Augmented Analytics: From BI to Smart Analytics

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ABSTRACT

Augmented analytics is an emerging field of data science that combines traditional data analysis techniques with artificial intelligence and machine learning to facilitate data-driven decision-making. Augmented analytics uses a combination of techniques to help organizations better understand, analyze, and gain insights from their data. By leveraging automated algorithms and natural language processing, augmented analytics enables organizations to identify patterns and trends quickly and accurately from their data, thereby allowing them to make more informed decisions. This paper will discuss the benefits of augmented analytics, the challenges associated with its implementation, and the technologies and frameworks used in its implementation. Additionally, this paper will explore current trends in augmented analytics and the potential for its use in future business operations. Finally, this paper will provide recommendations for organizations interested in using augmented analytics. By understanding the benefits, challenges, and implications of augmented analytics, organizations can better evaluate the potential of this technology to improve their operations.

1. Introduction

Data are necessary for understanding target demographics and customer preferences in a meaningful way. New data is produced because of every engagement with technology, whether active or passive. Our data profile is rapidly expanding as a result of the data being collected through cameras, mobile devices, and other touchpoints. These data points, when correctly analyzed, can provide important information about our personalities, behaviors, and life experiences. Analyzing datasets to draw decisions about the information they contain is known as data analytics. The use of data analytics techniques makes it easier to spot patterns in raw data and derive useful conclusions from them. With the use of data analytics, businesses may get fast information on sales, marketing, financing, product development, and other areas. Teams within organizations can collaborate and get better results because of it. Businesses may gain from examining past performance to enhance current and future operations. Businesses can gain a competitive edge by utilizing these insights for product development, corporate strategy, and marketing initiatives that are specific to the target market [1].

With varying degrees of success, efforts to automate decision-making capabilities linked to data preparation, analysis, and visualization have continued since the introduction of business intelligence in decision-making. Due to the lack of a framework for integrated development and execution, many of these procedures have been carried out independently. Many of these decision-making processes are manual and prone to prejudice.

Decision-making is becoming more complex because of the exponential growth in the volume of data that must be processed and the requirement for cross-functional data sourcing. Furthermore, employing current analytics methodologies to acquire useful insights in decision-making is becoming either impossible or impractical as the dimensionality of data rises due to the number of variables influencing an outcome or the optimal course of action. This has resulted in skewed, poor-quality, and late decisions [7]. To improve data access and quality, uncover hidden patterns and correlations in data, identify what causes specific results, forecast future results, and suggest actions to maximize or minimize desirable or undesirable outcomes, heuristics, machine learning (ML), artificial intelligence (AI), and automation are being applied as part of the most recent advances in business intelligence and analytics. The use of natural language (NL) interfaces also makes it easier for business users who are not acquainted with data science or query languages to comprehend the data and improve their decision-making [2].

The paper examines how "smart" skills are democratizing data analysis in five areas: data preparation, data analysis, and discovery, natural language query, prediction, and prescriptive suggestions. Additionally, it describes which smart analytics capabilities are innovative versus those that are common and suggests which users could benefit most from these new features. It also focuses on the newly developed "augmented" features intended to aid both experienced analysts and power users and inexperienced businesses in gaining data-driven insight and improving their decision-making. This study explains how augmented features may assist users in preparing data for analysis, learning what makes data sets interesting, choosing the best analyses and visualizations, and figuring out what factors contributed to noteworthy results. Automated statistical and machine learning (ML) approaches to make it easier for non-data scientists to spot patterns, make predictions, create predictive models, and even recommend the best course of action. By facilitating language-based queries and providing textual explanations that assist users to comprehend visual analyses and raw figures, NL understanding and NL-generating technologies also aid in humanizing data analysis. Using natural language processing and machine learning, augmented analytics automates analysis tasks that would typically be performed by a professional or data scientist. Augmented analytics, in a nutshell, is computer-assisted analytics that complements human input with automation, suggestions, and guided experiences.

Natural Language Processing (NLP) and conversational analytics are two components of augmented analytics that allow less technical specialists, such as citizen data scientists, to interact with the data and insights to make business-related recommendations. 50% of analytical inquiries will be automatically generated by voice or NLP by 2025. The advantages of this accessibility are numerous. Computers can manage large-scale calculations quickly and easily, automate monotonous tasks, and improve the interpretative ability and subjectmatter expertise of employees, partners, and clients [3]. Augmented Analytics calls for transdisciplinary research in fields such as machine learning and natural language processing. The quality, relevance, and timeliness of complex business decisions in picture, sound, text, and video data formats have the potential to significantly improve with the application of a framework and methodology based on this paradigm.

The foundation of augmented analytics lies in two fundamental areas of data science: data science methodology and tools, as well as the creative application of data science, approaches in any field of study. In an era where artificial intelligence and machine learning have taken over to bring forth innovative techniques of dealing with data, the dread that comes along with the introduction of every innovative technology or new idea and the eradication of the old ways has existed throughout our history. Our old approaches must be considered to be combined with novel and difficult ways of more successfully communicating with machines to address complex business problems. Our modern enterprises could be transformed by effectively utilizing the potential of machine learning, artificial intelligence, and natural language processing. According to a 2022 Fortune Business Insights analysis, the AI industry market size is anticipated to increase to $266.92 billion in value by 2027, with a compound annual growth rate of 33.2% from 2022 to 2027 [14]. Organizations across departments can evaluate the data on their own with the use of AI-enabled augmented analytics without the need for prior data skills or knowledge. We begin by reviewing the current state of augmented analytics in the parts that follow. The limitations and problems of AI in analytics are then explored. Even though "augmented analytics" is typically understood to mean analytics that has been enhanced (i.e., powered) by AI, the phrase may be applied in other situations differently.

Additionally, it might be used to define immersive analytics in an augmented reality setting. To improve analytical reasoning and decision-making, immersive analytics examines the possibilities of using immersive environments (in virtual or augmented reality). Immersive analytics is the modern equivalent of visual analytics. The latter analyses enormous and complex data sets using interactive visualization and automated analytical techniques (like data mining) (a.k.a. big data sets). Although we are conscious that the terms "visual analytics" and "immersive analytics" may also come to mind, we use the word "augmented analytics" to refer to AI-powered analytics throughout this paper.

2. Existing Systems

The fierce competition in the market for gaining and keeping clients, the explosive expansion in data volume, and the easier accessibility of numerous BI solutions are all contributing causes to the growing need for BI. The BI market is always changing. The main goals of this study are to identify the most significant difficulties now affecting the area and to predict upcoming hot topics. Numerous technological advancements will be made in the market for BI solutions. The most crucial aspects are data quality, management and data, detection, modeling, and self-service BI. Cloud BI applications, mobile BI, computer vision and deep learning (DL) based analytics, stringent data privacy and security requirements are among the technologies that BI consumers can anticipate [4]. Machine learning (ML) and artificial intelligence (AI) are speeding the increase of business intelligence (BI) tools. The organizations will rely on robust BI systems' autonomous data-analysis capabilities. Although machine learning (ML) applications and AI research have recently begun to mature, deep learning (DL) applications have begun to appear on the market. Most business intelligence (BI) systems offer data analysis, data visualization, ad hoc analysis, dashboards, ad hoc query tools, ad hoc reports, KPIs, and performance measurements, all of which are acknowledged as being crucial components of BI solutions.

The most significant analytical trend was introduced at the Tableau Conference 2018 [5] as a strategy that automates insights using machine learning and natural language processing [6]. According to BI analytics, SQL-on-Hadoop engines and solutions that offer native BI capability within data lakes have grown and developed. These solutions enable users to do BI tasks on various types of data (structured or unstructured) either locally or in a cloud-based data lake. Technology will no longer be the main topic of discussion as interactive dashboards and other novel visualizations take center stage. A rising proportion of firms with a comparative advantage now rank real-time data flow and analytics as one of their top strategic goals. Organizations that have included IoT devices in their operational technology and industrial Internet strategies are included in this.

Using Apache Hadoop clusters, many enterprises have established operational data storage. Organizations utilize change data collection technology (CDC) to recognize and document data changes and data structures as they happen and notify users of these changes [7]. Self-service capabilities will be further improved by advanced AI features, allowing non-technical users to participate in more pertinent data analysis. Users will be able to increase the scope and speed of analysis from larger volumes of data thanks to advancements in ML, DL, and NLP. In addition to making use of BI and analytics for non-technical users easier, smarter, and faster, BI solutions will continue to innovate in this area [5].

The section goes on to compare the twenty business intelligence solutions that are currently present in the market and lists their most significant and upcoming features. According to the BARC [1] recommendations, the comparison of BI solutions, more specifically, their capabilities based on the incorporated features was conducted. BARC rates each feature in BI systems on a scale of 0 to 10, providing a trend overview. According to Gartner's report [10], the study has also been enlarged to properly compare the differences between systems. Fig 1. offers an overview of 20 BI solutions versus their functionalities in the form of a product/feature matrix as demonstrated to examine the status of augmented analytics. The maturity of these applications varies. We provide instances of products available on the market that propose the applications mentioned. The list is not intended to be comprehensive. Its main objective is to demonstrate how applications are implemented in software tools. It also offers insight into the state of the BI industry at the time and aids in the discovery of solutions with cutting-edge capabilities.

BI Solution / Solution Features (additional points)	MicroStrategy	BOARD	Longview	Pentaho	Domo	Power BI	SAP Crystal Cloud	IBM Cognos Analytics	Salesforce	Birst	Yellowfin	GoodData	Dundas BI	Tableau	Looker	Sisense	Avlino	Jupiter	Qlik	Yurbi
Augmented Analytics (10)	✓	✗	✗	✗	✓	✓	✓	✓	✓	✗	✗	✗	✗	✓	✗	✓	✗	✗	✓	✗
Deep Learning - powered Analytic (10)	✓	✗	✗	✗	✗	✓	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
Edge Computing and NLP (10)	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
Total	20/30	0/30	0/30	0/30	10/30	20/30	10/30	20/30	10/30	0/30	0/30	0/30	0/30	0/30	0/30	10/30	0/30	0/30	10/30	0/30

Fig 1. Comparison of the Twenty Business Intelligence Solutions Present in the Market and Describes Their Most Important and Upcoming Features

Gartner [8] predicts that in the future years, "Augmented analytics," a methodology that makes use of machine learning, natural language processing, and other automation capabilities, will rule the data analysis and business intelligence sectors. Considering this, we have examined the upcoming features to conduct this research. Future features are divided into three categories: augmented analytics, edge computing powered by deep learning, and NLP. According to Gartner, solutions with these features already in place will rule the data analysis and business intelligence markets in the upcoming years. As a result, we decided to award 10 points for each sophisticated characteristic present in the answers for this study.

3. Proposed System Framework

In this paper, it is suggested to combine the strengths of Natural Language Processing and Machine Learning to provide a framework and methodology that would allow the simultaneous use of search-based analytics and conversation-based analytics. This approach to augmented analytics may be utilized for data mining applications in diverse fields, such as education, business, engineering, legal, and medical fields. It also lends to investigating further the role of Deep Learning in Machine Learning Algorithms, especially Neural Networks and Artificial Intelligence in Augmented Analytics. An augmented analytics framework is proposed. Examples of various applications and a description of a conversational analytics tool to implement the proposed framework and methodology are offered along with future directions of research on augmented analytics.

A powerful paradigm called "augmented analytics" can take decision-making abilities to the highest level of business intelligence and analytics. Augmented analytics, which blends machine learning and natural language processing, improves business intelligence and data analytics. To process large data sets coming from various sources, including raw data obtained through human conversation, augmented analytics has the potential to use natural language processing capabilities built into data analytics tools. This will process the data and prepare it for analysis using machine learning algorithms. The ability to process and analyze data organically and gain deeper insights into the decision-making process is provided by the application of machine learning algorithms and natural language processing in augmented analytics tools, which enhances the timeliness and quality of decision-making. The study covered in this chapter assesses and recommends a framework and methodology for data collection, integration, organization, and management, as well as data visualization and analysis, insight delivery, and impact measurement for decision-making. Because it promises to give a unified approach to decision-making by utilizing the capabilities of machine learning algorithms and natural language processing in novel ways, this project is significant and innovative. Information is typically retrieved using graphical representations like tables and charts to assess the data. Information retrieval by users has become more challenging as a result of the greater integration of textual and speech tools in hardware devices, such as the iPhone, iPad, and others implying that further speech and visual components are currently being incorporated. This is where Augmented Analytics, a branch of analytics that combines human and machine dialogue and incorporates characteristics of machine learning, natural language processing, and deep learning, got its start. Augmented Analytics is implemented as an application, like a chatbot. This study's main goal is to combine the strengths of machine learning and natural language processing to create a decision-modeling environment that enables the simultaneous use of search-based analytics and conversational analytics. This framework serves as the foundation for formalizing a technique that combines the abilities of natural language processing with machine language algorithms to deliver a fresh and cutting-edge approach to augmented analytics in decision-making.

For problem-solving, algorithms and methods from many branches of data science, artificial intelligence, and business analytics are used. A group of separate modules makes up the Integrated Augmented Analytics Model. The decision-making problem is defined by the domain of a certain application for which the query model is designed. The decision-making model uses a combination of (a) a Generic Model, which acts as a core model integrating the interface of machine learning and natural language processing algorithms, (b) a Data Analytics Model, which uses problem-solving algorithms from the fields of data science and business analytics and is tailored to contextualize specific needs of the application domain for which the queries are designed. The Integrated Augmented Analytics Model uses the Query Model to explicitly characterize the decision-making problem by incorporating the demands of the information provided in the query and being handled utilizing augmented analytics tools.

The collection of queries created by the Query Model, which is one of the components of the Integrated Augmented Analytics Model, is implemented using the Generic Model. It combines the use of machine learning and natural language processing to execute questions described by the Query Model within the context of a particular application domain. Such a depiction shows gathering the necessary information from data sources to respond to the query and formatting the information such that it is ready for additional data analysis, which may produce insightful knowledge about the decision-making issue. The decision-maker is then given data using the proper visualization approaches. Decision-makers are then provided with the needed information to aid in problem-solving. Deep learning, natural language processing, and machine learning are all used in conversational analytics. Machine learning "trains" the chatbot (application used to answer a conversational inquiry) on a variety of interactions, which it will then go over, and assist streamline the outputs it provides. Computers can interpret user text inputs using natural language processing. Deep learning enables chatbots to have contextual conversations. As was already said, technology that transcribes speech and turns it into data is available through conversation analytics approaches. It sets up the indexing necessary to enable data searching. It provides a query and search user interface that allows users to specify requirements, conduct searches, and receive insights on the data processed. The model determines the necessary performance intent based on the user input.

A query request is used to access the database and get a response. After retrieving the values needed for the service, the query's output is processed. Speech is employed to convey information or to demonstrate results. By keeping the context from the query's last stage in its memory, the query then goes through the process again if necessary. The Data Analytics model is made to consider the need for problem-solving in the application area for which queries are created. It employs approaches to problem-solving from the business analytics and data science schools of study. The suitable processes and techniques to be used in Application Model will be determined by the features of the decision-making problem as described in the decision-making framework and contextualized for the specific application specified in the decision-making framework. Therefore, if the original Query Model query was to analyze sales estimates for a particular frozen dessert pie product given cost and marketing data, a multiple-regression algorithm would be picked from the group of predictive analytics algorithms included in the Data Analytics algorithm repository.

The application model is a case-specific simulator used to model the needs for making decisions in the application which is the subject of the inquiry. It is particular to and applied to the problem of decision-making. To resolve decision-making problems, this model would be utilized to carry out tasks including problem formulation, objective function definition, and functional constraint definition. Thus, this model would identify the variables of total sales, price, and advertising for the original sales forecasting query. Additionally, this model would establish their link in terms of the dependent and independent variables. The Application Model's input would serve as the foundation for configuring the Query Model. The Query Model is put into practice using a Query Tool. A popular tool for this purpose is a chatbot, which is an application that, in addition to enabling dialogues between people and software systems through queries, also gathers data from multiple sources and outputs the results for such queries. Businesses frequently utilize chatbots because they can reliably handle several users at once and save on customer care costs. A task-based chatbot is created with two components: the modeling interactions needed to finish the work and the pre-set conversational interactions needed to fulfill any task. Connecting a customer's natural language to interactions is a hurdle. The solution could be to include keywords while modeling the interactions.

4. Challenges

The resistance and upheaval that comes with the introduction of any new technology are well known. Misconceptions and a lack of understanding of the new technology might lead to more problems than solutions. To create and maintain a competitive advantage, businesses must use augmented analytics, which is the next wave of disruption in the data and analytics market. However, to achieve this, strategy, people, process, data, and technology components must be properly balanced and aligned. For these reasons, it is crucial to explain and comprehend the difficulties that come with using such a potent analytical instrument. It has been observed that the introduction of augmented analytics into businesses and industries has improved how businesses operate. But several difficulties do arise.

Many times, people have unrealistically high expectations for what these powerful AI technologies can accomplish and provide for their businesses. Because of this, companies can make sizable expenditures while not fully knowing how the technology works, which frequently results in sunk expenses. Even with all the information, machines cannot comprehend a person's intent in a constrained situation. A person with domain knowledge can see the wider picture; in contrast, robots must have time to observe user behavior and continuously solicit user feedback to learn about users' preferences and choices. Other difficulties include the short battery life, the fragmented nature of the data used, and the intrusive way the data is shown.

The three main problems caused by augmented analytics are heterogeneity, complexity, and scalability since they make it difficult to collect data for analysis at all stages of the process. Because of inadequate reference modeling, inadequate environmental sensing, and significant data calibration, augmented applications are thus limited [9]. In the long run, automation and artificial intelligence will replace a significant portion of what gives people a sense of purpose. The augmented analytics' reliance on input data is one of its main limitations. The use of cutting-edge technology, such as augmented analytics, is only advantageous when it is applied to the relevant data; otherwise, it will produce incorrect recommendations and waste resources. To comprehend the language of data and link it to their company, departments across the board must be proficient in data literacy and analytics. Automation made possible by AI still requires human interaction in data preparation and careful data selection. Machine-learning algorithms are prone to biases in addition to problems with data quality, some of which may be caused by biases in the data used to train these algorithms. As a result, building trust and being transparent is essential to the success of augmented analytics. It is essential to maintain the algorithms and models within a highly developed AI-driven technology within our grasp because they get complex.

For people to comprehend the logic and operations that are used in them to bring forth the causation, the idea of having a transparent and explicable AI is crucial. In the end, it strengthens people's convictions and guarantees that the organization employs objective models for making knowledgeable decisions. It can be difficult to provide transparency and explain model findings for some algorithms, including those based on neural networks. Certain parts of the analytics cycle are more explicitly tied to the limitations of augmented analytics. A common misperception about AI and machine learning is that they are primarily focused on technology and that ordinary people can't use them or engage with them. The idea that robots are replacing people's employment and making the adoption of AI-driven augmented analytics solutions more difficult is another fallacy. These solutions offer tangible advantages to those whose expertise resides in dealing with data. People won't invest in augmented analytics if they don't comprehend its true value and lack confidence in it.

Identification of company opportunities and problems mainly depends on managers and business users. Finding the business problem that analytics can solve during this vital time is a big challenge. Even while machines are excellent at solving problems, the act of creating issues is uniquely human.

Human judgment is still necessary throughout the data processing stage, for example, to evaluate outliers. Finally, only operational decisions can be automated, together with the activities that follow. Many decisions call for morality, empathy, and other qualities that, at the current stage of AI development, are still only found in people. A lot of questions about technologies, people, processes, and their interactions are raised by augmented analytics, which goes beyond the limitations of AI-enabled automation. Redefining the roles of the participants in the analytics cycle considering the changes brought on by automation is one problem. How should the role of data scientists change, for instance, if model development and evaluation are becoming more automated? What additional actions do they perform that provide the most value? The orchestration of the analytics process is another significant difficulty. This orchestration is complicated because it frequently involves numerous stakeholder types, a variety of tools, and various IT environments. The fact that the analytics process is not entirely sequential and can be instantiated in a variety of ways further complicates its orchestration and governance.

5. Results

The discussions' findings indicate that using augmented analytics technologies can simplify complex and highly fragmented data so that it can be easily visualized and interpreted by users. As a result, business organizations should think about implementing the technology as it will improve customer satisfaction and operational efficiency. We can quickly identify the numerous connections between the processed data and derive insights that significantly shorten the time it takes to design a new product. By automating analysis across a wider range of data with an emphasis on statistically significant features and expanding future search efforts, augmented analytics can assist eliminate bias. By combining automated analysis with manual review by the analyst, the risk of missing important insights is reduced.

6. Conclusion

This paper focused mainly on the use of augmented analytics tools to extend the outlook by developing new applications for reducing the highly fragmented data into straightforward statements that can be understood easily by the consumers or users. The elements that improved also added to obstacles that none of the technologies had before encountered. The underlying assumption is therefore that new, more effective, and efficient apps must include essential components. Even so, these technologies require meticulous attention to the details of each component, especially when augmented analytics is involved. The participants have not fully utilized the potential of these technologies since many users are not conversant with the underlying concepts. Even though each user's augmented analytics experience is unique, users may still complete challenging tasks fast and simply by hitting a button. To evaluate data and its solutions, a data professional with a reasonable degree of knowledge will still always be required. Because the quality of the input data determines the quality and dependability of the output data, organizations need to adopt AI-powered augmented analytics to have good data governance and management. Finally, business organizations and managers need to act decisively to understand the true implications of big data and enhanced analytics technologies and transform their industries.

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