

Data Analytics Using Generative AI

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Abstract: Data analytics plays an important role in gaining meaningful insights from big data across different domains. However, traditional data analysis tools often face problems such as limited data availability, difficult data classification, and uncertainty. In recent years, artificial intelligence (AI) technology has emerged as a powerful tool to solve these problems. This research paper presents an exploration of the intersection of data analysis and artificial intelligence, focusing on the use of ai models such generative adversarial networks (GANs), variational autoencoders (VAEs), and autoregressive models. We examine many applications of artificial intelligence in data analysis, including data processing, data mining, data manipulation, visualization, and feature extraction. , check the time and reduce the size. Through observational analysis and case studies, we demonstrate the effectiveness and versatility of AI tools in improving the traditional data analysis process. We also discuss the implications of our findings, identify current limitations, and suggest avenues for future research. Our research contributes to the understanding and application of artificial intelligence techniques in data analysis, paving the way for new solutions to complex data-driven problems.

1. Introduction

In the era of big data, businesses and organizations are constantly inundated with vast amounts of information. Extracting actionable insights from this data deluge has become a critical task for decision-makers across various industries. Traditional data analytics methods have long been relied upon for this purpose, utilizing techniques such as statistical analysis, machine learning, and data visualization. However, in recent years, a new approach has emerged that promises to revolutionize the field of data analytics: Generative Artificial Intelligence (AI). Generative AI refers to a class of algorithms and models designed to generate new data samples that mimic the patterns and characteristics of a given dataset. Unlike traditional AI models that are trained to classify, predict, or optimize based on existing data, generative models have the unique ability to create entirely new data instances. This capability opens up a wide range of possibilities for data analytics, enabling analysts to explore and understand data in novel ways. At the heart of generative AI lies deep learning, a subset of machine learning that involves training neural networks with multiple layers to learn intricate patterns and representations within data.

Generative models such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and autoregressive models have gained prominence for their ability to generate realistic data samples across various domains, including images, text, audio, and more.

In the context of data analytics, generative AI offers several compelling advantages:

- **Data Augmentation:** Generative models can be used to augment existing datasets by generating synthetic data samples. This augmented data can help address issues such as data scarcity, imbalance, or privacy concerns, improving the robustness and generalization of analytical models.
- **Anomaly Detection:** Generative models can learn the underlying distribution of normal data and identify deviations from this distribution, making them effective for anomaly detection tasks. By flagging unusual patterns or outliers in data, analysts can uncover potential fraud, errors, or anomalies that may otherwise go unnoticed.
- **Data Exploration and Visualization:** Generative models can generate new data instances that exhibit the statistical properties and relationships present in the original dataset. Analysts can leverage these synthetic samples to explore different scenarios, visualize

data distributions, and gain insights into complex data structures.

- **Scenario Planning and Simulation:** Generative models enable analysts to simulate various scenarios by generating synthetic data under different conditions or constraints. This capability is particularly valuable for forecasting, risk assessment, and decision-making, allowing organizations to evaluate potential outcomes and devise strategies accordingly.
- **Personalization and Recommendation:** Generative models can be used to create personalized content or recommendations tailored to individual preferences and behavior. By understanding underlying patterns in user data, analysts can generate customized products, services, or experiences that enhance user satisfaction and engagement.

However, leveraging generative AI for data analytics is not without its challenges. Training generative models requires substantial computational resources and data expertise, and ensuring the quality and validity of generated samples remains an ongoing research area. Additionally, ethical considerations surrounding the generation and use of synthetic data, such as privacy, bias, and fairness, must be carefully addressed to mitigate potential risks and consequences. generative AI presents a transformative paradigm for data analytics,

offering new opportunities to uncover insights, solve problems, and drive innovation across industries. By harnessing the power of generative models, analysts can unlock hidden patterns in data, generate valuable insights, and make informed decisions in an increasingly data-driven world. e AI, with its ability to synthesize data and generate novel

Foundational Background: Generative AI and Data Analytics

Generative Artificial Intelligence (AI) and Data Analytics represent two pillars of modern data-driven technology, each offering unique capabilities in understanding and manipulating data. Generative AI, characterized by algorithms like Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), empowers machines to create new content, whether it's images, text, or even music, by learning the underlying patterns and structures from existing data. On the other hand, Data Analytics involves extracting meaningful insights from vast datasets, employing statistical techniques, machine learning models, and data visualization tools to uncover trends, correlations, and anomalies.

2. Generative AI

In the realm of data analysis, the emergence of generative AI serves as a potent catalyst, infusing creativity and innovation into the analytical process. Unlike traditional approaches reliant solely on historical data, generative AI empowers organizations to transcend the confines of the past, utilizing

sophisticated algorithms like Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) to learn data structures and synthesize realistic outputs. By generating synthetic data and envisioning alternative scenarios, it not only augments traditional analytics but also unlocks novel possibilities, paving the way for data-driven innovation and discovery. Generative AI not only enhances data analytics by creating new data but also simplifies tasks such as coding and analysis through the capabilities of large language models (LLMs) like GPT-3.5. These models understand and generate SQL, Python, text summarization, and visualizations from data, albeit with limitations in handling short contexts and errors. Future improvements target specialized LLMs, multi-modal abilities, and better user interfaces for streamlined data workflows. Initiatives such as TalktoData aim to democratize data analytics by leveraging user-friendly Generative AI platforms, ultimately simplifying and broadening data analysis for everyone.

How does generative AI work?

Generative AI is a fascinating field that uses various techniques, like neural networks and deep learning algorithms, to identify patterns and generate new outcomes based on them. It's like the AI version of tapping into the human brain's creative processes!

Generative AI uses various techniques—including neural networks and deep learning algorithms—to identify patterns and generate new outcomes based on them.

The training process for a generative model involves feeding it a large dataset of examples, such as images, text, audio, and videos. Then, the model analyzes the patterns and relationships within the input data to understand the underlying rules governing the content. It generates new data by sampling from a probability distribution it has learned. And it continuously adjusts its parameters to maximize the probability of generating accurate output. For example, a generative model trained on a dataset of cat images could be used to create new images of cats by sampling from the learned distribution and then refining the output through a process called “inference.” During inference, the model adjusts its output to better match the desired output or correct any errors. This ensures that the generated output becomes more realistic and aligns better with what the user wants to see.

3. Generative AI models

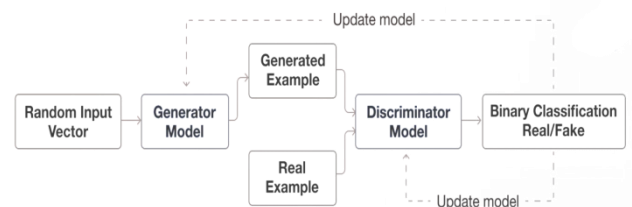
There are several popular generative AI models, each with its strengths and weaknesses. We will discuss the most commonly used models below.

Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) have emerged as a transformative approach in the realm of artificial intelligence, enabling the generation of realistic data samples across various domains. Like any generative AI model, the goal of GANs is to generate new data based on a fed dataset. To achieve this, it uses two neural networks: a generator and a

discriminator. Let’s say we want to generate cat images using GAN. The generator takes a random input vector and uses it to generate a new cat image. Initially, it might look like random pixels, but as the training progresses, the generator learns to generate realistic images of cats.

The discriminator then takes both – real images of cats from the dataset and the fake ones generated by the generator – and tries to classify them as either real or fake. Based on this classification, it learns to get better at discriminating images in the next round. On the other hand, the generator learns how well, or not, the generated samples fooled the discriminator and gets better at creating more realistic images in the next round. This dynamic interplay results in the creation of high-fidelity images, text, and other data types, pushing the boundaries of what is achievable in generative modeling. Despite challenges such as training instability and mode collapse, GANs continue to drive innovation and shape the future of artificial intelligence.



Variational Autoencoders (VAEs)

Variational Autoencoders (VAEs) represent another pivotal advancement in the realm of generative artificial intelligence, offering a

different approach compared to Generative Adversarial Networks (GANs). Introduced by Kingma and Welling in 2013, VAEs combine elements of variational inference with autoencoder architectures, providing a powerful framework for generating new data samples while also learning meaningful latent representations.

At their core, VAEs consist of two main components: the encoder and the decoder.

Encoding: The encoder network takes input data and maps it to a latent space, where each point represents a latent representation of the input.

Latent Sampling: Given the learned distributions from the encoder, samples are drawn from the latent space using techniques such as the reparameterization trick to ensure differentiability during back propagation.

Decoding: The decoder network takes these samples from the latent space and reconstructs the input data points.

Loss Optimization: VAEs are trained by optimizing a loss function that consists of two terms: the reconstruction loss, which measures the difference between the input data and the reconstructed data, and the KL divergence between the learned latent distributions and a predefined prior distribution (often a standard Gaussian).

During training, VAEs aim to learn both the parameters of the encoder that map data to the latent space and the parameters of the decoder

that reconstruct the data, optimizing a variational lower bound on the log-likelihood of the data.

4. Data Analytics

At its core, data analytics serves as the compass guiding organizations through the labyrinth of data, illuminating patterns, trends, and anomalies hidden within the digital deluge. From optimizing operational efficiencies to refining customer experiences, its applications span across industries, transcending boundaries and unlocking untapped potentials. Whether it's the healthcare sector leveraging predictive analytics to forecast disease outbreaks or financial institutions harnessing prescriptive analytics to mitigate risks, the significance of data analytics reverberates far and wide, shaping the contours of our interconnected world. Data analysis plays a pivotal role in today's data-driven world. It helps organizations harness the power of data, enabling them to make decisions, optimize processes, and gain a competitive edge. By turning raw data into meaningful insights, data analysis empowers businesses to identify opportunities, mitigate risks, and enhance their overall performance.

Informed Decision-Making

Data analysis is the compass that guides decision-makers through a sea of information. It enables organizations to base their choices on concrete evidence rather than intuition or guesswork. In business, this means making decisions more likely to lead to success,

whether choosing the right marketing strategy, optimizing supply chains, or launching new products. By analyzing data, decision-makers can assess various options' potential risks and rewards, leading to better choices

Improved Understanding

Data analysis provides a deeper understanding of processes, behaviors, and trends. It allows organizations to gain insights into customer preferences, market dynamics, and operational efficiency.

Competitive Advantage

Organizations can identify opportunities and threats by analyzing market trends, consumer behavior, and competitor performance. They can pivot their strategies to respond effectively, staying one step ahead of the competition. This ability to adapt and innovate based on data insights can lead to a significant competitive advantage.

Risk Mitigation

Data analysis is a valuable tool for risk assessment and management. Organizations can assess potential issues and take preventive measures by analyzing historical data. For instance, data analysis detects fraudulent activities in the finance industry by identifying unusual transaction patterns. This not only helps minimize financial losses but also safeguards the reputation and trust of customers.

Data Analysis Methods

Data analysis encompasses a wide range of methods and techniques used to inspect, clean, transform, and model data with the goal of discovering useful information, informing conclusions, and supporting decision-making processes. Here's an overview of some common data analysis methods:

Regression Analysis

Regression analysis is a powerful method for understanding the relationship between a dependent and one or more independent variables. It is applied in economics, finance, and social sciences. By fitting a regression model, you can make predictions, analyze cause-and-effect relationships, and uncover trends within your data.

Statistical Analysis

Statistical analysis encompasses a broad range of techniques for summarizing and interpreting data. It involves descriptive statistics (mean, median, standard deviation), inferential statistics (hypothesis testing, confidence intervals), and multivariate analysis. Statistical methods help make inferences about populations from sample data, draw conclusions, and assess the significance of results.

Cohort Analysis

Cohort analysis focuses on understanding the behavior of specific groups or cohorts over time. It can reveal patterns, retention rates, and customer lifetime value, helping businesses tailor their strategies.

Content Analysis

It is a qualitative data analysis method used to study the content of textual, visual, or multimedia data. Social sciences, journalism, and marketing often employ it to analyze themes, sentiments, or patterns within documents or media. Content analysis can help researchers gain insights from large volumes of unstructured data.

Time Series Analysis

Time series analysis deals with data collected at regular intervals over time. It is essential for forecasting, trend analysis, and understanding temporal patterns. Time series methods include moving averages, exponential smoothing, and autoregressive integrated moving average (ARIMA) models. They are widely used in finance for stock price prediction, meteorology for weather forecasting, and economics for economic modeling.

5. Generative AI in Data Analytics

Generative artificial intelligence (AI) has introduced groundbreaking capabilities to the field of data analytics, revolutionizing traditional methodologies and opening up new avenues for exploration. Within this domain, generative AI serves as a catalyst for innovation across multiple fronts, including synthetic data generation, data augmentation, and predictive modeling. This section delves into the pivotal role of generative AI in data analytics, shedding

light on its methodologies and transformative impact.

Synthetic Data Generation

One of the most significant applications of generative AI in data analytics is synthetic data generation. Conventional methods of data generation often fall short in capturing the intricate nuances of underlying data distributions accurately. Generative AI models, such as generative adversarial networks (GANs) and variational autoencoders (VAEs), usher in a new era of sophistication, enabling the creation of synthetic data that mirrors real-world instances. By assimilating the statistical properties of given datasets, these models produce novel samples that exhibit remarkable fidelity. Synthetic data generated through generative AI finds utility across diverse applications, from training machine learning models to safeguarding data privacy and simulating rare events for predictive modeling.

Data Augmentation

Data augmentation stands as a cornerstone technique in bolstering the performance of machine learning models by enriching the diversity and size of training datasets. Leveraging generative AI for data augmentation injects a new dimension of complexity and efficacy into this process. For instance, in image classification tasks, generative AI models can seamlessly integrate augmentation techniques like rotation, translation, and scaling to generate an array of augmented samples from existing data instances. These augmented samples not only

fortify the generalization capability of machine learning models but also mitigate the risk of overfitting. Moreover, the inherent semantic coherence preserved in generative AI-based augmentation techniques ensures the quality and relevance of augmented data, further amplifying its efficacy.

Predictive Modeling

Generative AI techniques have transcended traditional boundaries to find applications in predictive modeling tasks, wherein the objective revolves around forecasting future outcomes based on historical data. By harnessing the intrinsic data distributions and capturing intricate patterns, generative AI models elevate the accuracy and resilience of predictive models to unprecedented levels. Take, for instance, time series forecasting, where recurrent generative models generate realistic future sequences grounded in past observations. Similarly, in anomaly detection, generative AI models decode the normative behavior of systems and pinpoint deviations, signaling potential anomalies. The integration of generative AI into predictive modeling pipelines not only enhances prediction accuracy but also furnishes decision-makers with invaluable insights for informed decision-making processes.

In essence, generative AI stands as a cornerstone in the landscape of data analytics, fueling innovation, and driving transformative change across diverse applications. From synthetic data generation to predictive modeling, its prowess continues to shape the

trajectory of data analytics, ushering in an era of unparalleled possibilities and discoveries.

6. Advantages of Generative AI in Data Analytics

Generative Artificial Intelligence (AI) has revolutionized the landscape of data analytics, offering a multitude of advantages that empower organizations to derive deeper insights and unlock previously untapped potentials within their datasets. In this section, we delve into the significant advantages that Generative AI brings to the realm of data analytics, showcasing its transformative impact on various facets of decision-making, predictive modeling, and pattern recognition.

Enhanced Data Generation

Generative AI techniques enable the creation of synthetic data that closely mimic real-world datasets. This capability is invaluable, especially in scenarios where access to large, diverse, and representative datasets is limited or restricted due to privacy concerns.

Augmented Data Preprocessing

By generating synthetic data, Generative AI aids in augmenting existing datasets, thereby addressing issues related to data scarcity and class imbalance. This facilitates more robust and accurate model training, leading to improved performance and generalization.

Unbiased Data Analysis

Generative AI algorithms have the potential to mitigate biases inherent in datasets by

generating synthetic data that represents diverse demographics, ensuring fair and unbiased analysis. This fosters greater inclusivity and equity in decision-making processes across various domains.

Anomaly Detection and Fraud Prevention

Leveraging Generative AI, organizations can develop sophisticated anomaly detection systems capable of identifying irregular patterns and deviations within datasets, thereby bolstering fraud prevention measures and enhancing security protocols..

Personalized Recommendations and Content Generation

Generative AI algorithms excel in generating personalized recommendations and content tailored to individual preferences and behaviors. This capability enhances user engagement, fosters customer loyalty, and drives business growth in sectors such as e-commerce, entertainment, and digital marketing.

Time and Cost Efficiency

By automating repetitive tasks such as data generation, augmentation, and preprocessing, Generative AI streamlines the data analytics pipeline, reducing the time and resources required for complex analysis. This allows organizations to allocate their human capital more effectively, focusing on high-value tasks that demand creative problem-solving and strategic decision-making.

Forecasting and Scenario Planning

Generative AI empowers organizations to develop advanced forecasting models and conduct scenario planning exercises by generating synthetic data that simulates various future scenarios. This facilitates proactive decision-making and risk management strategies, enabling businesses to adapt swiftly to changing market dynamics and emerging challenges. The advantages of Generative AI in data analytics are multifaceted, encompassing enhanced data generation, unbiased analysis, improved model

performance, personalized recommendations, and increased efficiency. Embracing Generative AI technologies holds the potential to revolutionize the way organizations leverage data to drive innovation, optimize operations, and achieve sustainable growth in an increasingly competitive landscape.

7. Applications of Generative AI in Data Analytics

Generative artificial intelligence (AI) has witnessed widespread adoption in data analytics, offering a plethora of applications that enhance various aspects of data processing, analysis, and modeling. This section delves into some key applications of generative AI in data analytics, including data augmentation, anomaly detection, data imputation, and other relevant areas such as visualization, feature extraction, time series analysis, and dimensionality reduction.

Data Augmentation

Generative AI models play a pivotal role in data augmentation by generating synthetic data samples that enrich and diversify training datasets. By leveraging techniques such as generative adversarial networks (GANs) or variational autoencoders (VAEs), these models can create new instances of data that closely resemble the original distribution. Data augmentation enhances model generalization by exposing it to a wider range of data variations, thus reducing overfitting and improving performance across diverse tasks such as image classification, natural language processing, and speech recognition.

Anomaly Detection

Generative AI models are adept at detecting anomalies within data distributions by learning the normal patterns and identifying deviations. By modeling the underlying data distribution, generative models can flag data points that exhibit significant deviations or abnormalities, indicative of anomalous behavior or events. This capability finds application in various domains such as cybersecurity, fraud detection, predictive maintenance, and healthcare, where detecting anomalies in real-time is critical for proactive decision-making and risk mitigation.

Data Imputation

Generative AI techniques offer effective solutions for data imputation, where missing values in datasets are filled in using inferred values generated by the model. By learning the underlying patterns and correlations in the data, generative models can accurately impute missing values based on the available

information. This application is particularly valuable in scenarios where missing data can impede analysis or modeling efforts, such as in healthcare, finance, and social sciences, where incomplete datasets are common.

Other Relevant Applications:

In addition to the aforementioned applications, generative AI finds utility in various other areas within data analytics:

Visualization: Generative models can aid in data visualization by generating synthetic data samples for visualization purposes, enabling the exploration and interpretation of complex datasets.

Feature Extraction: Generative models can extract meaningful features from raw data, enabling dimensionality reduction and facilitating downstream analysis tasks..

Time Series Analysis: Generative models can generate realistic time series data, aiding in forecasting, trend analysis, and anomaly detection in time-dependent datasets.

Dimensionality Reduction: Generative models can learn low-dimensional representations of high-dimensional data, facilitating dimensionality reduction and improving computational efficiency in data analytics tasks.

Overall, the applications of generative AI in data analytics are diverse and far-reaching, encompassing a wide range of tasks and domains. By leveraging generative AI techniques, organizations can unlock new

capabilities, derive valuable insights, and make informed decisions in the era of big data and AI.

8. Challenges and Limitations

While generative artificial intelligence (AI) offers promising solutions to various data analytics tasks, it also presents several challenges and limitations that need to be addressed. Understanding these challenges is crucial for harnessing the full potential of generative AI and ensuring its effective and responsible application in data analytics. This section discusses some of the key challenges and limitations associated with generative AI in data analytics:

Data Quality and Fidelity

One of the primary challenges in using generative AI for data analytics is ensuring the quality and fidelity of the generated data. Generative models may produce synthetic samples that lack semantic coherence or exhibit unrealistic features, leading to biases in downstream analytics tasks. Addressing this challenge requires rigorous evaluation and refinement of generative AI models to ensure that the generated data accurately reflects the underlying data distribution.

Interpretability and Transparency

Generative AI models are often complex and black-box in nature, making it challenging to interpret the underlying data generation process. Lack of interpretability and transparency in generative AI models hinders trust and understanding among stakeholders,

particularly in sensitive domains such as healthcare and finance. Enhancing the interpretability of generative AI models requires developing explainable AI techniques and providing insights into the factors influencing data generation decisions.

Ethical Considerations:

The use of generative AI in data analytics raises various ethical considerations related to privacy, fairness, and accountability. Synthetic data generated using generative AI models may inadvertently capture and propagate biases present in the original data, leading to unfair or discriminatory outcomes. Moreover, the use of synthetic data for training machine learning models may raise questions about the representativeness and validity of the generated samples. Addressing these ethical concerns requires adopting robust governance frameworks and ethical guidelines for the responsible use of generative AI in data analytics.

Computational Resources and Scalability

Generative AI models often require significant computational resources and time for training, particularly for large-scale datasets and complex model architectures. Scalability remains a challenge, as scaling up generative AI models to handle big data and real-time analytics tasks may pose practical limitations. Moreover, deploying generative AI models in production environments requires efficient hardware infrastructure and optimization techniques to meet performance and latency requirements.

Generalization and Transferability

Generative AI models trained on specific datasets may struggle to generalize to unseen data or transfer their learned knowledge to different domains. Ensuring the generalization and transferability of generative AI models across diverse datasets and domains is essential for their practical utility in real-world data analytics scenarios. This requires careful consideration of model architecture, training procedures, and regularization techniques to promote robustness and adaptability. While generative AI holds immense potential for advancing data analytics capabilities, addressing the challenges and limitations outlined above is crucial for realizing its full benefits. By addressing these challenges through interdisciplinary collaboration, research innovation, and responsible AI practices, organizations can harness the transformative power of generative AI to drive innovation and address societal challenges in the era of big data and AI.

9. Future Directions and Conclusion

The field of data analytics using generative AI is poised for significant advancements in the coming years, driven by ongoing research and technological innovation. Future research directions in this domain include developing more robust and interpretable generative AI models, addressing data quality and fidelity challenges, and exploring novel applications in emerging domains such as healthcare, finance,

and climate science. Moreover, there is a growing need to establish ethical guidelines and regulatory frameworks to govern the responsible use of generative AI in data analytics and ensure transparency, fairness, and accountability. By addressing these challenges and leveraging the transformative capabilities of generative AI, organizations can unlock new opportunities for data-driven innovation and decision-making across various domains.

In conclusion, this paper has provided an overview of the application of generative AI in data analytics, discussing its methodologies, advantages, challenges, and future prospects. Generative AI techniques offer promising solutions for synthetic data generation, data augmentation, and predictive modeling, enabling organizations to enhance their analytics capabilities and derive valuable insights from large and complex datasets. However, the widespread adoption of generative AI in data analytics requires addressing challenges related to data quality, interpretability, and ethics. By fostering interdisciplinary collaboration and adopting responsible AI practices, organizations can harness the full potential of generative AI to drive innovation and address societal challenges in the era of big data and AI.

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