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Big data analytics leverages AI for better data analysis.

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Abstract:

Big data and artificial intelligence have a synergistic relationship. AI requires a massive scale of data to learn and improve decision-making processes and big data analytics leverages AI for better data analysis. With this convergence, you can more easily leverage advanced analytics capabilities like augmented or predictive analytics and more efficiently surface actionable insights from your vast stores of data. With big data AI powered analytics, you can empower your users with the intuitive tools and robust technologies they need to extract high-value insights from data, fostering data literacy across your organization while reaping the benefits of becoming a truly data-driven organization.

By bringing together big data and AI technology, companies analytics improve business performance and efficiency by: **Analysing** consumer behaviour and automating customer segmentation Personalizing and optimizing the performance of digital marketing Using intelligent decision campaigns support systems fuelled by big data, AI, and predictive analytics

AI can assist users in all phases of the big data cycle, or the processes involved in the aggregation, storage, and retrieval of diverse types of data from various sources. These include data management, pattern management, context management, decision management, action management, goal management, and risk management.

AI can identify data types, find possible connections among datasets, and recognize using natural language knowledge processing. It can be used to automate and accelerate data preparation tasks, including the generation of data models, and assist in data exploration. It can learn common human error patterns, detecting resolving potential flaws in information. And it can learn by watching how the user interacts with an analytics program, surfacing unexpected insights from massive datasets fast. AI can also learn subtle differences in meaning, or context-specific nuances, in order to help users better understand numeric data sources. And it can alert users to anomalies or unexpected patterns in data, actively monitoring events and identifying potential threats from system logs or social networking data.

Keywords: Descriptive analytics, Diagnostic analytics, Predictive analytics, prescriptive analytics.

Introduction:

Traditional vs. AI Data Analytic

Traditional analytics can be performed without relying on artificial intelligence techniques and is broken out into 2 main types Descriptive and Diagnostic.



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Descriptive analytics will provide information about what happened while Diagnostic will give you insight of why it happened.

Descriptive analytics involves the analysis of historical data to uncover patterns, trends, and insights without making predictions or prescribing actions. It provides a snapshot of past events or behaviours, offering valuable insights into what has happened in the past. This branch of analytics is foundational, serving as a crucial first step in the analytics process before moving on to more advanced forms such as predictive and prescriptive analytics.

One of the key objectives of descriptive analytics is to summarize and understand data in a meaningful way. This often involves using statistical techniques and data visualization methods to present information clearly and concisely. Summary statistics such as mean, median, mode, and standard deviation provide a quick overview of the central tendency and variability Frequency of the data. distributions, histograms, and bar charts help visualize the distribution of data, highlighting patterns and outliers.

Data visualization plays a crucial role in descriptive analytics, as it enables analysts and stakeholders to quickly grasp insights from complex datasets. Visualizations such as scatter plots, line charts, and heat maps allow for the exploration of relationships between variables and the identification of trends over time or across different categories.

Descriptive analytics is widely used across various industries and domains. In finance, it can help analyse historical market data to understand past trends and inform investment decisions. In marketing, it can be used to segment customers based on past purchasing behavior and identify target demographics for promotional campaigns. In healthcare, it can assist in analysing patient data to identify trends in disease prevalence and healthcare outcomes.

Overall, descriptive analytics serves as a fundamental tool for understanding historical data, providing valuable insights that can inform decision-making processes and drive organizational success. By leveraging descriptive analytics, businesses and organizations can gain a deeper understanding of their past performance, identify areas for improvement, and make informed decisions for the future.

Diagnostic analytics is a more advanced form of analytics that goes beyond descriptive analytics by delving deeper into data to identify the causes of past events or behaviour's. While descriptive analytics focuses on summarizing historical data, diagnostic analytics aims to uncover the reasons behind those summaries, providing insights into why certain outcomes occurred. By understanding the root causes of past events, organizations can make more informed decisions and take proactive measures to address underlying issues or capitalize on opportunities.

One of the primary objectives of diagnostic analytics is to answer questions such as "Why did this happen?" or "What factors contributed to this outcome?" This involves analysing historical data in greater detail and applying various analytical techniques to identify correlations, relationships, and causal factors. Unlike descriptive analytics, which provides a high-level overview, diagnostic analytics involves drilling down



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into the data to uncover insights that may not be immediately apparent.

Diagnostic analytics often involves more sophisticated statistical techniques and data mining algorithms to identify patterns and relationships within the data. For example, regression analysis can be used to determine the strength and direction of relationships between variables, while correlation analysis identify can associations between different factors. Additionally, machine learning algorithms such as decision trees, random forests, and neural networks can be employed to uncover complex relationships and make predictions about future outcomes based on historical data.

One common application of diagnostic analytics is in identifying the root causes of business performance issues or anomalies. By analysing various factors such as sales data, marketing campaigns, economic indicators, and customer feedback, organizations can pinpoint the underlying reasons for fluctuations in sales or deviations from expected outcomes. This enables them to take corrective actions to address underlying issues and improve performance in the future.

Diagnostic analytics is also valuable for identifying opportunities for optimization and improvement. By analysing processes, systems, and workflows, organizations can identify inefficiencies, bottlenecks, and areas for optimization. This can lead to cost savings, productivity improvements, and enhanced operational efficiency.

Overall, diagnostic analytics plays a critical role in helping organizations move beyond simply describing past events to understanding why they occurred. By uncovering the root causes of past outcomes, organizations can make more informed decisions, mitigate risks, and capitalize on opportunities for improvement and innovation.

Similarly AI analytics can be performed in two main types Predictive and prescriptive. Predictive analytics will provide information about what will happen? While Prescriptive will give your insight of what should we do?

AI Predictive analytics

AI predictive analytics combines the capabilities of artificial intelligence (AI) with predictive analytics techniques to forecast future events or behaviours with greater accuracy and efficiency. This fusion of AI and predictive analytics enables organizations to leverage advanced algorithms and machine learning models to uncover insights, make predictions, and automate decision-making processes based on historical data.

At its core, AI predictive analytics aims to answer questions such as "What is likely to happen next?" or "What is the probability of a particular event occurring?" By analysing vast amounts of data from various sources, including structured and unstructured data, AI predictive analytics algorithms identify patterns, correlations, and relationships between variables to make accurate predictions about future outcomes.

One of the key advantages of AI predictive analytics is its ability to handle complex and high-dimensional data more effectively than traditional predictive analytics techniques. AI algorithms, such as deep learning neural networks, can automatically learn representations of data at multiple levels of abstraction, allowing them to



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capture intricate patterns and dependencies that may be missed by simpler models.

The AI predictive analytics process typically involves several stages:

- 1. Data Collection and Preparation: Gather relevant data from various sources, including databases, sensors, social media, and other sources. Cleanse, preprocess, and transform the data to ensure it is suitable for analysis.
- 2. Feature Selection and Engineering: Identify the most relevant variables (features) that are predictive of the target outcome. Create new features or transform existing features to improve predictive performance.
- 3. Model Selection and Training: Choose appropriate AI algorithms, such as neural networks, decision trees, or support vector machines, and train them using historical data. Optimize model hyper parameters and regularization techniques to improve performance.
- 4. Model Evaluation: Evaluate the trained models using validation data to assess their predictive accuracy, generalization ability, and robustness. Compare different models and select the one with the best performance.
- 5. Deployment and Monitoring:
 Deploy the trained model in
 production environments to make
 real-time predictions. Monitor
 model performance over time and
 retrain the model periodically with
 new data to ensure its accuracy and
 relevance.

AI predictive analytics finds applications across various industries and domains. In finance, it can be used for credit scoring, fraud detection, and algorithmic trading. In marketing, it can help personalize customer recommendations, optimize advertising campaigns, and forecast sales trends. In healthcare, it can assist in disease diagnosis, patient risk stratification, and treatment planning.

Overall, AI predictive analytics enables organizations to anticipate future events, make data-driven decisions, and gain a competitive advantage in today's rapidly evolving business landscape. By leveraging the power of AI to analyse data and make predictions, organizations can optimize their operations, mitigate risks, and capitalize on opportunities for growth and innovation.

AI Prescriptive analytics

Prescriptive analytics powered by artificial intelligence (AI) represents a cutting-edge approach to decision-making that leverages the capabilities of advanced AI algorithms to recommend optimal actions in complex and dynamic environments. Building upon the foundation of traditional prescriptive analytics, AI prescriptive analytics takes advantage of machine learning, natural processing, language and other techniques to provide more accurate, adaptive, and context-aware recommendations.

At its core, AI prescriptive analytics aims to answer the question: "What action should be taken to achieve a desired outcome?" This involves analysing vast amounts of data, identifying patterns and trends, and generating actionable insights that guide decision-making processes. Unlike



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traditional prescriptive analytics, which may rely on predefined models and rules, AI prescriptive analytics can adapt and learn from new data and changing conditions, leading to more dynamic and effective decision support.

One of the key advantages of AI prescriptive analytics is its ability to handle complexity and uncertainty inherent in real-world scenarios. By analysing large and diverse datasets, AI algorithms can uncover subtle patterns and relationships that may not be apparent to human analysts. Additionally, AI techniques such as reinforcement learning enable systems to learn from experience and improve over time, leading to more accurate and robust recommendations.

AI prescriptive analytics finds applications across a wide range of industries and domains. In healthcare, it can assist clinicians in making treatment decisions by analysing patient data, medical literature, best practices to recommend personalized treatment plans. In finance, it can help portfolio managers optimize investment strategies by analysing market data, economic indicators, and risk factors to identify the most promising opportunities. In manufacturing, it can optimize production processes by analysing sensor data, equipment performance, and supply chain dynamics to minimize downtime and maximize efficiency.

The implementation of AI prescriptive analytics requires careful consideration of data quality, model transparency, and ethical considerations. It is essential to ensure that AI systems are trained on high-quality data, are transparent in their decision-making processes, and adhere to

ethical principles such as fairness, accountability, and transparency.

Overall, AI prescriptive analytics holds great promise for organizations seeking to make data-driven decisions in today's and fast-paced world. complex harnessing the power of AI to analyse data, generate insights, and recommend actions, organizations can optimize their operations, capitalize mitigate risks, and opportunities for growth and innovation. However, it is crucial to approach AI prescriptive analytics thoughtfully and responsibly to realize its full potential while addressing potential challenges and risks.

Similarly AI analytics can be performed in two main types Predictive and prescriptive. Predictive analytics will provide information about what will happen? While Prescriptive will give your insight of what should we do?

Predictive analytics refers to the use of statistical modelling, data mining techniques and machine learning to make predictions about future outcomes based on historical and current data. These predictions help guide your decision making to mitigate risk, improve efficiency, and identify opportunities.

Methodology:

Big data analytics leverages artificial intelligence (AI) in several ways to enhance data analysis:

1. Data Processing and Preparation:
AI techniques such as natural language processing (NLP) and machine learning (ML) are used to pre-process and clean large datasets.
This involves tasks like data



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normalization, outlier detection, and missing value imputation.

- 2. Pattern Recognition and Prediction: AI algorithms, particularly machine learning and deep learning, are employed to identify patterns, correlations, and trends within large datasets. These models can then make predictions or recommendations based on historical data.
- 3. Anomaly Detection: AI-powered anomaly detection techniques can sift through vast amounts of data to identify unusual patterns or outliers that may indicate potential issues or fraud. This is particularly useful in cyber security and financial fraud detection.
- 4. Real-time Analytics: AI enables real-time data processing and analysis, allowing organizations to derive insights from streaming data sources such as IoT devices, social media feeds, or financial transactions in real time. This facilitates faster decision-making and proactive responses to changing situations.
- 5. Personalization and Recommendation Systems: powered recommendation systems analyse large volumes of user data provide personalized recommendations in various domains such as e-commerce. entertainment, and content streaming platforms. These systems techniques leverage collaborative filtering and content-

- based filtering to deliver relevant content to users.
- 6. Optimization and Automation: AI algorithms can optimize various business processes by analysing large datasets and identifying areas for improvement. This includes supply chain optimization, resource allocation, and inventory management. Additionally, powered automation tools can streamline repetitive tasks and workflows. freeing up human resources more strategic for activities.
- **Processing** 7. Natural Language (NLP): NLP techniques enable the analysis of unstructured data such as text documents, emails, social media posts, and customer feedback. AI-powered sentiment analysis, topic modelling, and entity recognition algorithms extract valuable insights from textual data, helping organizations understand customer sentiments, market trends. and emerging topics.
- Visualization 8. Data and Interpretation: AI-driven data visualization tools help users datasets interpret complex automatically generating insightful visualizations and summarizing key findings. These tools facilitate easier understanding of data patterns and trends, even for nontechnical users.

In summary, the integration of AI techniques with big data analytics enhances data analysis by automating tasks, uncovering insights from large and



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complex datasets, enabling real-time decision-making, and improving overall efficiency and accuracy.

Conclusion: Big data and artificial intelligence are also linked in terms of research and technological innovation for each field. Big data technology uses AI theories and methods and AI relies on large volumes of data and the supporting big data technologies to improve and evolve decision making capabilities.

AI analytics refers to the application of artificial intelligence techniques algorithms to automate analysis processes, analyse and interpret data, derive insights, and make predictions or recommendations. involves It leveraging advanced technologies like machine learning, natural language processing, and data visualization to enhance decision-making capabilities. AI data analytics can help you lower costs, reduce errors, improve accuracy, and free up human resources to focus on more strategic tasks.

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