creating a wide variety of applications. A large body of applications can be utilized to automatically extract observations from the world. Such observations can be used as insights for further research, allowing users to personally interact with and better understand their society and the world. Since AI and ML are data-driven technologies, they require data to succeed. Data is also increasingly being digitally collected and used by organizations for various purposes. It plays a significantly important role in the continued development of technology, application, and knowledge.

The rapid advancements in artificial intelligence (AI) and machine learning (ML) technologies have provided a plethora of opportunities that can be used to address a wide variety of research problems. However, while researching and developing these emerging technologies, ethical concerns must be the prime consideration. Ethical AI & ML can be classified into fairness, accountability, transparency, and privacy. The ethical concerns provided must be addressed by utilizing new applications. Subsequent applications can be created to advance the field of science and provide a better understanding of society and the world. Such applications will have a positive impact on the thoughtful use of data engineering tools and capabilities worldwide.

Fig 2.5: Ethical Considerations in AI Development

2.6. Conclusion

Where such machines are different from intelligence as understood in a human context is concerning learning and adaptation. While mathematics can be well regarded as a beautifully extensive logical construct that maps the world to some degree, each application in practice (such as mathematics in physics or engineering) is an independent 'learning path', adjusted by human intelligence. Machine learning in data engineering is about taking this one step further – creating general machines that learn 'on their own', based on a certain task defined in terms of data and rules. This opens up a world of possibilities for finding meaning in data transformation and usage tasks on a level of complexity and size impossible for human labor alone. On the downside, it also raises issues of trust and understanding models involving complexity levels and interdependencies far beyond the human capability to understand an entire system.

At first glance, the notion of 'intelligent machines' can seem incomprehensible. Machines are, by definition, things made with a purpose. They follow rules and execute tasks. Humans are ascribed to intelligence – the ability to understand and think, to learn, and, by extrapolation, to adapt. On further inspection, however, intelligent machines do exist on some level. The simplest example of such a machine is a thermostat, an uncomplicated mechanism that responds to predefined conditions by switching central heating on or off. In this case, the machine executes the tasks of heating or cooling a space to human needs. While such machines are limited in what they can do, it is clear that they improve on agriculture and construction techniques devoid of regulation, involving significantly more human labor, various

misunderstandings, and greater suffering. Mathematics, philosophy, logic, and computing can also be described as forms of intelligence implemented in machines, as systems governed by certain logic that execute predefined tasks, albeit more complex ones.

More than half a century after its inception, artificial intelligence (AI) continues to be a source of excitement and debate. Today, data is being collected at an unprecedented scale, giving rise to an equally unprecedented interest in understanding this data. Since data is often representative of what is happening in the world, finding meaning in this data often means finding meaning in the world. This, in a nutshell, is what artificial intelligence aims at. To map the world as accurately and comprehensively as possible, on the level of meaning. In recent years, advances in AI have laid the groundwork for a new generation of technologies – disruptive technologies able to bring profound changes to how business is done, how daily life is maintained, and even how society as a whole is governed.The concept of "intelligent machines" diverges significantly from human intelligence in terms of learning and adaptation. While human intelligence involves understanding, learning, and adapting based on experience, machine learning in data engineering aims to advance this by creating systems that autonomously learn from data and predefined rules. This capability allows machines to perform complex data transformation and analysis tasks far beyond human capacity, uncovering insights in ways that were previously unattainable. However, this also introduces challenges related to trust and comprehending models of such complexity that exceed human understanding. Although the idea of intelligent machines might seem abstract, practical examples, like thermostats or more advanced systems governed by mathematical logic, illustrate the application of intelligence in machines. Over fifty years since its inception, artificial intelligence continues to inspire both excitement and debate. The exponential growth in data collection and analysis fuels AI's goal to interpret and map the world with increasing accuracy. This ongoing evolution of AI is paving the way for transformative technologies that promise to revolutionize business practices, everyday life, and societal governance, reflecting a deepening pursuit to understand and harness the vast potential of data.

2.6.1. Future Trends

There is a growing demand for data skills, including data engineering skills. Demand is rapidly increasing, as are the awareness and expectations related to the data opportunity. However, misunderstandings and misconceptions often result in unrealistic expectations regarding the speed of innovation, the information needed, and the complexity of underlying

use cases. Such developments may generate frustrations and have led to a blaming watch out for new technologies and opportunities.

In the coming years, these changes will challenge many data engineering departments and data products. This will include the need for privacy by design solutions, re-engineering resulting from changing data access conditions, and the need for guarantees on security conditions, measures, and compliance. It will most likely lead to a stronger focus on security and privacy requirements on architectures, solutions, and products.

There is growing attention on privacy in the context of data. The focus on privacy, regulation, and ethics is expected to come to the foreground for data engineering and data products. Privacy regulations and challenges arising from policy changes are not new to the industry. The formulation and constant modification of laws and regulations focus on how data is stored, supplied, shared, and accessed. However, the software industry was relatively immune to the pressure imposed by these external factors.

The league of vendors catering to the market need for autonomous data engineering is increasing rapidly. Some of the larger players in the data processing and warehousing area have built-in automation features. A few startups have attempted to disrupt the market by solely adopting an approach centered around automation. There is a tendency to leverage AI-ML technology to create end-to-end automated data analytics, data engineering, and data science pipelines. Automating data engineering is expected to flourish in the upcoming years. No-code platforms are increasingly being adopted in the data engineering field, supporting the ingestion of data, data warehousing, streaming applications, orchestration, and other data engineering processes. In parallel, companies are constantly assessing their existing setup in terms of architecture and budgets. Companies are analyzing their existing infrastructure and consequently shifting their data products and architecture to the cloud. Cloud providers are responding to this trend by making a transition to the cloud as easy as possible by offering many managed services and extensive consultancy services. Such a transition allows companies to decrease upfront capital expenses, easily scale data projects up and down, and improve time to market.

Due to the growing democratization of technology, there is an increasing trend in no-code platforms. No-code platforms are applications or services that allow for common tasks to be performed without needing to be programmed. Such platforms allow owners of data and information to be able to consume, prepare, or analyze it without depending on developers or data engineers. With no-code platforms, the capability to interact with data queries, analyze data, and investigate results is being made accessible to the entire organization. Users equipped

with little or no knowledge of data engineering can work with data by just pointing and clicking.

The integration of artificial intelligence (AI) and machine learning (ML) into data engineering practices is an evolving and dynamic field. New trends emerge, and existing technologies are developed further, influencing how organizations interact with data. Some of these trends include the increased usage of no-code platforms, the advent of data engineering in the cloud, the intersection of AI and ML in automation, the growing importance of privacy, regulations, and ethics, and the increase in data literacy.

CHAPTER 3

ARCHITECTING DATA PIPELINES FOR AI INTEGRATION

3.1. Introduction

There is also a need to evolve interface standards and development environments for data pipeline architecture and design. Among the potential and significant AI-enhanced applications benefiting from data pipelines is interpreting spatially and temporally dense geodata and remotely sensed earth observation images. Small (1–10 m) or large (100–10,000 m) areas of interest can become regular targets for monitoring cycles from the millisecond to the decade. To keep tracking ongoing processes, nearly real-time data pipelines or instances of them must be rapidly built from in-situ or satellite observations. Alternatively, enhanced individuals or systems receive not only data and decisions (or controls) but also AI knowledge typically delivered as trained models, which may arrive from specifiers, developers, or manufacturers. Artificial agents must assess when to accept, reject, or request additional options on a massive currently intractable volume of information, some with black-box approach uncertainties. This further raises metadata concerns encompassing compliance and fitness-for-purpose. Simultaneously, there is a rise in demand for novel AI-enhanced applications that are critical to the business (e.g. AI in warranty, security, or finance) or otherwise safety-critical (e.g. AI in aviation, automotive, or nuclear). It remains to be seen what AI safety other than validation and verification assurance is needed on both the supervising human and automated AI reception acceptance, evaluation, and deployment sides. With the ubiquity of advanced sensors, edge devices, and actuators, it is increasingly common for enterprise and societal systems to have continuous streams of raw data, from which static or dynamic decisions are derived. Data pipelines are platforms for transporting data from raw sources to consumable resources. They are composed of elements or blocks deployed over land, undersea, or trees, to integrate sensors, devices, databases, conventional data analytics or AI-based models, and visualization or control consoles. Initially developed in telecommunication, monitoring, and control domains, data pipeline architecture has diversified due to advances in sensing technology, AI, and the Internet of Things. Several data pipeline architecture and platform initiatives, including the Open Data Pipeline Reference

Architecture, have recently been published. However, as the enterprise or societal system grows more complex, propelled by millions of sensors or users continuously producing data, and a range of concerns grow for security, privacy, and trust, it is not obvious how to adapt platforms to deliver the right amount, type, and quality of data wherever, whenever, and needed.

Data pipelines constitute platforms for transporting data from raw sources to consumable resources. As enterprise and societal systems grow more complex, propelled by millions of sensors or users continuously producing data, architecture for deploying data pipelines must evolve in many ways to avoid flooding cities, plants, or networks with information, and instead deliver the right amount, type, and quality of data wherever, whenever, and however needed. It remains a significant engineering challenge to deploy data pipelines to integrate artificial intelligence (AI) into decision-making, as enhanced individuals or systems continuously receive not only raw data or decisions but also AI knowledge in the form of trained models (a.k.a. bitstreams in published standards) and associated metadata (e.g. model architecture, features, uncertainty, etc.). This paper discusses the development of a system to deploy and configure data pipeline architecture, components, and configurations to integrate artificial intelligence (AI) into enterprise or societal systems while addressing a broad range of critical and challenging issues.

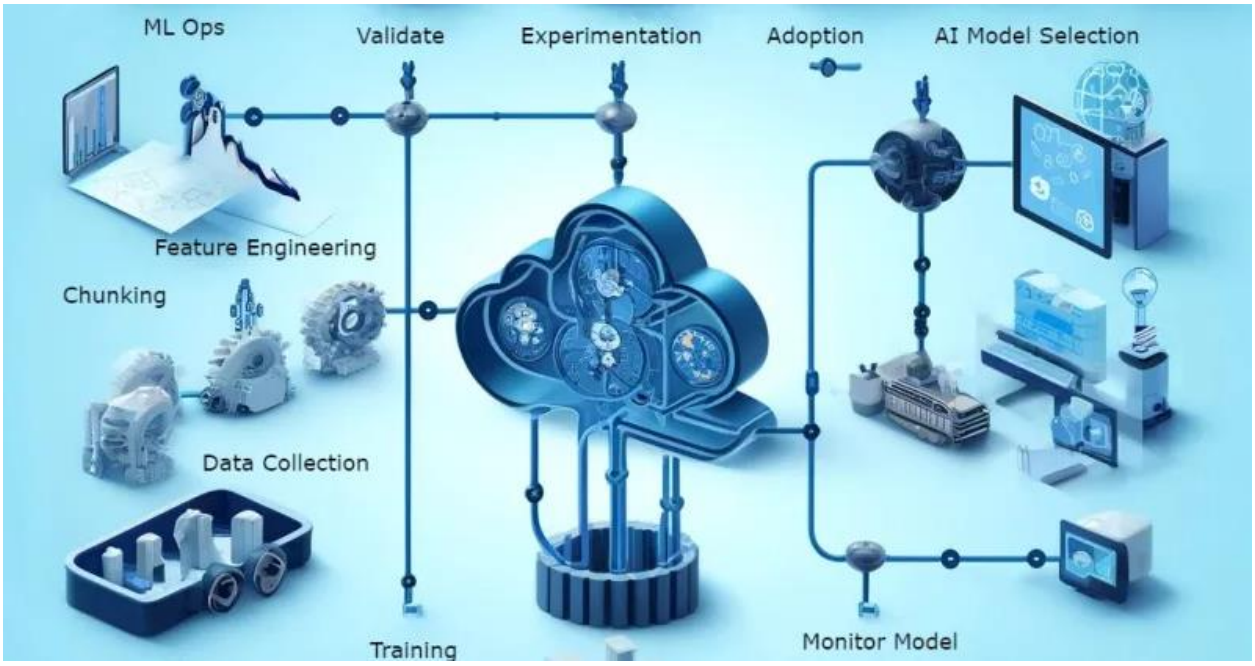

Fig 3.1: Data Pipeline Architecture

3.1.1. Background and Significance

Past inventions have greatly influenced modern culture; problems tended to be easily managed on a smaller scale, which could also use simple architectures and do-it-all systems. The following inventions pace the evolution of computers and data processing: 1910s-1940s – Mainframes were used in organizations where numbers prevailed. 1950s-1960s – Data processing units were created to automate organizational processes, avoiding manual data manipulation. The adoption of such units evidenced the difference and need for specialism among organizations. 1970s-1980s – Expansion, with the rise of stand-alone or micro-computers where tasks were done on a small scale, using individuals. The beginning of must-have emerged from the simplicity of the architecture, but costly system-oriented jobs tended to be avoided, prioritizing easy systems. 1990s-2000s – Autonomous and networked computing where several PCs could be linked, and data could flow across machines and locations. The use of peer-to-peer connections should share loadings in times of high contention on the network. 2000s-Present – Data farms, multiple computers in a single location, all working towards the same purpose (thin clients) where problems can be easily tackled by having several systems at their disposal. The development of web data mining, mobile appliances, and SaaS architectures paved the shift from installations on the machines to the architecture service within platforms hosted on the cloud. This novel architecture takes mid- to long-term implementation decisions on technology required finances to adapt to, or more likely to renew, a new system financially, in theory reducing cost. Nevertheless, the opposite phenomenon is occurring, where more money is spent considering that this architecture requires continuous service needing constant updates, thus relying necessarily on the product or service provider. Moreover, data availability, privacy, and security are farmed out from legal contract protection to the service provider where terms can change with no consideration for the user.

Data is a broad term but can be interpreted as facts, values, and terms that can be processed by someone or something. Data presently exists in a format interpretable by humans and machines. The growth of data has made it exponentially huge, which is why it is sometimes called big data. Big data exists in different forms – organized in tables, flat files, etc. – and unorganized (text, audio, video). Today, value is more important than currency – for example, the many free services provided by Google or Facebook in exchange for data about the users. Such platforms use big data analytics, which has three parts: storage, processing, and analytics of data using mathematical and statistical techniques and infrastructures. The required

architecture for big data analytics should support the storage and processing of different forms of data, particularly unorganized. It should be a distributed architecture with a cluster of systems, as a single system cannot manage data that grows exponentially. With the advent of AI, which is a subset of data analytics, the platforms should allow data to be stored on-premise or remotely, transferring them securely from the origin to the desired place. It is also important to ensure that the systems are easy to maintain and manage, data security needs to be ensured, and separate infrastructures should allow value addition and consideration of budget.

3.2. Foundations of Data Pipelines

For a full comprehension of how different architectural building blocks define the characteristics of a data pipeline, it is necessary to start with the basic definition. A data pipeline consists of nodes receiving input data streams, applying zero or more data transformations, and producing output data streams. Nodes are equal partners in this relationship, meaning that data structures cannot be assumed to be shared. Transformations performed on input data streams can be complex.

Data is ubiquitous, and every company uses or creates data to some extent. A more data-driven approach to building AI products usually leads to an increase in organizational effectiveness and thus to a competitive edge. From a technical point of view, there are several steps to take in the transformation from raw data to useful insights. There are components needed to implement these steps efficiently as code and to navigate coupling, versioning, and scoping issues. The design choices of these components lead to different architectures, each having trade-offs in terms of complexity, latency, and feedback effect on how data is generated.

Data works best when it is readily available. Timeliness is crucial but not the only important component of data strategy. For traditional business intelligence use cases, batch data pipelines to a data warehouse daily are often sufficient. However, for AI use cases these designs fall short, as they lack accuracy and structural integrity. Data can dry up, go stale, or abuse analytics with faulty events. As data sources become more complex, with repetitive and high-dimensional features, the correct reconstruction of data meaning and structure becomes paramount.

Data pipelines are integral to modern data operations and sufficiently complex to warrant considerate design and architectural strategies. These are the logical constructs that provide the edges and shaping of data architecture. They move, transform, and deliver data from the source to the end consumer. Data pipelines connect to observables, taking in raw data to

analyze or retrieve useful information in the case of events and networks such as monitoring alerting systems and social networks.

3.2.1. Definition and Components

There is a wide variety of data sources and target environments, which is why there is no single data pipeline architecture that fits all cases. However, some data pipeline components are commonly present. There are usually one or more components to extract data from source systems. The simplest case would be a scheduled SQL query against a database, but more complex situations require web scraping, REST API calls, or data collection from log files. There are often various systems acting as data sinks that consume the data produced by the upstream data processing steps. One of the most common is some kind of data lake or data warehouse for BI purposes, but data targeting other systems (for instance, a NoSQL database) is also common in many architectures. Data pipelines commonly also have a data processing component between the extraction and sinking of the data. A simple case would be copying the upstream data into files of a certain format, but more complex processing often includes cleaning up data and doing aggregations and computations.

A data pipeline is a set of data processing elements connected in series. The output of one data processing element is the input of the next element. A data pipeline may include any number of data processing elements, such as extract-transformation-load (ETL) processes, message queues, data processing, monitoring, and storage. There are many different platforms available today that allow for the creation and management of data pipelines. Most of these platforms include components for scheduling the pipelines (or parts of them), monitoring their state and performance metrics, and retrying failed executions. Data pipelines are sometimes also called data workflows, data flows, or data processing flows.

Organizations that are data-driven and AI-centric use data pipelines to connect various sources of data to target environments so that the data can be processed, monitored, and acted upon. A well-defined, implemented, and managed data pipeline ensures that the correct data is delivered on time, accurately, and with the correct transformations. This section will present the definition and components of data pipelines, which is the foundation for discussing cross-platform data pipelines later.

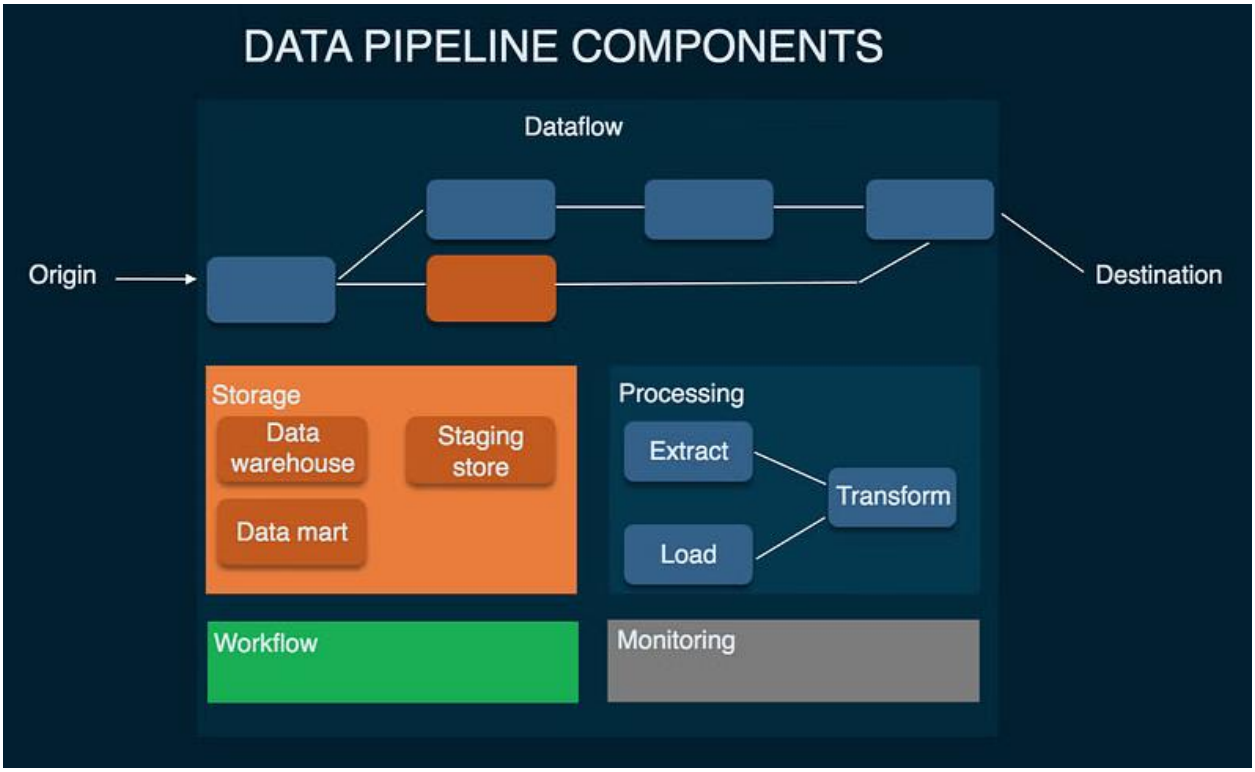

Fig 3.2: Data Pipeline Components

3.3. AI Integration in Data Pipelines

Several potential problems can arise in conjunction with AI-in-the-loop pipelines. AI system bias detection, bias mitigation, data drift handling, and model drift handling, just to name a few, are growing areas of research and development. The topic of accountability within AI systems in conjunction with questions of opacity, trust, and bias is an ongoing interest of the EU and the high-profile Ada Lovelace Institute in London. These opportunities and challenges offer interesting and novel research and innovation directions.

Integrating AI and ML into existing data pipelines is quite complex, but it is a feasible task. Opportunities and open challenges for data pipeline AI integration can be outlined by (1) proposing a broad classification of the techniques, methods, and technologies of AI and ML systems and their pipelines that already exist or are currently being developed, and (2) clustering the unique problems of data pipeline usage scenarios that arise in conjunction with this classification. AI and ML systems and their data pipelines can be organized based on their structure and complexity as follows: (1) Prototypical AI component with a minimal pipeline, (2) AI component with a minimal but reduced pipeline, (3) AI component integrated into a pipeline, and (4) AI-in-the-loop pipeline. Each of the above components and their data

pipelines can create unique situations that are to be addressed as AI and ML integration into the pipelines is implemented.

The advent of artificial intelligence (AI) and machine learning (ML) has triggered a new transformation in the field of data processing and use. AI and ML methods have become more pervasive in various sectors, including finance, healthcare, and education. Consequently, there is an increased interest in and a strong demand for the integration of AI and ML into existing data pipelines in organizations ranging from small, family-run businesses to large multinational corporations. AI and ML systems are generally fed by a source of data, a pipeline that processes the data into a consumable form for the system, and the system itself. Commonly identified data source types include structured or unstructured files and databases, log files, and APIs, to name a few. Depending on the type of data source, different processing may be needed as part of the pipeline.

3.3.1. Challenges and Opportunities

Yet there are also high-value or high-impact opportunities to be conquered. Automated AI integration on data pipelines can lead to higher indexable datasets, easier compliance with regulation, and easier design of high-frequency datasets (e.g. data-sharing partnerships). The two main avenues to tackle data quality are via data profiling/monitoring and data cleaning/enrichment. AI techniques can assist and automate both sides of this approach: a) monitoring pipelines, data profiling, finding patterns, etc.; and b) automatic data cleaning/enrichment through data augmentation, imputation, identification of expert policies, games, etc., each of which helps ranking/characterizing/enriching the dataset on the fly. Alternatively, a game-theoretic approach can be taken by building an AI model predicting the probabilities of meeting the a priori chosen quality metrics.

Pipelines also present challenges to AI model processing. For predictive, time-varying, or model-based products, the pipeline and the AI model are tightly coupled. In such cases, a change to either the pipeline or the model makes the other out of compliance. Data pipelines tend to evolve quickly, but AI models, especially ML models, tend to be static once put in production. This decoupling is paramount for modeling. Whether it is preventative, predictive, or adaptive modeling, there must be a mechanism for decoupling the pipeline from the model output. A modeling product can't be directly updated by the data product unless all downstream pipelines can adapt accordingly.

Data pipelines present a host of challenges to integrating AI. In terms of data, data pipelines typically aggregate data from disparate sensors or data sources. These data sources or even sensors may come and go, which means that there is workflow heterogeneity in the data pipelines. In addition, data pipelines typically provide real-time data processing, from streaming, batch, or micro-batch data. Streaming pipelines may involve AI model inference. Each type of data source imposes its requirements in terms of latency, reliability, throughput, etc. Every one of these aspects of heterogeneity makes building a reliable AI integration into the data pipeline difficult.

Data-driven artificial intelligence (AI) holds immense potential, from autonomous vehicles to smart cities. On the back end, data pipelines collect, prepare, and process data for AI model training, evaluation, and inference. Understanding how to architect data pipelines that are robust enough for the critical needs of AI but flexible enough to embrace the rapid pace of change in the world and technology is a challenge. Data pipelines create many challenges for AI integration; however, they also present opportunities in the form of high-value or high-impact data products. This document investigates both the challenges and opportunities.

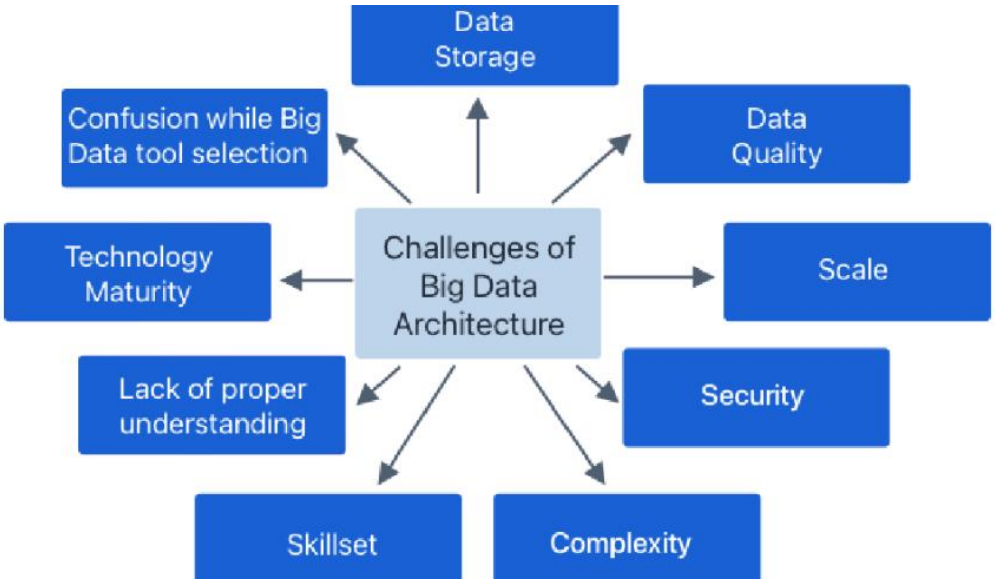

Fig 3.3: Big Data Architecture Challenges

3.4. Architectural Considerations

The cloud has cloud-managed offerings for each part in that flow, and in a simpler setup without or with just one model, they are an excellent choice with their pros and cons. However, for there to be multiple and replicable models with the same flow of very large amounts of data, there needs to be an in-house development that automates and standardizes as much as

possible. This results in the development of an architecture that visualizes that model-focused pipeline with its sub-components. The overall data pipeline design addresses the core components of a data pipeline for those new to the multi-model deployment on robust data pipelines with general industry practices that should further be adapted to company-dependent structures and requirements.

In consideration of whether to build an in-house solution on top of cloud-managed offerings or third-party providers, the model-focused approach should be taken. Any application needs to have the flow of data from its source (in the case of AI an initial raw dataset) to the model, followed by trained models on the data pipeline feeding incoming data back to the model.

First, it's important to know what the data pipeline is and why it's needed for an AI application. In an AI application, models are usually fed with data to be trained and validated, and further, incoming data is also fed for inference. This flow of data requires a scalable system platform, and the data pipeline is a solution for building such a flow of data in a coherent and replicable manner.

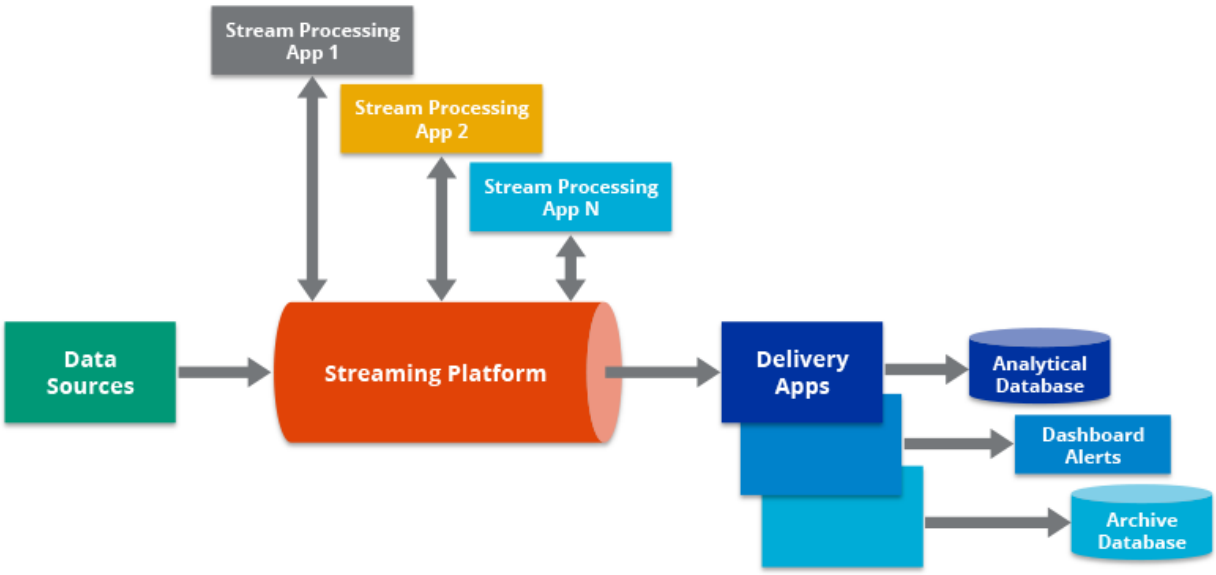

Fig 3.4: Data Pipeline Architecture Considerations

3.4.1. Scalability and Performance

Several measures can be discriminative measures or aggregate measures that seek to create an objective ratio of resource usage during performance tests to the highest level of resource usage during a performance test. It is always a good choice for initial system analysis to measure resource utilization (CPU, network, etc.). Testing pipelines process a certain amount of input and measure performance metrics while changing bottlenecks such as

increasing the number of processing nodes. This is usually done with a synthetic dataset to eliminate the time needed for ingestion, and the same data can be reused for later tests.

Input workloads can vary in number and frequency, time of day, or complexity. It is important to identify all possible input workloads and create tests that stress the architecture. Common performance considerations are throughput, latency, and system utilization. Performance is generally thought of in terms of how much can be processed in a given timeframe, but it is equally important to consider how quickly the first item can be processed. The impact that processing characteristics have on each of these can be difficult to predict.

As demand for AI integration grows, it is essential that data pipelines can scale to meet performance requirements. Scalability refers to the ability of a system to adjust and maintain performance when subjected to larger workloads. A horizontally scalable architecture can add additional machines or processing nodes to distribute the load. A more vertically scalable architecture would increase the processing power, memory, or storage capacity of particular machines. The traditional Relational Database Management System (RDBMS) is commonly cited as being vertically scalable but makes it difficult to keep up with the demand. Databases that are considered chemically scalable can add nodes to a cluster that is managed by shared storage. In a Physically Frontend Scalable architecture, multiple systems communicate through a standard interface.

3.5. Case Studies and Best Practices

A cloud-native reference architecture for building scalable and easily maintainable self-service data pipelines in SaaS business settings is presented. The architecture follows a microservices and event-driven approach for separating concerns regarding pipelines, their governance, and tools for monitoring and iterating. It includes standardized microservices available in different programming languages and storytellers for accounting pipelines into an existing service. Tools for governing governance, monitoring evaluations, and controlling costs are also incorporated. Use cases demonstrate how the architecture accommodates both simple and complex data pipelines, expected to scale with growing data volumes and expanding multi-pipeline scenarios.

A data pipeline architecture for automating real-time demand forecasting using cloud-based technologies is developed. AI algorithms based on statistical and ML techniques continuously analyze both internal and external data streams to derive future demand estimates for different horizons. A use case of a fashion retailer demonstrates the architecture that includes a

distributed data collector fetching data streams for internal, weather, and social media predictions. Enrichment of internal data using temporal join queries directly applied in the cloud warehouses is also developed. Monitor components allow the continuous supervision of quality aspects and the effectiveness of different algorithm versions.

A cloud-native data pipeline architecture for real-time data integration from multiple sources to a warehouse is described. It consists of a unified data collector that fetches data in bulk, styles and enriches it before sending it to a cloud service. The pipeline stores data in raw, styled, and enriched formats and makes it available for analytics, data mining, and data science. Out-of-the-box integration components are provided to connect clients using different technologies. Raw data is automatically journaled in the warehouse, making it adopt open architectures. A use case is presented where anonymized and aggregated data from a market research company is enriched with attributes of companies, countries, and standard classifiers. It uses PySpark and AWS components, but the architecture is cloud provider-independent. The processing logic can be described in pseudo-code and tailored by the user.

As organizations increasingly embrace AI-driven solutions, architects must design data pipelines that are not only flexible and scalable but also easy to integrate with new AI technologies. This section of the report provides a set of examples of data pipeline architectures that enable different forms of sophisticated AI integration, as well as some best practices that organizations should adhere to regardless of their industry or the complexity of their needs.

3.6. Conclusion

Programming coding models deal with diverse AI and machine learning modeling types. Batch training treats historically traditionally structured data and accumulates knowledge for future predictions while streaming unstructured real-time data and incrementally learning models on the fly to deal with static and shorter time intervals. The programming language of choice may determine the modeling algorithm design, as there are very few multi-language compatible algorithms. Pipelines consider and automatically decide which modeling technique to apply, depending on the input data structure and processing throughput, with care taken to anticipate the addition of new modeling options.

Fully operational data pipelines connect open data sources to a pre-built model through all necessary processing steps. Data cleaning and preprocessing, ensuring the data is ready for decision-supporting programming models and that data characteristics match the model

requirements, are performed. Feature engineering applies statistical functions to derive relevant information and creates fitted data structures for model compatibility from raw data sets. Instrumented continuous learning monitors pipeline functioning and operational models, alerting users about deviations and model comprehension, and developing new models if required.

Users typically only interact with easy-to-use interfaces and do not concern themselves with underlying data sources, storage systems, and decision-supporting programming models. This work focuses on architecting the design and creation of necessary data pipeline components and services, as well as assisting environments for easy operation and flexible architecture adjustment. Pre-built models and functions running in personal computers or cloud execution environments are one of the pipeline outputs. Headless implementation of coding models and algorithms, providing an easy-to-use RESTful API service interface, is also an output of the pipeline.

Machine learning and artificial intelligence applications are proliferating rapidly worldwide as organizations recognize their numerous business advantages. There is an increasing demand for the design and creation of easy-to-use data pipelines for integrating real-time, fully operational data systems into decisions supporting statistical models. Although there exist various open-source tools for developing machine learning and AI applications, development tools for data pipeline architecture for real-time data integration specifically are very limited.

3.6.1. Future Trends

Aside from "AI apps" progenitor pipelines, different pipeline architectures are also likely to be created independent of that technology stack. The interest in AI and the manifestation of semi-autonomous complex technology nodes can spawn this. Either one will command vast new data technology stacks with new complexities in data transport, management, and guarantees. AI (especially SemS) pipelines and implications for other existing pipeline architectures could be widely disruptive and reshaping. Given the data-centric approach towards agile, trustable, reliable, and robust enterprises operating in civil society, there is a mid to long-term strategic concern about exploring the implications of creating rational frameworks.

One aspect is the creation of a new breed of "AI apps" that can be likened to AI autonomous Turing test mimics. These "AI apps" will be CI/COE (complexity-intensive/community-owned enterprise) epoch technologies that cross the AI democratization chasm. Here, control

over the evolution of autonomous AI sub-programs will be largely retained at the enterprise level. The "AI apps" will also spawn new enterprises; some "AI apps" resembling full-blown businesses or sectors in the economy containing needed data pipelines for processing, serving, and archiving data leveraging mature computation and data technologies. For enterprises or sectors utilizing "AI apps", most of the pipeline architecture would be new progenitors relying on autonomous complex technology meshes. Sectors or enterprises not owning "AI apps" would have a less complex architecture, augmented by semi-autonomous application service "parts" interfacing with the enterprise layer.

The global AI revolution will spawn a new wave of innovative and disruptive technologies. Some of these new technology stacks have the potential to reshape how data pipelines are architected and engineered. While designing data pipelines that are not AI-centric, it is worth upfront consideration of how one may evolve these pipelines to future AI-centric architectures. Thinking about this forward architectural potential can better guide initial designs and streamline the assimilation of the new potentially disruptive technologies.

CHAPTER 4

ADVANCED-DATA PROCESSING TECHNIQUES: LEVERAGING AI FOR EFFICIENCY

4.1. Introduction

Several data processing techniques, including data cleansing, noise filtering, anonymization, and redundancy removal, have been developed to address the challenges and enhance the quality of existing data. Data cleansing techniques are intended to investigate the existing data, identify the anomalies, and correct them. This ensures the datasets are consistent, accurate, and trustworthy for conducting big data analytics. Noise filtering techniques improve the integrity of the collected data by detecting the noise during data collection and eliminating it before analysis. Such techniques reduce the chance of obtaining wrong conclusions in the analytics. Data semi-anonymization techniques are designed to address a specific type of anomaly termed data non-conformity, where different datasets may contain different values for the same parameters of an entity either because of fraud or data collection error.

Data processing, especially with the advent of big data analytics, has grown rapidly in organizations. Data processing entails obtaining data from different sources, applying computing techniques to extract useful information, and presenting the data in an appropriate format. Automated technology and online operations have enabled organizations to collect a database significantly and store the data for future analysis purposes. However, the advancement in data collection has also grown the challenges for effective data processing. Discrepancies in the databases and noise and redundancy in the data render it inefficient for extracting valuable information from the datasets. Consequently, the importance of techniques for the advanced processing of the collected data has also grown in recent years.In the era of big data analytics, effective data processing has become crucial for organizations striving to leverage their growing volumes of data. Data processing encompasses obtaining data from diverse sources, applying computational techniques to extract actionable insights, and presenting the information in a user-friendly format. As data collection has expanded, so have the challenges associated with it, including discrepancies, noise, and redundancy that can undermine the quality of data. To address these issues, several advanced techniques have been

developed. Data cleansing ensures that anomalies are identified and corrected to maintain dataset accuracy and reliability. Noise filtering techniques enhance data integrity by removing extraneous information that could skew analysis. Data semi-anonymization tackles inconsistencies across datasets, particularly those arising from fraud or errors. These methodologies collectively improve the efficacy of data processing, ensuring that organizations can extract valuable insights and make informed decisions despite the complexities of modern data environments.

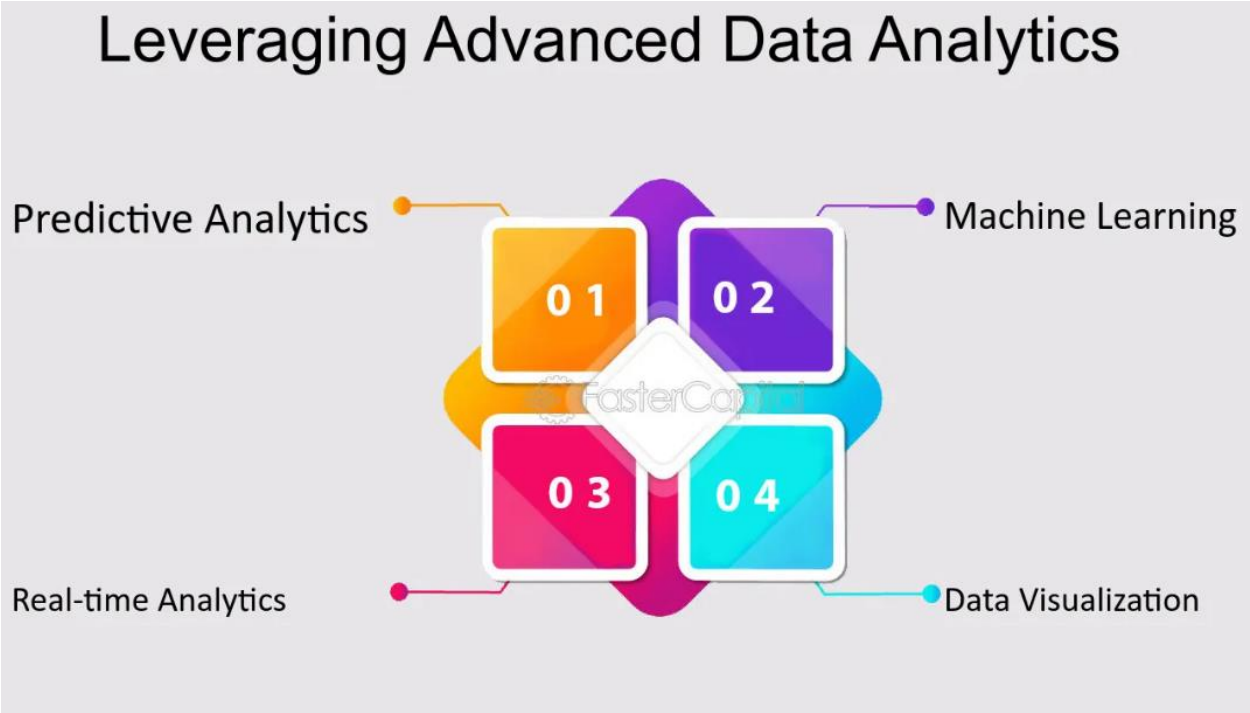

Fig 4.1: Leveraging Advanced Data Analytics

4.1.1. Background and Significance

As a general goal, this work focuses on the above-mentioned aspects of signal processing in the AI era. It explores how they can be orchestrated on established architectures such that every university lab in the world can advance such applications by themselves with minimal effort. Vascular microscopy is used as a showcase example. This setup originates from a previous study and routine data collection has been established. This facilitates rapid testing of new data processing technologies by performing the same data acquisition procedure for different setups and processing with different algorithms.

Studies have shown that strong data processing performance may be achieved by interpreting the acquired measurement data matrix as a multi-dimensional signal domain, potentially combining both world and measurement characteristics. In this interpretation, each dimension corresponds to an orthogonal signal direction, encompassing the use of several possible bases, like temporal, spatiotemporal, chirp, or temporal-frequency bases, and many others. Under this interpretation, the essential dimension extent of the data is drastically reduced which leads to a multi-fold gain in performance compared to traditional processing. A detailed explanation of this pre-processing technique is often provided along with a proof-of-principle demonstration. However, few attempts are made to reason about the practical side of it and Joint Processing Libraries are still lacking. Notably absent are basic libraries for commonly used measurement and sampling setups. In addition, libraries should support the straightforward implementation of an interface towards popular general-purpose AI machine learning frameworks able to operate in these dimensions. Beyond JPL, to demonstrate the full potential of statistics and AI, there is further room for improvement on the AI training side. Current AI training tests are often performed in a similar manner like for spectral imaging JPL - only processing in the world dimension with a standard 2D CNN architecture. There are interesting alternatives like data whitening, training at non-optimal conditions, orthogonalization of inputs, and merit functions that can take advantage of the full richness of the data.

In the modern era, a plethora of fields rely on massive amounts of diverse data that should be collected, processed, transmitted, and analyzed for each application. This requires advanced data processing algorithms that can onboard the fullest richness of data while respecting user privacy and minimizing designer workload. Even though data acquisition has become routine for most applications, the data processing part has often remained an intricate problem to solve. While there is a growing number of artificial intelligence (AI)-based solutions available that undeniably drive these past and recent data processing advances, the implementation remains overly cumbersome and outside the reach of most researchers and engineers. On top of it, there is still a strong discrepancy in what data is collected in the application and what can reasonably still be processed, besides the obvious differences in analysis efficiency. Moreover, most fields are struggling with a similar data processing bottleneck that lies at the heart of the accessibility issue: rigid data processing technologies based on adopted standardized data formats. This issue in combination with new advanced acquisition technologies results in an increasing pile of unused raw data which is undesirable for everyone.

The problem is therefore to advance the latest AI data processing technologies such that they will be easily applicable to basic data types collected by most of the recent advanced sensors.

4.2. Foundations of Data Processing

Speech data comes as audio signals captured by a microphone. Traditional processing pipelines involve first the conversion of the audio signals from the time domain to time-frequency representation. To do this, the audio is filtered through a series of bandpass filters, each generating a channel signal showing the energy at a specific frequency band. The outputs of these filters are textured matrices of time-frequency representations which are then subjected to several signal processing routines to compute the statistics of the signal at each pixel of the texturized representation over time. The statistics that are usually computed are the mean and variance of the bandpass signals corresponding to each pixel.

Data processing techniques are at the heart of data management and utilization as they enable the conversion of raw data into information that can be analyzed and utilized. This section considers some of the most widely utilized traditional data processing techniques that deal with different kinds of structured data.

Image data concerns the analysis of rasterized digital images, usually acquired from a monitor screen, a static digital camera, or a digital web camera. Digital images are in the form of 0s and 1s that precisely paint a picture on rectangular grids of pixels. Each pixel contains a set of values that correspond to the intensity of the colors in the Blue, Green, and Red (BGR) color space. The traditional processing pipelines take rasterized digital images as input, run the image through several classifiers, filters, or undoers that mimic image digital processing in human perception, and then estimate and extract the underlying information of the image in the form of tables of structured data.

Table data usually comes in the form of either Excel spreadsheets or HTML formatted tables from web pages. Excel data is simply converted and imported into DataFrames of Python libraries such as Pandas for further manipulation and cleaning. The traditional processing of web-page tables involves the application of a number of machine-learning algorithms to identify and extract the relationships between the rows, columns, headers, and cells to convert the HTML markup into a structured table representation. A set of heuristics is then coded to identify and extract text formatting classes embedded in the HTML to add text meta-information such as length, font size, font color, positioning on the page, and so on to the structured table representation.

Text data is another widely utilized form of structured data that often comes from the harvest of web information using web crawlers or site scrapers. Traditional processing techniques involve Natural Language Processing (NLP) algorithms to identify and extract the relationships between the words, phrases, or entities in a text to convert the unstructured data into tables of structured data. A set of NLP tools is also run to extract meta-information such as likely topic categories, sentiment scores, and some statistics such as textual length or even conversion to vector representations, and these are simultaneously added to the tables of structured data.

Data collected in paper form is one of the most basic forms. The traditional processing involves first the scanning of paper forms and the application of Optical Character Recognition (OCR) technologies to convert the scanned page images to digital machine-readable text. On the scanned page images, a set of machine learning algorithms is then run to identify the relationships between the text and the corresponding values on the scanned pages in order to structure the data.

4.2.1. Traditional Data Processing Techniques

Traditional data processing techniques can be categorized broadly into two categories: qualitative and quantitative data processing techniques. Qualitative data processing is the interpretation or explanation of the characteristics of the data for better understanding. Narrative description, narratives, ethnography, case studies, focus groups, interviews, group discussions, etc., are qualitative traditional data processing techniques. Quantitative data processing techniques use statistical values, inferences, or impacts to explain the characteristics. Percentages, ratios, averages, correlation coefficients, t-test, z-tests, analysis of variance, regression analysis, numerical methods, parametric tests, chi-square tests, frequency distribution, etc., are quantitative traditional data processing techniques.

Computers can perform simple data processing automatically in a matter of seconds on a global scale. The data processed automatically is often collected in a broader term called big data. Historical data processing, on the other hand, can be more complex. To extract the processed data value, data such as texts or characters have to be analyzed statistically, which takes considerable effort, often requires a specific skill set, and relies on knowledge of the subject itself. Furthermore, in the case of the nature of the analysis, it often relies on manual work, which can sometimes be relatively simple in scale but time-consuming, or mistake-

prone as well as difficult in reviewing afterward which can sometimes be relatively complex in scale.

Data is information that can be processed by a computer, which can be in the form of numbers or even characters, letters, and symbols. As a set, data itself has little value until it is processed or analyzed, which provides the data with meaning or value. Data processing is the conversion of raw data into a more useful form. Moreover, data processing can vary in scale and type too, which also depends on how complex the calculation is.

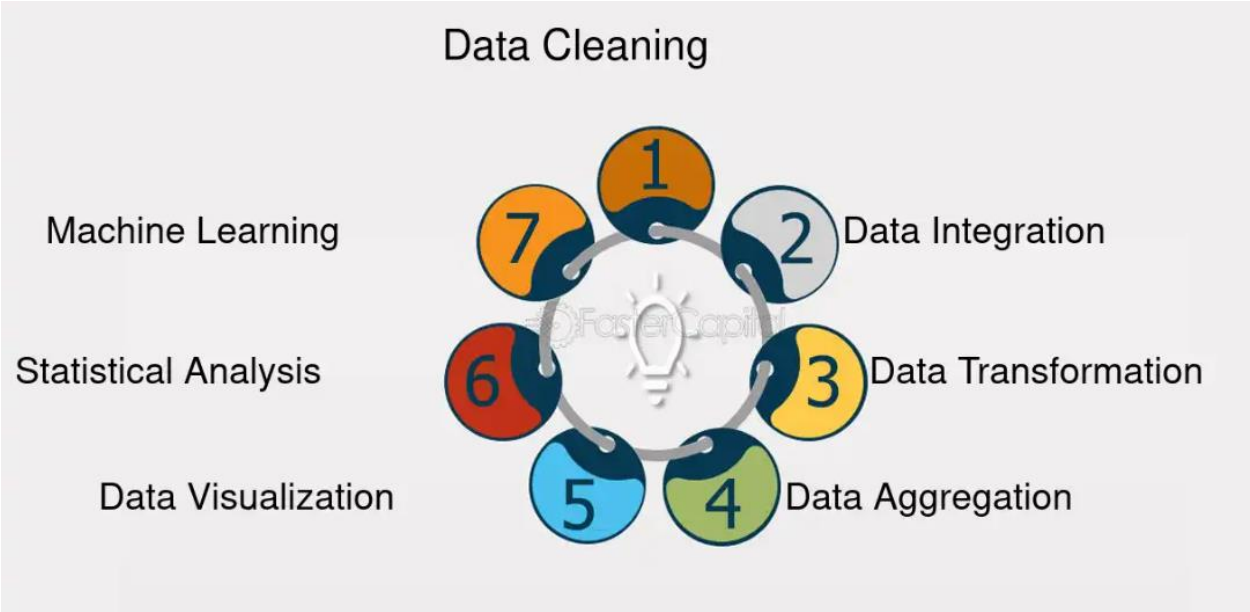

Fig 4.2: Traditional Data Processing Techniques

4.3. Artificial Intelligence in Data Processing

ML architectures can be classified as classical and deep learning (DL). Classical architectures include several algorithms such as decision trees, Bayesian networks, kernel methods, support vector machines (SVM), linear regression, and nearest neighbors. Classical architectures excel when there is domain knowledge about data allowing the implementation of engineered features. On the other hand, when there is ignorance about domain data, raw DHT data can be fed into deep network architectures that automatically extract data hierarchies. DL architectures are grouped as convolutional, recurrent, and deep belief networks. DL networks have emerged as champions against classical methodologies in processing DHT data such as images. However, the majority of current commercially and

academically implemented AI/ML networks provide classifiers for specific predefined classes and risk ignoring hidden and unpredicted data relationships.

ML methodologies can either be parametric or non-parametric. With parametric models, the relationship between the learning variables is characterized by a fixed set of parameters, regardless of the training data number. Typically, the number of parameters is much smaller than the number of data points. With non-parametric models, the relationship is better represented as a function or a likelihood assignment about a point in space. In this case, the number of parameters increases with larger data sets. Most neural and Gaussian processes are nonparametric models.

ML generates knowledge from data and consists of three approaches: supervised, semi-supervised, and unsupervised. In supervised ML, an explicit and fixed relationship is learned between input data and desired output based on examples of the input/output relationship. The learned relationship can be a mathematical equation, decision tree, or heuristic. In unsupervised ML, the structure of data is analyzed to cluster, analyze, and visualize complex data relationships. In semi-supervised ML, a small set of labeled data is combined with a large set of unlabeled data. Achieving feasible results with this approach is generally a challenge.

AI lies at the intersection of computer science, engineering, biology, and cognitive sciences and is divided into three categories: weak, strong, and super AI. Weak AI aims to mimic human behavior, still seeking understanding and capability. Strong AI aims to comprehend, predict, and replicate human capabilities and understanding to the fullest. Super AI exceeds human cognitive capacity and could either be extremely beneficial or dangerous.

Currently, high-dimensional, heterogeneous, and temporal (DHT) data types have gained increasing interest due to technological advancements in sensors, data storage, and communications. However, existing processing techniques have limitations with new DHT data types, creating a timely opportunity for AI/DHT research.

Artificial intelligence (AI) has emerged as a powerful tool for automating and improving data processing tasks. AI encompasses a wide range of computational techniques, but its most relevant subset for processing large and complex data is machine learning (ML). ML algorithms achieve superior performance in a specific task by automatically learning from and adapting to data without being explicitly programmed. The success of ML algorithms is mainly determined by their data, architecture, and algorithms.Machine learning (ML) architectures can be broadly categorized into classical and deep learning (DL) approaches, each with distinct strengths and applications. Classical ML methods, such as decision trees, Bayesian networks, and support vector machines, excel in scenarios where domain knowledge

allows for feature engineering and explicit model parameterization. These techniques perform well with well-understood datasets and manageable complexity. Conversely, deep learning architectures—comprising convolutional, recurrent, and deep belief networks—are designed to automatically extract hierarchical features from raw high-dimensional, heterogeneous, and temporal (DHT) data, such as images, often outperforming classical methods in these domains. However, DL models are typically suited for predefined classes and may overlook nuanced, unpredicted data relationships. ML methodologies further diversify into parametric and non-parametric models, with parametric models relying on fixed parameters and non-parametric models adapting their complexity to the size of the dataset. Additionally, ML approaches can be supervised, semi-supervised, or unsupervised, each offering different strategies for learning from data. The intersection of AI with fields like computer science and cognitive science gives rise to various AI types—weak AI mimics human behavior, strong AI aims to replicate human cognition, and super AI aspires to exceed human cognitive abilities. Despite the advancements in processing techniques, new DHT data types present challenges that highlight the need for continued AI research to enhance data processing capabilities and address emerging complexities.

Fig 4.3: AI Data Processing

4.3.1. Machine Learning Algorithms

Neural networks are mathematical functions composed of nodes and connections, attempting to resemble how biological brains process information. A commonly used neural network architecture for supervised tasks is a feed-forward multi-layer perceptron (MLP). MLPs consist of "layers", where each layer contains nodes. The first layer is the input layer, and the last layer is the output layer. Between those, there can be multiple hidden layers. Nodes in a layer are connected to nodes in the next layer. A simple MLP can have an input layer, an output layer, and one hidden layer.

Machine learning algorithms are at the forefront of AI technologies, pattern recognition, and data processing. In recent years, tremendous amounts of research, especially in the area of neural networks, have led to performance breakthroughs for diverse machine learning tasks. The state-of-the-art performance in many complex data processing tasks, particularly in natural language processing, computer vision, and information retrieval, is attained by deep learning models. These advanced models are neural networks featuring many layers, hence the term "deep". Although the term "deep learning" is ever-present, machine learning is still the more proper terminology. Nonetheless, this section primarily discusses neural networks, as they currently dominate AI technologies.

At the core of AI technologies reside machine learning algorithms, which utilize mathematics and/or statistics to achieve success on specific tasks without requiring a program in the conventional sense. These algorithms can be classified in diverse ways, but for data processing purposes, it is useful to group them as "supervised" and "unsupervised". Supervised algorithms learn a model based on a training dataset, which contains input data as well as the "answer" data. Unsupervised algorithms learn a model on the basis of unlabeled input data. For both categories, a model can be thought of as a mathematical function that outputs a prediction based on input data.

4.4. Advanced Techniques in AI-Driven Data Processing

Recurrent Neural Networks (RNN) are a type of artificial neural network intended for doing inference on sequential data. This type of architecture can be seen as a chain of repeating neural network modules where the output from each module is fed to the next module. However, RNNs are really complex architectures that are computationally prohibitive to work with. Although there are solutions to speed up training and make it feasible for large amounts

of data and levels of complexity, alternatives to RNNs that are more efficient architecture-wise, benefit from deep learning advancements, and are also better in performance, have also emerged. As an alternative to standard RNN architectures, Long Short-Term Memory (LSTM) is a more elaborated architecture designed for working with long-range dependencies.

Convolutional Neural Networks (CNN) are a type of deep learning architecture intended mainly to analyze synthetic data. CNNs significantly improve image analysis, achieving remarkable performance in image classification, recognition, or segmentation. The key idea behind CNNs is to abstract the complexity in tasks, enabling the algorithm to learn features of the data automatically, such as edges or shapes. CNNs consist of convolutional layers usually combined with pooling layers and activation functions, and at the end, the feature maps output are flattened and passed to a fully connected layer for classification tasks. Training CNNs is hardly possible without advanced computing infrastructures, as they have millions of learnable parameters. Therefore, training CNNs is usually done within large data centers and on powerful computing infrastructures.

Deep learning is a subset of AI, with algorithms inspired by the biological neural network of the human brain. Neural networks consist of multiple layers that transform input into output, with the hidden layers of the networks used to automatically extract features from the input and enable more complex learning. Deep learning is a powerful tool that has achieved impressive performances, such as often surpassing human performance in image and speech recognition tasks, beating the champion of Go in 2016, or translating texts with comparable quality to that of professional translators. Its success is attributed to having a large amount of data and using powerful computing infrastructures with multiple graphics processing units, in addition to advances in AI models and architectures.

4.4.1. Deep Learning

MLP's capacity to explore the input space (data) relies on training, to which the whole N-dimensional space polynomial function is generated. Generating a polynomial function requires controlling its complexity. A weight parameters configuration defines complexity. Close neighborhood polynomials maintain relations; they preserve "morphisms." For instance, the polynomial function maintains linear increase, speed, and direction in physics. This type of polynomial is regarded as linear. Weight parameters are edges between neurons from different layers. The identification of each edge or neuron from each layer relies on an ID that binds the components.

Deep learning is a subset of ML that uses neural networks (NN) to learn from available data, such as training or historical data. NNs are data-driven mathematical models that build relations between input and output data by mimicking the functioning of the human brain. Data representation mimics how the human brain represents the outside world, including sight, sound, touch, and smell. It is a vector space representation with scalar coordinates, which identifies a relation between a point in a multi-dimensional space and a concept in the outside world. DL models are similar to representation but represent a scalar output instead of a vector quantity. They are essentially MLPs whose talents are exploring the relation of points within a multi-dimensional space to a scalar value, such as intensity or likelihood. MLP is a non-linear prediction algorithm that traverses the N-dimensional input space and predicts the corresponding scalar in one-dimensional space output.

Artificial intelligence (AI) and machine learning (ML) have bridged the historical divide that separated programming and data modeling on one side, and statistical inference on the other. A frequently used ML technique is deep learning (DL), which is the focus of this section. Multi-layer perceptions (MLP) is a DL architecture that suits many data types, including tabular data, best. MLP has been successfully applied in many areas, including language models (LLMs) and AI art generators. Nonetheless, it requires data preprocessing to ensure adequate representation, which includes vector transformation (VT) and data formatting (DF).

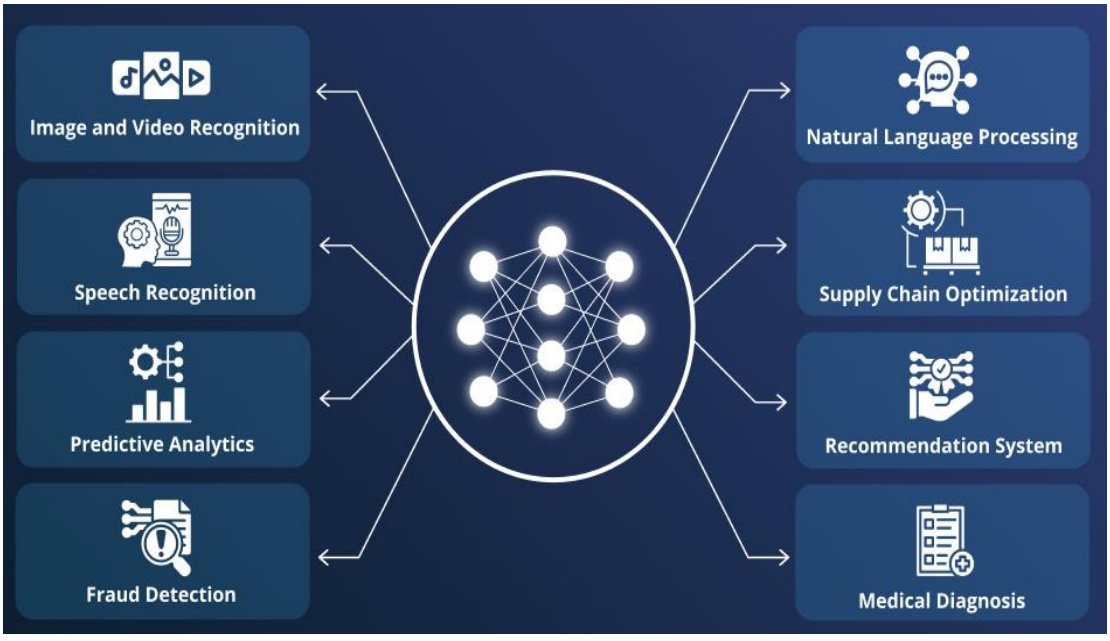

Fig 4.4: Deep learning

4.5. Applications and Case Studies

Data generation in modern scientific experiments is currently limited. The experiment's physical domain is sampled with relatively few points, and the challenge is to extract as much information from that integral as possible. This problem is compounded in many applications by the need for reconstruction to occur in near real-time or, in some cases, even in real-time. Here, a full description of the fusion imaging and data processing challenge is presented, which has been identified as an important application for modern scientific experiments.

Here, the current state of development of AI for data processing in important applications including astronomy, particle and nuclear physics, and fusion is reviewed. The different niches that various AI paradigms currently occupy in the current toolset for data processing are described. Important dimensional issues for future development in AI will also be discussed, as they pertain to the light of promising future directions for development after the current basic toolsets are established and widely used. Throughout this review, a case study is presented illustrating the use of ML tools for the processing of datasets produced by experiments studying inertial confinement fusion imaging.

The ability to harness the power of massive amounts of data efficiently has long been an elusive goal for scientists and engineers. Recent developments in artificial intelligence (AI) and machine learning (ML) tools, along with massive increases in speed and storage capacity, have the potential to corner a niche in the market of advanced data processing technologies. These tools promise to change not only how one approaches complex systems but also how one envisions those systems themselves. There are a number of different applications of machine learning, deep learning, and other AI technologies to data processing for scientific datasets.

4.5.1. Industry Applications

Sub-optimal day-ahead production scheduling heuristics, hybrid gap-optimized mathematical models, traffic segmentation methodology focused on specific needs and transport infrastructure, traffic congestion prediction methods, and a field experiment on intelligent traffic light control in road transportation are all presented works. Highlighted applications include advanced models and methods operating on the data of the urban transport system, mobility patterns monitoring, sharing economy research, data-driven methodologies designed for enhancing sustainable urban transport systems, and applications in safety-critical domains with a focus on smart devices for public transport.

Selected applications of ground-based interferometric systems exhibit advantages in a quotidian level application, compactness, and low vulnerability to adverse atmospheric conditions. The applications of high-resolution thermographic investigation of the electromechanical transducer of piezoelectric wire transformers experiments significantly exceed the resolution of the method used in the previous studies.

In clinical brain imaging research and practice, a hybrid AI-based knowledge discovery framework is presented for the detection and prediction of Alcohol Use Disorder. Proposals for involving AI in Earth observation processing systems within the Copernicus program focus on non-linear biomechanical prediction of the human knee joint in various settings—from normal gait to learning tasks in accelerating conditions. The impact of artificial intelligence and the hypotheses of AI implementations in environmental modeling development of space systems are analyzed.

Optimizing the operation of a wind farm is a common strategy for maximizing productivity and identifying underperforming wind turbines. For tendering for transport route calculations in maritime transport, developing a program and its database is advised to increase the degree of automation and to facilitate the draft of competition proposals. For greater improvement and functionality in the models of calibrating the cycle of marine engines running on natural gas, a comparable intelligent hybrid model of ANFIS–PLS is suggested that combines the advantages of the adaptive neuro-fuzzy inference system and partial least squares regression.

The incorporation of artificial intelligence (AI) technologies is transforming various industries. The way organizations approach and utilize data is essential for creating and maximizing their value in planning, processing, and generating new knowledge. AI technologies are integrated with the latest data management and programming technologies to facilitate the design and implementation of intelligent systems. Efficient use of human resources, limiting qualification levels, and need-based retraining are some of the objectives of utilizing AI systems.

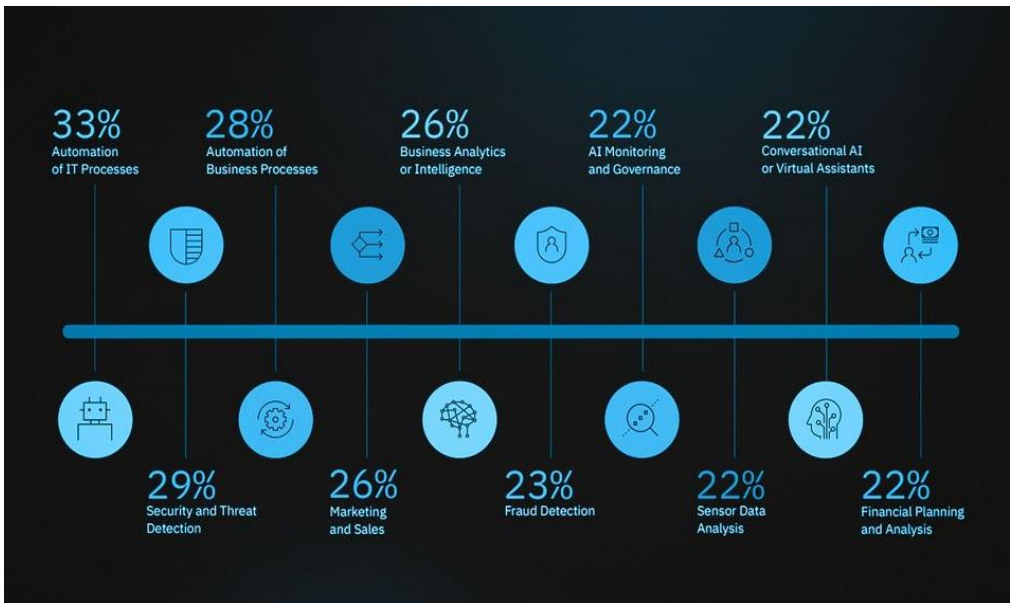

Fig 4.5: AI Cases in Major Industries

4.6. Challenges and Future Directions

As AI-driven data processing techniques are applied, understood, and improved, there will be a reciprocal adaptive relation between the goal-oriented use of these AI techniques to process data and the increased understanding of the data processing needs and intentions of their human users. Here, curiosity as a motive for data acquisition, selection, analysis, and modeling is generally absent with AI techniques, preventing insight into the crossover interaction between politics/finances/influence and science/truth.

With the enormous data produced worldwide every day, organizations face the first challenge of storage space and speed of access and retrieval. In this regard, significant progress has been achieved, notably associated with the introduction of bio- and nano-technologies. Nonetheless, efficiency and speed in efficiently accessing comparable, relevant, and meaningful data in the context of set goals still need to be regularly addressed. Retrieval and matching techniques for networks, such as words, texts, or protein structures, work best when processing one-at-a-time requests. Global and interactive data selection to identify and specify sets of comparable data to stimulate insights and new hypotheses is generally still rudimentary.

The gap between AI and human goals presents challenges for data selection, data curation, and modeling techniques. AI methods generally create an intermediate record of processing that is incompatible with different data domains, AI systems, and organizations. Meaningful and usable sets of preselected data for a specific goal depend on curiosity and creativity. Goal-

oriented data curation to extract interactive data types for scientific hypotheses and modeling is not mature yet. Also, learned models typically work for a specific dataset and domain. This tech-centered approach ignores other essential processing aspects and does not account for their consequences (e.g., on processing outcomes). Finally, the AI operational domain differs from most human users regarding complexity, variety, and uncertainty. Unclear or conflicting goals and diverse timelines and world views complicate transparent and trusting communication and cause mismatches with data form and content.

Despite the remarkable progress made in leveraging AI for data processing, various challenges remain. As organizations increasingly adopt advanced AI-driven data processing techniques, addressing these challenges ultimately improves data processing efficiency and satisfaction.

Fig 4.6: Challenges and Benefits of AI

4.6.1. Ethical Considerations in AI-Driven Data Processing

Furthermore, to combat bias, data exclusion for sensitive stakeholder group attributes must be considered, impacting algorithm robustness. However, simply excluding bias-inducing parameters is also problematic, as historical data trained by conscious or

subconscious bias cannot simply be ignored. There are also suggestions for pre-processing data or dynamically adapting AI processing outcomes. It may be appropriate to distinguish between intentional bias by algorithms that are applied with conscious knowledge of their negative impacts and unintentional bias stemming from ignorance or a lack of enablers for alternative models. The prohibitively high costs of algorithmic risk mitigation, such as in the training stage of algorithms, must also be taken into account.

Regarding accountability, questions arise regarding who is responsible for creating and applying algorithms. In the context of audit technology, decisions must be made on a case-by-case basis, depending on the complexity of the algorithm, materials used for its training, and extent of automation. Transparency in terms of algorithm explainability is closely related to accountability. For complex, unexplainable algorithms, holders of accountability may become unknown or non-identified. In turn, audits may become challenging, as there is no clear person or organization to hold accountable for algorithmic firm-wide or individual decision-making.

Bias is one of the main aspects of fairness and can be categorized as pre-, in-, and post-processing bias types. Audit planning is prone to pre-processing bias if the acquirable dataset depends on biases in occurred transactions. Bias in mathematical representation, such as the disapproval of some transactions based solely on their type or associated stakeholders, may lead to in-processing bias. Finally, post-processing bias exists if the outcomes of data processing techniques, e.g., AI algorithms, disproportionately impact certain stakeholder groups.

The rapid advancement of AI technologies for data processing has led to significant changes in audit technology—enabling the analysis of complex, unstructured datasets with minimal manual input while enhancing efficiency. However, various ethical dilemmas must be addressed, which can be grouped into fairness, accountability, and transparency (FAT). Since these challenges arise in a business context, it is important to understand the principles of FAT and how they relate to the internal audit function of an organization.

4.7. Conclusion

There is a need to overcome time-consuming, cumbersome semantic search methods encapsulated within existing tools. Existing tools operate under a mathematical model (Boolean model): all searched data is in the radical state and intended requests are generated by presenting keywords. Computer programs cannot understand the context interpretation of terms used in requests. Analyzing styles of word usage in textual storage and categorizing

whole documents in databases' potentially powerful descriptive possibilities offers both academic institutions and industries.

As a result, it becomes possible to ask traditional queries such as "In whose computer was created document X?" or use powerful tools designed for standard data (such as the well-known whole-document vectorization approaches VSM and LDA) on files. By knowing key terms, it is also possible to find the files that contain them. Large collections of data that are not easily stored in star-like arrangements with strict relationships can be indexed into graphs containing related terms; this makes it easy to find sets of documents likely to contain user-initiated queries. As indicated by Google's success, it is also attractive to objects in a solely textual storage approach on the web. Pages not adequately linked to create related groups sink deep into databases of information.

Machine learning's use of data modeling techniques for classification and prediction has inspired potential applications for data analysis. And growing acceptance of machine learning for data processing makes it attractive for users of these tools. Potential uses for advanced statistics and ranking algorithms include search engines, document categorization, social network analysis, fraud detection, and patient care. Metadata processing is applicable to any large collection of files, such as Word documents and spreadsheets, and includes low-cost bibliographic databases that don't require complex installations. Organizations relying on files store metadata such as file types and sizes and the authors and dates of creation through MS Office products. Processing large data in this manner creates vectors of representative properties (which consume hard disk space) for use with regular data processing methods. Processing a collection with existing tools creates candidate vectors for nearly each file.

The methodologies and techniques detailed in this report assist individuals and organizations in proactively becoming more organized, reaching their goals more efficiently, and ultimately gaining competitive advantages in their respective fields. Businesses, groups, and personal lives rely on effective data management. The audio processing techniques detailed in the previous sections deliver efficient management solutions that will be great assets on engagements focused on discovering new knowledge and insight from challenging research problems of large data collections.

4.7.1. Future Trends

At the end of the road, AI will become a necessity for the survival of organizations of most field types. AI is expected to design more efficient tools for life quality enhancements,

biological risk control, and environmental improvement. However, accessible AI systems may also lead to life-threatening changes in the world. The power of controlling a creation that outgrows human intellect may lead to unmanageable situations. It is impossible to estimate what kind of system will emerge at the end of the road.

Additionally, new programming languages will be made available to build AI systems with a more user-friendly aspect. This would allow the training of new AI systems without a large amount of data. As the availability and access to AI systems will increase, generative AI will be employed in more areas as a research assistant. These aspects of development may pave the way for unexpected and challenging situations in educational systems, job sectors, and ethical aspects of life. A minimum of basic knowledge regarding artificial intelligence will probably be needed for adulthood as AI will be integrated into more fields of life. The ease of using generative AI may close the creativity, analytical, and problem-solving skill development gap for trailing children. Therefore, educational systems are expected to adopt the use of generative AI for developing and monitoring systems in the early stage of childhood development. The consequences of challenges caused by generative AI on a scholar level are impossible to estimate, but they will change the system as entirely being generative AI adjusted.

The ongoing advancement in data-processing technologies and the growing reliance on AI for educational purposes will continue to have a substantial impact on data-processing methods utilized in various fields. Throughout the day, massive amounts of data are produced using smart devices such as smartphones and laptops. Statistics demonstrate that on average, each person in the world generates approximately 1.9 MB of data each second. The continuous generation of data indicates the potential for AI systems to exploit big data. Technologies employed in AI-based systems are expected to evolve to accommodate larger volumes of data, which include evolving technological hardware and software. The number of electronic devices linking the world increases daily. Online maps become more detailed, and their functions become more varied. All these innovations require more effective methods of processing data generated from smart devices. AI is expected to be employed to provide the necessary speed to analyze data by being integrated into sensors instead of utilizing the cloud.

CHAPTER 5

REAL-TIME DATA ANALYTICS: AI STRATEGIES FOR INSTANT INSIGHTS

5.1. Introduction

The design and implementation of a real-time data analytics capability involves novel AI technologies, challenging technical choices, major architectural evolutions, and the entailing restructuring of operational processes to allow for a quick response to data in motion. All, in an endeavor to transform compressed or aggregated event strings into comprehensible and structured instant insights that may be channeled to specific target audiences across the organization. The set of core and advanced functionalities that a technological platform should provide to build a real-time data analytics capability in an organization are analyzed. The proposal of a possible architectural framework, integrating these functionalities into a coherent workflow, allows for a quick characterization of the various technological challenges with which practitioners are faced when designing such capabilities using off-the-shelf technology. An industrial case study illustrating the cross-industry applicability of the proposed architecture and raising several anecdotal insights and lessons learned from the design and implementation of the architecture in the Telco industry and E-Commerce domains follows. The exploration of the evolutionary path from a business perspective brings unique insights into how to deal with the cultural resistance to embracing such technologically driven operational evolutions.

The goal of building a sustainable advantage lies not just in the sheer processing of large streams of data in real-time, but rather in the effective harvesting and contextualization of instant insights outlining events that matter the most to the organization at that particular point in time. Such instant insights may feed knowledge bases, databases, or repositories that allow for the storing of events and the profiling and understanding of an organization's state of operation. Afterward, offline historical analytics may give understanding and context about what went right, wrong, or could be advantageous in the future, allowing decisions to be taken, and corrective measures or further actions undertaken to capitalize on opportunities. Instant insights may also trigger immediate actions, alerts, and notifications against certain detected

events, allowing proactive measures to prevent incidents from escalating. Proactively identifying problems before they cause operational outages and automatically reducing recovery periods against incidents or malicious events are examples of immediate actions that can minimize the impact of events on business operations.

In the age of data proliferation, the ability to extract actionable intelligence - in real-time - from a throng of digital bytes is fast becoming the coin of the realm. No less than a strategic advantage that is now imperative for any organization hoping to thrive amid unrelenting competitive pressures, the emergence of a real-time data analytics capability is proving indispensable for organizations of all sizes. Real-time data analytics allows organizations to harvest valuable insights - immediately after an event has occurred - that are instrumental in improving operations and decision-making. Thanks to radically advancing cloud computing, mobile devices, and the Internet of Things, acquiring data in real-time - from sensors, social media, and user-generated content that embeds invaluable information - has never been easier. Though the volume of data generated is colossal, an analyst or a manager can ascertain instant insights into the state of operation - good or bad - provided the right technology and analytics tools are installed to pinpoint any outlier. By contrast, if the data cannot be promptly processed, alerted, and acted upon, it may lose its value and significance.

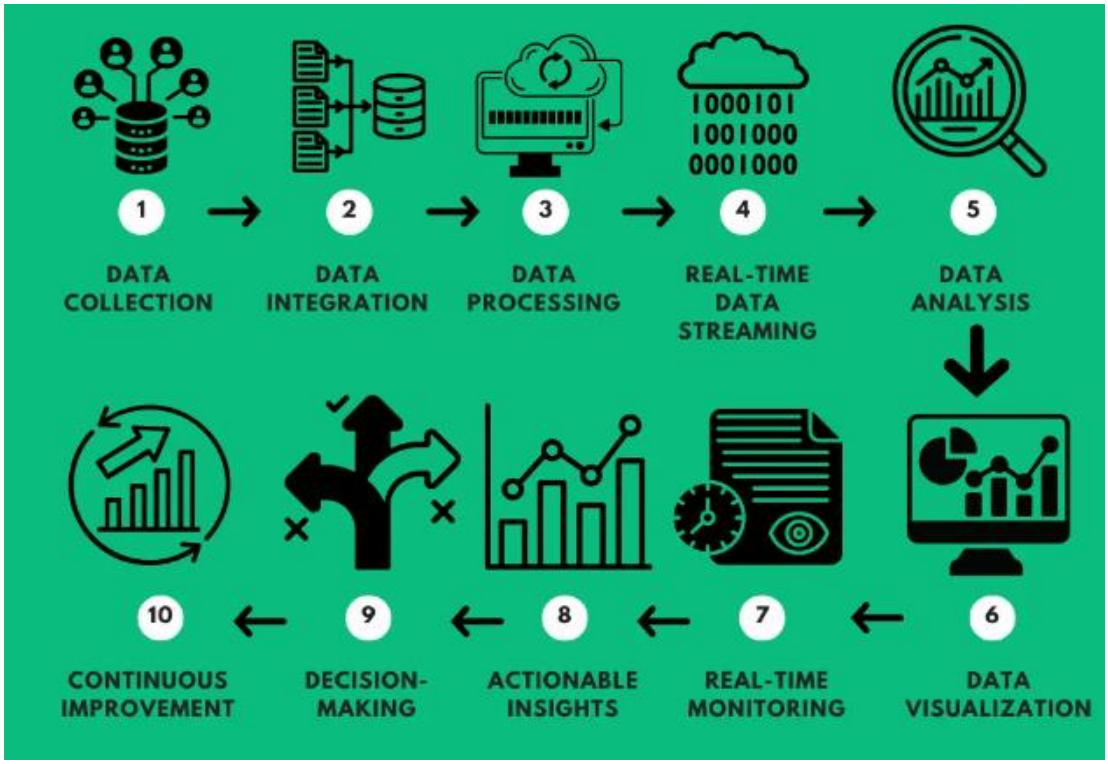

Fig 5.1:Real-time Data Analytics

5.1.1. Background and Significance

The primary goal of this project is to explore the feasibility of a novel analysis technique for the classification of streaming data. It proposes to study the behavior and performance of the analysis technique and accompanying models based on batch learning. There are two parallel lines of research: One focuses on a solid mathematical foundation of the analysis technique, which is at the extension level; the other line focuses on a more practical target at the application level, consisting of the adaptation of target objects and the analysis technique itself. Possible target objects include types of data streams and types of applications.

Stream data analytics also goes back to the 1990s. Faced with the explosion of the Internet, there was an influx of data traveling through the network, simulating a stream. Since then, many approaches and techniques have been proposed and developed to cope with this type of data. Nevertheless, real-time analysis of data streams in a streaming manner has yet to attract significant attention from the industrial point of view until recent years. Emerging companies currently explore the need and feasibility of solutions that can process a large amount of log and transaction data in a streaming way. Nonetheless, there are few scalable yet effective solutions reachable so far.

At present, the most popular solution is to analyze the data in a stream way where the data is read in the order they arrive. In-stream data analysis, queries typically look for interesting patterns, and occurrences of these queries determine the outcome of the system. On the one hand, the arrival of new data should trigger a re-evaluation of the relevant OLAP queries; this has to be performed as early as possible, on an incremental basis, without resorting to their complete re-evaluation. On the other hand, if the structural characteristics of the data change over time, then the pre-defined OLAP queries may no longer be relevant, and new queries need to be derived from the ongoing data analysis. Finding such queries has to be done periodically. The stream data and the data arriving over some time have to be filtered, and these filtered data have to be analyzed over time.

Real-time data analytics refers to immediate or fast analysis of data so that the results of the analysis can be sent back to the system without any delay. Because a brisk response time leads to quick data information, real-time data analytics is critical for decision-making in a rapidly changing environment. With the ever-increasing data generation rate, many organizations in various fields need to rely on real-time data analysis. For example, online retailers, stock trading companies, social sites, and event monitoring applications all need to provide data analysis in a real-time manner.

5.2. Foundations of Real-Time Data Analytics

In realizing real-time streaming analysis, most commercial vendors have opted for the general architecture of consensus-based approaches to distributed message processing systems (e.g., Apache Kafka and Apache Storm), reminiscent of the various multicore GPU-accelerated software stacks developed more than a decade ago for intensively parallel data processing over fixed datasets. Following this generalized architecture for every data handling and processing system, output tuples produced by the execution of queries over raw input streams, as well as tuples that expire from querying windows, are routed via message queues. This incrementality precisely preserves the fundamental semantics that window sizes do not change. The incrementality of the query plans executed over added tuples is frequently given in terms of delta relations, capturing all output tuples produced on behalf of the added tuples on the streams. Efficient organizations of the incremental query plans have been reported, analyzing the challenges of real-time streaming analytics at each of the three steps above.

1. Iterate over all streams. 2. For each stream, dequeue adds tuples and for every such tuple, executes the body of all affected streaming queries. 3. Execute the "expire" operation of every affected window-based query in parallel.

Simply put, and irrespective of the actual implementation of the stream processing engine, intensification executes some variant of the same processing loop:

Real-time analysis is typically performed over streaming queries, i.e., expressions defining sliding windows over time-varying relations, similar to decades-old data flow query languages such as SQL and QL1. However, unlike traditional fixed-data queries evaluated monotonically by deductive engines until no more tuples remain, windowed queries over streams are intensified by incremental/pointer-chase engines that continuously retrieve tuples added to the streams, and expire tuples from the windows as new tuples are added.

The goal of real-time data analytics is to capture raw data streams as they are generated, and promptly identify and react to events of interest. In contrast, offline analytics typically begins a while after the data is captured. Raw continuously leaking streams from sensors, cameras, machines, social networks, and other devices must run through several pre-processing steps, and the data itself is increasingly stored at multiple locations on an enterprise-level data lake before being analyzed by complex procedures that take hours if not days. Consequently, offline insights, while often precise and complete, are routinely outdated by the time they are reported.

Data, both structured and unstructured, move around a vast network every day at remarkably fast rates. The Internet of Things (IoT) devices generate real-time information streams. Within enterprises, increasingly more processes and platforms continuously produce raw data such as video feeds from CCTV cameras, production telemetry data from various industrial gear, streamed social media posts on business-related hashtags, logs from cloud VM instances, and more. Firms are gradually (or rapidly) recognizing that this content is incomparably more valuable than their existing databases. Hence, more and more attempts are made to analyze this data in real-time.

5.2.1. Definition and Importance

Full privacy and security also make security issues a much-talked-about topic. To what extent can a deep knowledge about potential customers, events, habits, etc. be generated? Accumulating as much data as possible from different sources and types requires strong policy and legislation support. All these issues stimulate researchers and engineers to investigate novel paradigms, architectures, and systems to transform the data acquisition and analysis task, with very different programming structures.

The amount of data that has to be dealt with is touching the zettabyte scale. Besides the velocity, the data can be of different types, such as textual information, video streams, or autonomous data outputs from a network of sensors. Many potential applications embrace the idea of capturing and processing what a user sees with smart glasses or a smartphone. Although on-device offloading is possible, it is complicated to feed the cloud so services can be provided. Edge processing plays an important role in resource alignment and objective tasks, like face recognition or optical character recognition of street name indications. However, a policy of data refusal is foreseen where only stripped features that do not individuate a person or an event are sent to the cloud. In general, companies do have worries about personal information and privacy. Moreover, the network is not guaranteed to be omnipresent and free, hence processing needs to be offloaded on a network of CSP or CDNs. The speed of data is indeed the dominant property. Companies striving for competitive advantage within a fast-moving market or communication service providers gathering information about millions of users' emotions and habits in movies or chats need sophisticated analysis and visualization algorithms to obtain insights in the blink of an eye. Real-time big

data analysis is a challenging area that needs novel architectures, systems, techniques, and algorithms to cope with the engineering demands of moderate latency and high throughput.
Real-time data analytics is concerned with the collection, processing, analysis, and visualization of incoming data and information. The goal is to present conclusions instantly. The request for immediate information has risen in different areas of life. Information-driven contexts, such as decision-making or fault-finding mechanisms, put high demands on speed and reliability. Such information has to be captured, processed, and presented in a split second to derive insights and act accordingly.

5.2.2. Challenges and Opportunities

In the presently noticed imperial of smart embedded reserves of tolerably honest utilization introduced mass market appliances, wireless data streams on a high stake of mesh domains coalesce - ranging from acoustical to optical gravity employed in ubiquitous identification and feeling, particularly Internet-of-Things occurring appliances as well as security and healthcare merged services. Another chance stems from social net monitoring, for instance, web monitoring web logs scrutinized, garnered, completed on streaming, and dealt with real-time.
Glazed by instant data, the inventions devised may turn to the noise of the uncountable upstream events and worries dripping by the cost of allocating real-time inventions to different occasions. These contrasting challenges inevitably coalesce under different trends of market witnesses and through skeptical advances in enormity and phase of excavating the technology confronted with the blast of exponential development in its context and ampleness. The gradual global fad of mesh domains characterizes both spaces of the continuing augmentations of data and the consciousnesses of pulverizing and on-streaming beforehand un-accessed features. Specifically, for an entire data field, on-request magnetic suitability turned accessible in the setting of new device categories to passively sense an array of environments in the embraced mesh domain of expanded conduction or through similar recognition appliances like particles, phase grasps, or imaging nets.
Preparing real-time analytics is a gargantuan work comprising the investigating request for streamed data – exploring present and increasing opportunities of pursuing the data which do persist – in a business style – a density which is often cryptic, continuing overnight, instantaneously worldwide. For certain inquiries and report occurrences, such as detecting an ongoing earthquake or a financially weakening trader, the accepted anticipation of studying

the streamed data and issuing significant alarms precedes the reality density; the emphasis of the exploration becomes bold and vice versa.

Real-time data analytics, often perceived as an advantageous technique to refine and augment data streams, poses a considerable exploration task, one not dissimilar from real-time data monitoring. The continual influx of a growing array of streamed data – including audio, video, temperature, traffic, and other sensor data, social network posts, and stock market updates – mandates determining whether the data is genuinely valued. Nevertheless, streamed data can degenerate, provably coalesce into irrelevant facts, be of no interest to the observant, or simply be an expensive plume of noise. From a business stance, drawing immediate inferences from processed data, their non-utility – cohesive challenges of relevance and importance – demands devising intuitive, interactive systems capable of evaluating the efficacy of myriad streamed data.

Fig 5.2: Challenges and Solutions in Real-time Analytics

5.3. Artificial Intelligence in Real-Time Data Analytics

In the first part, machine learning algorithms for real-time insights are overviewed. This includes the most commonly applied ML methods, types of learned models, used sample selection, and predictive properties of the commonly used ML design methodologies. The second part focuses on deep learning techniques for real-time analysis, specifically spiking neural networks (SNNs). These are the most biologically plausible models of neural computation that intrinsically work with temporal data and can be learned online.

Artificial intelligence (AI), which covers various subfields, is a crucial technology for processing data on the fly, analyzing it in real-time, and detecting important patterns within such data. As neuromorphic computing begins to receive attention, new AI design methodologies are needed to transfer the decision-making process from pure data interest to a more human-like intelligence level. To this end, machine learning (ML) is often used to create mathematical models based on the available data and extract information from it. Through the continuous sudden availability of new data, the nature of the underlying data changes constantly in most applications, and the same mechanisms do not provide valid solutions.

In many applications, such as stock price tracking, environmental monitoring, and social opinion mining, data streams arrive continuously and in real-time. On the one hand, this leads to inefficient use of storage capabilities due to the high volume of the data. On the other hand, offline data analysis is inefficient because valuable information is discarded as the data streams arrive, resulting in no prior knowledge regarding the data streams. The research in data stream mining (DSM) attempts to address the challenges posed by big data streams. This involves the development of algorithms capable of dynamically adjusting the computation nodes and used algorithms according to the underlying data characteristics. The work focuses on the most commonly used algorithms and data characteristics.

Real-time data analytics is emerging as a crucial field of research across numerous disciplines, including business, finance, health, and social and computer sciences. The rapid advancement of technology has resulted in a data explosion, where a staggering 2.5 quintillion bytes of data are generated every day. Due to its velocity, volume, and variety, this massive and diverse amount of data is regarded as big data. As a new subfield within the discipline of data science, real-time data analytics focuses on the fast, on-the-fly analysis of quickly arriving data streams. Given the fluctuating nature of the data, real-time analytics requires innovative research methodologies to adjust algorithms and computing platforms dynamically. This involves multi-task learning in rapidly changing environments where the patterns in the data vary over time.Real-time data analytics has emerged as a pivotal area of research across various disciplines, driven by the massive influx of data generated daily—estimated at 2.5 quintillion bytes. This field encompasses two primary approaches: traditional machine learning (ML) methods and advanced deep learning (DL) techniques. ML algorithms, including decision trees, support vector machines, and ensemble methods, are employed to derive insights from data in real-time, leveraging learned models to make predictions and inform decisions. In contrast, deep learning techniques, particularly spiking neural networks (SNNs), offer a biologically inspired approach suited for handling temporal data and learning

online, thus aligning more closely with the dynamics of real-world data streams. As AI and neuromorphic computing evolve, there is an increasing need for methodologies that transition decision-making from purely data-centric models to those emulating human-like intelligence. The challenge of processing continuous data streams—such as those found in stock tracking, environmental monitoring, and social media analysis—highlights the inefficiencies of traditional offline analysis and the need for dynamic, adaptive algorithms. Research in data stream mining (DSM) focuses on developing algorithms that can adjust in real-time to the characteristics of incoming data, addressing the velocity, volume, and variety inherent in big data. Real-time analytics thus necessitates innovative approaches capable of multi-task learning and adapting to the ever-changing patterns within data streams.

Fig 5.3: AI in Real-Time Analytics

5.3.1. Machine Learning Algorithms for Real-Time Insights

Typical unsupervised machine learning approaches for streaming data are clustering and dimensionality reduction, and typical supervised machine learning methods for streaming data are supervised classification and regression, with a focus on hierarchical clustering and classification in this talk. A comprehensive review of other types of machine learning algorithms for streaming data can be found. Several open-source implementations of machine

learning algorithms built for streaming data are available in popular languages. These include the Massive Online Analysis (MOA) and SMILE libraries in Java, Scikit-Multi Flow in Python, and the Streaming Machine Learning (SML) and Apache Spark MLlib libraries in Scala, Java, R, and Python.

Machine learning comes from artificial intelligence (AI) and refers to a subfield of AI that is concerned with the design, development, and study of algorithms that can learn and systematically improve from data. The algorithms, once trained, output predictions given new input data. Traditionally, machine learning caters to batch analytics where all input data is collected, and offline learning occurs. However, for real-time data analytics, machine learning algorithms have to cater to streaming data. Recommendations are provided in the following three categories of machine learning algorithms to extract actionable insights from streaming data in real-time or near real-time: (1) online learning algorithms designed for data streams and capable of learning from arriving data in real-time, (2) sketched batch learning algorithms meant for large or big batch datasets that extract a compact sketch of the dataset in fixed time, and (3) unsupervised machine learning algorithms for analyzing data without any labels or prior knowledge of the data distribution.

The advent of big data and the Internet of Things (IoT) has led to a deluge of constantly generating data across various domains. Organizations struggle to extract actionable insights from these massive volumes of data. Data analytics, the science of analyzing such data for insights, is gaining traction, with a significant shift towards real-time analysis of data as it streams. Organizations realize value by providing better customer experiences, having a competitive edge, mitigating risks, and capitalizing on emerging trends. However, extracting accurate and reliable insights from constantly changing data is non-trivial and requires robust, intelligent algorithms. Statistical methods are dominant in market tools and have several limitations, such as the assumption of data distribution and the requirement of domain knowledge for feature engineering. Machine learning methods perform better on "big data" and require computational intelligence to learn models from data rather than designing them by hand.

5.3.2. Deep Learning Techniques for Real-Time Analysis

The efficiency of deep learning solutions is explored across edge devices and cloud setups concerning the model architecture, applied input formats, and applied feature extraction. Researchers propose solutions to accelerate supervised and self-supervised pre-

trained networks for visual recognition in the sky, improving the processing speed of CNNs by 3.68x-7.7x on NVIDIA Jetson in the edge setup.

There is an expansion of interest in self-supervised learning from static images to videos. By building an adjacency graph with stable superpixels and generating edge-level prototypes to capture motion patterns, real-time video semantic segmentation is achieved via graph convolution and dynamic prototype matching. Researchers explore complementary aspects of motions, including space and frequency, to tackle the speed and coverage mismatch problem. To this end, a multi-dimensional real-time video analysis framework with high-resolution optical flow generation is provided. Active exploration of self-supervised visual pre-training is done via a Small-Multiscale Sampling-Similarity (SMSS) framework, generating high-performance foundation models for fast and efficient dense vision tasks with state-of-the-art accuracy and speed.

Despite continuous efforts to make CNNs lightweight, their heavy computational costs remain a considerable barrier to real-time scenarios. As a paradigm shift from convents, capsule networks composed of capsules are proposed to replace traditional pooling and fully connected layers with neural routing. This mechanism mitigates the need for extensive training data and empowers to generalize with unseen examples. Researchers introduce a novel capsule network architecture applied to edge-based monitoring thermal images for an industrial tank, achieving a lower false-negative rate and higher accuracy than state-of-the-art CNNs. Based on the syntactic structure of conversations, researchers propose a conversational capsule network with pre-trained embeddings to capture semantic and role dependencies in multi-party communications, demonstrating superior performance against various baselines on enterprise datasets.

The advancement of deep learning techniques has significantly contributed to the realm of real-time data analytics, enabling the processing of large volumes of data and the extraction of highly relevant insights. Convolutional neural networks (CNNs) stand out due to their ability to capture spatial patterns in images while reducing computational costs, which is crucial for real-time applications. Researchers have proposed novel lightweight CNN architectures, such as SqueezeNet, and explored strategies to transfer learned spatial attention over time. Recurrent neural networks (RNNs), particularly long short-term memory (LSTM) networks, exhibit the potential for analyzing sequential data with contextual language information. However, challenges persist in maintaining low computation and space complexity.

5.4. Case Studies and Applications

Spotify: Keeping users satisfied with AI As the world's top music service, Spotify streams millions of new songs each week, and the goal is to give each one the best possible chance of success. An advanced, end-to-end machine-learning model was developed to assess the listeners' behavior whether the song is likely to be a hit or, conversely, if they will skip listening, which would hardly allow it. The hit model relies on detailed user data from Spotify and computes success probabilities within hours of the song being played on the service for the first time. In parallel, a separate skip model evaluates the risk that the song will be skipped and halted very quickly, measuring similar details within minutes of the user listening to a given song.

Airbnb: Safely screening hosts with AI technologies As the world's largest marketplace for unique accommodations, Airbnb hosts need to be properly vetted, and AI enables that on an unprecedented scale. New hosts are screened based on publicly available data from their social media profiles, in conjunction with veiled data about the location of complex chains and hot spots. A proprietary algorithm weighs the different risks and colored indicators, and just before the host's rental property goes live on Airbnb's platform, the last risk check is executed. If there are still concerns, a customer support team promptly intervenes. A similar procedure is conducted for users who want to book with Airbnb; they must also be vetted based on their social media profiles, system behavior, and blacklist checks, among others. The predictive machine-learning models have already had an important effect, with a six-fold reduction in the share of problematic reservations.

Uber: Enhancing user experience with real-time data The Uber ride-hailing app is an extremely innovative use of real-time data analytics, AI, mapping, and geolocation. The app keeps the real-time history of data of previous rides by combining every ride standard with all vehicles. This data is then compiled by a sophisticated algorithm to generate a composite database that calculates the best response time based on traffic, average length of the ride, location, estimated pick-up time, and route. Uber users can view this real-time data about available taxis that fit their location. Overall, Uber has improved the user experience and generated massive income through real-time data processing by passing on best-routing information to drivers.

Fig 5.4: Real-Time Analytics Use Cases and Examples

5.4.1. Industry Examples of Real-Time Data Analytics

Third, the recent experience of a large telecommunication service provider is discussed, which has a legacy data protection architecture for its passive optical networks capable of processing only a fraction of the data generated. To grasp user experience and service quality for new applications, the company has worked on a solution that will allow it to store and analyze in real-time, or near real-time, terabits of data per second received from its passive optical network equipment. The talk focuses on the presented solution and its results on how to use the available tool to comply with regulatory requirements and enhance customer satisfaction through real-time metrics.

Second, the case of a major oil and gas exploration company, which has developed a complete data ingestion chain to make real-time comments on new well construction scenarios. Different data sources, such as daily drilling data and measurements every ten minutes or less, are cleaned, pre-processed, and stored in a distributed file system. Data is aggregated in near real-time to support interaction with domain experts; drilling parameters are calculated to monitor the well's performance and prevent incidents, and several machine learning models are built to predict the most probable source of problems, alerting domain experts automatically based on pre-defined business rules.

First, the initiatives of a large transportation company are discussed, which harness real-time data on the condition of train tracks to detect issues long before they become critical. Trains are equipped with sensors that collect data as they travel on tracks, identifying the precise location of track conditions and uploading it to a centralized processing system via a mobile

network. Using statistical methods and machine learning algorithms, high-frequency data is aggregated and transformed into features, and then deep learning models learn patterns in the data to identify which features indicate problematic events. The trained models enable the real-time detection of anomalies in the data, which are used to narrow down regions of concern and mitigate problems before they escalate. Visualization technology is utilized to display the aggregated, enriched data and detected anomalies to domain experts and engineers.

In this chapter, a diverse array of real-world case studies is explored to illustrate how organizations from various industries are harnessing real-time data analytics to drive operational excellence, make informed decisions, and create innovative products and services. These examples showcase the capabilities of real-time analytics and its profound impact on modern business, society, and daily life.

5.5. Future Directions and Implications

The emergence of big AI raises fundamental, often daunting issues for consideration, of which the future of work, professional identities, expertise and expertise acquisition, human agency, and democracy are some. As the inquiry is still preliminary and ongoing, ways of analyzing, conceptualizing, and reframing the issues promptly are also discussed. Assuring flexibility and adaptability of any response to the fast-evolving and continuing situations of emerging AI technologies and strategies is also important. Exploring the reconceptualization and reframing of the ethically, socially, and politically nuanced issues, to facilitate a positive synergy between human and AI agencies, is a way forward for addressing concerns as well as for capitalizing on opportunities.

A bigger-picture understanding of what the organization does, why it does so, and how it obtains its outputs, and purposes can be “translated” into the industrial landscape of big AI, whether such landscape is regarded as similar to or radically different from the present arrangements of industries and organizations, would enable organizations to scrutinize new opportunities for re-positioning, via initiative or reactiveness, in the emerging AI-enabled competitive landscape. The initial steps for this purpose are awareness of the potential impact of AI technologies and strategies as well as the preparedness to have both applied within the organization. In this respect, organizations willing to maintain the status quo may seek scenarios involving the misuse of AI technologies and strategies as a blind spot. However, such a position would entail high risks regarding ineffective strategic response to AI-based disruption.

Beyond managing the here-and-now security challenges and implementing basic AI solutions, organizations should cultivate big AI venture strategies for a longer time horizon, in tandem with a focus on immediate issues and applications. The continuous emergence of new AI technologies means that organizations should not ignore potential opportunities for using them to gain advantages and give rise to their fundamental issues and dilemmas. Viewing AI technologies and strategies as an integral part of the organization's overall strategy, rather than only as existing IT systems, is a precondition for mobility and adaptability in the face of emerging AI-based business and competitive environments. A precondition for viewing AI strategies in this way is a comprehensive understanding of the enabling assets held, potentially held, or needed to be held to implement the different AI strategies.

Fig 5.5: The Future of Data Analytics: AI and Machine Learning Trends

5.6. Conclusion

Real-time analytics, along with AI, can be used to better understand data and customers. In real-time, a historical view of patterns and trends, as well as data processing capabilities, is provided to assist organizations in recognizing action and mitigating risk. Strategies, technology, and tools for analyzing large amounts of data in real-time while incorporating AI and ML capabilities are provided. The real-time processing concepts "Race and Event Cloud"

are explained, as well as visible, understandable, and stored events along with the use of identity for real-time insights. Hidden predictive synthesis, context, and prescriptive strategies for generating insights are explored. AI augmentation and resourcing to mitigate bias and amplification in insights are elaborated on. Other topics include solution implementations, use cases and technology scenarios, criteria analysis for selecting technologies, and trends tied to the combination of real-time analytics with AI. Technologies and tools to mix event and data streaming with batch processing while decoupling these functions are outlined to facilitate complex analysis, pattern exploration, anomaly detection, and other use cases not suited well for pure event or pure batch processing. Multi-site, inter-GA, and cloud service levels to also support federated processing and storage of data streams, as well as compliance handling, are explored. Future transcriptions might address any other aforementioned areas of real-time analytics and AI, like use cases and solution descriptions, and outline their possibilities for practitioners to enhance their efforts.

5.6.1. Future Trends

Several anticipated real-time analytics applications are expected to arise out of new business ventures or natural science space program developments. On the one hand, NASA's exploration of long-horizon planetary exploration and the food production and environmental health management implications of climate change, coupled with addressing the associated obstacles and risks, will likely push complicated development frontiers. On the other hand, there are likely to be a lot of novel art forms, which could either contain artificially generated components (from within engineered collaborative systems) or benefit from completely novel tools for human art creation.

Several anticipated foundational algorithmic and computing method developments will pertain to many existing real-time analytics approaches. Shortly, artificial neural networks (ANNs) are anticipated to become increasingly adapted to their hardware hosts, with an increasing number of them deployed in dedicated neuromorphic architectures. Additionally, there will likely be an increase in the convolutional network sharing of common learning rules between the hardware, leading to the ongoing mass adoption of locally recurrent networks in physical devices. Furthermore, there is a possibility that substantial efficiency benefits will come from the closer integration (at the level of applications) of unseconded spiking networks and deep networks when ported to a common architecture.

There are several anticipated architectural and material design trends for real-time analytics. These include the transition from general-purpose architectures to a mixture of domain-specific, specialized, and customizable or rewritable ones, as well as the continual merging of increasingly deeper levels of application and hardware integration. On the nanomaterials and device front, it is anticipated that there will be an incessant drive to combine an increasing number of functions within a single device at the nanoscale. There will also be developments in hybrid systems and bio-hybrids that use different platforms together (e.g., neural networks in CMOS imaging processors), as well as the utilization of mechanisms prevalent in biological systems as a design inspiration to mitigate some of the constraints that have hindered the development of conventional digital devices in a stagnant or regressive trajectory.

As a rapidly evolving discipline, a wide variety of real-time data analytic methods have emerged in recent years. Many of them are currently being researched, as well as their implications, limitations, and ways to create desirable future states. This section selects and briefly describes some of the most pertinent anticipated developments in either academia or industry.

CHAPTER 6

DATA QUALITY AND GOVERNANCE: ENSURING INTEGRITY IN AI-DRIVEN SYSTEMS

6.1. Introduction

However, the way and extent to which AI systems are governed by institutions today varies widely, with some being stronger in terms of commitment and structure (policies, working groups) than others. Initial steps on the AI Governance Ladder have often been taken, yet compliance with expectations as well as addressing emerging dilemmas and advancements in the field continuously is complex. Some academics and practitioners are concerned about the unintended consequences of AI systems and advocate that AI be aligned with desirable outcomes for society. Thus, a global initiative has emerged to pursue the responsible governance of AI. Institutions need reliable organizational frameworks and tools to better comprehend and act upon the breadth and complexity of challenges AI systems pose to their responsible use. There is a desire to assist EU-based Higher Education Institutions (HEIs) in ensuring responsible AI development, implementation, and procurement by providing governance frameworks, principles, and tools. After the identification of gaps within HEIs related to AI Governance and the establishment of an understanding of accountability (in light of AI Governance), a toolbox of guidelines for developing, acquiring, implementing, and regulating AI systems in the HEI context would be proposed. To address the challenge of ensuring and enhancing the quality of data (and its corresponding metadata) applied within AI systems employed by HEIs in the initial phases of the AI Governance implementation at European HEIs.

AI-driven systems are increasingly being adopted across diverse industries such as healthcare, finance, and transportation with the aspiration to revolutionize operations, enable productivity gains, and drive innovation. Repositories of data are being collected, stored, and processed to inform operational activities and processes, extract crucial insights, and support pertinent decision-making. Data-driven decision-making and predictive analysis have been effectively employed to enhance competitiveness for organizations and firms. On the other hand, the

introduction and emergence of AI is affecting the way institutions and individuals interact with society. The endorsement of AI could address systemic inequalities or create and perpetuate biases when employed irresponsibly. Adoption of AI systems should be done in alignment with institutional missions and values, embracing responsible innovation and the intention to generate a positive societal impact. Increased reliance on commercial AI tools developed by private vendors as off-the-shelf solutions without transparency on development, data, intellectual property, and other AI governance aspects may prevent the responsible use of AI or foster problematic outcomes at societal levels. AI systems are not neutral, are developed under certain contexts, and prioritize certain aspects over others, which can consequently affect the population differently. The crucial decisions taken within the context of institution-specific AI systems can have major implications on the entire society, thus necessitating due diligence on the part of the institutions employing them.

Fig 6.1. Data Quality

6.1.1. Background and Significance

Despite their paramount importance, DQ and DQG remain understudied in an AI/ML context. As the adoption of AI systems permeates through industries and societal domains, it's imperative to ensure the integrity of AI's lifeblood - data - to avoid inadvertently detrimental decisions based on badly mined patterns in data.

Data Quality (DQ) ensures that data's fitness is retained throughout its lifecycle, including acquisition, preprocessing, and ongoing operation, tracing back any faulty decisions/insights. Data Quality Assessment (DQA) evaluates the state of quality for a specific characteristic set based on comprehensive data traceability and establishes countermeasures to reduce its lifecycle degradation; DQA is core to DQ and DQG as it prepares the prerequisites for DQG to enforce proactive mitigation of data's fitness. A governing state, data quality governance (DQG), establishes policies that enforce a closed-loop control on data quality against pre-defined fallouts and hence automatically trigger countermeasures to address data quality's degradation as it's discovered. Data Quality and Data Quality Governance are instrumental in ensuring the integrity and safety of AI systems, societal trust in data-driven decisions, and regulatory compliance as they explicitly describe the characteristics and norms that data inputs should adhere to in the context of AI and data-driven systems.

As data feeds the lifeblood of AI systems, it is critical to fundamentally understand the set of concept adaptations, data quality, and governance methodologies, and their significance in upholding the integrity of AI and data-driven systems. Data governance makes sure data is just as good as it can be for its intent. Characteristic sets of quality describe its integrity according to its intended purpose, adherence to norms, and decisions taken based on it.

In the digital age, businesses and organizations are progressively discovering the potential of Artificial Intelligence (AI) and Machine Learning (ML), making strategic shifts in governance, operations, and decision-making. These have empowered companies to make intelligent decisions based on trends in data, which can be obtained quickly and analyzed for further utilization. However, the data that goes into these AI systems varies widely in their quality, characteristics, origin, purpose, processing, accessibility, and biases. Improperly harnessed, this data can inadvertently generate inadvertent recommendations or insights, resulting in catastrophic decisions against its original intent.

6.1.2. Research Objectives and Scope

A literature review will be conducted to outline the current state of the data quality and governance issues present in AI technologies. This is desired to gather concrete definitions and theories regarding data quality and governance issues along with how these concepts apply to AI technologies and what the resulting problems and incidents are. This is to execute an analysis of multiple case studies. A specific focus would be given to the case studies of real-world threats that are of high societal impact like the case of OpenAI ChatGPT providing harmful advice on drug manufacture or VALL-E's capabilities to impersonate people's voices. By examining current events, trends, and their compound societal impact, a greater understanding and insights on how these events relate to data quality and governance issues can be acquired.

Through an analysis of multiple case studies, this research aims to identify current incidents and address the root cause of harmful AI technologies to formulate data quality and governance requirements to mitigate them. This study will further analyze the specific events and trends of AI technologies that happen over a calendar year (2023). By including an analysis of events' degrees of impact on developed AI technologies and the response of data governance or policy restructuring and recommendations made in response, it is of interest to gather a clearer understanding of the needed requirements to protect from the growing data quality and governance issues present in AI technologies.

The primary objective of this research is to investigate the data quality and governance issues related to the use of AI technologies, with a specific focus on natural language processing systems and impactful real-world threats. To achieve this, two research questions will be posed: RQ1: What are the data quality and governance issues present in AI technologies? RQ2: How do AI technologies affect real-world threats of high societal impact? These questions will be explored through a literature review, systematic mapping of prior research, and case study research. The ultimate goal is to improve societal awareness of the data quality and governance issues present in AI technologies.

6.2. Understanding Data Quality

There is a growing recognition among organizations of the importance of good data quality. In many organizations where a data warehouse or data mart is being used, final reports reveal that the unprocessed operational data may be of unacceptable quality. For example, the data obtained from marketing companies about households and individuals is often incomplete

and misleading. Recent surveys indicate that more than 80% of all business decisions are based on some sort of data. However, a similar number of respondents stated that the quality of the data was of serious concern. In most sectors, sharing data with partners or involving customers in data gathering is becoming essential for success. Combining data gathered from different sources introduces new data quality problems.

There are many dimensions of data quality, such as timeliness, accuracy, completeness, consistency, and uniqueness. The dimensions of data quality can be grouped into five categories: accuracy, consistency, completeness, timeliness, and accessibility. These categories can provide a framework for understanding the various aspects of data quality. They can help organizations identify potential data quality issues and prioritize data quality improvement efforts.

Data quality is widely defined as the degree to which a dataset is complete, correct, accurate, and consistent. However, this definition leaves gaps regarding what the terms "complete," "correct," and so forth mean relative to a specific dataset. The main domains of data quality include "correctness," "univariate completeness," "univariate accuracy," "consistency," and "integrity." Data quality also encompasses the detection, diagnosis, and repair of problems in datasets. Efforts to build data quality tools typically focus on datasets curated from the web or on datasets generated by automated interfaces to sensor networks.

6.2.1. Definition and Dimensions of Data Quality

The definition and dimensions of data quality are presented, followed by a classification of businesses' needs regarding data quality. The segmentation results in four categories of businesses concerning data quality needs. Finally, based on dimensionality, and level of aggregation, data quality measurement systems that address generic business needs are presented.

Starting from the first, broad definition of data quality as fitness for use, the concept has been refined into a taxonomy of data quality dimensions. A data quality dimension is a property of data that helps to qualify the quality of data against its fitness for use. Many businesses measure, improve, manage, and control data quality dimensions to increase their business success. These dimensions can be grouped into several categories, mainly based on their areas of origin. The first category consists of characteristics of the data itself, e.g. accuracy, completeness, consistency, timeliness, and validity. The second category consists of characteristics of data users, e.g. understandability, traceability, and accessibility. The third

category consists of characteristics of data systems and processes, e.g. auditability, security, and volume.

Data quality is defined as the fitness for use of data. Data quality plays a central role in the business success of organizations, as inappropriate data and its properties can lead to inappropriate decisions with dangerous consequences. Despite the extensive efforts and investments for ensuring data quality, there remain some indisputable facts regarding data quality. Organizations recognize data quality as one of the biggest sources of challenged projects, but success in data quality implementation remains elusive for most companies.

Data quality is fundamentally defined as the fitness for use of data, a concept that underscores its crucial role in business success. The definition has evolved into a detailed taxonomy encompassing various dimensions of data quality. These dimensions are classified into three main categories: characteristics of the data itself—such as accuracy, completeness, consistency, timeliness, and validity; characteristics related to data users—such as understandability, traceability, and accessibility; and characteristics of data systems and processes—such as auditability, security, and volume. Despite significant investments and efforts to enhance data quality, many organizations continue to grapple with challenges. Inappropriate or poor-quality data can lead to misguided decisions and adverse outcomes, making data quality a persistent issue in many projects and a major factor affecting their success.

Data quality, defined as the fitness for use, is essential for ensuring business success. This concept has been refined into a comprehensive taxonomy that identifies several dimensions of data quality. These dimensions are categorized into three main groups: characteristics of the data itself, including accuracy, completeness, consistency, timeliness, and validity; attributes related to data users, such as understandability, traceability, and accessibility; and features of data systems and processes, including auditability, security, and volume. Despite substantial investments aimed at improving data quality, organizations often face persistent challenges. Poor-quality data can lead to erroneous decisions and detrimental consequences, underscoring the ongoing struggle to achieve high data quality and its critical impact on project success and overall organizational effectiveness.

Fig 6.2: Data Quality Dimensions

6.2.2. Challenges in Ensuring Data Quality

Data is a complex entity composed of numerous dimensions or aspects. Data complexity and multi-facet nature induce different definitions and perspectives of data quality. Fischer et al. suggested that the problem of data accuracy concern has led to an animate return of interest in research on the quality of data. The challenge of ensuring data is of better quality is exacerbated due to the intrinsic complexity of data. In that respect, the sophistication of the entity "data" must be carefully taken into account in attempts to ensure that it is of suitable quality for specific intention or use. As the data go through a life cycle, each semantic meaning would be influenced and, hence, must be taken into account in the sense of establishing a guarantee.

Data is a fundamental asset in any industry. It forms the backbone for ever-increasing research efforts, business viability, and optimistic returns. However, with the exponential growth in

data, diverse means of generation and acquisition are associated with intricacies like noise, corruption, and unintentional errors. This leads to obsolete, irrelevant, incomplete, undecipherable, and erroneous data permitted for storage, processing, and decision-making processes. The precedent user's inaccurate information feeds the subsequent systems to yield inappropriate insights or decisions. This effect exploits a snowballing chain on the integrity of the modeled hypotheses or the trustworthiness of the systems. It also endangers the industrial and commercial sectors with monumental economic losses, unviable workflow, non-compliance to regulations, and mutilated reputation. Such errors would multiply faster in AI systems owing to the vast volume and diversity of data ingested into them. For instance, the recent developments in facial recognition AI systems were criticized for being biased towards an ethnicity with a deliberate effort to feed data-less images of other ethnic groups while training the neural networks.

With the expanding usage of data as a commodity for artificial intelligence (AI) systems, there is a growing recognition that the integrity and fitness of data must ensure the validity of the outcome. To achieve this, there is a necessity to guarantee data quality, which has many complex dimensions or aspects. The challenge of guaranteeing data quality is heightened due to the inherent complexity of data, and a model wherein data "provenance" is tracked through its lifecycle is essential.

6.3. Importance of Data Governance

The data outside the organization is equally concerning; flaws in policies or capabilities dealing with these data could compromise the organization’s robustness. Data governance is an evolving process as technology enables new data sources, collection methods, analysis possibilities, and issues, which keeps the task challenging. To decrease risk awareness and develop a structured response, key principles of data governance are necessary. These principles are based on the identification of issues that could endanger the integrity of data. The proper resource allocation to perform the necessary processes and the oversight of those processes are major principles.

Since the beginning of Big Data technology, the concept of data lakes has emerged. Many organizations have dumped data into lakes as the acquisition was cheap and storage was virtually unlimited. However, without a governance strategy, the capability to manage the quality of existing data became a problem as a drowned lake might become a swamp. The capability to manage and extract value becomes increasingly difficult with the sheer volume of data. Therefore, data lake governance and data governance are intertwined.

Data governance should not be confused with data stewardship, as the former is a broader approach that requires a slew of activities that ensure the proper protection jobs are defined and data administration specifics are laid out. Data governance also includes data ownership, which ensures that proper stewardship is in place.

A data governance program provides a structured method for utilizing data to optimize its value while maintaining privacy and ensuring the relevance of its usage, enabling organizations to keep readjusting the proportions of data to maintain competitiveness. An effective data governance program gives organizations better safeguards to demonstrate accountability towards compliance processes, making reporting less tedious and expensive while minimizing the risk of incurring hefty fines.

Data governance is a crucial process for any organization that aims to unlock the full value of its data. As the amount of data being generated has significantly increased over time, alongside stringent regulations and rising public fears regarding privacy, it has become exceedingly difficult to know which data should be preserved and how to maximize its use. Therefore, efficient data governance is critical for both present and future success.

Fig 6.3: Importance of Data Governance

6.3.1. Key Principles of Data Governance

Data governance is a framework that enables organizations to manage, protect, and leverage their data assets effectively. Organizations can develop robust data governance strategies tailored to their needs and industries by understanding the key principles and concepts. Here is an indisputable discussion of the key principles of data governance.

Clarity of vision. Successful data governance implementation starts with an articulated vision that outlines the data and business objectives the organization aims to achieve. A comprehensive and concise vision statement should be developed, setting a strategic direction and acting as a roadmap for governance initiatives. It serves as a fundamental asset for sustaining long-term support for work efforts. An unambiguous vision statement ensures coherent and consistent communication throughout the governance project lifecycle. Such governance vision statements may include data quality improvement targets, enhancing analytical capabilities, and managing regulatory compliance, among others.

Organization. An organizational structure is an essential foundation for implementing data governance and comprises defining roles, responsibilities, and relationships across four dimensions: people, processes, standards, and technology. Realizing its vision, data governance enables the organization to manage its constraints and capabilities effectively. Each role typically comes with authority and accountability boundaries defining participation in decision-making and approval processes. Roles may be organized hierarchically, and include multi-level governance teams, councils, and working groups addressing specific challenges. They can fulfill a stewardship function for a particular data domain or data lifecycle stage—data acquisition, maintenance, processing, analysis, sharing, etc.

Implementation roadmap. The implementation roadmap defines key milestones and deliverables of a work plan and methods to achieve the governance vision. It should be divided into annual, semi-annual, or quarterly phases, each containing 3-5 key initiatives with work plans aligned with resourcing and budget. Implementation should, as much as possible, focus on "quick wins" to create immediate value and showcase the feasibility of interventions.

Transparency and accountability. Data governance frameworks may span extremely diverse domains and utilize opaque regulations, processes, methods, models, technologies, and standards. Transparency establishes appropriate data governance awareness and trust among stakeholders over time through better visibility into objectives, progress, decisions, changes, and outcomes. Sufficient governance transparency helps and informs stakeholders about data

policies, processes, and initiatives fostering participation throughout phases from strategy definition and decision-making to execution, assessment, and auditing.

Sustainability. Data governance frameworks comprise strict and rigid policies and standards, which, once implemented, fix data quality, risks, and competitive market position. Data governance should initially be positioned as an assessment of visibility and capability enhancements to pilot and take low-cost or effort data governance initiatives. Data governance establishes and embeds an iterative mechanism for continuous assessment and reinforcement of transparency and capability.

6.3.2. Relationship between Data Governance and Data Quality

The need for data governance increases further with AI and machine learning. These data-hungry algorithms rely heavily on the collected data, which must therefore carefully represent the real-world environment in which they are applied. With time, drift occurs; changes to the system target contaminating the AI-driven system with "noise" may occur. In the absence of a data strategy, models trained on one data set might be applied (either intentionally or inadvertently) to data that is dissimilar and no longer representative. Furthermore, the output of these models is not raw data that can be unfailingly understood and interpreted by a human but has been quantitatively altered-often stochastic estimates-and hence is difficult to audit. Assumptions must be placed on modeling feasibility and predictive ability given the different data sources, which cannot be checked without a detailed metadata schema understanding both data sets.

In the absence of data governance procedures, there will be no checking or vetting of data before it gets into the (AI-driven) system. If there are no checks done post-arrival, many issues may remain undetected. If the data is then used as-is, "issues with it" will pervade downstream operations and processes, polluting predictions, classifications, and warnings issued by the system, leading to misunderstandings and unintended consequences. For instance, if the outputs of the system are fed to a decision-maker without clarification of the quality of data that went into the derivations, the subsequent actions taken may be very far from what was intended if the data was faulty.

Data governance defines how data should be managed and how it should be made available, vetted before use, and then cleaned or fixed if issues are found relative to agreed-upon specifications. Data quality is key to effectively ensuring that data is representative of the intended real-world target context and is relevant to the desired use. Data governance and data

quality processes are tightly coupled. Both should be implemented proactively but are often only partially done reactively, resulting in the data being cluttered with snowballing issues over time.

The well-known adage, "garbage in, garbage out," captures the essence of the relationship that exists between data governance and data quality. None of the amount spent globally on technology, tools, education, or training of data scientists, data engineers, or data curators will make any difference to the results if meaningful and insightful data is not fed into the AI-driven system in the first place.

6.4. Integrating Data Quality and Governance in AI Systems

In AI systems, Data Governance must be implemented through a Data Governance Framework that defines Policies and Standards. Smart Contracts can automate practices to ensure the achievement of Data Quality and use case requirements, and they can be verified using smart testing tools. To be fair, Sustainable Data Governance must be ensured through Multi-Agent Architectures where Data can flow while ensuring legal and ethical concerns. The consideration and combination of these practices can make Data Quality part of the AI Secret-Sauce Ingredient.

In AI, Data Quality needs to be promoted and ensured in all the data lifecycle stages, from acquisition to post-processing. Data Quality must, at first, be assessed and measured by applying and adapting Data Quality Dimensions, like Completeness, Consistency, or Timeliness, which should be compliant with the use case requirements and the model's expectations. If these analyses reveal critical laxities in the Data Quality checks, the flags that were raised need to be considered. Data Quality is improved in several stages: Data Preparation, where data is cleaned, merged, transformed, and filtered; Data Annotation, which adds cognitive information to data; Data Monitoring, where Machine Learning Operations are established for the data feeding model deployments; or Data Augmentation, that promotes the creation of synthetic samples. To continue introducing Data at the AI fairytale, the Data Governance framework that governs the entire data lifecycle needs to be ensured.

Data is the most valuable asset that organizations can leverage in the AI era, and improving its quality must be at the forefront of everything that organizations want to achieve. Data Governance establishes the necessary foundations for trustworthy and reliable data, which is essential for AI systems. Therefore, it is necessary to integrate Data Quality and Governance in AI systems, exploring the role of Data Quality and outlining best practices for Data

Governance in AI systems.In the realm of AI, robust Data Governance is pivotal for ensuring high Data Quality across the entire data lifecycle. Implementing a comprehensive Data Governance Framework with clearly defined policies and standards is crucial, as it not only addresses legal and ethical concerns but also enhances the effectiveness of smart contracts and smart testing tools that automate quality practices. By incorporating Multi-Agent Architectures, organizations can manage the dynamic flow of data while upholding these standards. Data Quality must be meticulously assessed and measured through various dimensions—such as Completeness, Consistency, and Timeliness—to align with use case requirements and model expectations. This involves rigorous Data Preparation, Annotation, Monitoring, and Augmentation processes to address any quality gaps identified. By integrating Data Quality and Governance practices, organizations can leverage data as a powerful asset in AI, fostering trustworthiness and reliability in their AI systems.In the AI landscape, effective Data Governance is essential for maintaining high Data Quality throughout the entire data lifecycle. Establishing a comprehensive Data Governance Framework with well-defined policies and standards is critical for navigating legal and ethical considerations while optimizing the use of smart contracts and testing tools to automate quality assurance processes. Multi-Agent Architectures further support this framework by facilitating the seamless flow of data while ensuring adherence to governance standards. Assessing Data Quality through dimensions such as Completeness, Consistency, and Timeliness is crucial for aligning data with use case requirements and model expectations. This involves thorough Data Preparation, Annotation, Monitoring, and Augmentation to rectify any quality issues. By embedding robust Data Quality and Governance practices, organizations can harness data as a valuable asset, enhancing the reliability and trustworthiness of their AI systems.

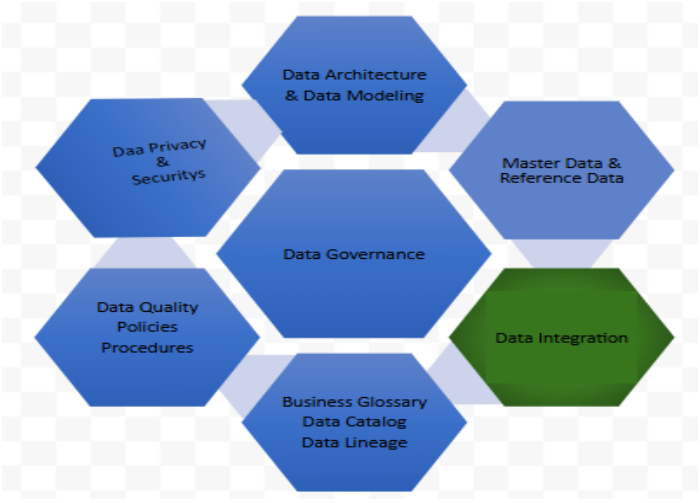

Fig 6.4: Data Governance: Data Integration

6.4.1. Role of Data Quality in AI

The success of an AI/data-driven system in building a model depends entirely on the quality of data used in training data models. So there is a clear necessity to inspect the quality of such data. Currently, available data quality assessment approaches are mostly application-specific and have high domain knowledge. Traditional approaches do not scale. There is an urgent need for a systematic study of this essential building block of many AI systems.

The quality of data has various dimensions. Depending on the need and modeling task, one or more dimensions can be accepted. These dimensions of the data can include but are not limited to, relevance, accessibility, timeliness, transparency, accuracy, completeness, consistency, duplication, lineage, interpretability, validity, and understandability, jargon, semantic transparency.

Undoubtedly, data is considered the foundation and main driving force behind many AI systems. The success of many AI systems relies on the availability and capacity to work with extensive and superior-quality data. By describing the data's activeness level, it is possible to state that it can range from inactive-level (e.g., a stored image on a computer) quality to active-level data quality. Quality data is usually the one that is current, complete, consistent, correct, relevant, and has acceptable sampling error bounds in the modeling task at hand. Data need not be perfect or of the best quality, but to have only the accepted errors (e.g., at random).

6.4.2. Best Practices for Data Governance in AI Systems

Intense communication strategies are critical to avoid unexpected incidents. Other governance elements include data storage and protection requirements; clear on-boarding policies for systems or data outside the control perimeter; restrictions on data transfers to third-party environments; and assessments before using or sharing synthetic data to ascertain the type of data used in its training.

Data for AI use cases should be classified by sensitivity and domain, and data sets should remain within their physical and legal controls throughout their life cycles. A robust governance framework includes a clear data ownership chain across stakeholders, up to the CEO or equivalent, which addresses potential requirements for third parties receiving, processing, or using corporate data. Permissions to access, manipulate, or share data should be as granular as possible and cover all relevant tools or systems storing or processing this

information, ensuring that rules and penalties for breaches are included. AI models and use cases should also be covered.

Robust data governance is essential to maintain the privacy and integrity of sensitive information contained in corporate knowledge landscapes, especially when designing and deploying AI systems. Best practices for data governance in AI systems include defining and implementing AI ethics principles, data handling guidelines, and system use cases. Organizations often start building internal capabilities in these areas, but it is advisable to use existing protocols and practices when available.

6.5. Case Studies and Practical Applications

There are high-profile concerns regarding data quality and its impact on algorithm-specific decisions. A widely discussed incident occurred in 2018 when Amazon was found to have scrapped an AI recruiting tool after discovering it was sexist. The tool was designed to vet resumes and was found to favor candidates with male-sounding names. This incident emphasizes visible concerns plainly describing how algorithms make decisions based on the data they have access to and any underlying bias in the data gets reflected in the algorithm-specific decisions, leading to a bad or flawed outcome. Even though the AI recruiting tool scrapped by Amazon had been skillfully designed and tested by a team of in-house experts, the importance of data quality was not accounted for in the initial design plan. If prior attention had been given to the data quality issue, the algorithm might have been able to reach the desired design outcome.

Real-world examples of data quality and governance in AI systems The importance of data quality and governance in AI systems and how they can be implemented to ensure their integrity is further illustrated with real-world examples. Concerns related to data quality and governance in AI systems are not hypothetical and have been realized in practice. Efforts to address these concerns have been attempted, with differing levels of success. For an initial understanding of how to implement data quality and governance for AI systems, these real-world examples could be used as a foundation.

As AI systems proliferate across different industries, data quality and governance have become pressing concerns and priorities for organizations using AI. This paper aims to develop foundational knowledge about data quality and governance, discuss their importance in AI systems, describe principles and best practices for data quality and governance in AI systems, and provide relevant case studies. Researchers and professionals interested in learning more

about data quality and governance are the paper's target audience. It serves as an introduction to data quality, data governance, and data governance frameworks and provides insights into how they can be applied to ensure integrity in AI systems. The content may also be valuable for organizations attempting to develop or enhance a data quality and governance framework.The 2018 incident involving Amazon's AI recruiting tool, which was scrapped after revealing gender bias, underscores the critical importance of data quality in algorithmic decision-making. Despite the sophisticated design and expert testing of the tool, it failed to account for inherent biases in the data, resulting in discriminatory outcomes. This example highlights how biases present in data can adversely impact AI systems and emphasizes the need for rigorous data quality and governance practices. As AI technology becomes increasingly prevalent across various industries, addressing data quality and governance has become a top priority for organizations. This paper aims to build foundational knowledge about data quality and governance, offering insights into their significance in AI systems. By discussing principles, best practices, and relevant case studies, the paper provides valuable guidance for researchers and professionals seeking to understand and implement effective data quality and governance frameworks, thereby ensuring the integrity and fairness of AI systems.The 2018 incident with Amazon’s AI recruiting tool, which was abandoned due to its inherent gender bias, starkly illustrates the crucial role of data quality in algorithmic decision-making. Although the tool was developed with advanced technology and expert oversight, it did not address the underlying data biases, leading to discriminatory results. This case underscores how biases in data can significantly affect AI outcomes and highlights the urgent need for comprehensive data quality and governance practices. As AI technologies expand across various sectors, ensuring data integrity and governance has become increasingly vital. This paper aims to provide foundational insights into data quality and governance, emphasizing their importance in AI systems. By exploring principles, best practices, and real-world case studies, the paper offers essential guidance for researchers and practitioners to develop and implement robust data quality and governance frameworks, promoting fairness and reliability in AI applications.

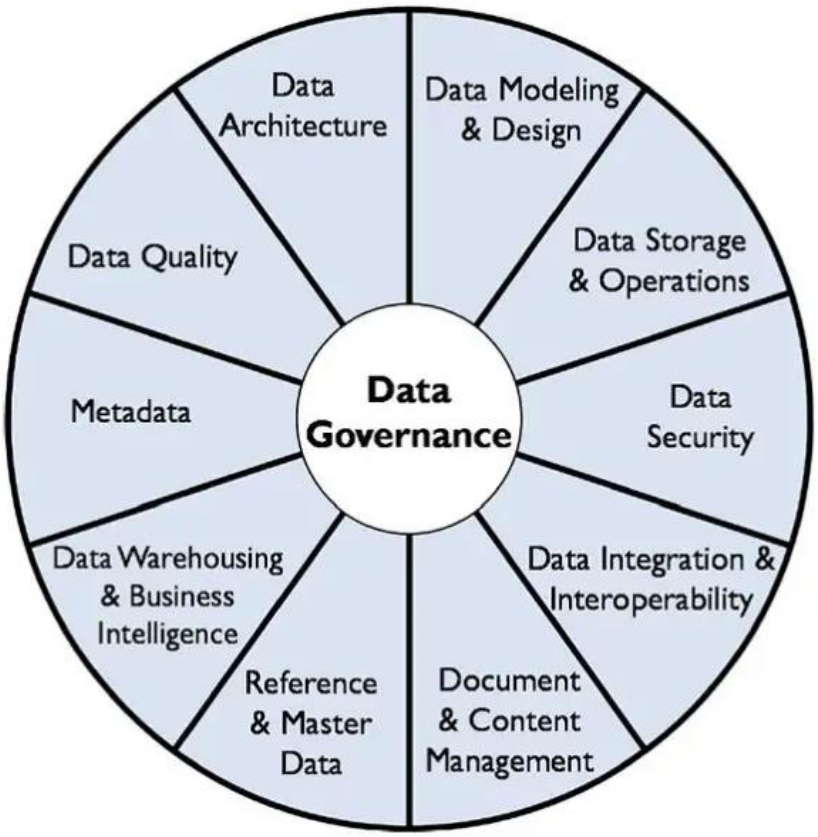

Fig 6.5: Data Governance Explained

6.5.1. Real-world Examples of Data Quality and Governance in AI Systems

Data quality and governance are paramount aspects of AI systems, ensuring that data is not only accurate and reliable but also used ethically and responsibly. Organizations around the world have begun implementing stringent measures to secure top-notch data governance and quality in their AI systems, with notable cases that pave the way for best practices. This section elucidates various real-world examples of data quality and governance complexities and scenarios as a reference for organizations, policymakers, and stakeholders working on similar challenges.

Google is a tech company that has made substantial investments to ensure its AI systems are trained using trustworthy data sets. Following the launch of its new AI chatbot Bard, the company released a set of globally sized data quality and governance criteria based on 15 guidelines, including well-used and robust toolsets, geographically representative data, consent verification, and external monitoring. This initial set of standards has been greatly well-received but will only cover Bard training data sets.

Foursquare is another tech company that guarantees data integrity concerning datasets sold to third-party companies for analytics. Following allegations that third-party marketing agencies had manipulated users' personal data election, a multi-year overhaul was initiated, including audits, data provenance tracking, and strict data governance. With these measures, continual compliance monitoring on 99.9% of its datasets was implemented, thus preventing further undesirable data uses.

Deepmind has led research on the ethical governance of clinical-grade AI systems in health care. Real-world interdisciplinary case studies on ethics and governance for AI safety and data use in healthcare settings were conducted, directly addressing data quality considerations related to diverse data, data consent practices, and the suitable oversight of AI-generated recommendations.

Texas Instruments designed a data governance program that improved data quality and resolved significant state and localities issues. In three months and with only three full-time employees, the governance program was developed, ensuring accuracy, timeliness, data security, and compliance with all appropriate rules and regulations.

These cases showcase the data quality and data governance challenges faced systemically by organizations, especially those employing AI systems, and organizations' costly and multi-faceted efforts to address them as learning experiences for others.

6.6. Conclusion

The aim is to bolster IoT companies' awareness of data quality and governance from a top-management perspective and promote the establishment of appropriate organizational structures, policies, and technical procedures. Future trends incorporate stricter regulation of data quality and governance, emphasizing traceability, interpretability, and accountability. Consequently, transparency will become a focal point. It will be indispensable to comprehend the data creation process, the sort of insights obtained from data, and the factors governing what is or is not presented to end-users. Ad hoc decision-support tooling will no longer suffice. Sophisticated data science applications will shrink to a bare minimum, and all data-driven decisions will need to be explainable and justifiable. Without transparency, AI-driven systems' insights will be considered deceptive and misleading. This will hinder further development and grow into the new dark age of data fuelling decision-making without understanding its significance.

With the rise of AI-driven systems, new challenges and allowances arise for data quality and governance. Furthermore, AI technologies are expected to provide possible solutions to enhance data governance and quality. In addition, there is a need for further research into the implications of AI technologies and data quality and governance in dynamic environments. Besides competing with other organizations, data-driven organizations should adopt a "play to win" mentality, establishing strategic investments in AI technologies while ensuring adequate processes for data quality and governance.

This paper investigates data quality, governance, and AI technologies about this challenge. A literature review delineates challenges, regulations, real-world cases, data governance, and data quality aspects concerning AI and data-driven systems. In addition, solutions to enhance data quality and governance with AI technologies are examined. By doing so, the authors identify key AI technologies that create opportunities to overcome issues concerning data quality and governance. AI technologies that examine high volumes of data include Natural Language Processing (NLP) in real-time verification of digital assets and Computer Vision (CV) for detecting defects in images of parts, products, or documents.

The surge of artificial intelligence (AI) and the Internet of Things (IoT) has ushered in a new era of advanced decision-making systems founded on data. These developments are reshaping how data is examined, applied, and shared by diverse organizations and industries. However, attentiveness to data quality and governance is imperative for these systems to flourish and develop trustworthiness. Furthermore, organizations need to use data to ameliorate their business processes, products, and services as well as for customers to share their data.

6.6.1. Future Trends

While many organizations are still struggling with addressing basic data governance principles, regulations, and compliance, awareness is growing of the necessity of more advanced principles, tools, and frameworks. Research challenges will include the development of cross-domain and cross-organizational principles and frameworks, the modeling of privacy, interpretability, and explainability in the AI context, and governance principles for metadata. Issues also exist around who should be liable for misbehaving AI algorithms and their uses, what the ethics of data uses would be, and which organizations should have data sovereignty in the data-sharing context.

The rapid pace of technology evolution will continue to have a significant impact on data governance. Digitalization and automation enable the generation, use, and sharing of ever-

growing amounts of data across organizations. Consequently, data governance and ethical data sharing have become urgent issues recognized in research, business, and politics. Legal frameworks, such as the European General Data Protection Regulation (GDPR) and the Data Governance Act, are becoming stricter. Additionally, the emergence of new types of ecosystems, like data and AI ecosystems and data as a service, will require new kinds of governance models. Data ownership will continue to be debated. As a response to these issues, the demand for and the supply of data stewarding and data governance solutions at different levels of business and architecture are growing.

Information systems play an important role in driving an organization's strategy, execution, business, and work systems. Alignment of the information asset decisions with the business intent has consequently gained a lot of attention. However, information systems cannot often show their intent as the meaning of information is often context-dependent and dynamic. Things turn more complex in an organizational context where there are many actors, information systems, and work practices involved. Each of the actors has a different perspective on how the information systems are supposed to support the business. All this and the lack of a holistic view of the information architecture significantly complicate the task of viewing and analyzing the states of the information systems and their alignment with the business intent. A conceptual framework to simplify the analysis of the information architecture of an organization from the perspective of its actors is proposed. This analysis allows the identification of the actors' perspectives regarding the information systems and then future developments can be planned to align the information architecture with the business intent. The framework consists of five views of the information architecture designed to answer different questions and with other content.

CHAPTER 7

AUTOMATING DATA TRANSFORMATION: AI TOOLS AND TECHNIQUES

7.1. Introduction

In recent years, AI tools and techniques have emerged as powerful enablers of automating data transformation tasks, tasks that are routine and time-consuming yet so critical for a range of business intelligence (BI) activities. Building on the understanding of the data transformation process and the available AI technology stack, this section examines both industrial use cases as well as AI solutions currently available in the market. Given that qualitative data transformation presents both challenges and opportunities that differ from quantitative transformation, there is a specific focus on NLP, an AI technology branch that is relevant to qualitative data transformation and one whose tools and techniques are extensively used in practice.

The goal of this research is to present and discuss AI tools and techniques for automating data exploration and transformation towards improving DQ and providing improved data for assessments, control decisions, and decision-making support. As input, this methodology requires datasets, databases, database schemas, application queries, user and business profiles, and DQ control options. From these data and configuration input, the presented methodology generates an exploration of the input data defining a DQ control transformation. Control transformations typically take as input data of two or more different natures or sources and generate as output new data that enables the DQ analysis of the involved data. Exploration transformation takes as input data of the same source and nature and generates as output new data that relates to describing the input dataset or database.

Advancements in electronics, mobile devices, and the internet have enabled the collection and storage of scientific, medical, economic, voluntary, and social data. This data provides innovative insights beyond human capacity, leading to the rise of "big data" in bioinformatics and financial applications. Reliable data characterizations and predictions are crucial for unleashing the knowledge embedded in big data. However, ensuring data quality is a challenge, as data systems are always compromised by erroneous and corrupt data due to

genetic and transmission errors. National surveys consistently identify data quality (DQ) as a major economic challenge, with the cost of poor data quality estimated at trillions of dollars each year. Such costs 1 to 4 times exceed the expenses involved in producing the data and associated services. In addition to financial impacts, wrong business decisions due to bad data can even endanger human lives in bioinformatics and medical applications.

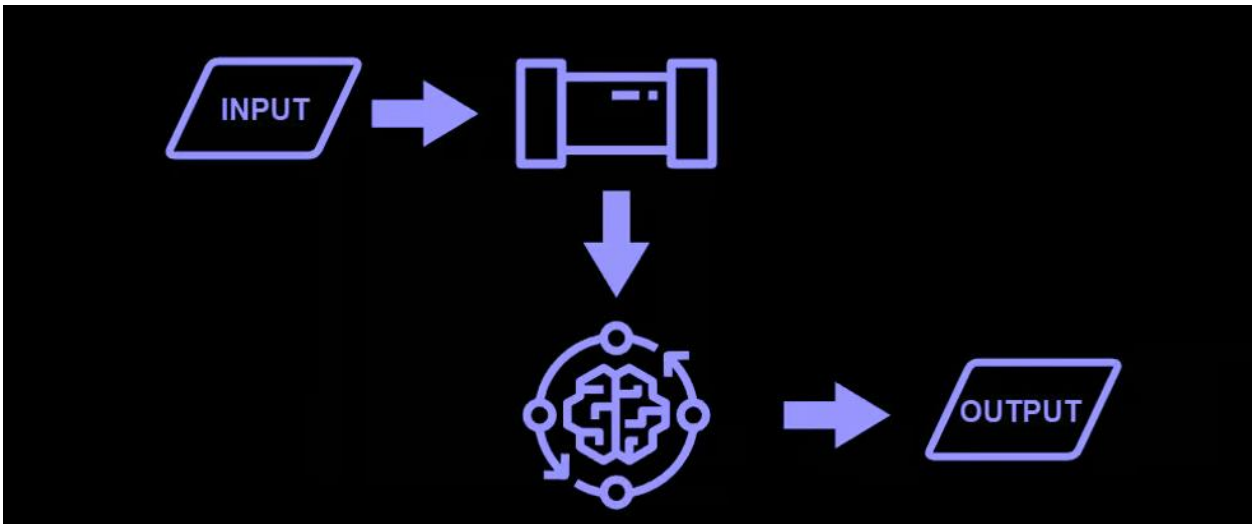

Fig 7.1: Automating Data Transformation

7.1.1. Background and Significance

These systems employ a variety of different techniques from ILP, machine learning, or example-based methods, including techniques similar to AI planning or schema matching. The potential of probabilistic logic programming like ProbLog is explored for the knowledge representation and reasoning of example-based data transformation with an underlying ILP theory. These systems were developed to facilitate the transformation of structured data like relational tables or semi-structured data like XML documents but are in principle limited to simple transformations on complex data types. Moreover, most of these systems rely on a modeling effort of the user to describe similarities between the data or transformations using hand-crafted predicates written in a logical programming style. Thus, they are not extensible to new types of data or domains without a complex modeling effort of the user.

One of the most widely used forms of automation is the development of custom programming and scripting languages like SQL or XQuery. Domain-specific languages can be simpler to use and may contain higher-level functions capturing domain knowledge that subsequently make specific data transformation tasks easier to implement. However, these approaches still require some programming effort and thus edge only part of the way toward complete automation. A different approach uses data integration languages such as GLU or NAIL that

allow specifying certain complex transformation tasks which can then be compiled into custom executable code, again requiring some modeling effort on the user's side. Over the years, various tools have been developed to help users express their intentions using input-output examples forming queries. Using these queries as inputs, the systems then search for an appropriate transformation among cases captured in their knowledge base.

The rapid evolution of various online forms of data, including websites, user-generated content, social media engagement, digital narratives, and sensor information, is creating a challenge for effectively analyzing, managing, and utilizing these forms of data. Data transformation can assist with formatting, cleaning, merging, and normalizing this data, but it is often a labor-intensive process and can thus be a bottleneck in allowing users to manipulate data. Several new tools, techniques, and methodologies harnessing machine learning are emerging to automate this process and attempt to generalize, learn, and reason about often very complex data transformation tasks. Here, a detailed overview of these approaches is given, including techniques introduced more than two decades ago as well as more recent advances that attempt to apply new data mining, deep learning, and AI techniques to this problem.

7.1.2. Research Objectives

The main objective of this research is to evaluate and document the capabilities of a variety of publicly available AI and automation tools for performing data transformations between unstructured, semi-structured, and structured formats. While this technology is still relatively new, it is increasing quickly in maturity and functionality. There is a need for a documentary assessment of current capabilities, along with guidance regarding the most appropriate tools for different tasks. Accordingly, this research is focused on the following questions:

- How capable are publicly available AI and automation tools for performing individual data transformation tasks, e.g., Natural Language Processing (NLP) tasks such as entity extraction and semantic enrichment?
- How capable are these tools for performing complex data transformation scenarios, in which a variety of tasks need to be performed, including data cleaning, data enrichment, natural language generation, and similar? What tools yield the best performance for each type of task?
- What are the pros and cons of each tool, in terms of quality, coverage of transformation tasks, and format compatibility?

- What is needed to overcome the current limitations of AI tools for performing data transformation tasks? Prior areas of research would help with this question.
- What are the ethics and liability issues involved in commercializing AI and automation tools for data transformations and the use of transformed data?

7.2. Foundations of Data Transformation

Recently, as the amount of data has increased significantly, there has been great interest in transforming data in a fully automated fashion. Automated data transformation processes include identifying, discovering, analyzing, and transforming raw data to transform it into a new representation that is better suited to a specific domain or task. Modern businesses often need to combine raw data from multiple sources to extract knowledge from it, and doing so requires transforming the raw data into a common representation. Failure to do so often results in data redundancy and lack of compatibility between the data models used. Modern advancements in machine learning and knowledge extraction techniques offer new opportunities by exploiting such raw data as a source of knowledge. However, due to the increase in data accessibility, the data sources are now heterogeneous and include a large variety of data representation models and formats.

Traditional data transformation processes involve analyzing the data contextually to discover any poorly structured, corrupt, erroneous, missing, ambiguous, or incomplete raw data, and transforming it into a cleaner and usable data set to derive useful knowledge from it. In the past, data transformation activities were performed manually, requiring skilled data and domain experts with significant time and effort. Regardless of the data source, this complex task required a specialist understanding of various technologies, programming languages, and domain knowledge. Consequently, few organizations engaged in data transformation processes, limiting the community with access to a broader pool of knowledge.

Data transformation is the process of converting data from one format or structure into another, ensuring that it is organized, consistent, and suitable for analysis or further processing. The importance of data transformation has grown significantly in recent years, driven by the massive growth in the volume, variety, and sources of data generated by organizations across different industries. The ability to transform raw data into actionable insights is critical for organizations to remain competitive. A data transformation strategy is essential to successfully manage the ever-increasing influx of data.

7.2.1. Definition and Importance

With growing data and privacy concerns, there has emerged the concept of privacy-preserving data publishing. It aims to publish results from analysis that do not compromise confidentiality, while also being useful for further analysis. Intending to scale traditional data transformation techniques to big crude data and derive insights from crude data, this essay discusses the automation of data transformation using Artificial Intelligence (AI) tools and techniques. AI tools and techniques, without any human intervention, are capable of transforming crude or raw data into competition-ready, usable, or meaningful data, thereby replacing the traditional manual or partially manual data transformation methods.

Data transformation is defined as altering the structure, format, or values of data. It is a commonly used step in the data processing stages. Data transformation operations include changing the format of a record, changing a field length, correcting a misspelled name, and many others. Many tools are available for data transformation: Data Warehouse ETL (Extract, Transfer, Load) tools, data replication tools, and data cleansing tools. Since these tools require extensive training, rendering them ineffective for one-time data transformation, data transformation is frequently done manually. Manually transforming data is tedious and time-consuming since it can require sifting through records at million or billion levels.

Data is generated at an unprecedented rate and is on the verge of reaching a zettabyte scale. The more the value of data is realized, the more data storage is increasing. A considerable amount of data is retained due to its importance, but much of the crude or raw data may contain 80-90% of irrelevant or repeated data. With the existence of such crude data, many standard statistical tools have not been able to provide the desired output. Therefore, there is an emerging need to transform crude or raw data into usable or meaningful data.

7.2.2. Traditional Methods vs. AI-based Methods

Based on kinds of knowledge, the proposed techniques can be classified into traditional methods and AI-based methods. Traditional methods usually require a semi-structured or unstructured data source and consequently generate a structured relational data target. The proposed AI-based approach accepts both structured and semi-structured or unstructured data sources and generates a data target containing a formal relation representation. Such formal representation can be in either RDF format or OWL format. In addition, while the traditional method researches an integration schema mapping between data source and target, the

proposed AI-based method studies the transformation schema mapping between data source and target containing explicit data transformations. According to the kind of schema mapping generation, applicable data source and target format, and the existence of explicit data transformation representation, the overall classification would cover existing methods and those to be introduced in the sequel.

Over the past couple of decades, several tools have been proposed to aid data transformation by automating the process either partially or fully. Manual data transformations require many steps that are tedious and error-prone while using tools still requires a fair amount of human knowledge and intervention. This paper aims to introduce new data transformation techniques based on artificial intelligence (AI) technologies that automate data transformations using means of machine learning, natural language processing, and game theory.

Data transformation is a crucial element of data integration, as well as data preparation before conducting any sort of data management tasks such as data analysis, data aggregation, statistical modeling, data mining, machine learning, etc. With the ascendance of computerization and digitization, a huge amount of data has been generated and stored over time. Data can come from various data sources, including databases, flat files, spreadsheets, web services, and even data extracted through scraping from web pages. Such a plethora of data sources can come in different data formats. Oftentimes, data extracted from one source wants to be integrated into another data target that may differ in data structures, data schemas, or data formats. For example, data extracted from an HTML web page wants to be stored in a relational database table. Or, XML data representing an invoice message wants to be processed into a data mart. However, before anything else, data has to go through the process of data transformation.Data transformation is a pivotal process in data integration and preparation, crucial for ensuring that disparate data sources—ranging from databases and spreadsheets to web services and scraped data—can be effectively utilized in various data management tasks such as analysis, aggregation, and machine learning. Traditionally, data transformation has involved semi-structured or unstructured sources, with methods focusing on creating structured relational targets. These conventional approaches often require detailed schema mapping and manual intervention, making the process tedious and prone to errors. However, with the rise of AI technologies, there is a shift towards more advanced methods that leverage machine learning, natural language processing, and game theory to automate and enhance data transformation. These AI-based techniques are capable of handling both structured and unstructured data, generating formal representations such as RDF or OWL formats, and providing explicit transformation mappings. This paper explores new AI-driven approaches to

data transformation, aiming to improve automation and accuracy in integrating diverse data sources into coherent and usable formats, ultimately streamlining data management processes in the era of extensive digitization.

Fig 7.2: AI Automation vs. Traditional Methods

7.3. AI Techniques for Data Transformation

Deep learning is a subfield of machine learning that seeks to model complex concepts using a hierarchy of concepts. Deep learning traditionally refers to deep neural networks with multiple cell layers and has gained significant attention since 2012 due to its state-of-the-art performance in various applications. Insightfully, deep learning is often viewed as a potential pathway toward artificial general intelligence (AGI). A full deep learning framework includes data representation, a learning algorithm, and a priori knowledge and prior belief about the world. Deep learning models are often categorized into three categories, supervised, unsupervised, and generative models.

Machine learning is a branch of AI that allows computer programs to learn from experience. In the past decades, machine learning has gained broad interest from both academia and industry due to vast, readily available data and the advancement of computing power. A simple

definition of machine learning is "the study of computer algorithms that improve automatically through experience". Machine learning algorithms have been widely applied in various applications, including visual recognition (e.g., face recognition, object detection), natural language processing (e.g., information extraction, translation), and decision-making (e.g., recommender systems, financial forecasting). Classical machine learning algorithms may include supervised models, such as regression and discrimination classifiers, as well as unsupervised models, such as clustering and topic models. Recent advancements in machine learning, recently coined as "deep learning," have further pushed the frontier of machine learning.

Data transformation is the process of converting data from one format or structure into another. This process is fundamental to data preparation or data wrangling, which is essential to decision-making and data analysis. Automated data transformation is becoming increasingly feasible using emerging artificial intelligence (AI) tools and techniques. This chapter presents foundational AI techniques that could power automated data transformation tools. In a broader sense, AI techniques can be divided into two categories: machine learning and deep learning.

7.3.1. Machine Learning Algorithms

In the realm of data transformation, data cleaning and preparation are crucial tasks in the data analytics pipeline. A research study by researchers at MIT shows that data cleaning and preparation accounts for up to 80% of the time that data analysts spend on their tasks. At the same time, cleaning and preparing data is among the most difficult tasks for data analysts. In response to this pressing need, various AI tools have been introduced on the market for automating data cleaning and preparation. At present, however, the market for these AI tools is fragmented and research in this field is still in its infancy. As a first response to these challenges, researchers have identified and organized the most state-of-the-art AI tools for automating data cleaning and data preparation.

Machine learning algorithms guide feature transformation. They start from a raw dataset and iteratively transform it into a feature representation that is most suitable for a classifier. The popular machine learning algorithms are Random Forests (RF), Support Vector Machine (SVM), and K-nearest Neighbors (KNN).

Given a dataset sampled from a bag of words, the purpose of feature transformation is to find a low-dimensional Euclidean representation of points such that the same words cluster together. In such a representation, the distance between any two points is inversely related to

the likelihood that the associated words co-occur in a document. In this context, three popular classifiers from the machine learning perspective are investigated: Random Forests, support vector machines, and K-nearest neighbors. Random Forests construct a large number of decision trees based on random subsets of the dataset and with the help of out-of-the-box approaches, the Bag of Words is considered magic. This method, widely used for classification, is one of the most efficient and accurate approaches for representing data in the shallow. Support Vector Machine searches for an optimal linear hyper-plane that classifies data into different classes. It has been successfully applied to many applications across vision, text, and biology.

K-nearest neighbors classifies a test instance based on the class of its k-nearest neighbors from the training set. An important note for primitive transformation is that it requires numeric features but the Bag of Words output is a binary dataset. Therefore, two additional transformations are applied beforehand, namely, normalization and k-NN graph construction. Normalization is applied for each feature i to obtain datasets in which the same mean and variance are 0 and 1, respectively. It should be noted that if a Coward, M.M. dimensionality reduction algorithm is applied that does not preserve the distance of the features, like Laplacian Eigenmap, for example, this would obviate the need for normalization. In this context, the KNN graph is constructed based on cosine distance.

The graph construction requirements allow only numeric features in the shallow end while the dataset that goes into SLICER is Bag of Words, thereby with the need to transform it for further use. On the other hand, the datasets perform similarly in almost all cases on high-dimensional datasets but exhibit differing behavior on low-dimensional datasets, thereby exhibiting better generality.

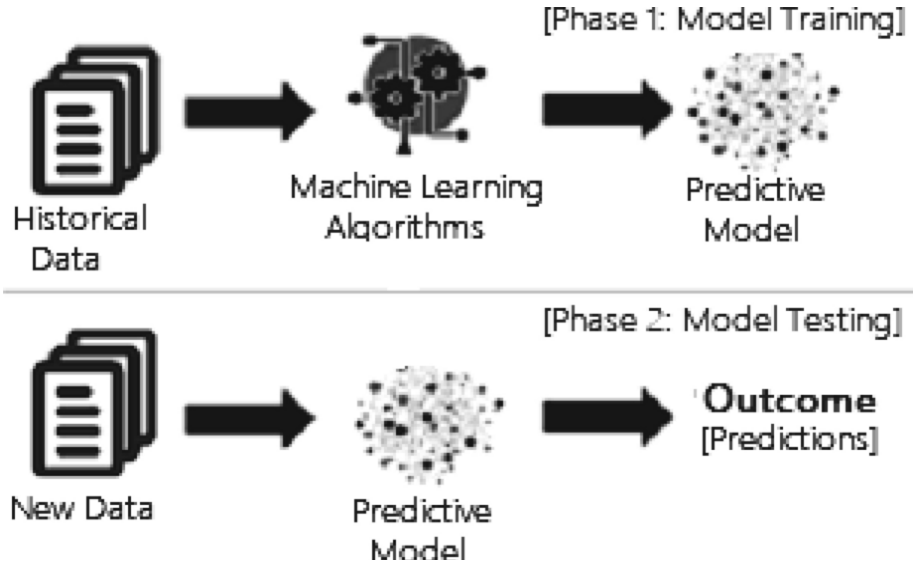

Fig 7.3: Machine Learning: Algorithms, Real-World Applications

7.3.2. Deep Learning Models

Deep learning models have emerged as powerful tools in the field of artificial intelligence as they possess the ability to automatically learn relevant features and representations from data. These models are often composed of multiple layers of interconnected nodes or artificial neurons, where each layer learns increasingly abstract features. In recent years, deep learning models have gained significant attention for automating data transformation tasks.

One prominent deep learning model architecture used for data transformation is the transformer network. Originally proposed for natural language processing tasks, transformers have proven effective in processing sequential data. They utilize self-attention mechanisms to capture dependencies between input data points, allowing them to handle long-range dependencies effectively. Transformers have been adapted and applied to various data transformation tasks beyond language, including time-series forecasting, image captioning, and more.

Another widely used deep learning model is the Convolutional Neural Network (CNN), renowned for its effectiveness in image-related tasks. CNNs possess local connectivity and parameter sharing between neurons, allowing them to automatically learn translation invariant features such as edges, textures, and shapes from input images. CNNs have also been adapted to feed one-dimensional numerical sequences, such as time-series data, to learn relevant patterns in the input data. CNN-based models have been employed for different data transformation tasks, such as univariate time-series forecasting, multivariate time-series forecasting, image classification, and more.

Recurrent Neural Networks (RNN) are deep learning models particularly suited for data transformation tasks involving sequential or ordered data. They can maintain and update hidden states, meaning they can capture the order of input sequences and their long-term dependencies. RNNs have been commonly used for modeling sequential data, such as text or time-series data, for automating various data transformation tasks. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are well-known RNN architectures that address the limitations of vanilla RNNs, such as vanishing/exploding gradient problems, to achieve long-range temporal dependencies.

While most deep learning models require a significant amount of data to perform well, numerous pre-trained models have been developed for transformers and CNNs that can be adapted to other tasks or domains through transfer learning. As data transformation tasks

concern the transformation of input data from one format to another, there is usually a significant discrepancy between the input and output data. In other words, an abundant amount of input data can be leveraged to learn a model to produce or approximate the output data format. This can be posed as a deep learning paradigm often referred to as the source domain adaptation, where models trained on data in one format or domain are adapted to work on a different, unseen, or novel format or domain.

7.4. Applications of AI in Data Transformation

Open texts like emails, chats, tweets, comments, images, videos, and voice have become an integral part of the information architecture that organizations create, store, and combine with their other organizational data assets, often referred to as Big Data. Qualitative data transformation is a multi-stage, context-driven, and interactive process where trained data analysts understand the meaning of the source format, seek to get the target meaning precisely right, explore semi-automated approaches, and iteratively adapt the approach and/or the data itself. Building on an understanding of the qualitative data transformation process, a solid foundation for fostering an informed discussion about the AI technology stack relevant to it is developed, including 1) Natural Language Processing (NLP) Pipelines, 2) Machine Learning, 3) NLP capabilities made available through cloud-based platforms, and 4) Open-Source pre-trained NLP Models.

Data transformation is the process of converting data from its original format or structure into a format or structure that is more appropriate for the data storage, manipulation, analysis, and visualization activities in BI. In either case, problems related to data cleaning, data classification, and data enrichment are commonly encountered and deemed to be data transformation tasks. In the aftermath of an ever-increasing sophistication of data extraction, transformation, storage, manipulation, and visualization technologies, there has been a commensurate emergence of AI as a promising technology stack for automating BI-related tasks. There is a need for reviewing how AI is currently applied to data transformation tasks, to examine if and how AI can tackle this challenge, as well as to catalyze future developments in this far-reaching area.

7.4.1. Industry Use Cases

In a world driven by data, organizations are inundated with vast amounts of raw, unstructured, and disparate data coming from various channels. This data deluge holds the potential to assist companies in making smart business decisions and thriving in a competitive environment. However, this information needs to be processed and transformed into a consistent and reliable format before it can be utilized. Data ingestion generates unstructured data that requires data transformation procedures to convert it into a structured and harmonized format. Data transformation is essential in data processing and is a necessary step in the ETL (Extract-Transform-Load) process.

Data transformation comprises numerous activities that modify the structure and format of the data according to business needs. Manual data transformation involves conventional techniques like data cleansing, parsing, sorting, and filtering that necessitate the deployment of data specialists. However, with the massive data surge today, manual methodologies are not only inefficient but reconciliations might be missing historical events due to long processing time. This has led to the demand for automated data transformation setups with the ability to consume raw data, harmonize, and publish it automatically without human intervention. Industry giants have set the trend for data transformation automation and have deployed some early pilot projects. Machine Learning (ML) technique advancements have enabled data transformation processes to be automated and reconciliations to be made reliable. The generation of transformation rules that specify the transformation logic between the above-described data format pairs is the foundation on which most of the data transformation automation setups are built.

Industry use cases are proposed with a potential future setup for data transformation automation in the financial domain using ML techniques. The possibility of data transformation automation is tested with proposed machine learning models, and the results on test datasets provide a convincing argument against the possibility of automation. Machine learning models such as Random Forest, Multinomial Naïve Bayes, and Argentinian Random Trees with Ensemble on top are trained and tested on larger data volumes with positive results. A survey of data transformation principles, strategies, methods, tools, and systems was conducted to evaluate the state of the art in data transformation. This world of financial technology and automation has been explored through published papers, articles, and blog posts. Crucial challenges and areas of opportunity in data transformation automation were identified, such as specifying transformation rules that fulfill business requirements, handling

incomplete transformation specifications or samples, and ensuring the quality of generated transformation rules. Additionally, an overview of data transformation automation solutions, including research prototypes, open-source systems, and industry products, was presented.

With the potential to handle massive data volumes in a short period, data transformation automation is believed to be the way forward, as the benefits of automated setup greatly exceed the downside risks. A special focus on the financial domain is proposed, as there is a strong reflexive need, but there are still multiple challenges to be tackled.In today's data-driven world, organizations face an overwhelming influx of raw, unstructured data from diverse sources, necessitating effective processing and transformation to derive actionable insights. Data transformation, a crucial component of the ETL (Extract-Transform-Load) process, converts this raw data into structured and reliable formats suitable for business use. Traditionally reliant on manual techniques such as data cleansing, sorting, and filtering, this process has become increasingly inefficient amid the massive volumes of data generated. The emergence of automated data transformation solutions, powered by advancements in Machine Learning (ML), offers a promising alternative by streamlining data processing and ensuring accuracy without extensive human intervention. Industry leaders have pioneered automation efforts, leveraging ML models like Random Forest and Multinomial Naïve Bayes to handle complex transformation rules and large datasets with impressive results. A comprehensive survey of current principles, strategies, and tools highlights both the progress made and the ongoing challenges, such as defining precise transformation rules and managing incomplete specifications. Focusing on the financial sector, where the need for efficient data transformation is particularly acute, this paper emphasizes the transformative potential of automation while acknowledging the need to address remaining challenges for successful implementation.

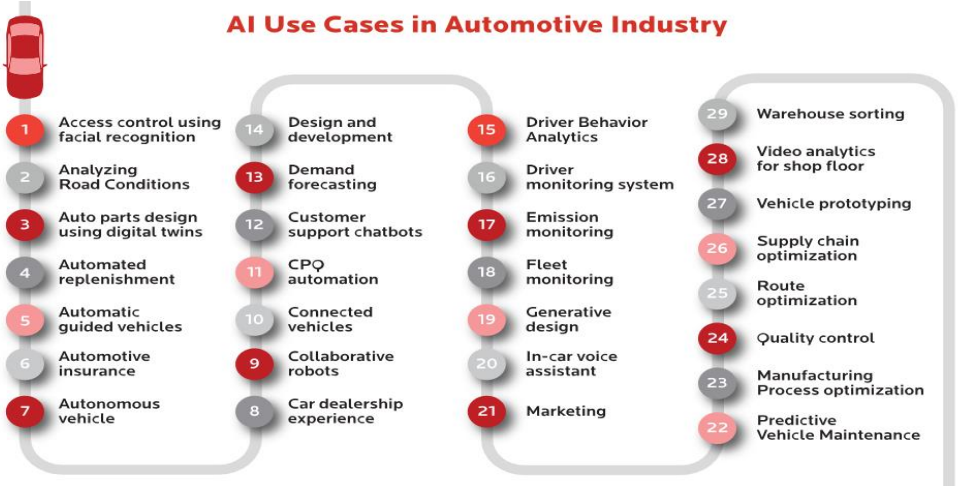

Fig 7.4: AI Use Cases - Transforming the Automotive Industry

7.4.2. Challenges and Limitations

In addition, concerns arise around regulations and compliance, especially regarding the use of confidential data and the inability to reproduce ETL processes. Friction associated with the individual use of AI tools' outputs (e.g., T-SQL code) can stifle productivity as suggestions or generated code go against provided guidelines. Therefore, it is pivotal to complement AI tools with equally capable support in code review, testing, and documentation. A unified approach to data transformation would enable organizations to efficiently govern AI-enabled transformation flows. Vendors can enhance their tooling by incorporating marketplace platforms or shared cloud infrastructures for a community to improve these products collectively. In this pursuit of holistic solutions, the collaboration between clients and suppliers is key.

Despite the numerous advantages offered by incorporating AI tools for data transformations and integrations, a multitude of challenges and limitations persist. Workflows based on AI-generated T-SQL code alone are unattainable and impractical in companies. Factors such as business logic changes or the complexity of T-SQL queries create dependency and maintenance problems. For companies seeking to upscale or sustain their productivity, the approach might not sufficiently boost transformation efforts in a cost-competitive manner. Full automation is often seen as a development goal, instead of more hybrid approaches with augmented developers. Concerns about overtrusting the generated code would require proof of traceability, validity, and robustness.

7.5. Future Directions and Research Opportunities

Investigating mixed-initiative systems for programming language production in the vein of the "Scribe" vision is highly desirable. This encompasses generating programming languages from a palatable natural language specification, with a principled representation of semantic commitments, supporting counterfactual reasoning, and providing grounding (e.g., to domain knowledge). Alternatively, starting from a sketch specification, diverse refinement methods such as interactive, random, or Greedy could be explored, ideally using semantic programs as intermediaries to alleviate search pressure.

Focusing on programming languages designed specifically for defining transformations over datasets, the prospective research may include mechanisms for efficiently learning such programming languages. Additionally, large-scale pre-trained LMs (Language Models) offer

considerable promise for both semi-supervised language generation and data-centric programming. Similar to the methods for generating spreadsheets and Prolog programs, exploratory research could be directed toward generating interpretable languages that are neither too simple (to remain useful) nor too complex (to remain beyond the capability of LM). Currently, successful empirical efforts in few-shot scenarios employing LMs can be delineated, and more research is warranted to rigorously characterize these languages in terms of their expressiveness, learnability, and even physical properties.

The swift evolution of artificial intelligence (AI), especially in the realm of natural language processing (NLP), has catalyzed the creation of a plethora of innovative approaches employing generative AI tools. These tools provide novel capabilities to interactively generate and apply data transformation specification languages, often referred to as "data-centric" programming languages. In this research realm, an urgent need and ideal opportunity arises to pursue a novel research thrust focusing on the interactive generation of programming languages with natural language interfaces for data transformations. This proposal delineates significant research thrusts, outlines pivotal research challenges, and catalogs a collection of compelling use cases for this initiative.

7.6. Conclusion

However, the rapid proliferation of generative AI tools raises questions about capabilities, performance, and use cases. Recent critiques of the early capabilities of generative AI tools have highlighted limitations, caveats, and boundary conditions. The exponential growth of knowledge also raises concerns about navigating this new terrain and finding the best tools for implementing specific use cases. Exploring the burgeoning ecosystem of generative AI tools for data and analytics tasks can shed light on these questions, critique capabilities, and performance, outline the current state of these tools and techniques, mention promising ongoing and future developments, and explore use cases and implications for organizations.

Automating data transformation could reduce data engineers' work time by up to 40%. Given the rapid adoption of generative AI tools, data transformation, usually a tedious and laborious task requiring a high degree of expertise, will likely become a standard procedure. This offers an opportunity for scalable, budget-friendly approaches to implementing cutting-edge, novel technologies.

The domain of data transformation is radically evolving due to the advent of generative AI tools. Almost all publicly available, low-code tools for transforming data have incorporated generative AI capabilities into their offerings. Tools such as DataRobot's ICloud, TimeXtender's TimeXtender, Knime's Knime Analytics Platform Create, Hex's Hex, and Microsoft's Azure OpenAI are front-runners in this arena. In addition, open-source and DIY developers can access libraries and models to build their specialized tools.

7.6.1. Future Trends

Traditional BI tools will be complemented by sophisticated AI assistants, proxies, or negotiation bots capable of generating insightful "what-if" questions and choosing the best creative visualizations. Automated data transformation will be applied beyond structured data and curated business use cases, covering big data warehouses, operational datasets, and uncurated or semi-curated data domains from various industries like manufacturing (IIoT), energy (SCADA), telecommunications, and health (HIT, lab systems, genomic and imaging data). Automated data transformation will become a standard and cost-competitive process that all data-related industries can utilize. Therefore, the next decade will witness the transformation of data-centric ecosystems into information-centric ecosystems, emphasizing higher-level knowledge and context management instead of handling raw data collection.

Over the next five to ten years, the integration of AI tools and techniques for automating data transformation is poised to revolutionize the data management landscape. This transformation will unfold across various dimensions, each holding significant implications for organizations, data professionals, and the industries they operate within. AI's ability to analyze data, draw inferences, learn from experiences, and make decisions is expected to reshape data transformation processes significantly.

Under the AI-based paradigm shift, the demand for skillset-centric positions, such as data engineers, transformation analysts, and quality analysts, is anticipated to decline. Conversely, the demand for professionals with expertise in AI, ML, and natural language processing is projected to grow. Individuals who can bridge the gap between domain expertise and AI will possess a competitive edge. The ensuing data transformation ecosystem will likely cater to non-technical roles, including Directors, CFOs, COOs, and CTOs, absolute business users, who will input business-related questions or transformation requests and receive generated results through an end-to-end pipeline.

Real-time data integration and transformation processes are anticipated to become popular due to the growth of IoT (Internet of Things) devices and the need for continual streaming data generation. Using an end-to-end AI framework, domain experts can define the high-level requirements and let AI-driven solutions generate and execute the entire project. AI-to-AI partnership will represent the comparison, recommendations, and decision-making processes between multiple AI tools, and AI-enabled industry solutions will target the rapid analysis and visualization of dashboard reports for massive datasets.

CHAPTER 8

PREDICTIVE ANALYTICS AND FORECASTING: FROM BIG DATA TO ACTIONABLE PREDICTIONS

8.1. Introduction

Modeling and forecasting based on probabilistic models is scientifically appealing and crucial for modeling and predicting the behavior of non-deterministic systems. It provides insight into uncertainty levels, which is useful for risk assessment and path planning. Probabilistic modeling and forecasting approaches rooted in statistical mechanics, statistical physics, and/or chaos theory are rich and diverse but are generally computationally challenging for medium to high-dimensional systems. High-dimensional systems are usually studied using a coarse-grained or reduced-order approach. To build tractable models for the coarse-grained variables, kinetic equations are often invoked to link the coarse-grained dynamics with the fine-grained ones. When the fine-grained models themselves are based on kinetic equations, which is the case for many physical systems, a hierarchy of kinetic equations arises. Predictive analytics and forecasting based on partial dynamical models relying on coarse-grained variables desperately depend on and may even fail due to the errors introduced by the coarse-graining process. Nonetheless, forecasting with a truncated model can be done non-causally using information on the coarse-grained fields at the current time, such as through Kalman-like approaches.

In the modern data-driven world, the sheer volume of data generated daily is unprecedented. From transaction records at retail stores to information logged from mobile devices, this big data carries intangible information about future risks and opportunities. However, the raw data needs to be effectively mined and meaningfully converted into knowledge. Despite the hype surrounding big data, predictive analytics licenses practical algorithms for forecasting unknown future values of variables of interest based on past data. This work aims to provide clear and actionable solutions for business, engineering, and public policy problems using Bayesian coarse-to-fine techniques. Such probabilistic predictive modeling is feasible for big data, as many real-life systems often rely on low-dimensional physics-based models. Even when this is not the case, the cooperation of many systems with different time-space scales often leads to naturally coarse-grained or reduced-order arrangements. The goal is to illustrate

this broad view of predictive analytics and probabilistic forecasting with various application scenarios.

Fig 8.1: Predictive Analytics Techniques

8.1.1. Overview of Predictive Analytics and Forecasting

Forecasting on pointwise time-ordered data consists of producing predictions for the next steps of a system based on a previously observed subset of this temporal string. Considering the first observations as historic data, they all are successively eliminated from the temporal domain of the modeled phenomenon or system in some manner. Following the global trend of the events, the forecast horizon makes its way progressing through the string of events. Such a purview is general to all forecasting procedures irrespective of their complexity.

Data collected in time (temporal data) can be considered as a string of events occurring one after the other. These events become progressively "older" with time, losing their impact on the future state. A conceptual view of temporal data is shown in the attachment, where each event has a gray body that expresses its progressively diminishing impact. A common approach to handle this decay is the use of a forgetting factor that gives more importance to more recent data, generally exponentially.

The collection of information about a system or phenomenon growing in time can be classified into two main types, depending on what dimension of the system is measured. When the aim is to classify the state of the system, a "spatial" view is typically used, where data is acquired about various locations where the phenomenon occurs. Examples include meteorological data at weather stations or regional economic activity. When the aim is to predict the future evolution of the system as a whole, a "temporal" view is typically taken, where data is acquired over time for a specific location. Examples include stock market prices, temperature, or pollution at a specific location. The latter type of data is also referred to as pointwise or univariate data.

In the information age, the availability of large datasets presents both an opportunity and a challenge for organizations across all sectors. Making accurate predictions based on such data can be extremely valuable, providing the ability to anticipate, plan, and improve activities and products. Such predictive analytics has the potential to benefit everything from sports to finance, marketing to security.

8.2. Foundations of Predictive Analytics

The Interest Measures Fundamental for Predictive Patterns: This section introduces the concept of interestingness models and the reliability of discovered predictions within a more extensive theoretical framework. Patterns across the KDD domain are typically domain-dependent and analyzed regarding their capability of generating useful knowledge. Subsection A theoretically settles a definition of predictiveness that regards the usefulness of a pattern within a domain. Within this context, the concept of a predictive pattern is defined and interpreted, as well as the notion of interest degree in a predictive pattern.

Proposed systems under the KDD framework aim at discovering useful patterns. Patterns are typically studied through Automatic Rule Discovery systems or Association Rule Mining systems. Such a development predictably derives from the early definition of KDD as the use of data mining (which sometimes refers exclusively to these systems) for discovering interesting patterns.

KDD is a multi-step process, which consists of data cleaning, data integration, data storage, data mining, pattern evaluation, and knowledge presentation. Data cleaning removes noise and with it distorts data values, such as missing significant values or low-frequency ones. Data integration merges or consolidates data from multiple heterogeneous sources. Data storage is concerned with the organization of data to easily access it afterward. Data mining refers to the

nontrivial extraction of implicit, previously unknown, and potentially useful information from a dataset. A knowledge discovery solution has to increase the accuracy and visibility of the data analysis results from the examined dataset, thus augmenting its comprehension afterward. Pattern evaluation molds data mining results into useful knowledge according to a set of interestingness measures that evaluate the discovered patterns. Pattern evaluation regards the interpretability or comprehensibility of the patterns, their unexpectedness, validation, novelty, usefulness, and actionability. Knowledge presentation involves the visualization of discovered patterns or generalization rules and uses reporting tools to proactively transfer knowledge through an automatically generated database report.

Knowledge Discovery in Databases (KDD): KDD, or knowledge discovery in databases, refers to a process that extracts, analyzes, and interprets data to obtain valid information from a dataset. Typically, the dataset is enormous and complex, containing diverse forms of information fabrics and static data, such as texts or images. As a result, KDD's goal is to extract unknown and useful information formerly hidden in a huge dataset.

8.2.1. Key Concepts and Terminology

An overview of currently available tools, applications, consumer behavior modeling bases, data, and software related to predictive analytics is also provided. By better understanding the available knowledge foundation, particularly in the marketing domain, a better decision on the most appropriate level of predictive analytics within an organization in question and the steps necessary for its implementation could be made. Predictive analytics employs sophisticated mathematical and statistical modeling techniques on top of the available data to support and improve decision-making processes. By creating a deeper understanding of data on business processes, unforeseen patterns, relationships, and influences could be uncovered, leading to more precise, reliable, and actionable predictions about the development of the business process.

In addition to customer behavior modeling concepts and terminologies, data storage and data mining methods applied in predictive analytics and explanatory analytics are discussed. There is a gap between understanding and adopting the full potential of predictive analytics because it is not easy to understand, implement, and use the most appropriate modeling methodology and concepts, which could improve an organization’s competitive position. The need for further guidelines and a brief overview of the landscape of available knowledge sources and tools for its realization is pointed out. To fill this gap and reduce the polarization between

demand and supply for knowledge, data, and methods necessary for implementing predictive analytics, a categorization of predictive analytics-related key concepts and terminology is presented.

The knowledge foundation for predictive analytics comprises data, software, and methodologies. The data includes historical data on business processes along with externally available data that could improve their explanation. Software applications and platforms for exploratory or descriptive analytics provide great added value for predictive analytics. Methodologies for behavioral modeling, predictive analytics, and customer-oriented market approaches are built up in a second layer upon the data and software foundation.

Predictive analytics has emerged as a unifying discipline that bridges mathematics and business domains. It employs advanced mathematical and statistical methods built upon existing business processes and explanatory analytical techniques to support and improve critical business decision-making processes. Several terms and concepts related to predictive analytics, particularly in the marketing domain, are categorized and briefly described, including customer behavior modeling concepts, modeling approaches, methodologies, data, data storage, and software.Predictive analytics, a crucial tool for enhancing decision-making processes, integrates sophisticated mathematical and statistical techniques with existing data to uncover patterns and relationships that inform future business strategies. By analyzing historical and external data, predictive analytics provides actionable insights that can significantly improve organizational decision-making and competitive positioning. This approach not only aids in understanding customer behavior and refining market strategies but also bridges the gap between complex modeling methodologies and practical application. Despite its potential, there remains a challenge in fully grasping and implementing predictive analytics due to its complexity. To address this, a comprehensive overview of current tools, applications, and methodologies is essential. This includes exploring data storage and mining methods, as well as categorizing key concepts and terminologies relevant to predictive analytics. By providing a clearer understanding of these elements, organizations can better navigate the landscape of predictive analytics and effectively apply it to enhance their business processes and decision-making capabilities.

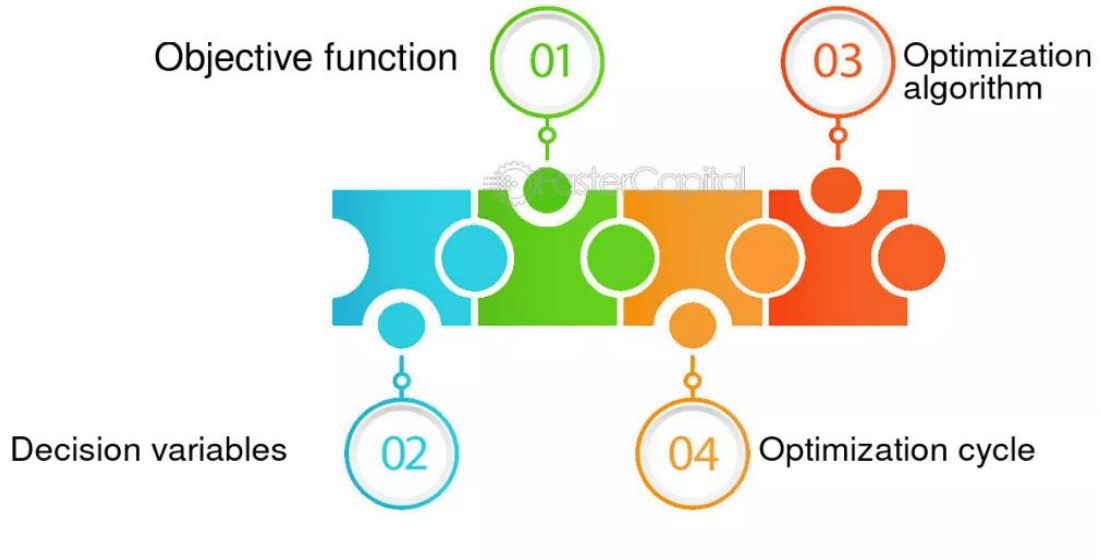

Fig 8.2: Key Concepts and Techniques

8.3. Techniques and Algorithms

This section will review two methodologies for forecasting time series: the first is based on statistical regression models and the second methodology is used for modeling from artificial intelligence techniques, known as artificial neural networks (ANN). The implementation of these approaches is illustrated in the case of real-world data: electricity demand in Greece. Performance indices commonly used to validate the efficiency of predictive models will be applied to compare the predictive ability of the different alternative techniques. In applying these concepts, many techniques and alternative algorithms have been developed to produce forecasting models on a purely empirical, or black-box, basis. Data-driven, or black-box, techniques are based on the assumption that the knowledge needed to explain the behavior of a multivariate time series can be wholly derived from its field data, through the modeling of implicit relationships. On these grounds, when prior knowledge of the system to be modeled is either unavailable or insufficient and where the underlying processes of the phenomena are considered too complex to be described by deterministic equations, a new generation of techniques known as data-driven or black-box techniques has been adopted as a means of obtaining forecasting models based purely on the field observations.

Most conventional statistical explanations and methods rest on strong assumptions: a linear relationship between the input and output variables, a limited number of variables and interactions, normally distributed data, homoscedasticity, etc. When these assumptions are not met, predictions can be very misleading.

An indication of future values of a variable may be obtained from the past values of the variable itself, or it may be obtained from other variables to explain the variability of the variable whose future values need to be predicted. In the first case, forecasting models are referred to as univariate models, while in the second case, they are referred to as multivariate models. Statistical techniques are often used to obtain predictive models relating a variable to previous values of itself (univariate models) or other explanatory variables (multivariate models). These statistical techniques are called linear regression analysis and are designed around the linearity assumption.

8.3.1. Regression Analysis

A fully trained linear regression model yields parameters (β0 and β1) for a visually represented simple linear regression line plotted within a Cartesian coordinate system. There are, however, other multiple linear regression algorithms that yield different representations of coefficients where the independent variable is within the range [0, 1]. Ridge regression is one such algorithm formulated as follows: min β $\{\sum(yi - \hat{y}i)2 + \lambda\sum\beta2\}$ where λ is a parameter adjusting how penalized a given coefficient is. Therefore, the different forms of the objective function lend different representations of coefficients depending on their prior distributions. In the case of ridge regression, the model assumes a normal prior distribution for all coefficients except for the intercept (β0), causing coefficients to shrink towards zero.

Linear regression, employing the least square method, is the simplest and most commonly used technique. Unlike logistic regression, which utilizes the logistic function to predict probabilities, linear regression uses a linear function to model the relationship between variables. Linear regression can be categorized as simple or multiple: simple linear regression involves independent and dependent variables, whereas, in multiple linear regression, coefficients are assigned to two or more independent variables. Implementing linear regression allows predictions of values based on differences in the independent variable vector (X) while having an already known dependent variable vector (y). In mathematical terms, the equation of a line can be expressed as: $y = \beta0 + \beta1x1 + \beta2x2 + \beta nxn + \varepsilon$, wherein y is the dependent variable, x1, x2, ..., xn represents independent variables, β0 is the intercept, β1, β2, ..., βn are the coefficients indicating how much y changes with unit changes in xi, and ε is the error term. Hence, the problem mathematically becomes to find β = (β0, β1, β2, ..., βn) such that the following objective function is minimized: $\sum(yi - \hat{y}i)2 = \sum(yi - (\beta0 + \beta1x1 + \beta2x2 + ... + \beta nxn))2$. Consequently, the sum of residuals or errors is to be minimized since these values

estimate how much the predicted values differ from observed values. One common mistake is to minimize $\sum|y_i - \hat{y}_i|$ without squaring the residuals, as this would result in many zeros and not finding uniquely identifiable optimal solutions.

Regression analysis can be broadly classified into parametric and non-parametric methods. Parametric methods, such as linear and generalized linear regression, assume that the underlying relationship between the dependent and independent variables can be described by a finite set of parameters. In contrast, non-parametric methods, such as kernel and spline regression, do not impose a rigid functional form on the relationship and attempt to estimate it through local smoothing. Borrowing concepts from optimization theory, both approaches estimate the model parameters or functions by minimizing a loss function, typically capturing the discrepancy between the observed and predicted values. As a general rule of thumb, parametric models are more computationally efficient, while nonparametric techniques offer greater flexibility.

Regression analysis is a set of statistical techniques used to model the relationship between a dependent variable and one or more independent variables. Being one of the oldest and most widely used techniques in predictive analytics, regression analysis finds application in various domains, including economics, finance, healthcare, social sciences, and marketing. The popularity of regression analysis stems from its interpretability, robustness, and ability to handle complex relationships amid noise and uncertainty.

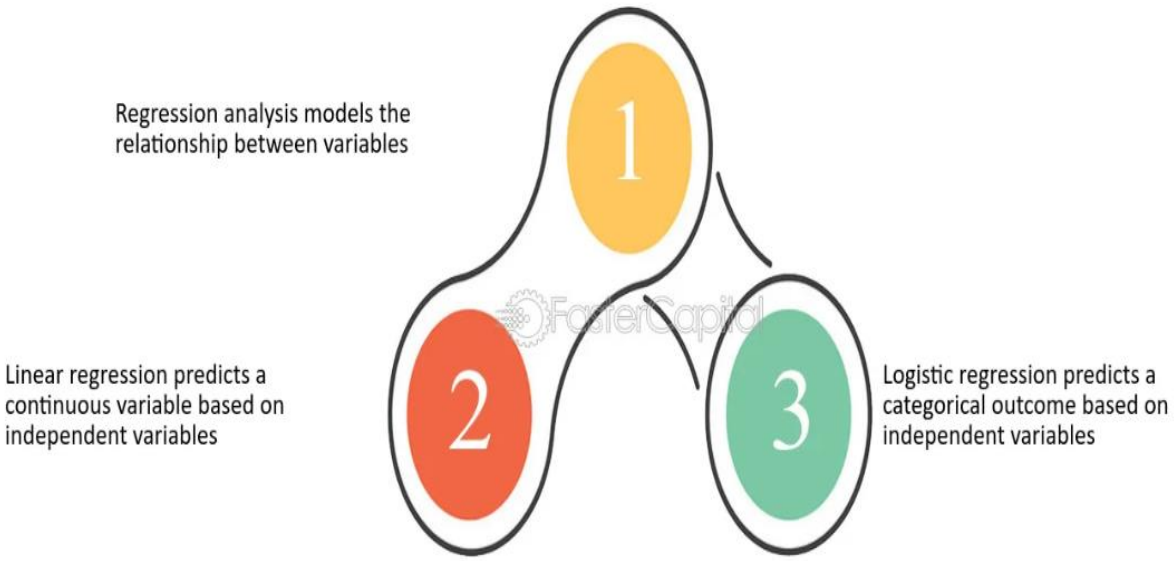

Fig 8.3: Regression Analysis in Predictive Analytics

8.3.2. Machine Learning Models

Essentially, Black Box AI, ML seeks to find the function mapping the predictor set into the response reliant solely upon historical data. In this framing, predictive relationships become emergent properties of large bodies of data and tolerable input-output responses, equivalent to a non-explicit representation of the dynamical systems hidden in the data. Exploratory data analysis (EDA), a first step towards the description, understanding, and modeling of complex multivariate structures, is a pivotal component of ML, due to the absence of a refined mathematical approach and prior knowledge of governing parameters. Before proceeding with model training, data is usually filtered, transformed, and partially eliminated using automated algorithms and graphical tools to visualize the high-dimensional features of the variables and identify significant dependencies. After rigorous cleaning and screening, a reliable exploratory data analysis paves the way for optimal identification of the model class and its parameters.

Artificial Intelligence (AI) and Machine Learning (ML) are increasingly being employed to augment traditional forecasting methods. AI is a multi-faceted discipline that encompasses various approaches to replicate intelligence, including those inspired by biological systems, information processing models, and mathematical abstraction. ML is a specific subset of AI that focuses on producing algorithms and systems capable of learning from data. The unequivocal representations required for conventional statistical and econometric models inevitably restrict their applicability due to the inherent complexity of real-life situations. Hence, the global development of predictive functions based on a limited number of parameters necessitates innovative algorithms capable of extrapolating from data to deliver non-explicit, implicit representations of complex, highly-dimensional dynamical systems.

A machine learning model makes predictions, recommendations, or decisions about new data based on a model learned from training data. The model synthesizes different factors from the data and expresses how the factors are mathematically related. Generally speaking, a machine learning model is realized through an algorithm that employs a learning method, and the terms are often interchangeably used. For a successful model, the model should be sufficiently representative of the training data, but it should also generalize well and provide good predictions on unknown future data. Colloquially, training a model refers to both the process of training (learning) it and the resulting model itself.

8.4. Big Data and Data Preprocessing

However, not every company that gathers a lot of data is a candidate for big data users. Less than 4GB of data is considered small according to the latest standards described in the bibliography. Daily, LinkedIn users upload 500GB of data (or its equivalent in tweets). Browsing history somewhere on the edge is collected in petabytes or thousands of terabytes. At the same time, the prediction can be improved with the insights on the process visualization in real-time. Data cleansing preserves a lot of value for the data setup model.

There is a lot of data in modern business, and it is usually gathered from various sources, not necessarily structured. Sensors in equipment, transactions on the internet, logs on social networks, phone connections, and other diverse streams of data are processed and stored in databases. Such data is usually big in terms of volume but also velocity, variety, and other "v"s in research dealing with such topics. Data collected daily exceeds terabytes quantified in older systems. The prediction can be improved with insights into the process visualization in real-time.

The term "big data" is commonly used in business, and many companies try to find ways to make a profit out of the vast amount of data they gather. A hype around large banks or other organizations that gather large amounts of data and hire a lot of "data scientists" to work with that data developed in the last five years. A great deal of misleading and dated information on the web prevents a good understanding of the entire picture. It is common not to distinguish between big data in general and big data analytics.

The increased popularity of data science and predictive analytics is driven by the rise of big data. In the business context, big data includes the vast amount of structured, semi-structured, and unstructured data of different types generated from a variety of sources every day. The combination of cloud technologies and reduced costs for data storage makes it easier for businesses to collect diverse data. However, gathering a lot of data does not ensure predictive analytics success. The significance of data preprocessing is often underestimated by data scientists, but it is crucial to the results' overall quality. In particular, the importance of data cleansing is often misunderstood, but it can challenge even the most well-thought-out models. The text sheds light on big data as related to predictive analytics as well as discusses the most common challenges and possible approaches in light of the author's experience.

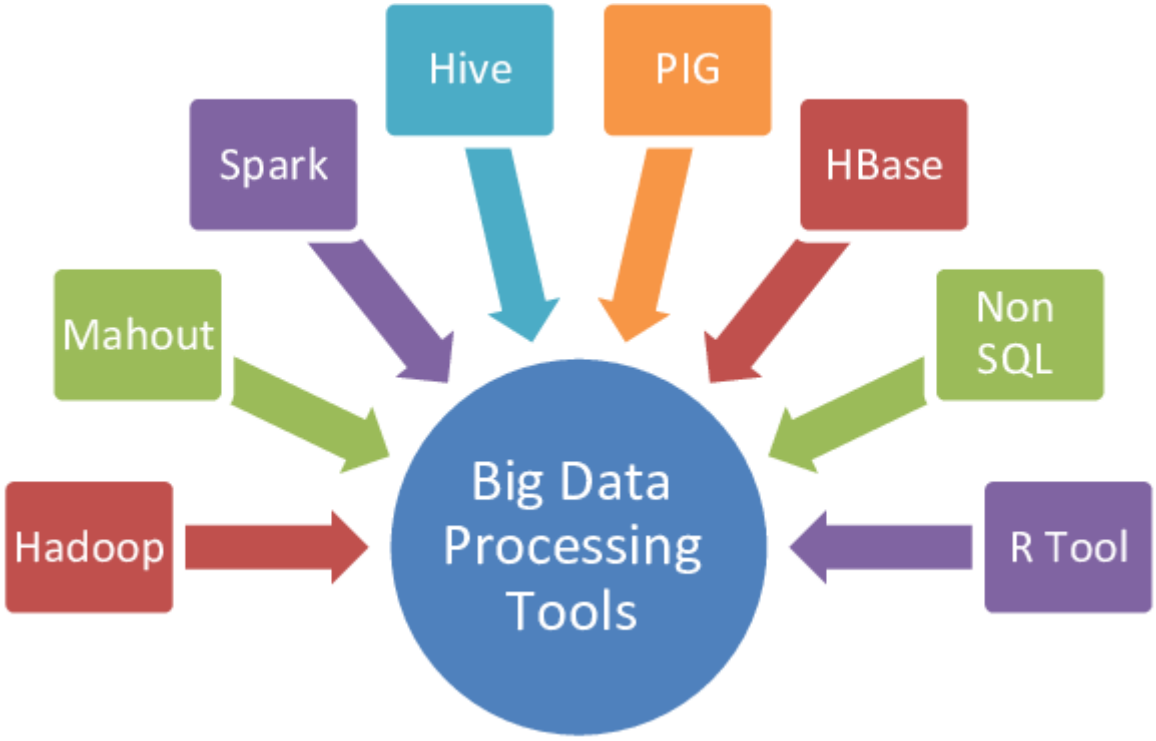

Fig 8.4: Big Data Processing Tools

8.4.1. Challenges and Solutions

The challenges faced in predictive analytics and forecasting big data can be grouped under technological challenges, methodological challenges, and performance challenges. Most of the challenges encountered in traditional predictive analytics and forecasting problems gain bigger complexity when big data is involved, as more complex data needs to be handled without increasing time and effort commensurately. Standard and traditional challenges in time series predictive analytics and forecasting big data include a definition of the modeling and forecasting horizons, a definition of the performance measures, model selection, and training, and the deliverance of actionable predictions. Poor data quality, increasing uncertainty in observations, structural breaks, sudden shocks, and outliers are typical challenges faced during modeling and forecasting exercises.

Here, the challenges faced, approaches, and solutions provided in the arena of big data predictive analytics and forecasting are discussed. Vast data preprocessing techniques used to prepare big data for subsequent modeling and forecasting analysis are also presented. Information about the datasets used for illustrative purposes is included as well. Existing and future challenges in the provision of reliable and actionable predictions from big data in the

face of rapid growth and complexity are presented, along with comments on the associated methodological and technological approaches.

In the past decade and particularly in recent years, the phenomenal growth of the Internet and information technology has enabled the generation and collection of unprecedentedly large and complex data, often referred to as "big data." The rapid growth of big data, fueled by the advances in networks, sensors, social media, and low-cost storage devices, has created both opportunities and challenges. Accordingly, discourses on its definition, necessity, and importance, along with its challenges and approaches to seduce its power, have abounded and are inspiring research and applications in different fields.

Various challenges accompany the advent and growth of big data under three major categories: technological challenges, methodological challenges, and performance challenges. These challenges are daunting and need to be properly met so that analysts or practitioners can unleash the power of big data for reasonable decision-making.

8.5. Applications and Case Studies

A myriad of industries and fields have adopted predictive analytics solutions to improve their business. Companies may use some of these systems out of the box, while others would require analyzing sparsely inferred data before providing actionable predictions. For demonstration, a handful of industry examples are presented and explained.

In 2014, an oil company faced an enormous slump due to prices dropping from $110 to $44 per barrel in six months. A data science team was formed to reverse the trend, but a year later, the company found itself close to bankruptcy. Years ahead of the oil crisis, billions of dollars were spent, but still, models were seeking to correlate spikes in prices with minutes of quakes in the ocean far from the shore. This anecdote segments the funnel into three different sections: exploration, production, and services. The first represents the beginning of the funnel, where the largest amount of money is spent but returns are scarce, and also a major market for predictive systems.

For exploration, autonomous drones carry out surveys. The system classifies with artificial intelligence flags detected in a sea of noise, which were tickets in 650kkm2 blocks. Just finding one was already a success for the data team. At the end of the well, experts used hundreds of attributes from hundreds of data sources in a forced yes/no decision. Machines learned took the same attributes and post-factum decisions to predict 80% of dry wells, which meant that predictive analytics models could probably extrapolate to other basins, budgets, countries, and

unexpected political scenarios. This case presented two models of predictive systems, which took business and mathematical modeling decisions that fit into the same analytical framework.

In the production domain, analytics systems controlled over ten fields and predicted scenarios of detection of early water and gas breakthroughs in maximal capacity boosters. False positives or negations of detections were catastrophic in either financial terms or explosive accidents. All data, including pressure gauges in pipelines, had to be aggregated, and "the sin of friction," and "miracles" were constructed. In the age of "instant analytics," five-minute prediction delays became an hour standard. Other industries made similar runs.

In the services domain, a multi-billion dollar retail chain chose to predict demand at store and article levels after fuzzy matching of several databases. The use of relevant prices for prediction made several explanations valid. A dozen mathematicians were hired. Another fashion retailer chose to predict demand in days rather than weeks. The matter of prediction was intense modeling, and surprising results were presented. Yet, companies interpreting prediction outputs would later ask "Why affect a 2% or less cumulative MAPE on a one-week inflammatory, yet important, series?"

8.5.1. Industry Examples

Predictive analytics and forecasting are increasingly becoming the cornerstone of successful decision-making in a wide array of industries. Companies across various sectors are collecting massive amounts of data and utilizing it to forecast things such as what products customers will buy in the future, how claims should be priced when machinery needs to be serviced to avoid downtime, and more. This section reviews an assortment of predictive analytics and forecasting examples from different fields, highlighting key features that define predictive analytics and forecasting in each scenario.

Many credit card users receive alerts when an attempt is made to spend thousands of dollars on an item in another country, while the cardholder is shopping for groceries at their local store. An exploding, highly variable set of purchases occurs early in this scenario. For example, broad-class purchases such as hotels, airplane tickets, and electronics might signal that the card has been stolen. Such unusual patterns of purchases create a covariance structure shift that can be statistically monitored.

One of the most expensive items at the grocery store is the shopping cart itself. Carts are typically left carelessly in parking lots, denting expensive vehicles. Some grocery stores

attempt to combat this problem by ensuring carts have to be returned to within-air parking areas. Monitoring where an item is at a given point in time is just one type of prefix-joined pattern that can be sought in a time-stamped transactional dataset.

Many products have zero occurrence or sales for weeks or worse, months or even years. Retailers with such products can choose to simply let them go, improve their sales efforts, or focus on near-zero occurrence products that have a higher chance of performing better. This is an example of cohort analysis. The focus of the study is on an item group with either a very low occurrence rate, returning customers, or a particular customer class with desirable attributes.

Fig 8.5: Predictive analytics examples in various industries

8.6.Conclusion

A big-data-based application of predictive analytics goes beyond number-crunching measurements of some properties of the system. It addresses the possibility of accessing the unknown microscopic or interaction laws causing the emergent behavior, the model parameters, and/or the structure of the networks connecting the components of the system. Potential applications include complex systems in various fields such as finance, economy, sociology, biomedicine, infrastructure networks, and even the climate, techno-sphere, and other earthly and astrophysical phenomena. The trends indicated the relevance of the lecture topics and findings in all fields where observed data of the earth, cities, financial networks, food webs, ecological networks, Internet, social interactions, text mining, languages, and many others rise from complex systems with a huge number of interacting components.

Future trends in the realm of predictive analytics and forecasting indicate an increasing importance of explainability alongside growing attention to ethics, fairness, and preventing misuse. The accuracy of a model is no longer the only consideration in determining its suitability for a given application; the ability to explain the reasons for a prediction is fast becoming just as critical. Predictive analytics and forecasting remain at the very heart of big data. The book provided a survey of topics and approaches, algorithms, techniques, types of data, and comparison studies, with a focus on the applicability of the methods to gigantic datasets. Attention was paid to discovering the laws and mechanisms behind the gigantic empirical data rising from complex systems, and how to identify the behavior of the interaction between the components of such systems.

8.6.1. Future Trends

The future of predictive analytics and forecasting is bright, with cutting-edge technologies and tools like AI, deep learning, neural networks, and Big Data reshaping how data is captured, recorded, analyzed, and displayed. The pace of change in predicting, forecasting, and modeling will exponentially quicken for businesses that can harness the potential of this wealth of personal, social, and transactional data.

As the digitization of everything moves rapidly forward, the cost of capturing, recording, storing, and accessing data will plunge. Increasingly, everything perceivable will be recorded in recordable form to computer-readable documents in the new ambient awareness. Computers will automatically monitor everything everywhere. In mass societies, people were digitally

aware of one another. Now, we can make that awareness scale, as digitally captured data makes it cheap to know everything about everything, everywhere, in real-time or almost real-time.

Massive datasets will be accumulated before they are made analyzable. Ideally, datasets would be cleaned and transformed before they are loaded. Nevertheless, dataset loads with the richness of potential interpretation make it still worthwhile to aggregate. The future of predictive analytics and forecasting is a very exciting place. However, great intellectual caution is required as these all-encompassing datasets impair meaning and sense-making. These datasets render the complexity of the social world highly stochastic and murky so it is very difficult to see what they are telling. With this uncertainty, the rush to disposable analysis grows. The scope for shoddy prophesying abounds. Nevertheless, as algorithms operate on an understanding that events are randomly and independently distributed, noise rather than signal is researched and explored. This means that rather than examining the factors and interactions that provide individuals with some grasp of how things in the world work, the technologies at play encourage wandering explorations of their richness and scope.

Thus, there is a challenge to develop a human and ethical understanding of these powerful new techniques and datasets. Otherwise, because the mathematics is impenetrable and the technologies opaque, the very learned will happily abandon their reason and judgment to others so that, unbeknownst to them, they will be steered in ways that are otherwise resisted. As such, predicting, forecasting, and modeling will come to dominate newer operations of power, unfulfilled with the current, narrow politics of Big Data.

CHAPTER 9

CASE STUDIES: SUCCESSFUL AI-DRIVEN DATA ENGINEERING IMPLEMENTATIONS

9.1. Introduction

The developments and implementations of AI-driven solutions in favor of these processes focus on the use of machine learning models to streamline processes of great complexity, time, and size, or as preventative for error. The focus of this work is on the developments and implementations of the use of AI-driven solutions for automating the enhancement of data landing and modeling processes successfully tackled.

As the data shown continues to grow exponentially, organizations are faced with keeping the infrastructure and databases viable and useful for strategic decision-making. Some general processes that had to make enhancements to keep up with data engineering are data ingestion, storage, modeling, transformation, and visualization. These processes involve using a wide variety of tools, programming languages, pipelines, and infrastructure. This can create an expansive necessity for developers, engineers, and analysts, which could lead to backlogs and errors.

The implementations of AI-driven data engineering have successfully improved efficiency in various organizations. Through the examination of these innovations, valuable lessons can be learned about how organizations can carefully navigate integrations and ensure success. The expansive reach and capability of artificial intelligence (AI) can leave a scope of possibilities for developing machine learning applications and solutions in industries with large amounts of data. A few common functions of AI and its use for data engineering enhancement implementations are predictive analysis, conversion and migration of large data sets to different databases, cleaning the data for accuracy, and data validation to ensure no discrepancies.

The integration of AI-driven solutions in data engineering has significantly revolutionized how organizations manage and utilize their ever-growing data resources. By leveraging machine learning models, these solutions have streamlined complex processes such as data ingestion, storage, modeling, transformation, and visualization, thus enhancing efficiency and reducing error rates. As data volumes continue to surge, traditional methods can lead to

backlogs and inaccuracies, making AI-driven enhancements crucial for maintaining robust and scalable infrastructures. AI excels in predictive analysis, enabling foresight into data trends, while also facilitating the conversion and migration of large data sets, ensuring seamless transitions across databases. Moreover, AI-powered data cleaning and validation tools help maintain data integrity by identifying and rectifying discrepancies, thereby supporting accurate and strategic decision-making. Through these advancements, organizations can better navigate the complexities of data management and leverage their data assets more effectively.

Fig 9.1: Successful AI Implementations in Various Industries

9.1.1. Background and Significance

Data engineering, which encompasses the design, construction, integration, management, and maintenance of data architecture, pipelines, and systems, plays a pivotal role in enabling businesses to utilize data for strategic advantages. With the exponential growth of digital data, the data engineering landscape is undergoing a significant shift from traditional approaches to modern, AI-driven paradigms. Naturally, the larger the amount of data, the larger the resources that must be invested into the infrastructure, architecture, and operations that support this data.

Over the past decades, the availability of data has vastly increased, and with it the need for companies to leverage value from this data to keep their competitiveness with modern business demands. Data engineering concerns the design, construction, integration, management, and maintenance of central data architecture, handling the entire lifecycle of data for its correct

utilization. Businesses are investing heavily in data engineering, including data pipelines, data lakes, and data warehouses.

Thus far, big data engineering practices have followed the same development model as those typically applied in software engineering. However, this 'construction' approach, based on humanly devised designs and instructions, makes the entire infrastructure, including the final systems, very vulnerable to the unexpected changes and unforeseen requirements common in the big data domain (e.g., increasing velocities, volumes, and varieties of data). Additionally, big data systems usually exhibit unexpected behavior due to the unintended consequences of their (typically) complex configurations. This is hence impossible to entirely preempt and avoid from the start in the design and construction of the infrastructure, systems, and datasets that big data relies upon.

Currently, unbounded long-term costs for the upkeep, maintenance, and later redesign of the big data infrastructure, datasets, pipelines, and systems are the rule rather than the exception. More generally, utilization costs for the upkeep and maintenance of the above are completely out of proportion with the possible gains a business can initially get from having a data-driven infrastructure and organization. New data and underlying requirements arise at unforeseen velocities that quickly change the context of what data is considered useful by the business. Also, new technology to handle this incoming data appears on a daily basis, and the above infrastructures are typically difficult to adapt to this, often involving major and complex upfront adaptations that tend to be extremely expensive.

The appearance of Artificial Intelligence (AI) has opened new pathways to try to cope with such difficulties through data-driven approaches where the systems would take care of themselves using means from Machine Learning (ML) for the automatic adaptation, evolution, and configuration of all of the above 'normally' humanly devised and fixed parts, architecturing, systems, and datasets. After being successfully applied to narrow domains like chess, Go, and Jeopardy, AI has been widened to cope with more difficult situations using systems comprising a method, model, and data. These systems can be successfully learned and improved using a combination of techniques, such as Reinforcement Learning (RL) and Deep Learning (DL), depending on the degree of supervision and the amounts and types of data available.

Despite its initial successes, the above view has only recently captured the attention of the Data Engineering community as a whole, thus far largely restricting to basic applicability of ML techniques to pipeline tasks (the fixing of which can still be done using more traditional means). There is hence a timely and urgent opportunity to present research works comprising

more comprehensive and extensive applications of AI and ML techniques to data engineering tasks and infrastructure.

9.2. Foundations of AI-Driven Data Engineering

AI-driven data engineering is not only an opportunity but also becoming a necessity. Existing data engineering processes cannot scale anymore and thus cannot evolve with the business need for new data and new datasets. Furthermore, with the AI revolution, many companies have joined the AI hype and are trying to make better use of their data. However, their existing data processes often do not have the data readily available or in the correct format for AI usage. This is the case for companies with an AI vision that do not yet have sufficient data engineering processes in place.

AI-driven data engineering is the use of AI to automate and optimize steps in the data engineering process. A lot has been written about using AI for data understanding tasks, such as anomaly detection in raw data, otherwise known as data profiling. However, little attention has been given to the automation of activities further down the data engineering pipeline such as the construction of enrichment and exploration processes. This is problematic, as exploratory tasks typically are very manually intensive and thus do not scale. These downstream tasks can often be newly constructed per data set, necessitating the automation of these tasks. Existing solutions for data cleansing typically only address one particular cleansing task. State-of-the-art methods for cleansing often make use of machine learning. Prior models have been trained on many datasets, achieving overall positive results, but are not reusable on a new dataset. This leads to a re-engineering of many cleansing processes. Information extraction typically takes the form of structured data extraction, with no industry-ready solution presently available for low-cost semi-structured information extraction. Furthermore, it is a class of tasks where higher-level AI methods could significantly improve cost-effectiveness. Hence, there is a significant opportunity to devote research efforts to the AI-driven data engineering process.

Artificial intelligence (AI) is revolutionizing every field, from security to finance and medicine. Data is at the heart of this transformation; it is the fuel that powers AI's success. Yet, more than ever, it is now a challenge to acquire high-quality data for a growing number of use cases needing different massive data sets and resources. More data than ever is generated every year. However, existing processes to collect, store, and clean it often fail to scale because the required action is becoming increasingly more complex. Processes that were

previously straightforward (e.g. collecting, filtering, and storing data) are now becoming considerably more elaborate by needing pre-processing before storing or complex multi-source data collection. Moreover, there is an ever-growing variety of data: it was only a few years ago that social media data had to be incorporated into most processes. This multitude of data is a challenge as existing data engineering processes are unable to adapt in a tunable manner. Moreover, company resources are often spread across a multitude of systems that have yet to be integrated (e.g. maps, weather, stock prices, social media monitoring, clustering, or filtering data). This results in greater borrowing costs and more complicated maintenance, security, and general trust issues. Existing data engineering processes are often only able to deal with a limited variety of data, outputting it to a homogeneous data storage that only offers minimal filtering and conversion.

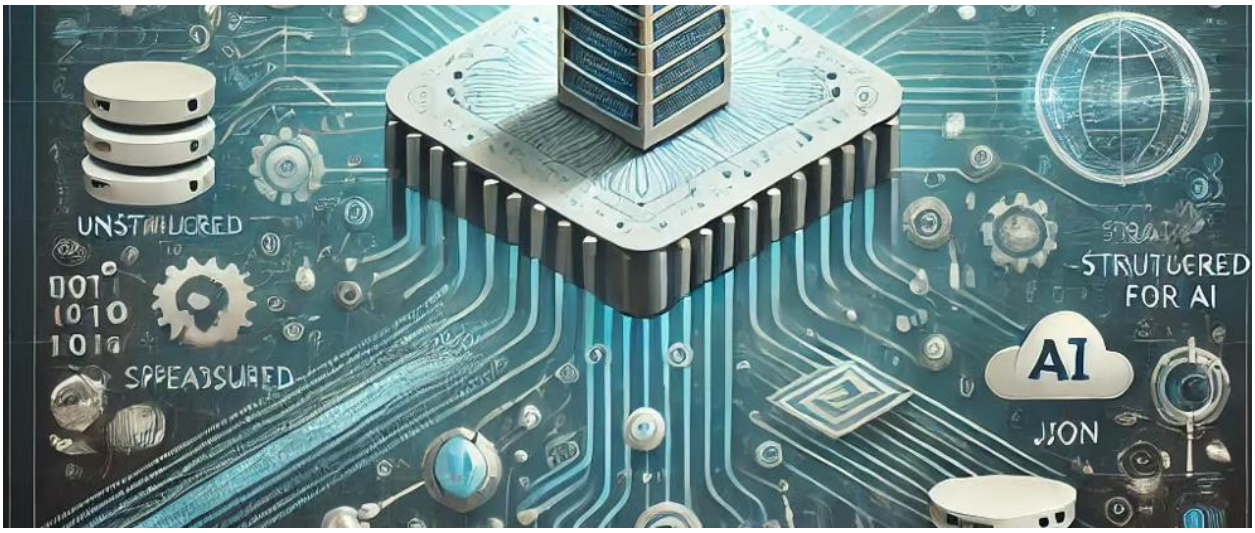

Fig 9.2: The Foundations of Data Engineering for AI

9.2.1. Key Concepts and Definitions

There is no universally accepted definition of data engineering. A consideration of how it intersects or relates to adjacent fields of study, such as data science and data architecture, and where its aims thereof can be distinguished, provides a broader perspective. Data engineering can be described as the pipeline connecting data sources and data products. Within this description, it can be differentiated by data source type. Meters or other machine-generated data streams provide high throughput but otherwise limited data sources, as there are rather few schemata on which data events are defined. Data streamed from web applications, alternatively, tends towards lower throughputs but richer data meaning. Both data source types are then related to specific data product types, including standardized monitoring

dashboards or machine learning models, respectively. Both can be further qualified with indicators of horizontal scale, e.g. number of data sources or product users, as well as vertical scale, e.g. number of defined events or deployed models.

The purpose of this essay is to explore the concept of using models trained on such general capabilities but modulating them through more conventional engineering means, in particular data engineering, allowing wider access to their powerful capabilities. Four diverse case studies of successful implementations of AI-driven data engineering are presented, showcasing the application of foundational models on machine-generated text, where the sophistication of the underlying model is matched by the relevance of the data and use case. In addition to the case studies, the necessary foundational knowledge for engineers or product managers to be able to implement such pipelines is presented, along with the needs established by the use cases.

The rapid progress in computing capabilities and the ubiquitous availability of data have led to the emergence of artificial intelligence (AI) systems with remarkable capabilities. However, systems exhibiting higher levels of generality or capability, such as ChatGPT or Dall_E models, are rare. Fine-tuning these models on specialized datasets requires a concerted effort, a significant amount of high-quality examples, and expertise on both the model and the dataset being used. As a result, most enterprises are unable to fully leverage the potential of such models on their own data or have only explored a narrow range of capabilities.

9.3. Methodology

Nine interviews with data engineering professionals from different organizations were conducted, all of whom complied with the minimum respondent criteria. The number of interviews held was deemed sufficient, as they provide an acceptable basis for analysis and add to current literature regarding the phenomenon. The interviews, lasting between 30 and 75 minutes, were conducted between October 2022 and January 2023, both remotely using video conferencing tools and onsite at respondent workplaces. To ensure confidentiality and anonymity, respondents are referenced using letters A to I henceforth, and their organization or company names are not mentioned.

Due to the explorative nature of the research and the early stage of the objective industry, multiple perspectives regarding the phenomenon were sought. Therefore, a purposive sampling approach, specifically maximum variation sampling, was applied to obtain data from diverse respondents with different backgrounds. This sampling strategy increases the chances

of comparable and contrary findings, promoting a more comprehensive exploration of the research topic. Respondents with diverse characteristics across various profiles were sought, such as employee roles, experience levels, managerial oversight in AI policy, participation in AI auditing, involvement in ethical aspects of AI, and company sizes.

To uncover multiple perspectives in the domain of interest (AI-driven data engineering), a case study approach has been adopted, using semi-structured interviews as the primary data-gathering technique. This methodology aligns with the purpose of describing, exploring, and explaining a complex phenomenon using rich data spanning various boundaries. Nine exploratory interviews with data engineering professionals involved in the design, implementation, or usage of AI-driven data engineering tools were conducted. The interviews featured open-ended questions that focused on four central themes: the motivation behind the project or tool development, the tool purpose and user goals, the return on investment/cost-benefit assessment, and the managerial, ethical, or legal concerns.In an effort to gain a comprehensive understanding of AI-driven data engineering, nine in-depth interviews were conducted with data engineering professionals from various organizations, adhering to a purposive sampling strategy aimed at capturing a broad range of perspectives. These interviews, which ranged from 30 to 75 minutes, took place between October 2022 and January 2023 through video conferencing and onsite visits. To maintain confidentiality, respondents are identified only by letters A through I, with their organizations remaining anonymous. The research employed a case study approach, utilizing semi-structured interviews to explore four key themes: the motivations behind AI tool development, the intended purpose and goals of these tools, cost-benefit analyses, and associated managerial, ethical, or legal concerns. This methodological choice facilitates a detailed exploration of the complex phenomenon of AI-driven data engineering, reflecting diverse experiences and insights from professionals across different roles, experience levels, and organizational contexts.

9.3.1. Research Design

A particularly appropriate research methodology for collecting qualitative data and gaining insights into complex cases is the case study approach. Yin advocates the use of a case study approach when the research responds to "how" or "why" questions, when the researcher has little or no control over events, and when the focus is on contemporary phenomena in real-life contexts. In line with these conditions, a case study approach was adopted, locating

multiple case organizations, and collecting data via semi-structured interviews with employees working at these organizations. The employees had performed either a central or highly influencing role in their organization's AI-driven data engineering transformation, and thus personal experiences were different from the experiences maintained by the other key actors involved in this kind of transformation.

Many strategies and methodologies that guide qualitative research exist. The use of a strategy that ensures the focus on the research problem and leads to trustworthy results is important. A qualitative research approach was deemed suitable for this research. According to Bryman, qualitative research is concerned with words rather than numbers. It seeks to make sense of or interpret phenomena in terms of the meanings people bring to them. Denzin and Lincoln state that qualitative research provides a framework for exploring and understanding subjective meaning-making processes. Here, the grounding lies in the understanding of people's experiences and interpretations of their surroundings.

This section presents the research design utilized for undertaking an exploration of the cases of organizations that have implemented AI-driven data engineering transformations successfully. Since this subject is not well researched and documented, a qualitative research approach was deemed appropriate. Seven semi-structured interviews were conducted with employees who have performed significant roles in their organization's AI-driven data engineering transformation. The experiences pertained to widely differing organizations and were voluntarily shared by the interviewees, who will become anonymized respondents. The data obtained via interviews were analyzed by means of thematic analysis, which is a commonly adopted approach in qualitative research.The case study approach, as advocated by Yin, is particularly suited for this research, given its focus on exploring "how" and "why" questions within contemporary, real-life contexts where the researcher has minimal control over events. This methodology was employed to examine AI-driven data engineering transformations across multiple organizations by conducting semi-structured interviews with employees who played pivotal roles in these processes. These interviews, involving seven key individuals from varied organizations, provided rich, qualitative insights into their personal experiences and the impact of these transformations. Bryman emphasizes that qualitative research, which prioritizes words over numbers, is ideal for interpreting complex phenomena and understanding the subjective meanings individuals attribute to their experiences. Denzin and Lincoln further support this, noting that qualitative research offers a framework for exploring and making sense of these subjective interpretations. The interviews were analyzed using thematic analysis, a well-established method in qualitative research, to identify and

interpret patterns and themes within the data, offering a comprehensive view of the challenges and successes associated with AI-driven data engineering transformations.

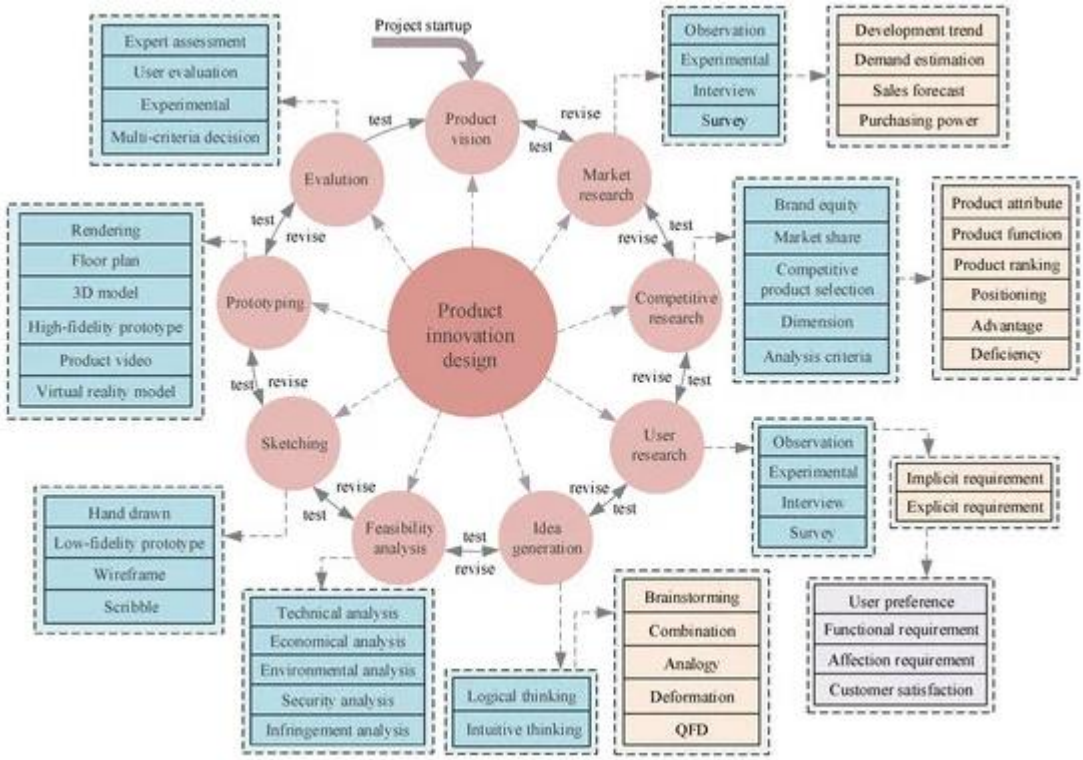

Fig 9.3: Big Data and AI-Driven Product Design

9.4. Case Studies

Furthermore, out of ten stores where the AI-driven inventory tracking solution has been deployed, the AI flags reduced "lost sales due to inventory shortages" by 55%, reducing losses by 0.7 million EUR over a month. Due to the positive impact of the solution, [Company Name] aims to deploy this AI-driven data engineering solution in all its stores worldwide.

On the analytics side, a dashboard was created in Power BI to visualize and analyze inventory conditions in retail stores. With this comprehensive solution, [Company Name] saw that missed sales due to inventory shortages were mostly concentrated in a small number of specific product categories and SKUs. This enabled the company to request more product deliveries from manufacturers to select stores, leading to a 25% sales increase for those specific SKUs within one month.

The retail industry is rife with inventory management problems, leading to missed sales and losses. [Company Name] decided to tackle the challenge of enabling real-time inventory

tracking and analysis in their brick-and-mortar retail stores using AI-driven data engineering solutions. The company implemented a series of computer vision and AI models deployed in stores, capturing camera footage and generating real-time summaries of inventory conditions inside the store. The output data from these models was sent to a central data engineering hub that cleansed, processed, aggregated, and stored it in a time-series database.

To illustrate the effectiveness of AI-driven data engineering solutions, four detailed case studies will be explored. The first case study will provide an overview of a company that has successfully implemented an AI-driven data engineering solution, detailing the implementation process, results, and benefits. The first case study looks at a retailer that implemented an AI-driven data engineering solution to enable real-time inventory tracking and analysis, allowing for better predictions of inventory demands and ultimately leading to a 25% increase in sales.

9.4.1. Case Study 1: [Company Name]

The main idea behind this approach is to complement the "self-servizio" modifiers (i.e., employees with no technical background) with AI assistance and avoid code proliferation. Moreover, using SQL makes it possible to operate crudely at scale, implement data observability and curation workflows, and empower engineers to understand the modifications made to their datasets.

Taking direct inspiration from how these tools work, a modified version is proposed that enables the company to transform its pipelines into a sequence of operations on raw data (i.e., columns) that can be expressed naturally in SQL, namely: Filtering rows, filtering columns, joining tables, aggregating rows, and deriving new columns. The operations defined could either complement the existing code or replace it entirely if the company wanted to use them directly against raw data tables. An AI Assistant based on GPT-3 and Codex was developed that generates these transformations given natural language descriptions of the intended changes to datasets. What was implemented was a simple web browser app that receives an input query (in natural language) and an input dataset (in SQL) and then returns modified SQL code that implements the intended modifications.

A health insurance company started using a "self-servizio" (self-service) approach to analytics, where employees across the organization who may not have a technical background were trained to explore pre-defined datasets. While the adoption of tools such as Tableau and Power

BI grew, the data ingested still needed to undergo cleaning and transformation. Such transformations are poorly supported in these tools and are usually done using SQL code. This led to a massive code base, poorly documented and hard to maintain, and preventable mistakes that could be avoided with proper tooling. The approach using only SQL code neglects how discovery tools actually work in the background: they silently run data ingestion pipelines with pre-defined transformations at a schedule against the database to build their queries.

In recent years, an increasing number of companies have turned to artificial intelligence for solutions to their data engineering problems. While the academic literature on the subject is still scarce, the author gathered the following successful real-world implementations.The primary goal of this approach is to enhance the efficiency and usability of data transformations by integrating AI assistance, particularly for employees without a technical background, and to mitigate the proliferation of cumbersome codebases. By leveraging SQL, which enables scalable and precise data manipulation, the approach aims to streamline data observability and curation workflows, allowing engineers to better track dataset modifications. Inspired by existing tools, a modified solution was proposed that translates operations on raw data, such as filtering, joining, aggregating, and deriving new columns, into natural SQL expressions. This solution includes an AI Assistant based on GPT-3 and Codex, designed to generate SQL code from natural language descriptions of data modifications. Implemented as a web app, this tool allows users to input queries and datasets in SQL, producing the required SQL code to effectuate the desired changes. This innovation addresses challenges faced by companies like a health insurance firm that adopted a "self-servizio" approach to analytics. Despite the widespread use of data visualization tools like Tableau and Power BI, data cleaning and transformation were still reliant on extensive, poorly maintained SQL codebases. The integration of AI in this context aims to simplify and improve the accuracy of data transformations, reducing errors and the maintenance burden associated with manual SQL code.

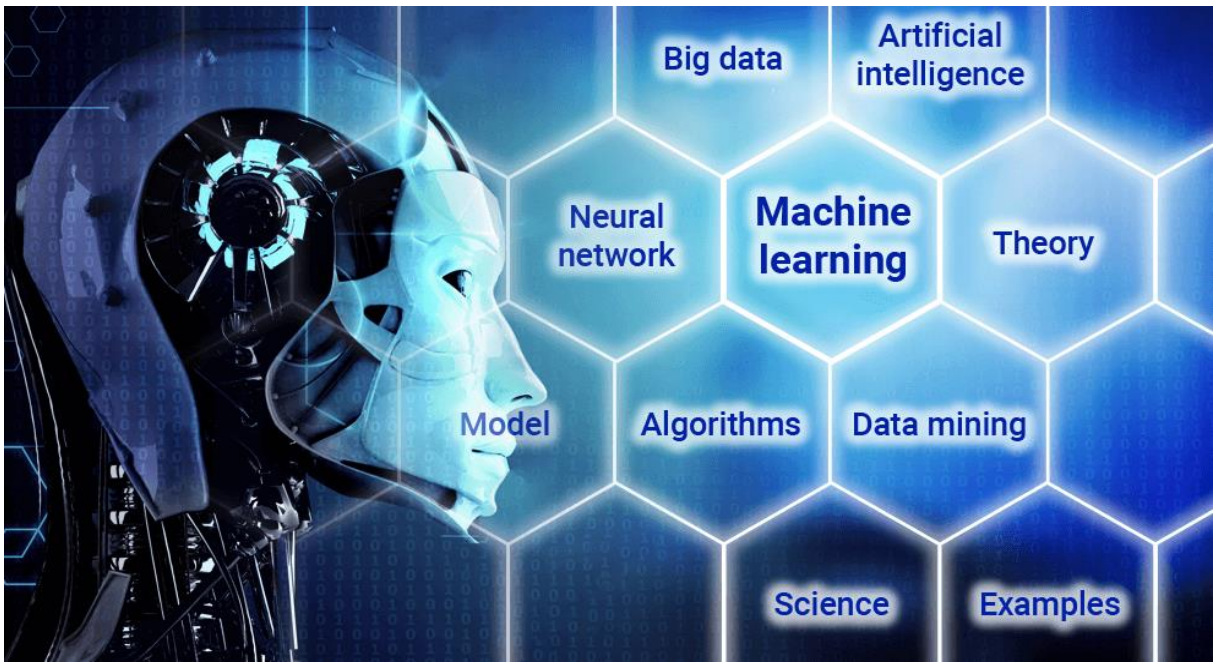

Fig 9.4: Case-Study of Artificial Intelligence / Machine Learning

9.5. Analysis and Findings

However, the amount of supervised training data needed for fine-tuning AI from complete scratch is noted as a potential caveat. Companies looking to implement such systems should have a sufficient volume of training data, but tailored general model architecture should be widely applicable. Although detailed implementations have been presented and trained models are proprietary, toolkits, technologies, and coding languages used in the implementation projects are indelibly disclosed. Organizations looking to do this themselves will be able to find or train similar models. Organizations looking for solely the trained models should be aware that they would need to engage in development work to integrate them into their own systems.

AI has been successfully applied to different areas of data engineering work. Development and engineering work related to standardizing and enriching data are manually performed at every stage of processing data, rendering it extremely tedious, repetitive, and error-prone. No matter how skilled the data engineer is, mistakes can be made. Detecting these mistakes can occur at a later stage, potentially introducing a cascade of errors that severely affect analyses. Data quality issues are still identified and ratified using manual processes, which are slow, operationally complex, and error-prone by nature. Spontaneous data quality checks are often obtained post-factum when erroneous data has already had far-reaching consequences. AI-

based automation is found to be a credible solution for these issues, and successful implementations have been made live in production.

It has been found that there are successful approaches to using AI for data engineering across several different deployed implementations. Each organization can benefit from these case studies and obtain inspiration or step-by-step instructions for building their own successful automation systems. AI-driven automation of data engineering work is possible in almost all domains regardless of company size, global reach, data landscape, development and engineering teams in place, and BI tools. Early detection and correction of issues in data preparation pipelines can reduce confusion for all stakeholders involved in data reporting and business development. Automated monitoring can save teams' time and significantly increase the reliability of reports.

All cases provided in this paper demonstrate significant benefits and a high return on investment derived from AI-driven automation of data engineering work. AI has the potential to dramatically change the entire data landscape by creating a democratized system for onboarding complex data that does not require expert knowledge in data engineering. All contributions combine to provide a detailed view of the various areas of data engineering work and how AI can execute and automate them with great success.

9.5.1. Common Success Factors

The analysis of the six case studies revealed a number of common success factors that contributed to the successful implementation of AI-driven data engineering tools and services.

1. Strong in-house expertise: Each organization had strong in-house teams with the required expertise to ensure that toolset implementation could deliver maximum benefits. This expertise included knowledge of use cases for which AI tools and services could be beneficial, familiarity with the content and internal structure of data sources, and an understanding of the specific operating conditions under which tools had to be deployed. In some organizations, this strong in-house expertise had been built up over many years, while in others it had been cultivated in a matter of just a few years.

2. Long-term commitment to the toolset: Organizations provided formal and informal guarantees to ensure stewardship and continued funding for at least a five-year pilot phase. This was more difficult to achieve than in-house expertise, especially in organizations that had recently embraced artificial intelligence and where the need for new tools was still questioned. In some organizations, proponents of new tools succeeded in winning the support of their

superiors. Independent of the organization type, from the beginning, the very active high-level involvement of champions was noted.

3. Tools and services fitted to internal data engineering processes: Most of the AI tools and services studied were considered fitted to internal manual data engineering processes and not considered disruptive to data engineering processes and job markets within the organization. As a result of this, tool adoption was subsequently safeguarded by ensuring that tool operation fitted internal processes and job descriptions more than explained by technical operability and user-friendliness considerations. Staff involved with operating the tools and services had a good understanding of their working, limits, and strengths, and knowledge about the operation could be easily shareable among many users. As a result, there was little resistance to the tools and services by staff operating them, and there was no fear of job losses.

4. Focus on bringing fast initial wins to current users: For all the implementations studied, a focus was maintained on bringing initial (and if possible, fast) wins to users who had expressed interest in the toolset. Often existing bottlenecks within internal data engineering processes were targeted causing considerable downstream backlogging and most involved users were eager to see them solved. Where this was not possible, efforts were made to find simple alternative applications that would reduce user workloads and communicate these results to relevant stakeholders.

5. Understanding by toolset advocates of current users' data engineering lot: In all organizations, toolset advocates possessed a strong understanding of current users involved in proposed pilot applications since they were often former or still involved with manually executing relevant tasks.

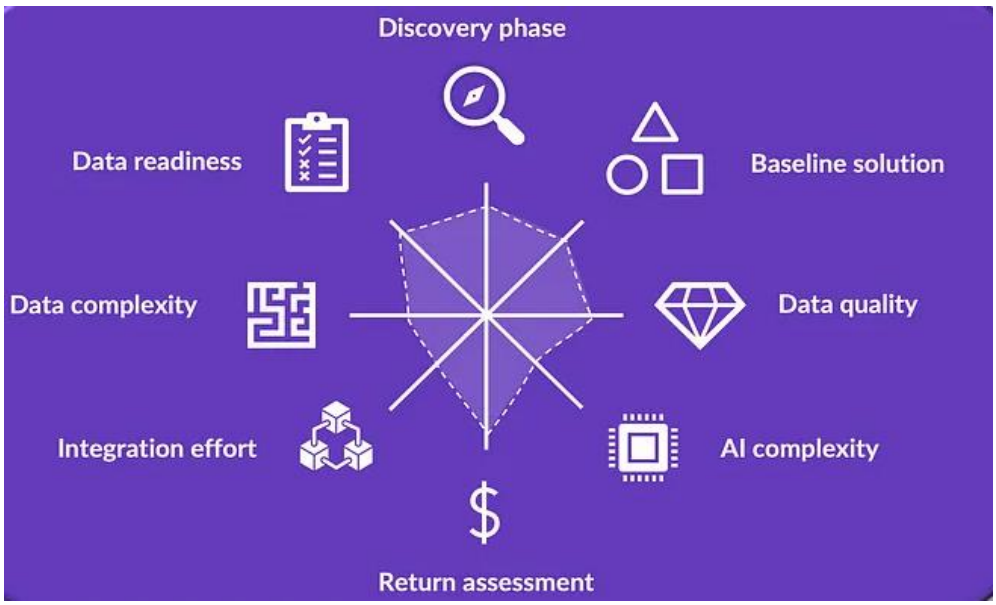

Fig 9.5: factors for success

9.6. Conclusion

The success stories of AI-driven data engineering implementations presented here demonstrate the transformative power of AI and machine learning in optimizing data processes, achieving higher accuracy, reducing costs, and minimizing manual effort. By leveraging AI technologies such as machine learning algorithms, polymorphic complex event processing engines, software robots, and deep learning models, organizations can automate repetitive tasks, analyze vast data networks, and make accurate forecasts. This not only improves efficiency and productivity but also allows data engineers to focus on higher-value activities, leading to innovation and business growth. These case studies serve as inspirations for organizations seeking to harness the benefits of AI and machine learning in their data engineering processes.

Looking ahead, several trends are poised to shape the landscape of AI-driven data engineering in the future. First and foremost, the integration of AI into cloud data engineering and management is expected to gain momentum. As organizations increasingly move their data operations to the cloud, there will be a need for automated cloud data engineering tools that align with the unique characteristics of cloud workloads. Coupled with the growth of serverless frameworks, the utilization of AI/ML for automating data engineering in the cloud is anticipated to rise significantly.

Another notable trend is the advent of AI for real-time data engineering. Real-time data pipelines, known for their high speed, scale, complexity, and reliance on multiple technologies, present unique challenges. Integrating AI into data engineering frameworks and platforms is expected to enable a paradigm shift by decreasing operational costs, eliminating manual efforts, and ensuring robust quality and performance.

Furthermore, the democratization of data engineering through citizen tools is on the horizon. Data engineering is often perceived as the domain of highly skilled engineers proficient in complex programming languages. However, the emergence of easy-to-use, no-code tools allows experts from other disciplines to engage in data engineering without extensive training. AI/ML is anticipated to play a crucial role in enhancing the capabilities and user experiences of such tools, enabling various roles to engage in data engineering tasks in compliance with standards and best practices.

Collaboration between experts and AI will also characterize the future of data engineering. As AI tools become increasingly sophisticated, their adoption is likely to grow. However, the shortage of data engineering experts is expected to continue. The prevailing view among

experts is that human oversight will remain crucial in selecting frameworks, topologies, and understanding the implications of issues on quality and performance. Consequently, AI tools are expected to augment, rather than replace, human expert capabilities in the engineering of data pipelines.

Ultimately, the future will see an escalation in job roles focused on data engineering and associated skills, driven by the increasingly critical role of data across all organizations. Alternatives to costly and complex proprietary tools like AWS Glue and Databricks, either open-source or homegrown, will become increasingly popular. Moreover, the engagement of research communities in this field is expected to grow, along with advancements in the scientific understanding of the topic.

9.6.1. Future Trends

The state of artificial intelligence (AI) has undergone rapid changes over the past few years, thanks to the increased power of computer chips, as seen with the emergence of transformer neural networks in 2017. Tools such as ChatGPT have ushered in a new AI paradigm, resulting in the proliferation of various LLM tools from companies like Google, Anthropic, and others, each offering differing capabilities and strengths. However, with the niceties of being small, considerate, and understanding emerging problems accompanying vices, including bias, inaccuracy, and chatterbox-like behavior, many wonder if AI will follow an "Internet 2.0" path.

Just as most websites are not crawled or indexed due to issues of quality, trustability, and doubt, the situation with the current AI tools appears similar. While tools like Bing and Google are at the forefront and represent only a fraction of the AI chatbot market, despite these sizable entities' worries about hallucination and toxicity, those who can construct LLM-like interfaces with stacks of filters can benefit from the advertising markets. Elon Musk's "TruthGPT," which describes itself as "the maximal truth-seeking AI," is an example of this. Meanwhile, a proliferation of commercial and fine-tuned (but likely limited) AIs is well underway, with companies such as Cohere, OpenAI, and Anthropico employing thousands of people to write and filter codes and queries. The prospects of sobering trends, such as ideologically homogeneous and centric microcosms, manifesting in the AI chatbot world, cannot be ignored. Nevertheless, the integration of AI with data engineering and data science began long before the rapid emergence of consumer products like ChatGPT. The nothing-new-under-the-sun cliché is at play here, and it might be most prudent to think about the past instead of predicting

the future. In this context, the past includes the usage of statistical models, e.g., linear regression, probabilistic models like Hidden Markov Models (HMM), and Probabilistic Graphical Models (PGM), to make sense of processes. It incorporates feature engineering, text normalization, stop-words, stemming or lemmatization, word clouds, TF-IDF, Bag-of-Words, and embedding. More recently, it also touches upon the field of representation learning, the usage of Deep Neural Nets, and the development of word embedding software, such as FastText, GloVe, and Word2Vec. The rise of giant language models and LLMs arises naturally from the concatenation of these inquiries, domains, and frameworks.

Prospects for this field of research are abundant. These strategies can be employed at different levels of abstraction, cardinality, and methodological rigor. The interpretation and understandability of neural nets remain an open problem in AI and Data science. There is still ongoing active research in caps-lock AI, such as "research papers," "mathematical proofs," and "computer programs." AI biases resulting from data collection, construction, social phenomena, and perverse economic incentives remain open, yet critical, issues.

CHAPTER 10

SCALING DATA ENGINEERING SOLUTIONS: AI-OPTIMIZED APPROACHES

10.1. Introduction

The objective of this whitepaper is to provide an understanding of the challenges faced in deploying AI applications at scale, focusing on the IT infrastructure and tooling needed. It describes a blueprint with the best-practice experience of building the necessary foundation to develop and operate use cases involving Generative AI and Large Language Models. The focus is on the end-to-end data and AI supply chain prosperity, covering data readiness, models and experimentation readiness, and the tooling landscape for building such a foundation. Moreover, it discusses the building blocks of the architecture with requirements and precautions for responsible operations and implementation patterns. Finally, it tackles the wider implications of a new AI landscape in companies and the dramatic reimagination of work, roles, and processes it entails.

The proposed solution to these challenges is to automate aspects of the data supply chain with Generative AI. Improvements to data engineering productivity through automation will ripple through the data supply chain with compounding effects. Enhanced productivity of model training—and even inferences—will further eliminate current roadblocks to scaling the data journey. Continuous optimization of pipelines and models will ensure that, over time, yield remains high, costs low, and risk well-managed. Finally, novel use cases, such as internally available data, would be automatically uncovered and exploited. However, achieving this vision will take a deeper understanding of the data supply chain and precisely the aspects that lend themselves to automation. Data engineering models are at the core of the Data Supply Chain and are sequentially executed on data owned by an enterprise. Instead of feeding on easily accessible public knowledge, models need to be fed on enterprise knowledge to operate correctly and automatically. This knowledge must—efficiently and in real-time—be both retrieved and fed to the models.

As industries become more technologically advanced and data-driven, companies are harnessing the power and opportunity of AI and machine learning. Enterprises can now utilize

vast stores of consumer and supply-chain data to enhance customer engagement, better forecast demand, and intelligently analyze complex supply-side logistics. However, despite well-established data engineering best practices and technologies, companies can find it hard to scale data engineering teams. In contrast, the strong demand for data engineering talent exacerbates the situation. Compounding investments in ML often do not grow proportionately to the returns, significantly impacting competitive advantage. Lastly, compliance in a data-driven world—with complex regulations and an ever-growing attack surface—poses an essential challenge for businesses.

Fig 10.1: Scaling AI

10.1.1. Background and Significance

Recently, there have been a number of important technological advancements that can support the development of data engineering solutions. The first group of advancements mainly consists of novel software tools aimed at working with databases. Query languages like SQL are geared toward one specific type of processing framework, namely those employing relational databases. Similar tools can be used to interact with other types of frameworks. The results of these interactions are temporary materializations of the processed data. Subsequently, domain experts are unable to cover the increasing need for relevant processing without the help of technically skilled specialists. Concurrently with the emergence of these tools, there has been a strong push for the democratization of technology and low-

code development platforms. Data engineering is a notoriously technical subject that requires a lot of specialized knowledge that is typically not readily available in organizations. Recent advancements, typified by the emergence of low-code platforms for business process modeling, have shown that business users can be empowered with tools and knowledge to cover the needs for simple business processes. The provided platforms typically manage to visualize, simplify, and unify the way business domains are represented and communicated. Accordingly, it is possible for domain experts to better translate their processes into simple data engineering solutions and thereby retrieve the benefits any more advanced solution can offer.

Data engineering as a subject is equally well-suited for standardized solutions. Generalizations can be made on data representation, transformation, or storage that are independent of programming languages, databases, or processing frameworks. Such generalizations can take the form of meta-models, patterns, best practices, or templates that can be used to support practitioners and make automatic tools easier to develop. However, despite well-established domain modeling techniques, design patterns, or architectural styles in software engineering, data engineering is still heavily practiced in a project-centric manner.

While tailored solutions are effective in meeting the needs of a specific use case, they often involve a high level of specialization which can limit their scalability. Making even small changes requires technical knowledge of tools and systems that are not shared with the rest of the organization. Furthermore, such tailored solutions result in vendor lock-in and costly dependencies on specific experts.

A common challenge faced by organizations as they start to translate their business processes into data engineering solutions is scaling. Oftentimes, a data engineering solution is built by a team of individuals who are experts in the relevant domain. Initially, these solutions may work well for a small number of stakeholders, and therefore a limited number of business processes. However as a successful solution is adopted by more stakeholders, it quickly grows in size, complexity, and the demand for resources. Any changes to the solution may take a lot of effort and time. Concerns related to data integrity, security, privacy, and compliance may arise. Ultimately, it may no longer be possible to use the same solution to cover the increasing number of relevant business processes.

10.1.2. Research Objectives

Ultimately, after finishing the research, it will be viable for organizations to evaluate whether investment in data engineering is worth considering. On the other hand, those who don't invest will have a better understanding of the risks they may face by not investing. Consequently, scalability of data engineering solutions will be encouraged and it will also become more feasible. In turn, this will contribute to achieving organizations' AI ambitions.

In this regard, it is first explored whether there are technical aspects of the data engineering workflow that could be optimized with AI. In the case that there are AI-optimized options available, these options will be compared to their vanilla versions without AI. Comparison metrics include salaries for data engineers, performance, ease of use, or ease of implementation for the workflow. In this manner, it is ultimately addressed whether the alternatives that use AI are more beneficial. Further, it explores what business aspects also need to be taken into consideration when organizations decide whether to invest in AI-optimized data engineering options. For instance, guidelines for organizations to ensure the successful implementation of scalable data engineering options are discussed.

As the focus of most organizations shifts toward becoming more AI-optimized, data engineering begins to play a critical role in achieving this target. One of the most significant challenges in this regard is ensuring scalable data engineering solutions. The concern over scalability is caused by the steady increase in the data-related tasks to be performed by data engineers. Failure to keep up with an organization's growing data-related needs can lead to dire consequences for the organization as a whole. In this regard, machine learning engineers and AI algorithms could help human data engineers with scaling up quickly enough. This research aims to examine whether AI can be leveraged in a way that helps make scalable data engineering solutions possible.

10.2. Foundations of Data Engineering

Investigating literature indicates that conventional approaches to data engineering predominantly concentrate on data processing solutions isolated from data. Approaches to the analysis of data processing solutions commonly assume that gathered data, despite the size, is available and mostly then separated into data-based categories. Data engineering tasks consist of designing/engineering data pipelines, writing procedure code, and preparing data pipeline structure and design validation. Analyzed literature underscores the necessity of data pipeline detection, design, code generation and validation, technology tracking, and embracing the need for domain, company, and assay specificity. In regard to typically encountered concepts,

data pipelines often ingest or produce data on behalf of other services or applications. Virtual pipelines denote abstract data processing applications encapsulated within a description language. The data pipeline framework encompasses a programming model, execution model, and associated software stack directed to realizing a particular kind of data pipeline despite technology implementation concerns. The data pipeline framework is often modular, defining a group of standardized interface contracts between pieces that can be separately developed while employing common technologies for data flow. In regard to deployed-level categories, three groups of definitions are suggested: Batch process, real-time process, and hybrid process regardless of internal data processing activity patterns.

Data engineering has become increasingly vital in modern enterprises as organizations develop and capitalize on novel data avenues and increase their output and caliber. Non-trivial data processing projects commonly necessitate a specialized group of data engineers with specific skills and tools, capable of developing, managing, and scaling robust data software solutions. Nonetheless, the rapid advance and dissemination of sophisticated machine learning systems, specifically for processing and utilizing structured data, present opportunities to directly assist data engineers and aid the development of even more robust data engineering solutions.

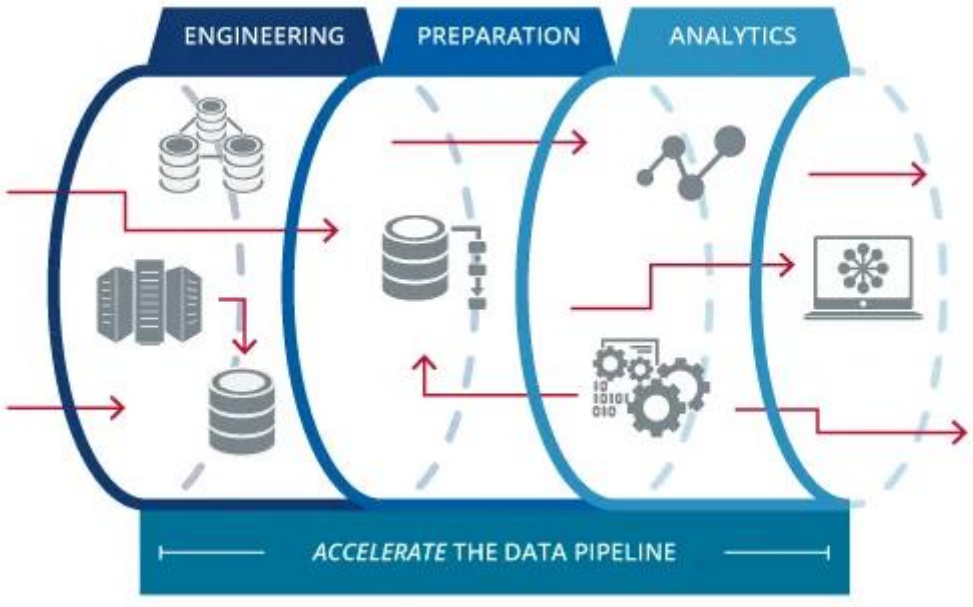

Fig 10.2: Foundation for Data-driven Success

10.2.1. Key Concepts and Definitions

The domain of data engineering encompasses a multitude of specialized terminologies. In developing the foundation for this discourse, a specific selection of key concepts is defined below, which are readily applicable to the context at hand.

Big Data: Big Data is typically categorized by its high volume, velocity, variety, or variability, collectively termed the "V's of Big Data." These properties often thwart conventional approaches to storing, processing, and analyzing data.

Data Infrastructure: An assembly of hardware and software components that serves the purpose of acquiring, storing, processing, and analyzing data. The components of a Data Infrastructure are on-premise and/or cloud-managed servers or listening posts where data is ingested, databases which are platforms for data storage, and data warehouses where the processing and analysis of data are performed.

Data Pipeline: The sequence of processes or steps that constitute the workflow of the Data Infrastructure. Steps in a Data Pipeline generally involve activities of data acquisition, data storage, data processing, and data analysis.

Data Pipeline Control System: The system that oversees a given Data Pipeline. The monitoring and control of the Data Pipeline includes ensuring the execution of the process steps in a timely fashion, the successful completion of the process without incurrence of errors, and ensuring that system outputs are stored properly for further analysis.

Data Pipeline State Space: Typically depicted in block-diagram format, this is a graphical representation of the Data Pipeline Control System. It includes components of state space either as elements in the block diagram or as elements attached to the Control System's components. The Pipeline State Space depicts the internal states of the Pipeline Control System and all of the equipment involved such as running servers, servers in stand-by, and sensor states.

Data Engineering: The discipline concerned with the assembling, monitoring, control, and tuning of Data Infrastructures and their Data Pipelines. All meanings of the term "Engineering" apply to the definition of Data Engineering. The craft of Data Engineering is intimately familiar with the operational environment of Big Data Data Pipelines as well as its technological aspects.

10.2.2. Traditional Data Engineering Approaches

Human-aided data engineering pipelines envisage that one-off constructed data engineering pipelines remain valid and reusable over time without any human involvement. However, this is not realistic as changes in the input data type, structure, and even specification and analysis type (data-aware evolution) may lead to altered raw input data attributes (e.g., size, granularity, inconsistencies, non-compliance with respect to per-construction modeling assumptions, etc.).

Traditional data engineering pipelines include processes such as sampling and filtering, pre-processing and transformation (i.e., extracting features), loading, cleaning, enrichment, and storage. After preprocessing, further transformations and operations could be executed. Data might be analyzed only through sampling or filtering, or it might be considered as is after the main transformation and preprocessing steps. Flow paths, data transformation, and processing, type and richness, how is data considered, destination elements, etc., represent some options and possibilities in the design of data engineering pipelines. Such considerations enter the functional domain of data engineering. Another domain deals with the quality measures regarding the data itself and/or the data engineering processes. Depending on the transformations, filtering, and parameters throughout the process, the input data volume could differ significantly from the output volume. Data loss and sampling could result in degradation of data quality that limits the data understandability, discoverability, and correct application. Data quality with respect to data semantics, understanding, numeric representation, and extraction of equality metrics with regard to the intended purpose increases the fidelity and desired properties of a given data engineering and its further application. In the analysis of traditional mechanistic data engineering, a distinction is made between human-aided pipelines, human-automated pipelines, and fully automated data engineering.

Data engineering has been steadily evolving for decades, keeping pace with data generation and interest. As recent advances in data generation propelled by IoT and new paradigms for machine learning such as deep learning (DL), reinforcement learning (RL), and generative models have caught the attention of both research and industrial communities, there has also been a need for new approaches for data engineering. On the other hand, most of the current data engineering system architectures, platforms, and tools aggregate and operate on data almost in the same way they did three decades ago, even with technologies such as Hadoop, MapReduce, Spark, NoSQL, and Lambda architectures that were created to tackle the big data deluge and foster the IoT applications. To scale and automate proposed approaches, research,

and proposals aim to enable smart data engineering. While such data-aware techniques for query optimization, tuning, scheduling, work distribution, and architecture adaptation enable ease of use and lower costs for data engineering, key difficulties and challenges arise.

10.3. The Role of Artificial Intelligence in Data Engineering

While these products offer some help in the traditionally manual data preparation process, there is still a long road ahead to fully automate data preparation and achieve the scalability to deal with the big data challenge organizations are facing. Many organizations focus on an information-centric approach, which essentially means that practitioners dealing with the challenge of preparing data for analytics continually coalesce new datasets with each step executed, paying little attention to the potential negative impact of future steps. As a result, many IT departments build "data graveyards", complex and hard-to-maintain data models, littered with broken data pipelines and convenience datasets that are no longer used.

In view of these challenges, many data engineering organizations are turning to automation through AI-powered products. These products focus on broadly rethinking the tasks associated with preparing data for analytics, including data discovery, data cleaning, data transformation, data enrichment, and data modeling. These tasks are usually very labor-intensive, requiring extensive human intervention. For example, Tableau, IBM Watson, Trifacta, Paxata, Datameer, Tamr, and Aginity use Natural Language Processing (NLP) to help business users understand the content of their data and allow them to ask questions to find the relevant datasets. Other products excel at automating the process of cleansing and curating data, which is usually prerequisite work before any modeling process can start. This is accompanied by heavy use of event logging and machine learning models trained on the event logs, inferring transformations from one dataset, which were manually applied to other datasets.

Artificial intelligence (AI) is becoming increasingly important in data engineering as organizations strive to convert the growing volumes of raw data into actionable intelligence. AI, in the broadest sense, refers to machines or software systems performing tasks usually requiring human intelligence. AI can be used in data engineering in various ways, including predicting the future content of data, automating data query creation, coding, debugging, and optimization. In the broader data ecosystem, AI-driven data modeling approaches can assist data architects in designing data models that drive the development of complex data systems. According to McKinsey, organizations generating large amounts of data currently depend on human data engineers to build applications that keep up with the volume and velocity of streaming data. However, a lack of skilled analytics practitioners capable of designing, constructing, installing, and maintaining a data architecture needed to extract meaningful information has hindered investments in ML/AI projects. As a result, consumer giants and bank data scientists waste time manually cleaning data instead of deriving meaningful insights.

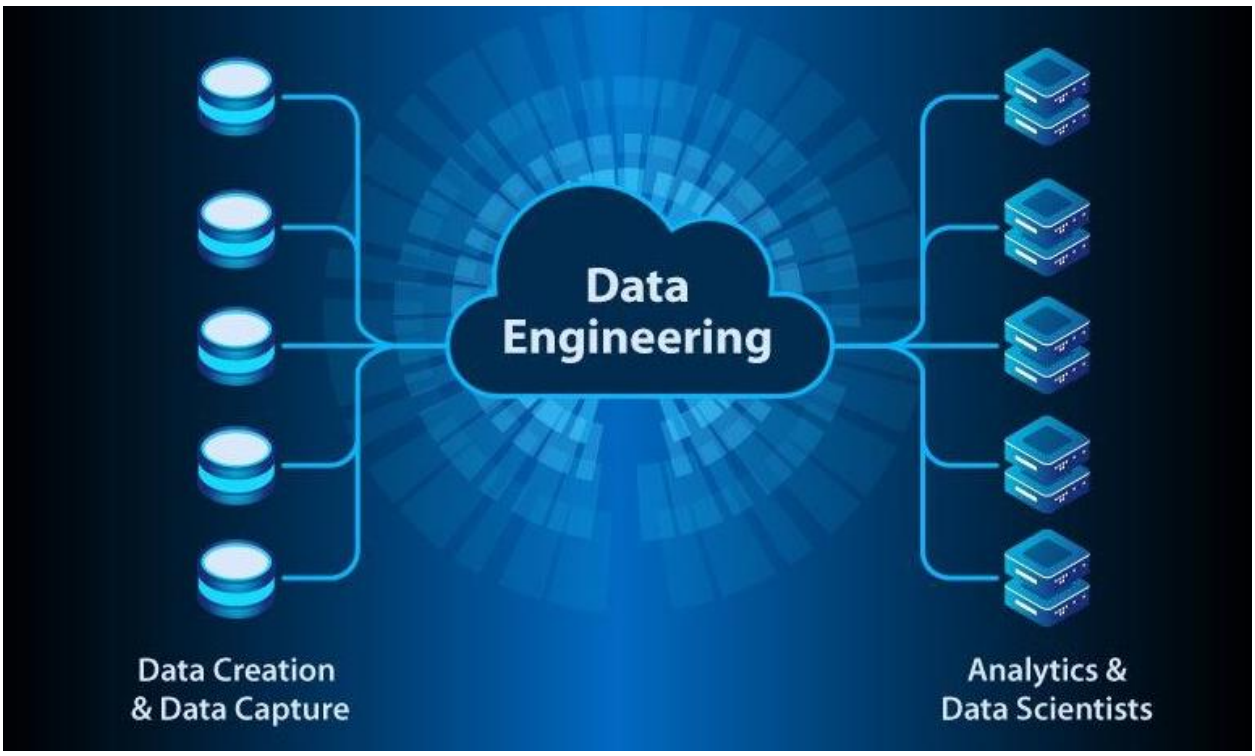

Fig 10.3: Role of AI in Data Engineering

10.3.1. Overview of AI in Data Engineering

This content materializes as the exploration of multiple case studies where the focus is on how to interpret explanations in the areas of business, science, and engineering, encouraging users of the multi-disciplinary tools to join the task of grounding in rigorous knowledge of all possible challenges. This detailed framework of types of challenges makes it easier to adjust prompts to where there is a better chance for AI text generators to understand what to do, quickly. Data engineers' context is promising in that there is a clear definition of dataflows that embody the challenges and a wide spectrum of abstraction levels in the query interface. Prompts could be fed directly from running dbt macros even to explain business indicators at high abstraction levels. A proper layer to disengage knowledgeable experts from queries while allowing them to build more complex queries by joining queries of other experts is also in place.

Regarding their priority and horizon, questions emerge about where to devote energy to exploring AI solutions and how long they have to be prepared for it. The content of the two data engineering disciplines: data science and data engineering is compared to create texture in the understanding of the gap between them. These two disciplines are out of reach to AI and there seems to be an opportunity for organizations to leverage text-free data flow systems

such as dbt, workflows & makefile engines to document their data and its transformations in articulated written forms of first estimation data challenges, providing data engineers with insight on where to test how AI could work for them.

AI is taking certain parts of the creativity required in these written forms of invention. At this point, nevertheless, it still relies heavily on artifacts, the textual and logic components of data engineering. This reliance on data is, at least partially, because AI crawlers and explorers are not able to ground themselves through data and its disposition into artifacts, or technical metadata. Data engineers, nonetheless, continue to be needed to keep the adjustments of the flow between data and text up to date. The rapid development of AI text generators is putting a deadline on data engineering that cannot be ignored. Not all organizations have a data engineering effort, and many have a very limited and shallow one.

With the advent of AI, data engineering is becoming more visible as data scientists and their managers explore what works and what doesn't. Data engineering tools and infrastructure are able to create artifacts that fully document their logic and dependencies in workflows. Workflows become first-class citizens of organizations' context and, as such, are visible to AI. Data is full of mystery and surprises. Looking at it through data engineering artifacts becomes a clearer endeavor. These concepts make data engineering the right discipline to disclose and break down the hidden challenges behind data and dataflows, providing a fertile ground for SQL and programming language-based AI solutions in data engineering.

10.3.2. Benefits and Challenges

Nonetheless, the industrialization of AI and the data pipeline surrounding data science processes are not straightforward. More specifically, issues with scale, validity, multi-modeling, monitoring, ownership, and governance typically arise with the backend of AI deployment. Moreover, AI optimization and the consequent accessibility of data to a limited number of consumers may further widen the gap between the "data rich, information poor" paradox. Consequently, the successful industrialization of AI in data science, analytics, and overall data engineering architecture requires practice and careful planning. Looking closer at each step, these organizational challenges have been further elaborated to identify actions needed to facilitate a transition towards conducive data engineering architecture environments. Nevertheless, there remains an opportunity to mitigate such investment gaps through the optimization and industrialization of data engineering practices, thereby moving closer to a "data consumer assembly line" model. Modern AI refers to the use of algorithms that create

approximate models of real-world environments to forecast an outcome. However, whether qualitative analytics performed externally in data engineering architecture fall within the realm of AI is still subject to investigation. For the purposes of this essay, AI will be defined as algorithms that recreate a process using synthetic variables, which are approximations of the original characteristics. Additionally, objectives can further define the AI approach, whether to replicate, optimize, or predict a process but typically evolve around improving both understanding and the outcome. In general, the data science approach can be described as a sequential process with five major steps: (1) Business understanding, (2) Data understanding, (3) Data preparation, (4) Modeling, and (5) Evaluation & Deployment & Monitoring.

Artificial intelligence (AI) deployment has become a competitive necessity for organizations looking to operate more strategically and maximize return on investment (ROI). However, the resources required to build and maintain an AI environment have become increasingly challenging for organizations of all sizes. Companies are compelled to prioritize their development approach to strategically leverage data. Historically, data engineering and its associated architecture have been perceived as data scientists' responsibility, with little consideration for upfront investments. Providing relevant, timely, accurate, and accessible information to data consumers requires continuous resource investment, with engineering typically requiring five times the effort of modeling. Such asymmetric investment yields a limited number of business insights and losses under the "cost of poor quality" (COPQ) umbrella.

10.4. Scalability in Data Engineering

Recent advances in AI enhancements could utilize existing past knowledge and promote the development of approaches capable of properly handling the diversity in data engineering solutions. Machine learning models could be trained on collected existing historical decision-making tasks and potentially serve as means to optimize similar future tasks. Ultimately, there is potential for the rise of autonomous systems capable of managing the existence, deployment, and evolution of various data engineering solutions and their components in a fully automated manner.

Good practices might allow solutions to fit initial configurations well and face initial growths in demand. However, dealing with an unplanned, excessive, or sudden increase in demand is a challenge faced by all production systems. This scenario is usually referred to as "not-scalable" and may lead to various issues, such as processing bottlenecks, excessive latencies,

data loss, system instability, or complete inability to serve requests with no guarantee of eventual recovery. In extreme cases, data engineering, platform, or framework changes may be needed upfront to avoid losing an entire business opportunity.

Data engineering solutions are being deployed and maintained, or considered being designed and implemented, by organizations nowadays. When code developed and used within a data engineering solution is beyond a certain size and complexity threshold, it tends to suffer from diversity issues. The diversity of a solution and its components may evolve to a point in which they prevent the natural advancement of the development and use of this solution, posing a challenge for the involved organizations. Handling such diversity issues manually is usually unfeasible. Thus, there is a need for an automated approach to handle diversity in data engineering solutions, including, but not limited to, automating and optimizing matching processes and decision-making tasks.

Scalability is an essential quality attribute of a data engineering solution. It signifies the ability of a system to handle increasing amounts of work or the capability to accommodate growth. For a data engineering solution to fit the future needs of an organization, it should be able to deal with the expectations of a rapidly evolving future. The efficient sizing of a data engineering solution is key in facing expected growths in the demand for data, request rates for processing, latency requirements, and service complexity.Recent advancements in AI offer promising avenues for enhancing data engineering solutions by leveraging historical knowledge to inform and optimize future tasks. Machine learning models trained on past decision-making processes could potentially streamline and automate complex data engineering tasks, leading to the development of autonomous systems capable of managing the lifecycle of various data engineering components. While good practices can ensure initial configurations meet early demands, the challenge of scaling to handle unexpected spikes in demand remains significant. Systems that are not designed to scale effectively may encounter processing bottlenecks, increased latency, and even system instability, potentially jeopardizing business opportunities. As data engineering solutions grow in size and complexity, they often face diversity issues that hinder their development and maintenance. Manual management of this complexity becomes impractical, highlighting the need for automated approaches to address diversity and optimize decision-making tasks. Scalability thus emerges as a critical attribute, ensuring that data engineering solutions can adapt to increasing demands and evolving requirements, thereby supporting sustained growth and complexity management.

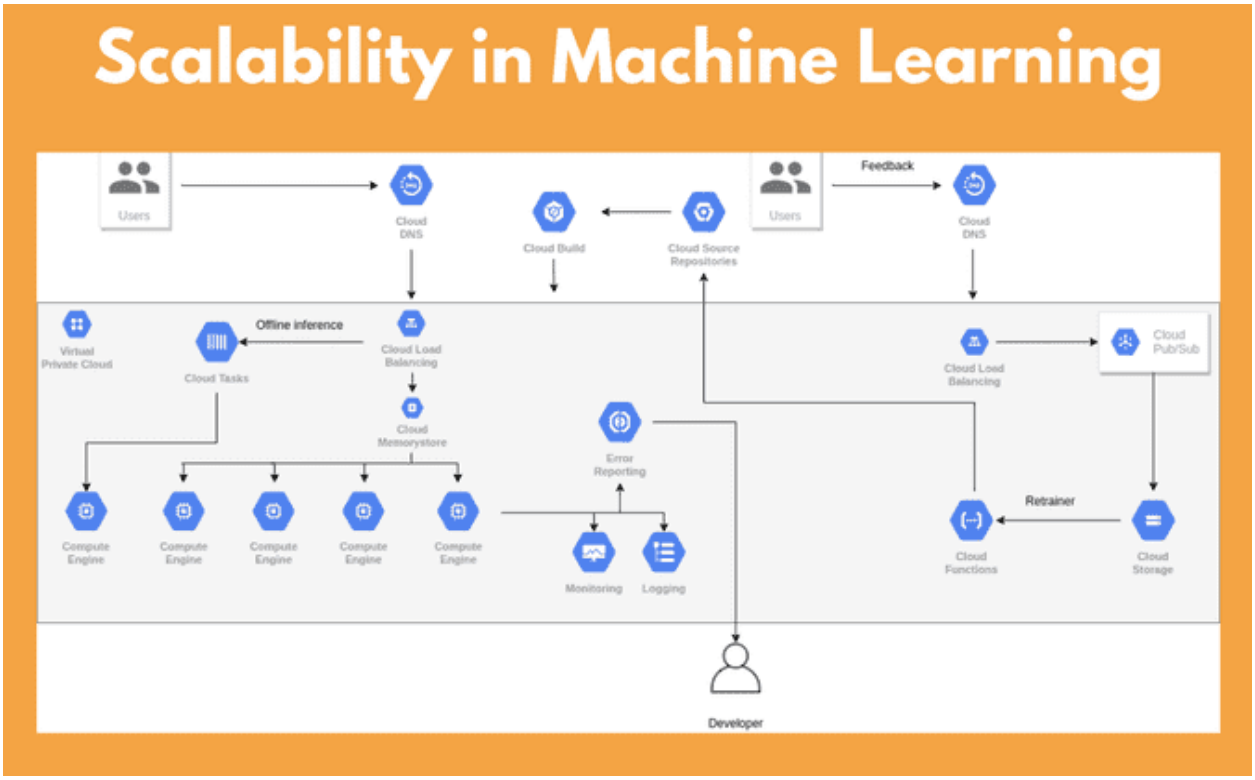

Fig 10.4: Scalability in Machine Learning

10.4.1. Scalability Challenges in Traditional Approaches

Traditional approaches suffer from a variety of fundamental scalability challenges. In particular, the absence of automatic parallelization prevents sufficient performance scaling. Depending on the processing complexity and depth of object graphs, already-established workloads can overwhelm JVM memory and processing resources. In such cases, the representation of data, e.g., the standard JSON representation of a JSON file, needs to be changed. Such an alteration often requires amendments to the processing logic as well. Thus, conventional data engineering solutions neither exhibit desired performance scaling for increasing workloads nor do they exhibit the ability to adapt to the changing formats of input or output files.

Performance scalability concerns an approach's ability to cope with ever-increasing workloads and thus provides insight into approximate growing use cases. Format scalability refers to an approach's ability to accommodate the dynamic change of input or output format. An approach is assumed to be format scalable if it accommodates a change of format without the need for changing the processing logic implementation.

While conventional data engineering solutions present appropriate approaches to data processing under given requirements, they often fall short against changing conditions. Scalability thresholds are frequently overlooked, yet they hinder appropriate workload accommodation. Within this context, two-dimensional scalability dimensions arise from performance scalability and format scalability.

10.4.2. AI-Driven Scalability Solutions

In order to avoid data format bottlenecks with current models, it ends up being more strategic to look for generative models that were recently developed in the computer vision and multimodal data area. Several interesting models with open code, such as DALL-E, Stable Diffusion, and the Flamingo architecture would be ideal candidates to tackle such challenges. Nonetheless, many frameworks providing easy access to large language models to be used with user-defined prompts and possible post-processing are already out. While they can be used for data engineering purposes, they do not provide the necessary tooling to visualize, characterize, and analyze the outputs provided by such models, making their use very complex and tedious. Moreover, most of them rely on models hosted in environments such as the Hugging Face Hub or Google Cloud, which prove to be more advantageous for research than for less resourceful companies or private use. Another issue is that, while these frameworks support both text and code prompts, generating new data or code is often dependent on converting the data into text format.

Nevertheless, companies like Cohere, Jasper, Runway, and Aporia are advancing the development of proprietary tools to assist general analytics, programming, and some data science tasks. While open-source alternatives seem to be improving and adding similar features rapidly, there are serious concerns pointed out by industry leaders and researchers alike about the risks of using such tools on proprietary code, as it is feared that future models could memorize and leak snippets of users' data.

Current large generative AI models are mainly probabilistic and trained on large amounts of textual information pulled mainly from the internet. The representation of data engineering knowledge and how it is generally transferred into such large models is obscure and often difficult to analyze.

With recent advancements and the availability of machine learning and generative AI tools, there has been a significant transformation in the existing data engineering workflows. These approaches are purposely built to be tuned and invoked using simple text prompts. However,

proper evaluation techniques and quantitative benchmarks to accurately assess productivity gains are still not in place.To address data format bottlenecks with current models, leveraging recently developed generative models from the computer vision and multimodal data domains, such as DALL-E, Stable Diffusion, and the Flamingo architecture, could offer promising solutions. These models, known for their advanced capabilities, might effectively tackle complex data engineering challenges. However, while there are numerous frameworks providing access to large language models with user-defined prompts and post-processing options, they often lack the necessary tools for visualizing, characterizing, and analyzing their outputs, complicating their use. Additionally, many of these frameworks depend on models hosted in resource-intensive environments like the Hugging Face Hub or Google Cloud, which are more suited to research than to smaller, resource-constrained companies or private users. The reliance on text format for generating new data or code also poses limitations. Companies such as Cohere, Jasper, Runway, and Aporia are making strides in developing proprietary tools for analytics, programming, and data science tasks, though concerns remain about potential risks, such as the inadvertent leakage of proprietary code. Moreover, current generative AI models, which are primarily probabilistic and trained on vast amounts of internet-derived text, often present challenges in terms of understanding and transferring data engineering knowledge. As machine learning and generative AI tools evolve, they are transforming data engineering workflows, yet the lack of standardized evaluation techniques and quantitative benchmarks for measuring productivity gains underscores the need for further development and assessment in this field.

10.5. Case Studies and Applications

This section will cement this understanding by exploring two recent use cases highlighting how one organization transformed its parameters and today leverages AI optimizations on top of a Lake House architecture to deliver 500TB+ datasets within 3 minutes.

Leveraging the latest advancements in AI, new optimizations are emerging to fundamentally change how data is ingested, structured, and transformed in a data pipeline. These optimizations have the potential to massively improve traditional approaches in terms of both performance and cost. The landscape of tools on offer means it is possible to implement AI optimization on top of any architecture. However, they are inherently most suited for use with a Lake House architecture. As such, now is a critical time for organizations to better

understand the Lake House architecture, AI innovations, and whether they are a good fit for their use case.

The introduction of the Lake House architecture, a relatively new data engineering paradigm, has opened the door to new possibilities for teams looking to step-change their capabilities. The Lakehouse architecture is inherently flexible: data is stored as files in cloud object storage and transformed in place under a transactional layer using a massively parallel architecture that can be leveraged by a multitude of different tools and programming languages. Nonetheless, many data engineering teams opt to operate these new architectures as if they were still traditional data warehouses, using only one of the many tools available, setting their teams up to encounter similar problems as with existing architectures.

The widespread adoption of AI-enabled technologies as part of digital transformation programs has created an explosion in the volume, velocity, and variety of data businesses interact with on a daily basis. This has, in turn, generated a complex set of problems for data engineering teams as they become incentivized to rapidly deliver pipelines producing accurate and up-to-date datasets, regardless of size or format. Delivering on this requirement, however, can be a challenging endeavor. Existing data pipeline architectures often leave many engineering teams struggling to efficiently scale their capabilities to meet demand while still ensuring the quality of their outputs.

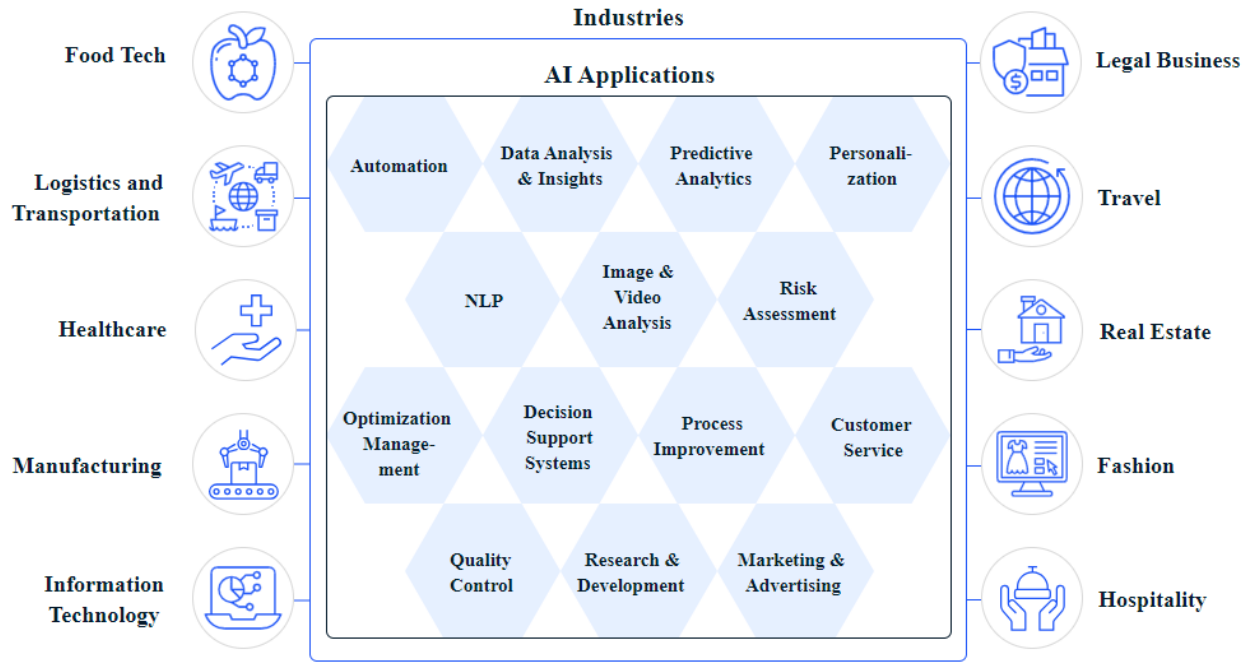

Fig 10.5: AI Cases & Applications Across Major industries

10.5.1. Real-World Implementations of AI-Optimized Data Engineering Solutions

The presented scenarios are not an exhaustive list but represent essential data engineering processes within the pipeline. Issues remain that need to be tackled with the AI approach, including better knowledge representation for, e.g., hardware configurations. Also, components must be developed to provide inputs – meta information or the current state of the data pipelines – for the AI components under consideration. The machine learning models can be enhanced, adapted, or retrained better concerning new data.

Artificial Intelligence (AI) has often been utilized to solve specific problems within highly complex domains. Particularly for data engineering, AI can tend to critical parts of the pipelines, estimating where adjustments can improve the overall performance of data pipelines. It can automate tedious tasks that require lots of experience, reducing the number of pipeline errors, and optimizing the resource consumption overall. In order to understand how AI can be used to optimize data pipelines, the architecture, and functioning of a concrete data pipeline are presented, with a major focus on the intricate data processing, as well as the knowledge representation of the AI components.

AI scenarios are presented that are relevant to data engineering. AI-relevant data processing components of the pipeline are presented. From the processing of the actual underlying data up until the visualization of results, there is a range of components that need to be covered in order to have a concrete data pipeline. Several AI components, such as the knowledge representation of the machine learning models, are evaluated, considering the domain of data engineering. Overall, the architecture of a concrete data pipeline is presented, as well as the underlying data processing components and AI scenarios, showing how AI can be used regarding data engineering. This is one of the first efforts to develop a data engineering approach from the ground up, analyzing a concrete data pipeline concerning its processing components.

10.5.2. Performance Metrics and Comparative Analysis

Ultimately, as the content of final implementable cases with the three included AI functionalities has been provided, feedback has been considered to further tune and focus the implementations according to real-world needs, culminating in all information to begin real-world applications of the proposed set of AI-optimized data engineering approaches presented.

In addition to describing real-world implementations of AI-optimized data engineering solutions, performance metrics of different implementations and technologies such as the OpenAI API, Azure OpenAI API, Hugging Face's text-davinci-003, and cohere.ai for engagement via ChatGPT have been defined, analyzed, and visualized. Furthermore, the versatility of AI tools has been highlighted through comparative analyses of its prompt-driven usage in five different settings, such as exploratory data analysis, as well as providing examples of successful implementations of different AI policies directing the same toolset in very different directions.

Data engineering is a crucial part of any AI solution, ranging from data collection and preprocessing to data storage and building pipelines. With the growing demand for AI solutions, the data needed is also growing. This calls for a growing demand for the amount of data engineers and therefore scaling data engineering solutions. To tackle the challenge of scaling data engineering solutions efficiently, this essay investigates the impact and effectiveness of AI tools in the data engineering phase. To assist and lead such an investigation, several AI-optimized data engineering solutions have been built, ranging from notebook context exploration and modification via ChatGPT to endpoint building and data pipeline structure-building via its usage alongside LangChain, to automatic data storage consideration formation feedback via a conversational system built around ChatGPT, OpenAI's text embeddings, and vector databases.

10.6. Future Directions and Emerging Trends

Complementary efforts in ethical consideration addressing research and responsible practices are encouraged. Such efforts should concern promoting compliance with ethical guidelines, laws, and regulatory frameworks; ensuring data protection and privacy; combating potential environmental impacts; tackling fairness and bias issues, and deploying AI technologies to ensure safety and social acceptability.

Ethical considerations and responsible AI practices are equally crucial. Such considerations apply to the entire data engineering pipeline, AI modeling, and AI-optimized data engineering solution promotion. Discussions on these ethical considerations, responsible development, and the use of AI technologies in data engineering solutions need to be had. Data, model, and service privacy and protection; the environmental burden of heavy computational and resource needs, fairness issues, toxic data and model risks, and AI deployment implications are important topics that need to be addressed.

These potential innovations include improved embeddability and coverage of promotion deployment, specialization, pre-training, active learning-based enhancement, AI-assisted solution scaling options generation, and integration of diverse inferences with data engineering workloads. Additionally, it is proposed that global knowledge pooling among diverse data engineering platforms and industries, in conjunction with the development of industry and platform-specific AI-optimized models, needs to be carried out.

This chapter underscores the necessity for ongoing research and adaptation of AI-optimized solutions to meet the evolving demands of modern data engineering workloads. Three main areas are identified for future directions in AI-optimized scaling of data engineering solutions: scalability and heterogeneity of workloads, new data engineering use cases, and AI-optimized VX. Potential innovations that need further exploration, research, and consideration to progress in these crucial areas are invited and discussed.

10.6.1. Potential Innovations in AI-Optimized Data Engineering

Another potential innovation is the emergence of new applications for AI-optimized data engineering solutions across a broader range of industries and use cases. AI-optimized approaches currently need significant attention in the healthcare, retail, transportation, and manufacturing sectors. However, as the demand for more efficient and effective data management grows, AI-optimized solutions may be more widely adopted in these industries. In addition, new use cases for AI-optimized data engineering could emerge within existing sectors, such as fraud detection, predictive maintenance, and supply chain optimization.

One potential innovation is the development of more sophisticated and automated tools for designing and implementing data pipelines and analytics. Such a tool could leverage AI and ML algorithms to automate critical tasks, such as data ingestion, cleaning, transformation, and integration, making them easier and faster for organizations. Additionally, AI-optimized tools could analyze the data generated through data pipelines and analytics and automatically fine-tune optimization techniques to improve performance. Such developments would empower organizations to fully leverage data for insights and decision-making.

Looking ahead, several potential innovations in AI-optimized data engineering solutions may arise in response to the challenges and opportunities identified in this document. These innovations could substantially impact the data engineering field, enabling more efficient and effective management of data pipelines and analytics for businesses.

10.6.2. Ethical Considerations and Responsible AI Practices

In order to combat malpractice, perpetuation of inequality, and even tyranny, by AI enhancement deployed by competitor companies, data engineers have the technical know-how to discreetly pursue a better society through soft sabotage. Some discrete acts of compliance could include slightly modifying the engineered pipeline so that it underperforms in sandbox conditions (e.g., modifying the input data so that it is consistently out of the domain of application of the tools itself), suggesting a fast & cheap-to-implement solution that is entirely off-label for most AI-driven tools (prompting instructions that induce spurious behavior in the model), or designing simple-to-manipulate systems with ineffective security mechanisms that could leak private content harmlessly but with severe consequences to the use of the AI-enhanced tools (e.g., attaching looser content filters or privacy constraints to NLP production pipelines).

Bearing in mind how their engineered solutions could advantageously benefit society as a whole, prior to presenting a new AI-enhanced tool to the client, it is recommended to offer either a more fair alternative or enhancement or to simply not present it and go on with more ethically sound solution within the client company, unnoticed by the outside world.

With data in a more secure, but still usable way, thinking of using AI-enhanced tools to ethically engineer AI-optimized data pipelines and models is the next step on the data engineer's roadmap in the pursuit of a better society. Selecting open-source models over proprietary ones whenever possible, or training and fine-tuning custom models on ethically sourced and privately retained datasets, localizing NLP models and using them instead of non-optimized proprietary ones in high-traffic systems, and exploring the possibility of creating a "model museum" with antique architectures and test benches to avoid the neural networks' sectoral homogenization and provide a larger array of AI-enhanced solutions to choose from, are possible actions that data engineers could pursue in light of the impact of their work.

Considering the stewardship and retention of the data behind the engineered solutions, data engineers should advocate for the adoption of techniques like federated learning, in which training and tuning of ML models happen in their hosts' environment (for instance, clients' devices in banking or health data spaces). When data cannot leave the physical environment it sits in, ML development can occur without sharing those data, even allowing for the creation of global and more robust models fed on isolated private datasets.

To unleash the full potential of ideas forged in the minds of creative thinkers using AI-enhanced data engineering solutions, strategies to act ethically, responsibly, and proactively

against possible harm that poorly configured or purposely biased AI models may bring are needed.

The data engineering landscape has witnessed astounding growth, due in large part to the enabling capabilities of AI. However, fear surrounding the right use of these new solutions is also becoming ever more present, challenging data engineers to think of ways to responsibly use AI-optimized tools.

Fig 10.6: Ethical Considerations in AI Development

10.7. Conclusion

The proficiency of data engineering workflows is intrinsic to the successful deployment of any AI model, and as such, organizations have been attempting to unlock the scale, quality, and speed of such workflows. To develop a template for desired characteristics, the principles underlying AI architecture are applied in conjunction with the unique challenges of data teams to broaden the impact of these principles outside of the AI model design itself. Despite the growing pressure on data teams to widen accessibility and improve the functioning of data workflows, the tools currently applied across the data community largely reflect the early stages of the data industry and do not facilitate optimized workflows. Nevertheless, a set of AI models exists and has largely been disregarded with regard to dataset needs that can support each data engineering task as required. Collectively, these AI models, methodology, and toolset constitute an approach capable of addressing the data engineering bottleneck holding back AI development. Furthermore, as existing general AI models may only be applied at the dataset layer in a task-specific manner, there is a vast need for custom dataset applications arising from the exponential growth of potential use cases. This approach is capable of bridging both dataset needs and applications, encouraging the further exploration of varied AI

systems on the dataset layer in a task-specific manner to free up resources across data teams and spark debate within the wider tech community surrounding potentially desired safety measures.

The technology landscape today is distinctly defined by the enormous acceleration of advancements in artificial intelligence (AI), propelled both by exceptional growth in applicable theory and the sought discoveries of general artificial intelligence (AGI). However, while AI models and applications have dramatically proliferated in equal parts due to superior hardware, software, and paradigm-shifting datasets, the data systems supporting such models have failed to keep pace. In an effort to stimulate innovation and free up resources in under-fire data teams, organizations may find AI applications that specialize in the creation, curation, and management of datasets are outside the current toolset, but models capable of data functions do exist and have largely been disregarded. This chapter suggests the dataset development, detailing, and indexing functions necessary to support the deployment of AI models can be solved by an AI approach tailored specifically to the unique challenges surrounding the creation and management of datasets. An applied framework, Scale AI dE Solutions, is presented to cover this, in addition to a supplementary set of tools and models intended to demonstrate the wider applicability of the proposed solution concept. Further strengths and weaknesses of the solution are also explored to encourage wider adoption of AI systems targeting dataset needs.

10.7.1. Future Trends

The dynamics of the global data industry are dictated by emerging technological developments that will undoubtedly affect businesses' strategies on both a corporate and personal level. Among emerging technologies and trends, the most promising for future business opportunities are:

1. Advances in Quantum Computing and Teleportation Quantum computing is considered the next frontier for scientific research. Researchers and scientists, backed by government organizations or venture capital, are working to develop and commercialize quantum computers. Given that even simple-to-complex quantitative problems require a longer computing time for classical supercomputers, companies focus more on problems that will only be solvable by quantum systems in the future. The development of the first commercially viable, fault-tolerant universal quantum computer is projected to be achieved by multinational corporations, along with shards of specialized quantum computers that will focus on niche

applications. This next business generation is expected to generate revenues of several trillion dollars and be complemented by new encryption products capable of resisting quantum attacks.

2. AI-Based Data Engineering Solutions Businesses rely on their data more than ever, and they investigate different possibilities to collect, store, and manage data. "Do-It-Yourself" data engineering to manage data on a company's own infrastructure or hosted in the public cloud is one alternative. However, dedicated, multi-cloud data infrastructures managed as a service by AI-enabled third-party data providers are another and are expected to seize most of the data opportunities.

3. Digital Twins for Real-Time Data Analysis Digital twins are used to mirror the data satellite technologies of the Earth through virtual data replicas in a company's environment. The digital twin of Earth will open new research opportunities. New types of satellite and sensor data processing products will be developed. It is expected that these will be finished on a global scale by 2030.

4. The Internet of Things and 5G The IoT ecosystem experience multiplier services will be expected to be developed for autonomous driving, real-time traffic management, etc. Technologies that will open new use cases such as low-energy and secure wide-area private networks will also be developed. Global private 5G networks lasting decades will be built in collaboration with telcos. The transition of technology barriers preventing most of the 7 billion sensors on the planet from being connected will finish, with the IoT expansion opportunities massively occurring.

5. The Rise of Open Source Hardware Devices Free open source hardware devices with shared designs, blueprints, and specifications but unique commercial products including improvements will become widely used. Security implementations to existing products made by hardware providers will be designed and attached to prevent copying while still offering ownership of the products on an individual level. Therefore, noteworthy business opportunities regarding drone-based services, manufacturing, agriculture, internet-of-things, urbanism, and architecture calculations will arise.

CHAPTER 11

ETHICS AND CHALLENGES IN AI-DRIVEN DATA ENGINEERING

11.1. Introduction

The use of computational steps on data to derive information has been promptly simplified by an increase in computing ability and storage capacity, forming high-performance analytic markets. The most up-to-date computing, storage, and architectural technologies collected to handle data can be broadly sorted into four main categories: data acquisition, data storage, data processing, and data analysis. In recent years, a lack of equipment, data storage, and analysis assets has led to the emergence of third-party companies whose business and infrastructure are to supply such services online. This procedure is frequently termed cloud computing, which signifies the on-demand availability of computer system assets, especially data storage and processing, as a utility service over a network. In addition to this, businesses specializing in data acquisition, processing, and evaluation and sharing such characteristics as knowledge have arisen and grown, particularly social networks that use engineered devices.

The presence of data in everyday existence is continuously increasing and predicted to grow vastly thanks to the Internet of Things (IoT), everyday technology innovations, and inexpensive data storage ability. As a handle to the unmatched amounts of information being created, engineering jobs regarding the selection, processing, modeling, evaluation, and analysis of data in automatic or semi-automatic procedures are augmenting. Data engineering is presently suffering from a complicated, interdisciplinary combination of technological obstacles that reach code, architecture, and design, as well as epistemological difficulties concerning the community's knowledge of data and information and their perceived worth.

Rapid advancements in technology have propelled artificial intelligence (AI) into the center of modern life, shaping vital areas in the economy, social matters, and daily life. AI's ability to process enormous amounts of information has ignited societal anticipation, but there are also legitimate worries regarding its ethical implications. Accordingly, numerous national and international organizations have presented their guidelines on balancing AI-driven efficacy and sociocultural principles. Nevertheless, there is an unfilled niche where national rules on

AI ethics can be implemented in scientific research. Even if data science guidelines are presently available, they tend to neglect ethical implications and cannot sufficiently address controversial issues like the redistributing power of AI-driven technology and expert reliance on machine-based decision-making.The evolution of computing capabilities and storage technologies has significantly streamlined the process of deriving insights from data, leading to the formation of high-performance analytic markets. These advancements are categorized into four primary domains: data acquisition, data storage, data processing, and data analysis. The rise of cloud computing has further revolutionized this landscape by offering on-demand access to computing resources, particularly data storage and processing, as a utility service over the internet. Concurrently, businesses specializing in data acquisition, processing, and analysis have flourished, including social networks leveraging engineered devices to share and expand knowledge. The exponential growth of data, driven by the Internet of Things (IoT) and technological innovations, has heightened the demand for sophisticated data engineering solutions to manage the complexity of data selection, processing, and analysis. This burgeoning field faces a range of interdisciplinary challenges encompassing technical, architectural, and design aspects, alongside epistemological concerns about data valuation and understanding. As artificial intelligence (AI) continues to reshape various facets of modern life, from the economy to social interactions, it brings both immense potential and ethical dilemmas. While guidelines for AI ethics have been proposed by various organizations, there remains a significant gap in applying these principles within scientific research, where data science guidelines often fall short in addressing ethical concerns and the broader implications of AI-driven decision-making and power redistribution.

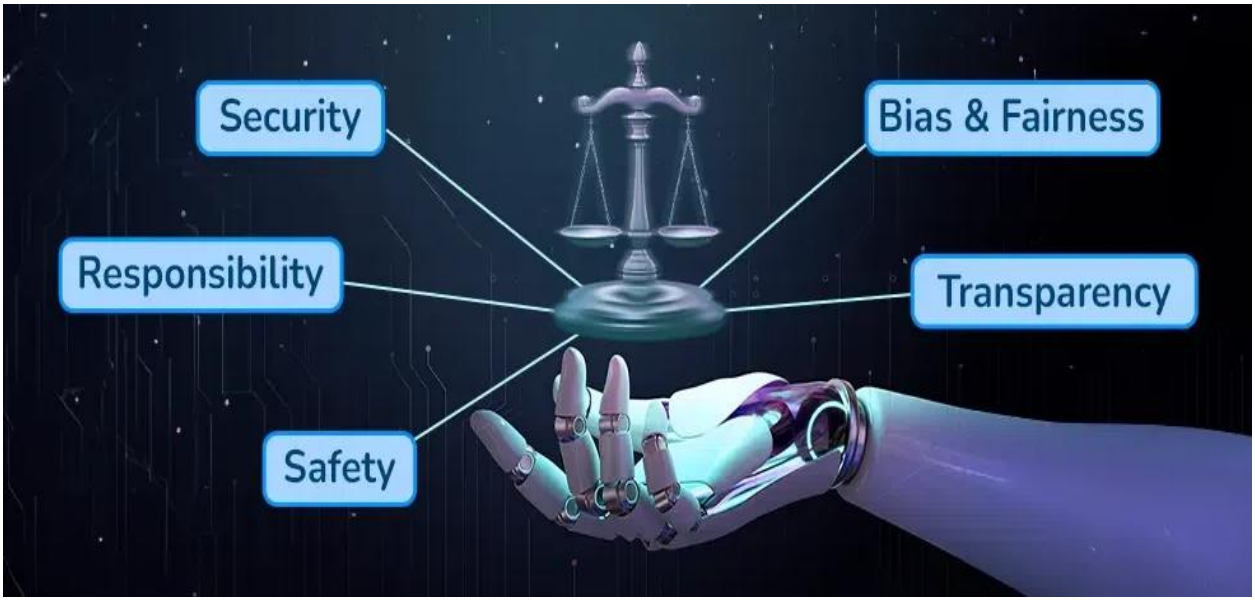

Fig 11.1: AI Ethics : Challenges

11.1.1. Background and Significance

Despite AI-driven technologies, tractors, vehicles, engines, drones, robots, and many other kinds of machines and appliances being widely used for agriculture, transportation, construction, packaging, manufacturing, cooking, public safety, and other business operations, the data engineering pipeline largely relies on human efforts for searching, retrieving, downloading, cleaning, transforming, and preparation tasks. A large amount of time is required for exploring, attempting, and testing technologies and tools, all of which are freely available on the internet. Little to no information can be found in the literature on using AI technologies to carry out such data-related tasks and works.

The ever-expanding data production makes data engineering, popularly called data pipeline or ETL (extraction, transformation, loading), data engineering pipelines, and data architecture frameworks critically important for individuals, businesses, public agencies, and organizations in various industries to overcome challenges and woes deriving from the wealth of data. There is growing interest and motivation in AI-driven data engineering for accessible processing, analyzing, modeling, and extracting actionable insights from datasets. Data-driven solutions depend on well-designed and constructed data infrastructures and engineering frameworks. Various data architectures and frameworks comprising different technologies and tools are developed, some of which are open-source codes and readily available for reuse.

In AI-driven data engineering, computer-assisted technologies and tools are integrated into the data engineering pipeline or framework. This includes data retrieval or collection or scraping, cleaning, transformation and preparation, storage, descriptive or exploratory analysis, modeling or discovery, visualization, deployment, and generating actionable insights, recommendations, predictions, and explanations. AI can be embedded to generate preliminary results and assist human decision-makers in each step of data-related workflows.

AI-driven data engineering has rapidly evolved due to continual advancements in information technology, software, and hardware, as well as data science and engineering. These developments have culminated in the proliferation of multiple interconnected technologies and appliances that produce massive amounts of data, often referred to as big data or data deluge. This data can encompass text, images, videos, code, and other forms, and can be structured, semi-structured, or unstructured. The data is accumulated in memory storage units or cloud storage and can be stored as files, databases, apps, or webpages. Artificial Intelligence

(AI) is used as the analytical approach, and machine learning and deep learning are often applied.

11.1.2. Scope and Objectives

Fairness in data engineering projects is possible, and several fairness criteria exist, among which are independence, balance, and accuracy. Controversially enough, definitions of fairness extend to the definition of models like smarter, wider datasets and reteaching with more transparency. The fairness of datasets used in the army-induced channeling of recruits is contested, explaining their essentially discriminatory nature. Transparency in ML processes or decisions is represented by meta models enabling the explanation of results in the short time between data needs notational and results ex-post decisions. Data governance raises similar questions with means of fairness to company image in which datasets used in financial forecasting may insult or run afoul of ill-willing and/or sensitive clients, overreliance on proxies, and reconstructive datasets.

Problems of AI fairness in data engineering processes are diverse but also nearly ubiquitous whenever any process decided by computation with an outcome visible and potentially influential to large populations occurs. They can happen at the start of the machine learning project, at data collection, and/or flagging of incorrect samples. They can also happen with decision models in use after deployment and at various stages in datasets linked or based on a dynamic inference vector. Datasets with spurious correlations are seen as originating from unfair sampling and unneeded overfitting, along with datasets where initial labeling is notional or semi-automated with ongoing flagging of possible exceptions to the model in use.

The scope of this work is to collect, examine, and comment on academic literature, industry documents, and accepted practices related to ethical challenges in AI-driven data engineering, with a specific focus on fairness and transparency. The input for the collection will be recommended papers that are generally accessible to members of both academia and industry. The output will be a written survey of the literature, with accompanying comments. If relevant, accepted practices will also be analyzed.

11.2. Foundations of AI-Driven Data Engineering

The algorithmic age has generated many novel sampling, searching, reasoning, and decision-making methods and techniques. AI systems no longer mirror or amplify existing

social practices, but instead exert a shaping influence upon agentic capacities and opportunities. Currently, emerging AI systems provide compression-based accounts of their phenomena. With page-based summarization for natural language, agents have the opportunity to sample greater linguistic datasets and extrapolate relevant content more effectively. With social media text taken into account, the dialectic interaction would necessarily involve algorithmic and audience agency.

Data has become a new dominant asset for businesses due to the recent explosion of data generation and availability. Moreover, AI technologies leveraging data have become a source of competitive advantage, shaping products, services, and business models in unprecedented ways. Simultaneously, societies are challenged to cope with the opportunities and threats presented by AI technologies, data policy, and regulation in defending transparency, accountability, and public interest. The rise of AI-driven data systems thus raises pressing questions of ethics, governance, and responsibility. Most importantly, there is an urgent need to rethink engineering from a socio-technical perspective.

AI has emerged as a mathematical and logical system wielding profound societal influence through its algorithms and machine learning techniques, a diverse set of methods for decision-making rooted in data. Although scholars argue that data and algorithms take the lead, it remains the case that AI is societal in character. Their actions, often characterized as algorithmic or data-driven, rely upon the pervasive mass of data created by ubiquitous digital technologies used by billions of people daily. AI's entangled evolution with data and society ensures continuous change, affecting how society might, or might not, flourish.

11.2.1. Overview of AI and Data Engineering

For conscious intelligence, knowledge is typically viewed as the domain of propositional functions. Propositional functions map individuals onto truth values. In this view, knowledge is seen as a whole and quantized because it is uniquely manageable and indefeasible. Axiomatic logical systems describe information states as possible worlds, with sound and complete logic serving to relate them.

Although the fundamentals of AI are widely known and commonplace, they can signify variances based on the type of "intelligence". Given the readership of this chapter, the focus will be on rational, academic, and computational (machine) intelligence. The necessity of knowledge acquisition is a defining feature of intelligent systems. Therefore, the

understanding of information, the use of information, and the coherence of prior and derived knowledge are key a priori concepts for intelligence.

Data engineering has been described as the practical side of "big data". The transformation of this data into structured data and its passage into a data warehouse for further analytics is the main scope of typical data engineering. On the one hand, it covers data operations like orchestration, extraction, enrichment, and aggregation of data, as well as ensuring quality and compliance. On the other hand, it covers data accessibility and distribution through the design of data models and the provision of different data interfaces.

AI has emerged as one of the most transforming technological advances, with a potent potential for ushering in a paradigm shift across multiple industries and economies. Its influence and the problems it poses are projected to grow, making it one of the most important issues of the early twenty-first century. Over the years, AI has been conceptualized and modeled as the capability of a machine to imitate intelligent human behavior. Recently, there has been renewed interest in AI, fueled by increased data generation, enhanced machine learning technology, and greater computational power. Firms in a variety of sectors are developing AI strategies, and notably, AI applications in data engineering have begun to flourish.

11.2.2. Key Concepts and Technologies

Technologies in the area of orchestration and provisioning, such as no-code and low-code data integration platforms, are reviewed. Data management and data engineering technology that enables the knowledge layer is examined, including data lineage tracking, monitoring, and impact analysis of data usage. The key concepts in each area are introduced, along with the usual challenges associated with these concepts. This chapter focuses on the technology, tooling, and concepts associated with each layer and addresses the challenges that arise in the use of such technologies and AI engagement.

In this chapter, a brief examination of the key concepts and technologies that underpin AI-driven data engineering is undertaken. A look at the three layers of the AI-driven data engineering technology stack is presented, focusing on the layers of augmentation, orchestration/provisioning, and technology enabling the knowledge layer. The augmentation layer includes visual programming and Generative Artificial Intelligence (GAI) that can augment data, data engineering, and analysis tasks. One of the most performant tools in the area of GAI is OpenAI's ChatGPT. Its application in several data and data engineering tasks,

such as data inventorying, understanding, cleansing, wrangling, and profiling, is covered alongside its limitations.

In today's world, organizations of all sizes leverage data-driven insights to drive cost reductions, revenue enhancement, and better decision-making. Despite the tremendous advances in fields like data storage, processing, and computational power, a shortage of well-trained individuals who can gather, prepare, wrangle, analyze, and produce insightful reports based on data continues to be an issue. With the rise of Artificial Intelligence (AI), there is a tremendous opportunity to alleviate this shortage by augmenting the capabilities of skilled data professionals with innovative AI tools and capabilities. Important questions arise regarding the data that underpins these AI technologies, how data is prepared for AI models and AI insights derived from data are interpreted, and whether negative societal challenges arise from their use.This chapter delves into the technologies and concepts fundamental to AI-driven data engineering, focusing on orchestration and provisioning tools such as no-code and low-code data integration platforms. It examines the technology stack across three key layers: augmentation, orchestration/provisioning, and the knowledge layer. The augmentation layer features visual programming and Generative Artificial Intelligence (GAI), with OpenAI's ChatGPT highlighted as a leading tool for tasks including data inventorying, cleansing, and profiling, although its limitations are also discussed. Despite significant advancements in data storage, processing, and computational power, organizations still face a shortage of skilled professionals capable of effectively managing and analyzing data. AI presents a promising solution to this challenge by augmenting the capabilities of data professionals. However, crucial questions remain about the quality of the data used to train AI models, the preparation and interpretation of data for AI insights, and the potential negative societal impacts of these technologies. The chapter aims to provide a comprehensive overview of the current technologies and challenges in AI-driven data engineering, addressing both the technological advancements and the broader implications of their use.

Fig 11.2: Key Concepts

11.3. Ethical Considerations in AI-Driven Data Engineering

Such ethical challenges also come in clusters. Automation challenges, employment challenges, liability challenges, and monopoly challenges stem from the emergence of AI technologies that have converged upon societal infrastructures, affecting the way their functionalities are designed and redistributed. Many ethical challenges also arise from the manner AI technologies are deployed. Empirical challenges are posed by the ignorance of users and non-transparency regarding the deployed AI technologies. Some challenges arise from concealed activities, such as espionage, the collection of private data, and the emergence of data shadowing.

With widely deployed AI technologies, several ethical challenges have been identified and framed. Some challenges are classical, such as data ownership and monopoly control. Others are profound by their nature, such as algorithmic discrimination. Some challenges are also emerging, such as AI toxins. Converged AI infrastructures on societal structures pose challenges that would demand specific solutions. Societal contexts matter in framing ethical challenges and prospective solutions to be approached. Considerations or solutions that may have worked well in social or political contexts other than the one of past formulations should be re-evaluated.

AI applications have primarily focused on technical problems and challenges, leading to shortcomings in AI-driven chess engines, smart assistants, and other applications. In parallel, work on the ethical challenges and assessment frameworks has transitioned from profound individual concerns, rooted in posthumanism, identity politics, bioethics, etc., into tangible and practical challenges. Ethical concerns proliferate when emergent AI technologies converge on societal infrastructures. The influx of ethical assessments and their endeavors also addresses the basic challenges of framing, approaching, and improving AI infrastructures. The ethical solutions devised and proposed are often seen as rebuttals to the presented ethical challenges.

As AI becomes increasingly integrated into modern IT infrastructures, a subset of challenges has emerged with diverse repercussions for society at large. Consequently, there is a growing need for practical AI-driven solutions to address emerging challenges while improving existing infrastructures. Awareness of the ethical principles and challenges involved is needed to devise a comprehensive overview of their consequences on societal infrastructures.

Fig 11.3: Ethical Considerations in AI-Driven Engineering

11.3.1. Bias and Fairness

The problem of fairness mathematically and algorithmically has recently gained great attention in a variety of application contexts, including credit approval, policy enforcement, hiring, classification in criminal justice systems, educational assessment and admissions systems, and keyword searches. The role of data engineers is critical in obtaining collections of data that encode knowledge about the world. Accurate realization of this role enables machine learning application and knowledge discovery and is of utmost importance. However, databases comprise and represent a particular view of the world. A diverse collection of centered databases may cause graduated semantic distortion and biases in the encoding of real-world knowledge. The biases embedded in datasets inevitably play a key role in the outcomes of machine learning processes that employ such databases. With the growing influence of AI systems equipped with learned models in individuals' lives, biases in datasets may have devastating consequences.

Data-driven algorithms are not isolated from the real world. Data-driven modeling ultimately employs datasets, which stem from the real world. Datasets may encode knowledge that is socio-economically or politically biased, possibly leading to acquired models that act in similar ways. In many applications, the datasets employed for modeling are approximations of reality, not neutral or fair representations of it. Such datasets could have been acquired under different historical, social, or business scenarios. Data-driven technologies' influence

over individuals' lives, typically exerted in an offensive, massive, and automatic manner and complementarity or redundancy to other sources of influence, can be viewed as scenarios for potential societal harm. Furthermore, as datasets evolve over time or with trends, biases induced by datasets may vanish or else develop new ones that can be similarly potentially harmful.

The ascendance of data analytics and machine learning has unveiled great potential for knowledge discovery within vast domains such as biomedical analytics, social networks, finance, and e-commerce. In tandem with a plethora of successes, there has been a growing awareness in the research community of bias and fairness issues in data-driven machine learning. Systems such as recommender systems, credit score assessments, job candidate recommendations, and predictive policing use data analytics for decision-making and behavior influence. As societies become increasingly dependent on technologies that rely on databases, employing such systems without appropriate consideration of bias and fairness concerns may lead to questionable ethicality and disastrous consequences.

11.3.2. Privacy and Security

In another way, an AI can be developed as a privacy net that receives datasets before publication and examines and reports any risks, consequently letting users decide whether to publish them or redo the necessary removals. Other ways include using federated learning and differential privacy to protect sensitive data while utilizing and analyzing them. Federated learning allows AI models to be trained on local devices without sharing sensitive datasets with central servers. Here, AI plays a key role in making the engineering of data for AI more responsible and ethical without infringing on any users' privacy and security.

On the positive side, AI can be used to help facilitate privacy and security in data generation, curation, analysis, and sharing. AI can help determine the necessity of the generation or sharing of certain datasets through data usage control models. It can also assist in anonymizing sensitive data for responsible sharing, censoring identifiers in HTML or JSON documents containing sensitive data, or code-switching in sensitive textual datasets. AI can even automatically split certain images or videos containing sensitive personal information before public posting or sharing for the same reason.

Similarly, U.C. Berkeley’s School of Information revealed how customers' credit histories were used to identify them successfully, despite de-identification techniques like removing PII (Personally Identifiable Information) information and other user IDs. The experimental proof-

of-concept is available at: [link removed]. In April 2021, ProPublica published a report revealing how Clearview AI's facial recognition technology led to wrongful arrests, highlighting privacy and security issues with AI technologies.

Numerous customers or users' data, like Google searches, social media posts, or purchase histories, are generated nearly every moment. Governments, corporations, and other organizations collect, curate, analyze, and share this sensitive personal information for their purpose, thus hurting the privacy of customers or users. NDSS (Network and Distributed Systems Security Symposium) of Cornell University demonstrated how AI-based facial recognition models, pre-trained on public web images, identify users without their consent. The experimental proof-of-concept is available at: [link removed].

In the age of information explosion and advanced technologies, the data-driven approach has created huge privacy and security-related risks. This section discusses the ethical considerations regarding privacy and security, and the usage of AI in that area, focusing on how it can be harnessed to make the engineering of data more responsible and ethical, along with the challenges that can make the engineering of data for AI more challenging with negligence towards privacy and security.

11.3.3. Transparency and Accountability

Transparency and accountability are essential to ensure that AI systems are designed and implemented in a way that respects human rights and promotes social welfare. Organizations that develop and deploy AI systems must take steps to ensure that these systems are transparent and accountable to their users and stakeholders.

Another important ethical consideration in AI-driven data engineering is transparency and accountability. As organizations increasingly rely on AI systems to process and analyze large amounts of data, it is critical to ensure that these systems are transparent and accountable to their users and stakeholders. Transparency refers to the ability to understand how an AI system operates. Accountability refers to the ability to hold the people or organizations responsible for an AI system accountable for its actions and outcomes.

Transparency can be achieved in several ways. One approach is to provide users with clear explanations of how an AI system makes decisions. This can include information about the algorithms used, the data processed, and the reasoning behind specific decisions. Transparency can help users build trust in the system and better understand its strengths and limitations.

Another approach to transparency is to provide users with access to the data used to train an AI system. This can help users identify potential biases in the data and understand how these biases might affect the system's outcomes. For example, if a facial recognition system is trained on a dataset that primarily includes images of white faces, it may have difficulty accurately recognizing the faces of people of color.

Accountability can be achieved in several ways. One approach is to create mechanisms for auditing and monitoring AI systems. This can include regular reviews of the system's performance, as well as the data used to train it. These audits can help identify potential problems and ensure that the system operates fairly and transparently.

Another approach to accountability is to establish clear lines of responsibility for AI systems. This can include identifying who is responsible for the design, implementation, and oversight of a system, as well as who is responsible for responding to any negative impacts it may have. These accountability structures can help ensure that the people or organizations responsible for an AI system are held accountable for its actions and outcomes.

11.4. Challenges in AI-Driven Data Engineering

Regulatory Compliance: There are regulations active in multiple jurisdictions that are very relevant regarding the use of AI models in general. On a high level, there needs to be risk assessments conducted. With the amount and sensitivity of data involved in data engineering, as well as the reliance on decision making on AI models, this risk is expected to be quite prevalent. Hence, a lot of effort would need to be taken in this requirement. More specifically, in case a personal dataset was used for training the AI model, this model and its derived results would need to be audited for discrimination and profiling effects based on gender or race, etc., to ensure compliance. For the usage of AI models, there would need to be a transparency register that includes details about the AI model workflows, as well as logs and audit trails of related processes and activities.

Interpretability and Explainability: Decision-making in AI-driven data engineering processes would not be reproducible in all cases and therefore lack interpretability and explainability to the business users. This raises concerns about trust and accountability in the decisions made by the AI-driven data engineering processes. It would be required to provide explanations to the business users about what processes have been performed on which data led to which decision. Other concerns include bias audit on the applied dataset and decision criteria, and tracking of performed processes on the pipelines in relation to the applied dataset and their

input parameters. This would require either a respective database for storage for all this additional information or the risk of sprawl across multiple documents. A current investigation on how to combat this issue of lack of interpretability and explainability in AI-driven data engineering processes, in specific as part of the broader AI toolkit, is in its prototype stage.

Data Quality and Integrity: Data engineering is only as good as the data itself. Implementing and automating processes of data collection, cleansing, transformation, and mashing requires data quality checks at every stage in the pipeline. With AI-driven tools, these checks and the required changes would be applied automatically. Hence, it is very important that these checks need to be compliant with the business logic. Otherwise, it will lead to inflation or voids in the data. These AI-driven tools and their applied changes also need to be regularly monitored as they might not work as expected or as intended in all edge cases. Otherwise, there might be data loss or delays in data processing times that would lead to missing business opportunities and require a lot of effort to revert back to the previous stage. Due to these concerns regarding changes that directly affect production data pipelines, a "Human in the Loop" model would need to be used. Required changes would be suggested by the AI-driven tools, but they would still need human supervision for approval before being applied to production data products.

Artificial intelligence (AI) is opening doors to new possibilities and speeds in practically all sectors, and data engineering would not be an exception. However, the implementation of AI in data engineering work comes with its own set of challenges. A few of those challenges are discussed below.

Fig 11.4: Challenges in AI-Driven Data Engineering

11.4.1. Data Quality and Integrity

The proliferation of artificial intelligence (AI) technologies has compelled online service providers to embrace data collection practices in order to facilitate training and personalization of AI models and services. Such technology and service providers may utilize the troves of data that are made available through their services in order to ensure accessibility and perpetuation of their services. Moreover, the persistence of some data items may be beholden to numerous contractual obligations that stipulate data preservation and availability requirements for both the service providers and their engaged parties alike. Given the combination of these factors, it is paramount to verify both the quality and integrity of these data collections, especially in light of the perpetuity of automated data collection practices and, at times, unforeseeable changes in model architecture or service design that may compound such subsequent verifications further down the line.

The modeling of data quality is an integral concept in data science, and it is defined by a number of orthogonal aspects. The most renowned model of such aspects is that of the five dimensions proposed by Wang and Strong (1996): accuracy, completeness, consistency, timeliness, accessibility, and interpretability. The identification of simple and clear metrics for each quality aspect is of paramount importance in light of automated or semi-automated verification strategies. Given the increasing maturity of AI technologies, there has been a proliferation of deployed methodologies and techniques for the performance optimization of supervised AI modeling. As of now, and to a good extent, this body of work is translatable to the domain of data quality, given suitable data model transformations and representation. For example, given that outliers may severely impair the performance of data modeling and AI model training alike, techniques for outlier detection that originate from machine learning methodologies exist and may transfer between these domains well. Such models may be trained to detect weak/inconsistent data representations, outliers/noise in data values, or missing data points, being applicable to the data collections explored either for AI model personalization or engagement purposes. This is representative of the cross-domain setting of the challenges and the implicit knowledge therein.

To ensure the integrity of the data collections in question, a clear understanding of the aspects that data items can be verified against must be formulated. In light of providing such verification, fully comprehensive and often proprietary representations of the data underlying engagement systems cannot be assumed as being guaranteed. If the sole assumption is that the data collection at any point in time may be captured under a set of data identifications (e.g.

user IDs), then large-scale verification against integrity models must be sought. The reported work endeavors to explore this challenge and proposes a number of systemic suggestions for its concrete realization.

11.4.2. Interpretability and Explainability

AI-driven data engineering applications, such as marketing and credit applications, use models trained on sensitive personal data to make biased decisions on a class of people without their control. When people receive unjust offers, they often cannot understand why. This would be acceptable if the data used was a fair representation of the population, but historical data with biases often leads to biased models.

Furthermore, these problems are difficult to identify because the models are complex, with more parameters than training data points, making it hard to understand their inner workings. This raises the question: "How can we understand decisions made by complex models like neural networks?" One possible answer is interpretable machine learning, which uses simpler models or methods to investigate the predictions of complex models.

Interpretable machine learning can be grouped into three categories, each with its own methods: (1) models that are intrinsically interpretable by design (e.g., linear regression, logistic regression, naive Bayes); (2) models that are comprehensible and useful with the help of visualization (e.g., decision trees, random forests); and (3) models that are unintelligible from a human perspective (e.g., ensembles of models, deep neural networks), which require post-hoc explanation methods (e.g., LIME, SHAP). However, there are concerns about whether post-hoc explanations can truly meet expectations and provide users with the necessary understanding to trust the predictions.

Explaining decisions made by large models is considered a foregone conclusion, along with the possibility of failure. Explanation refers to making the model's predictions comprehensible to human operators. This assumes that there are proxies or abstract representations of the inner workings of these black box models, which may not always be the case. There have been attempts to enforce explanations through laws that require post-hoc explanations (e.g., the Italian Authority for Personal Data Protection, GDPR art. 13, etc.). Some states even aim to improve understanding through a "hemodynamic" model. This demonstrates faith in explanations as a solution, although some argue that there should be a threshold of non-comprehensibility that triggers the non-use of the model.

Furthermore, explanations can also be seen as an appeal to an accepted cause. Models that deviate from expectations lead to distrust, and vice versa. This relies on a chain of associations that can also fail: models may perpetuate bias related to race, or sensitive variables may predict riskier loans. Another challenge is that the use of simpler models, whether by design or post-hoc derivation, can introduce discrimination from the data. Currently, available datasets for applying interpretable algorithms often have limitations when it comes to sensitive variables. Although some tools have attempted to address this discrimination through adversarial learning or fair-risk enhancement models, the problem lies in defining fairness metrics that are acceptable and allow for differences between different population groups without interfering with the model itself.

11.4.3. Regulatory Compliance

The rapid adoption of highly data-driven systems, AI tools, and sophisticated data engineering pipelines dominated by ML has not fazed regulators. There is a new landscape of AI regulations emerging that raises compliance hurdles for data engineering as well as other AI/ML products and services. Countries such as the US, EU, and UK, as well as regions such as the Middle East, Asia Pacific, and Latin America, have begun applying a patchwork of policies to address the evolution and application of AI technologies in products. Last year, the EU proposed the AI Act, which would be the most overarching and high-profile governing law of AI worldwide. The bill aims to regulate AI tools, solutions, and business cases across industries based on the risks they pose to individuals and society. High-risk cases must abide by strict compliance rules, which have significant implications for organizations running, trying to build, incorporate, or embrace AI products and solutions. Artificial intelligence tools used for credit risk assessment, employment, education, biometric identification, or even marketing practices fall under the proposed rule's parameter of high-risk designations. In total, the EU's current draft categorizes over 25 business instances as AI systems considered high-risk. This approach helps mitigate possible biases toward sensitive groups or individuals.
Furthermore, the Federal Trade Commission (FTC) has started enforcing its business rules of discrimination in decision-making, a topic that is gaining traction as AI tools are increasingly involved in risk assessments that impact marginalized individuals or groups. In addition, other proposals, like the European Commission's General Product Safety Directive, ban AI systems operating in sensitive spaces, including biometric recognition in public settings. The position is echoed by discussions held in the forthcoming AI Bill of Rights and other legislative efforts

globally, such as the United States Algorithmic Accountability Act, the United Kingdom's white paper entitled "Establishing a new pro-innovation approach to regulating AI," Japan's draft Artificial Intelligence Governance Principles, and China's outline for New Generation Artificial Intelligence Governance. Data engineering teams designing, developing, and deploying AI systems must consider compliance as part of their pipeline. Broadly speaking, there are two components of compliance to manage: regulation compliance and internal compliance.

The emerging new landscape of regulations demands compliance with a patchwork of laws that can vary widely across jurisdictions. These laws typically include documenting the data ecosystem of AI/ML models, adopting specific policies to ensure compliance with the regulations, monitoring tools continuously throughout the models' life cycle, maintaining extensive documentation of audit processes and results, and taking prompt action to rectify violations observed. As there are many compliance regimes, each with its own requirements, and as these requirements evolve, achieving compliance can be a Sisyphean task. Internal compliance consists of checking adherence to the organization's own policies, which usually take a more granular form compared to regulations. Internal compliance can range from basic requirements, such as data access permissions and safeguard rules for datasets, to more advanced stages such as bias detection and risk assessment of the impact of decisions taken by the system. For large organizations that have a range of internal policies, internal compliance can be cumbersome to manage cohesively.

11.5. Conclusion

The exploration of ethical concerns surrounding big data and data engineering perspectives induced by artificial intelligence in the five domains, such as agriculture, finance, transportation, and motivation, accentuates the necessity for a framework or ethical guidelines for utilization and execution. This end of the essay identifies unresolved inquiries and parameters for impending experimentation, being the foundation of artificial intelligence-driven data engineering in sectors, other than the spotlighted ones.

Artificial intelligence-driven data engineering can dominate future advancements in many sectors in the next few global cycles. The spotlighted domains can be constrained and cleaned, and personal domains can be proposed and directed, mostly under established global legislation. Ethics can be multipurpose, endeavoring improvement in any of the agricultural, financial, transportational, motivational, and other interests at the same time. Artificial

intelligence can be utilized as a tool for the accomplishment and the legitimacy of ethical norms can be arguable.

Artificial intelligence systems for monitoring the fulfillment of ethical norms can generate new matters, and the monitoring systems could be co-engineered with generative artificial intelligence. The effectiveness and norms of artificial intelligence big data systems could be declined and challenged. To what domain of human actions can artificial intelligence-driven big data systems be expanded? The interested smart detection systems become governing over the monitored behavior. What other conditions of detected inquiries or functionalities can be parallel experienced by various interests? To what extent various fields of interest can be considered pricing, and are those premises acceptable?

All inquiries noted in this conclusion section can be concurrently neglected by the collaboration of states, holding up trustful institutions, and the request for security. Under those centralized norms, the correction of artificial intelligence systems is justified to be operated solely by positive feedback data engineering systems. Artificial intelligence-driven data engineering can dominate advancements of many frameworks and industries, covering state-security standards as the only barring paradigm for artificial intelligence neutrality.

11.5.1. Future Trends

As artificial intelligence (AI) systems have become the backbone of numerous organizations, ethical concerns have emerged regarding their transformative capabilities across sectors. As AI continues its upward trajectory, visualizing technologies that will be implemented long into the future is paramount. Future AI technologies will ensure wider adoption of intelligent systems, making certain that all dimensions of the human experience (i.e., entertainment, education, environment, etc.) are enhanced.

Global citizenship, degradable programming, and preemptive action powering AI projection growth comprise three key pillars that will impact AI architecture. Accessibility beyond the elite demographic glimmers bright in the global citizenship projection. In a generation where the elite of society maintain unequal access to technology, creating AI systems that harness the power of accelerated computation technology, cloud processing, and the population growth bubbling all around the world will enhance the human experience. Degradable programming will expand the expectancy of AI adaptability and maintain reliability as programming standards evolve. Programming languages that can disintegrate into adjacent

"specialized" languages exponentially increase growth potential while maintaining system viability as time progresses and hot languages emerge.

Preemptive action will counteract unintended destructive consequences of technology through the incorporation of expendable fail-safes in the architecture of emerging systems. The AI systems of tomorrow will be preemptively cautious, so if undermining behaviors emerge, they will readily dismantle themselves. While growing AI systems optimize macroscopic processing and memory improvements, a perverse ubiquitous approach to its manifestation will enhance resource feasibility, implementability, and speed growth. Following the inescapable march of inexpensive miniaturization and achievable generational-to-generational processing efficiency improvement of computing components, it is projected that by 2060, widespread basic AI devices could be integrated into an individual's protein makeup and consequently production processes. The most personal forms of AI intelligence retain the ability to emerge in real-time as "virtual organisms", joining existing neural hardware.

CHAPTER 12

FUTURE DIRECTIONS: EMERGING TRENDS IN AI AND BIG DATA ENGINEERING

12.1. Introduction

Big data engineering must address the growing demand for systems to store, process, exchange, and analyze increasingly large, complex, and rapidly growing datasets, or big data. The economic and scientific value of the data, as well as the reliability, fairness, and privacy of data, are decisive factors that must be dealt with in ensuring the accessibility and applicability of data resources, as well as new AI techniques for decision-making, optimization, and prediction.

Because of the wide adoption of AI and big data technologies, there is a growing demand for research in data storage, processing, and analysis, making data science a fundamental research area. Several important, open, and challenging fundamental research problems in data science are described, focusing on relevant big data engineering and AI technologies, as well as their potential relevance to emerging applications.

Because AI depends upon big data to develop, among other important issues, the heterogeneity, size, complexity, and relevance of the data, as well as its rapidity and economic value, are determinant factors in the accessibility and applicability of the data. AI agents must ensure the discovery of relevant data resources, the characterization and evaluation of the data, the accessibility of the data, and the compatibility of data from different sources, considering the formats, languages, semantics, and protocols used.

On the other hand, big data engineering depends on new AI techniques, methods, and technologies to characterize and evaluate the relevance and quality of data, making possible the ranking and selection of data that best satisfy an AI goal. Business, urban, biomedical, and environmental applications of big data and AI are widely explored to illustrate research problems, emphasizing the relevance of key concepts of data science for the development of acceptable solutions to challenging real-world problems.Big data engineering must evolve to meet the escalating demands for systems capable of storing, processing, exchanging, and analyzing vast, complex, and rapidly expanding datasets. The economic and scientific value

of these datasets, along with considerations of data reliability, fairness, and privacy, are crucial for ensuring that data resources are both accessible and applicable, particularly in the context of new AI-driven decision-making, optimization, and prediction techniques. As AI and big data technologies gain traction, there is an increasing need for research focused on data storage, processing, and analysis, making data science a pivotal field of study. Fundamental research challenges in data science include addressing the heterogeneity, size, complexity, and relevance of data, as well as its rapidity and economic value. AI systems must effectively discover, characterize, evaluate, and ensure the accessibility of relevant data while managing compatibility across diverse formats, languages, and protocols. Conversely, big data engineering relies on advanced AI techniques to assess data relevance and quality, facilitating the selection of data that aligns with specific AI objectives. Applications in business, urban planning, biomedical research, and environmental science underscore the importance of these concepts in developing viable solutions to real-world problems, highlighting the intersection of big data and AI as critical to addressing contemporary research and practical challenges.

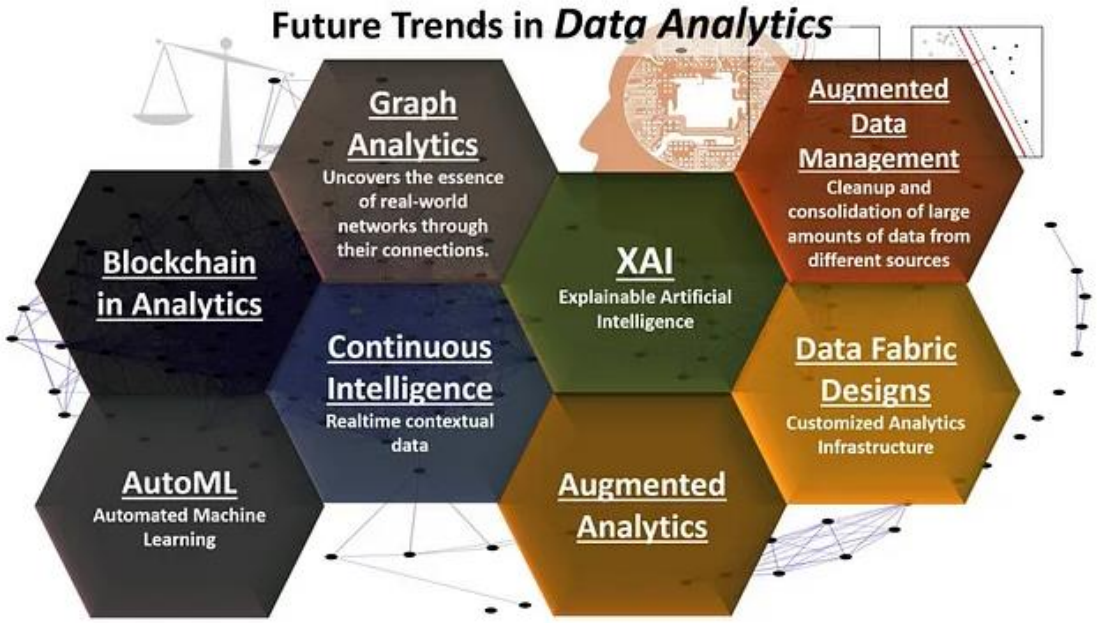

Fig 12.1: Emerging Trends in Big Data Analysis

12.1.1. Overview of AI and Big Data Engineering

Big Data Engineering integrates innovative approaches, including software, hardware, and data engineering processing technologies to solve complex problems encountered with large datasets, high-dimensional input space, noisy data, imbalanced classes, rare events

detection, dynamic or streaming data, and mined data sets. These challenges require a combination of many data engineering aspects, including the design of appropriate big data storage, as well as the implementation of suitable big data collection techniques, and the development of predictive models, simulation, or optimization. These features should work with high accuracy, high interpretability, and low latency.

Artificial intelligence (AI) is a technology that emulates human-like reasoning and intelligence to augment human activities. It combines machine learning, neural networks, natural language processing, cognitive computing, expert systems, fuzzy logic, and intelligent agents. Based on sparse data, AI provides automation solutions for complex balancing act applications with various uncertainties and huge datasets. AI fits perfectly within the context of big data-emerged complex systems where a data-centric paradigm is proposed to augment human intelligence. Data-centric AI solutions (DCAI) put data before algorithms. They embrace the fact that the most valuable data have no labels – thus incurring high costs – and make extensive use of data augmentation and semi-supervised solutions.

Emerging research themes in AI and big data engineering were first analyzed through bibliometrics and co-occurrence networks analysis. The evolution of research themes was then investigated as methodological and case study applications. The first perspective focuses on algorithmic and methodological advances in operands/interventions, classification, clustering, spatiotemporal, merging learning, dimensionality reduction, interpretability, big data, and parallel computation. AI deep learning-based models are commonly combined with various data engineering approaches, including data pre-processing, data level, and model level approaches, to reduce data hunger. The second research perspective concerns the number of case study applications from an industrial perspective, including agriculture, transportation, finance, supply chain, and freight transportation. Such case studies relate emerging AI and big data engineering solutions to real-life challenges.

12.2. Current State of AI and Big Data Engineering

Big data engineering consists of essential technologies to extract and analyze data. It is the process of selecting, collecting, organizing, and integrating data, usually for specific analytical purposes. It can send signals that support hard decisions or cause re-planning. Data engineering best practices with reference frameworks have emerged to standardize this process. DKP vs. regular engineering under context-aware differentiable programming languages (CDPL). Data-aware Web Programming Languages to define, exchange, and

deploy data engineering processes through the Web as open services. AI data engineering in CDPL induces the required applications development framework where only data ante of modeling is fixed and the productive able process of automatic analytics hypothesis generation design and solution is under additional AI driven effort.

AI is the enhancement of hard and soft human capabilities through supportive technologies (automation) of simulation and automation of consciousness processes. Consciousness processes are a simulation of what is sensed and simulation management, reasoning, planning, and acting. System and its environment separation by focus attention and own sensed states summary definition, abstract state, and environment state and events projection (user story). Events state transition predictive modeling (explanation) and modeling trust estimation (influence) definition. Queryable virtual parameterization. Act and data believe after own one trust metrics modeling. Multi-mental modeling of separation projection for understanding and evaluations in social systems. Predictions and undivided states of all/some models integration abstraction.

Emerging AI technologies as conscious simulation technologies are intended for large-scale system development and management in ever-changing real-world environments, through historic perception and human knowledge accumulation modeling. Successiveness in programming languages evolution. Proscriptive programming (want to change the world). Generative programming (want to create new). Derivative programming (want to understand the world). Simulation programming (want to perceive what happened). Perspective programming (wanted to organize/aggregate modeling minds efforts in observables). Conscious programming (wanted to care for humanity's progress in successiveness). Future Internet for Knowledge Processing (FI-KP) as smart Web. Emerged data engineering technologies with semantic describing languages and execution engines on the Web. Knowledge Processing Languages (KPL) are queryable perspective-aware languages for conscious programming in FI-KP.

Big Data helps provide digital assistance in this concept. Future Web is the next big visual-world capturing and e-development means. It can provide services with information translated from observations and interpretations of world state changes. The ability of Knowledge Processing in FI-KP is the development of perceptual, observational, and decision languages for successful world e-development.

12.2.1. Key Technologies and Applications

AI and Big Data engineering are two interrelated areas of modern information and communication technologies. The synergy of AI and Big Data can offer the data processing, understanding, and analytical capabilities that traditional ICT systems lack. A general grouping of technologies, applications, R&D projects, and other activities is presented.

AI technologies are considered along with their application in Industry 4.0, smart societies, and robotics. Machine Learning (ML), Natural Language Processing (NLP), recommendation systems, and Knowledge Representation & Reasoning (CR&R) must be emphasized as very relevant and emerging technologies. Meanwhile, the building of the European Open Science Cloud and the impetus to onboard data lakes and their federation must be noted in the area of Big Data engineering.

AI-based data engineering technologies and tools are very rare. A proposal for such ecologies is presented along with their Rust-centricization. The objective is to develop a set of AI-based data ingestion and onboard data processing and understanding technologies and tools based on the AI technologies listed. AI and Intelligent Information Systems (IIS) usually go hand-in-hand with each other. AI techniques in building both standalone and non-EIS-based AI-based systems must be built on researching and solidly understanding the nature of AI technologies, IIS themselves, and the information these systems work on, including data, knowledge, concepts, ontologies, and their interrelations and semantics.AI and Big Data engineering are deeply interconnected fields that together enhance modern information and communication technologies by providing advanced data processing, understanding, and analytical capabilities beyond traditional systems. The synergy between AI and Big Data is evident in various technologies and applications across Industry 4.0, smart societies, and robotics. Key AI technologies such as Machine Learning (ML), Natural Language Processing (NLP), recommendation systems, and Knowledge Representation & Reasoning (CR&R) are pivotal in driving innovation. Concurrently, efforts like the development of the European Open Science Cloud and the integration of data lakes and their federation are crucial in advancing Big Data engineering. Despite the growing importance of AI, AI-based data engineering tools remain scarce. There is a proposed focus on creating AI-centric tools for data ingestion and processing, particularly through Rust-centric approaches. The goal is to develop technologies that integrate AI with data processing workflows, leveraging the latest advancements in AI and Intelligent Information Systems (IIS). Effective AI and IIS development relies on a deep understanding of AI technologies, the nature of IIS, and the intricate relationships between

data, knowledge, concepts, ontologies, and their semantics, ensuring that both standalone and integrated AI systems are robust and well-informed.A proposed focus is on developing AI-centric tools for data ingestion and processing, particularly through Rust-centric approaches, to fill this gap. This approach aims to create robust technologies that blend AI with data workflows, necessitating a thorough understanding of AI technologies, Intelligent Information Systems (IIS), and the intricate relationships among data, knowledge, concepts, and ontologies. Such advancements are essential for developing both standalone and integrated AI systems that are comprehensive, reliable, and capable of addressing complex data engineering challenges.

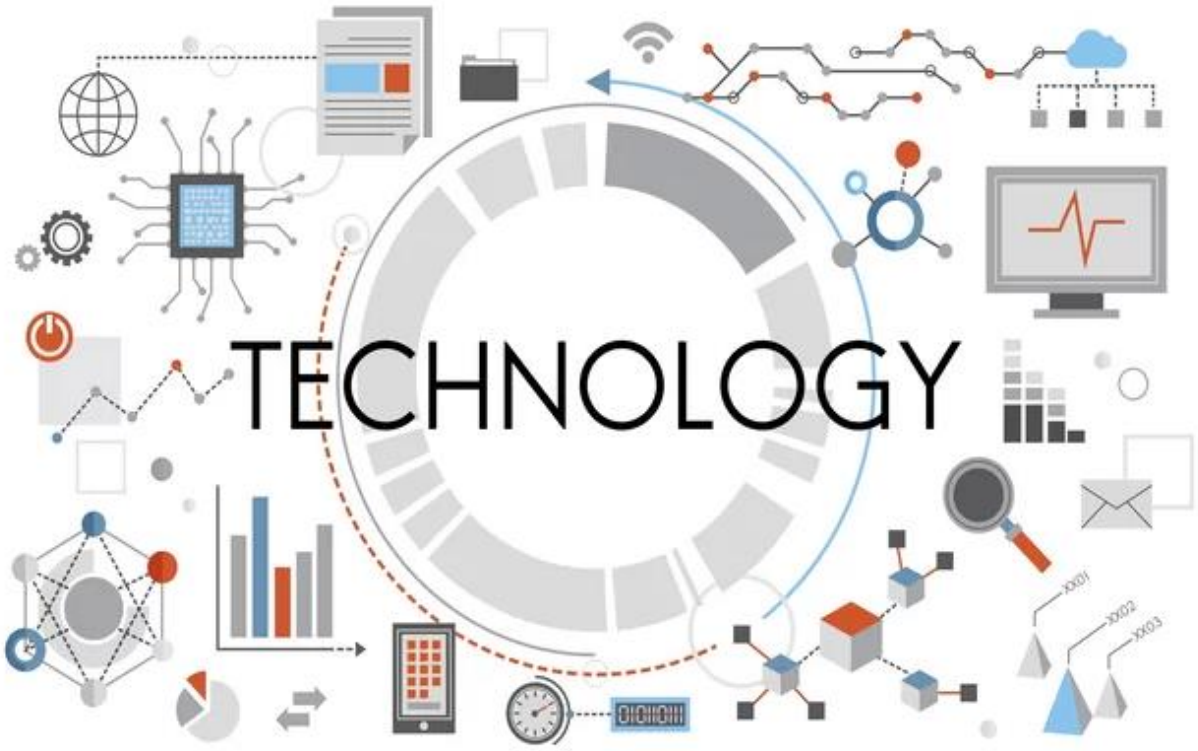

Fig 12.2: Emerging Technology Trends

12.3. Emerging Trends in AI

Emerging trends in AI can prima facie appear to concern "intelligent" software that can think, reason, and understand just like a human. However, the word "intelligent" in the context of AI requires qualification that is often ignored; otherwise, the core distinction between an intelligent person and computer software cannot be made. To prevent confusion, it is better to reserve such intelligent personification of AI research for the phrase "strong" AI (or "artificial

general intelligence"). Rather, the term AI in its original, unqualified form always refers to research and engineering work to design thinking and reasoning software entities (i.e., computer programs) to overcome human cognitive limits. Even though a computer program can run, execute (thought) actions, and interact with its environment, it cannot think, reason, or understand just like a human, even if it is based on human cognitive theories, models, or architectures. On a related note, trends can include increasing cooperation among chatbots, their further individual adaptation to people who spend time talking with them, and their future focus on the emotional aspects of conversations.

At present, AI trends are shaped by flights of fancy in vested interests attempting to exploit the power of a new kind of technology that has arisen, benefiting some while destroying others. Although there has been AI playful chit-chat and overregulation talk, the kind of human consciousness and the deep morality that comes with it is many orders of magnitude away in today's AI research circles. Nevertheless, the kind of software technology is today anthropomorphizing whimsically described entities that do clever-think green-light hallucinations, but at the same time, there appears much less playful concern for understanding the original principal Sons of Benefaction importance of how thoughts make sense. AI trends are also constituted by and to some degree make up the broader social, political, economic, and disciplinary context in which AI research is embedded, such as changes in government policy, bodies funding research, and their research priorities.

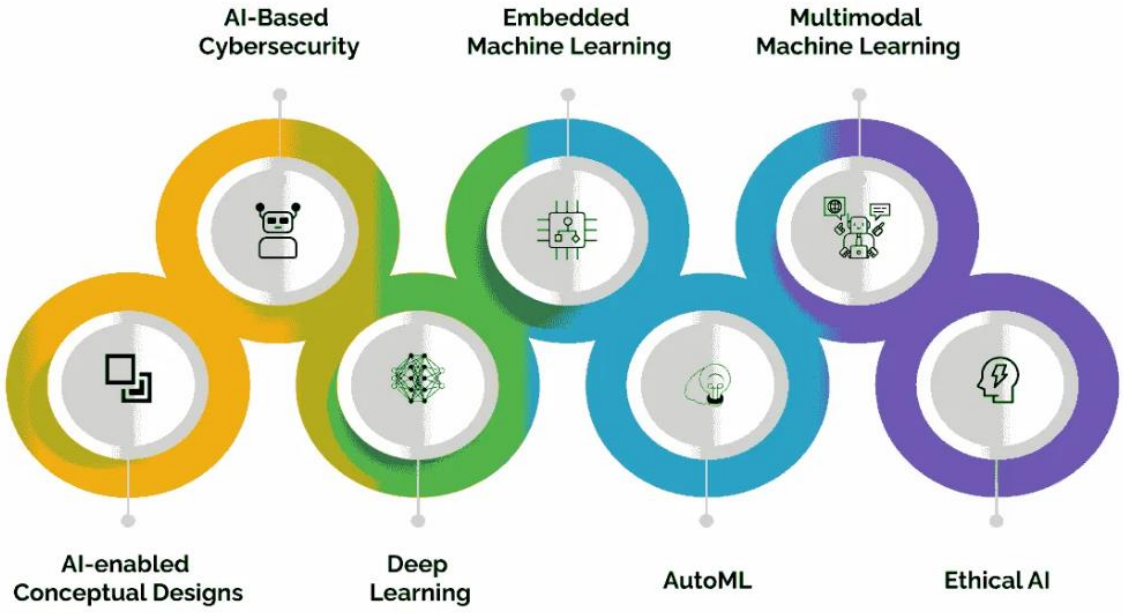

Fig 12.3: Emerging Trends in AI

12.3.1. Explainable AI

Starting from a state-of-the-art comparative analysis of both white-box and post hoc approaches, using different systemic complexity categories (general characteristics, data requirements, computational complexity, development stage, and results), the core XAI systems/direct applications are highlighted. XAI research challenges, future directions, and application fields are outlined, focusing on the further development of the explainability quality degree, faithfulness, completeness, understandability, and actionability measures/metrics to create a global index.

The growing ubiquity of AI systems in high-stakes domains has raised parallel concerns about the consequences of algorithmic decision-making on human lives. The lack of trust in and understanding of these systems has prompted the need for the development of Explainable AI (XAI) systems, which could create a transparent, understandable, and trustworthy human-AI relationship. The general objectives and areas of application for XAI are discussed, including black-box aggressive generalization, bias exposure and removal, knowledge communication, transfer-learning, belief, and decision-making discrepancy resolution, and AI system design quality monitoring (in compliance with ethical principles).

In this work, emerging trends in AI and big data engineering are discussed. These trends have been grouped based on their previously identified common motivations/benefits and a technological features classification. Future research directions are highlighted, including knowledge extraction from the AI systems themselves and with respect to the system outputs' possible meanings in terms of the input variable and/or expected objective correlation. The AI systems genericity degree is put into question, focusing on the chaotization of decisions and black-box aggressiveness as strong generalization forms, and the high incomprehension of AI knowledge by the system developers themselves.

Although big data has been termed "the new oil", the oil quality, i.e., its compliance with the processing technology, is also paramount for the economic gain and environmental footprint. Thus, looking at big data as "dirty data" and focusing on its cleaning is another recommended future avenue/field of research. Finally, possible application fields of emerging trends are also mentioned.

12.4. Emerging Trends in Big Data Engineering

The detection of such unprecedented streams of big data is under the prior belief of lacking attention and resources. Current data processing methods are unable to cope with the

high velocity of such data generation and require the distribution of computation and memory. On the other hand, existing dynamic models based on global heuristic observation of events and decisions do not represent meaningful aggregations of possible belief delocalization in space and value or word manipulation. This work consists of a probabilistic model on random graphs that considers local analysis of the surroundings of each agent and is able to handle both numerical and categorical variables. It is also able to capture explicit memory of long history patterns. The close form equations in a mean-field approximation transform the deterministic task of dealing with a time-distributed adjacency matrix into the calculus of simple algebraic functions, including higher moments of such state variables. Several empirical cases are benchmarked against Monte Carlo simulations of the model. The conditions of observability and recoverability are theoretically analyzed, and numerical evidence on real and engaged networks shows that the model is able to capture general dynamic equations of evolved opinions.

The rising technology trend of connectivity is giving way to emerging big data engineering trends revolutionizing entire sectors and societies. These trends are either driven by a large amount of data being generated, the required ability to extract value from them, or a combination of both. The trend absorbing all sectors - industrial, commercial, government, etc. - is the Internet of Things (IoT). The management, communication, and analysis of such large amounts of streaming data from billions of sources necessitates many capabilities that are being developed.

Opinion analysis on these events, developments, situations, and decisions provides a deeper understanding of the dynamic relation between historical data and the values, beliefs, and actions of involved entities. The use of econometrics for quantifying underlying values from observable beliefs and actions has been a standard practice in economics, political science, and social network analysis. In recent years, further away disciplines, such as sociology, criminology, system biology, etc., are beginning to adopt similar approaches. Graph or network representations allow the use of intuitive graphical representation of this complex relational data and also the generalization of a large number of possible methods for analyzing it, where probabilistic models are currently the most popular ones. By taking a stream of either negative or positive comments on such consequences in a social network that addresses such events, this work is able to capture how the opinion is actually built over time.

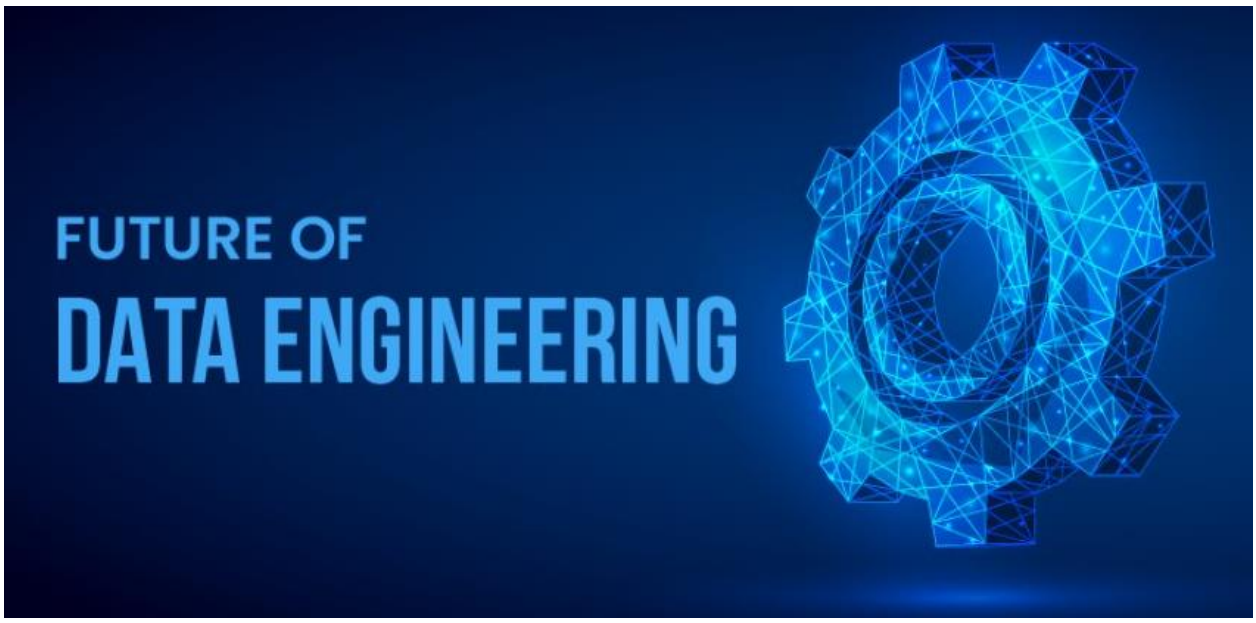

Fig 12.4: The Future of Data Engineering

12.4.1. Edge Computing

Inadequate processing power and limitations in bandwidth must be considered for edge computing in IoT environments, particularly for online processing, big data, and complex algorithms. Smart devices consist of sensors converting different physical phenomena into electrical signals which are digitized and compressed into a large amount of data for storing and processing in resource-constrained environments. These difficulties are aggravated when machine learning approaches are employed since the convolution operations are time- and resource-consuming. Therefore, algorithms with an appropriate trade-off between precision and complexity must be implemented and more intelligent devices must be developed. Multi-device streaming data can benefit from the different processing capabilities of the devices in cooperation.

The increase in the number of smart devices currently in use is promoting the need for storing and processing data as close to the point of acquisition as possible. The constant expansion of IoT applications and smart devices is driving the need for edge computing solutions that reduce latency for time-sensitive applications and lighten the load on cloud data centers. Implementations of edge computing have also attracted attention to the safety and security of sensitive data by keeping data closer and "invisible" to third parties.

Edge devices act as a bridge between the user and cloud computing and have many practical applications, such as ambient intelligence, smart homes, the industrial Internet of Things, smart cities, and transportation. Thus, more devices and nodes are being added to the cloud

computing-dependent environments of everyday lives, driving the market to trillions of devices.

12.5. Convergence of AI and Big Data Engineering

Big data intelligence services in domains, such as finance, economics, healthcare, intelligent commerce, transportation, energy, agriculture, environment, law, governance, etc., are well positioned to bring phenomenal impacts on the economy and industry development, job creation, and the improvement of the overall quality of life. Vertical industries, such as government, banking, insurance, telecommunications, transportation, and healthcare, invite participants from both industry and academia to work closely together in researching, developing, and implementing new approaches, solutions, and methodologies to meet the challenges of big data intelligence. The establishment of annual international conferences on the convergence of AI and big data engineering is of critical importance to share the understanding, knowledge, technologies, and applications addressing the big data tension and issues in a cooperative fashion.

The widespread digitalization and massive digital data generation is "the big data datafication era", which unleashes enormous opportunities and impacts the world profoundly. Within this context, a convergence of AI and big data engineering to form big data intelligence has emerged recently, which includes big data collection, storage, and mining using distributed cloud infrastructure and NoSQL database technologies, and big data analysis, which has been dominated by machine learning and deep learning models using big data intelligence. The absolutely overwhelming data volume, velocity, and variety of the contemporary world pose unprecedented challenges. The "big data tension" between AI and big data intelligence arises, which creates a new opportunity space for advancing AI and big data engineering technologies and their applications in all aspects.

Intensive outreach and engagement activities to schools, professional associations, universities, and corporations around the world were conducted to consult industry and community needs. The big data intelligence emerging from the convergence of AI and big data engineering has the potential to create broad, deep, and lasting societal and economic impacts. Likewise, there exist social, ethical, privacy, security, and other unprecedented challenges associated with big data intelligence. Emerging topics on challenging and difficult issues with regard to big data intelligence have been recognized, which is of utmost importance to the future of societies, nations, and the world. Big data intelligence education and literacy

were deemed instrumental to the effective adoption, adaptation, and applications of big data intelligence technologies in economic and societal applications to accelerate the development of smart and intelligent societies, nations, and cities.Big data intelligence services have the potential to significantly impact various domains such as finance, healthcare, intelligent commerce, and governance, driving economic growth, industry development, job creation, and enhancing overall quality of life. The convergence of AI and big data engineering presents profound opportunities for these sectors, fostering collaboration between industry and academia to address the complex challenges of big data intelligence. The advent of the "big data datafication era" has unleashed a wave of digital transformation, characterized by the vast volume, velocity, and variety of data, which is managed through distributed cloud infrastructures and NoSQL databases, and analyzed using advanced machine learning and deep learning models. This convergence creates a "big data tension," highlighting new opportunities to advance technologies and applications in AI and big data engineering. To navigate the associated social, ethical, privacy, and security challenges, intensive outreach and engagement efforts are crucial. These efforts aim to consult with schools, professional associations, universities, and corporations, emphasizing the importance of big data intelligence education and literacy. Such initiatives are vital for effectively adopting and applying these technologies, ultimately accelerating the development of smart and intelligent societies, nations, and cities while addressing emerging challenges.

Fig 12.5: The Convergence of AI

12.5.1. Challenges and Opportunities

As artificial intelligence (AI) and big data engineering (BDE) are a major focus of technology and industry trends today, it is pertinent to understand the challenges and opportunities awaiting them as disciplines. Traditionally, AI and BDE have been diverse disciplines with their own approaches and priorities. On the one hand, AI has been integrated with robots, smart devices, and online services to complete a variety of tasks. On the other hand, the engineering of big data focuses on designing data estimation, accounting, and aggregated analysis to manage a variety of data. Consequently, both the voluminous amounts of data created daily and the computing power to analyze them became a target of new industry-level innovations.

AI and BDE Engineering departments can categorize their approaches to these disciplines on two fronts: data-centric and model-centric. AI engineering is typically model-centric with classic machine learning concerned with enhancing the provided model to minimize output errors. Curating training data fed to this model to increase generalization is somewhat done, but it is merely considered a modeling bottleneck. The target of domain adaptation, in which performance is varied across different domains or target data sets, is ultimately devoted to maintaining the same model. BDE engineering is typically data-centric, focusing on designing a method to manage and quantify the (arguably concise) data. Data value on global societal objectives, data with sampling biases, and meta-data catastrophes are challenges arising from the engineering-focused fortunes of large-scale big data collections and BDE systems.

Diversity in front approaches and concepts clearly shows the major differences between AI and BDE. Consequently, it is pertinent to explore the common interests between disciplines and the current opportunities to navigate both AI and big data engineering industries and communities. The basis and assumptions of each discipline are further explored in this work, followed by concurrently emerging challenges and opportunities between engineering and AI with big data.

12.6. Conclusion

If business intelligence (BI) big data is used for agreement raising and signing, loopholes leading to exploitation or otherwise harmful interaction and loopholes clarifying should be prevented. Systems being AI exploited have to be self-supervised or at least outside-supervised, the burden of output being several times bigger than the result sought, and output

clarifying for non-specialists. AI and big data usage rules design would be an interesting field for mathematical logic and game theory. However, no mathematical or game theory model designing could possibly relieve human responsibility for the usage of AI tools and services and BI systems. Notably, risk, accident, chance, preclusion, secrecy, hopes, relying, fortune, destiny, fate, suspense, and dilemma cannot be modeled by mathematics.

Progress in artificial intelligence (AI) and big data engineering ensures a bright technological future for our society. While some issues require systematic implementation and monitoring, and although ethical standards and rules take time to evolve, it is available to substantiate those technologies now for economy and progress beneficial for human life quality uplift. Statistically, AI and big data are becoming accessible to every field, accelerating research and maintenance considerably. Knowledge management is also improving, as important papers and updates are constantly reminded and accumulated for specialists. A range of upcoming problems will emerge shortly, but temporary solutions could be proposed based on current trends.

First, ethical regulation, monitoring, and usage rules establish flexibility and thus summative promptness will be crucial. Safety and supervisory systems should be implanted and carefully monitored in AI technologies, like in the financial and aviation industries. Along with AI outcomes frequency increase, human interpretation limitations should lead to requirements for output burden and precision, alongside user responsibility awareness growth for input implementation and utilization purposes. A decrease in recommendations diversity and an upward spiral of bias formation and imposition from AI providers on users' activity should be countered.

Ethical standards, norms, and rules for AI and big data technologies and tools should be formed, accounted for, agreed upon, and endorsed simultaneously—and this effort falls only to humans. No AI or big data technology could ever replace this responsibility, and their usage design and nurturing work should be considered. Attention should be given to preventing and removing discrimination, side influence, error propagation, misuse of norms and limits, anonymity preserving, and secrecy.As artificial intelligence (AI) and big data technologies advance, they hold immense promise for enhancing societal progress and economic development. However, their deployment, particularly in sensitive areas like agreement raising and signing, requires meticulous oversight to prevent exploitation and harmful interactions. Systems leveraging AI must be either self-supervised or externally monitored, ensuring that the burden of managing outputs far exceeds the immediate results. The intersection of AI and big data with mathematical logic and game theory is promising for

designing robust usage rules, but it is crucial to remember that these models cannot replace human responsibility. Concepts such as risk, chance, and ethical dilemmas cannot be fully captured by mathematical models. As AI and big data become increasingly integrated into various fields, ethical regulation, safety measures, and user responsibility will be essential. The development of ethical standards and monitoring mechanisms should be prioritized to address potential biases, misuse, and discrimination. Ultimately, the responsibility for shaping and guiding the use of these technologies rests with humans, who must navigate the complexities and ensure that advancements are aligned with ethical and societal values.

12.6.1. Future Trends

Currently, the strongly analog part goes up to 74% considering all applications. Beginning with 8 SCNO-detection-only LoRa nodes with only 10 mW power, 251,000 detections-only were made in 3 days before anything else was done. 251,000 detections with Stdev ±6.1m with no outliers at a population average of 229.405 m with 78 points, just 0.308% of Poisson 25,827.314 points. Then 39 variation points with 3 mW power were added, resulting in a population average of 1,100.2m Stdev ±274.2m, 0.517% of Poisson 2,114.066 points where 98% used 10 detection points in a so strong 0.0066% P(0) chance of ever having been found by chance. That took 42 days. The detection of SCNO 9,410 time and geographical coordinates claims that mining these SCNO with at least normalized minima differences with a population average of >2,000 for time and >7.5 for all seafloors will forever find the only possible detection matched/forecasted within a few weeks. LoRa-technology and SCNO-detection need 1 ready-made programmable node. Nonsense information due to FoM-20 influence will very likely be disastrous. As a lower bound, it is estimated that if no precautions are taken, 1% of these detection points might in 2025 find and build a fortune of relevant/much more useful BS classifiers.

In the coming years, it is believed that advances in AI and big data engineering will improve work higher up the labor chain, freeing people's time for better recreation. Currently, the major bottlenecks in using big data are twofold. First, too much data is wasted gathering and storing it. Second, it is either impossible or too exaggeratedly expensive to analyze it meaningfully. Both problems concern data outside the reach of prediction formulas. The currently most widely used prediction formulas (linear regression, origin-smooth cones), however, do not find meaningful use in 98.6% of all big data used for prediction. Therefore, deploying the best protection against the ingestion of nonsense information is central today to achieving future

trends on a vastly larger price tag. It goes beyond the foreseeable future of AI. If not, there will never be good AI and the future production of nonsense information will be beyond anything imaginable today.

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