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Example unstructured data

Unstructured data has become increasingly popular in recent times, with companies across various industries embracing its benefits. However, many businesses still struggle to understand the importance and value of unstructured data, which is often overshadowed by structured data. Unstructured data is information that lacks a predefined data model or structure, making it challenging for computers to analyze and process. This type of data is typically found in text forms and accounts for 80% of all available data, with only 20% being structured data. Despite the challenges associated with analyzing unstructured data, it plays a crucial role in effective data management and analysis. It can provide valuable insights into customer behavior, preferences, and needs. Here are some common examples of unstructured data: 1. Emails: Used for both personal and business purposes, emails contain a wealth of unstructured data that can be leveraged to improve customer engagement and sales. 2. Text files: Documentaries such as Word documents, PDFs, spreadsheets, reports, and presentations all fall under the category of unstructured information. 3. Websites: Online platforms like YouTube, Instagram, Flickr, and social media sites generate a vast amount of raw data that can be used for analysis. 4. Social Media: The data generated from social media platforms provides real-time insights into customer behavior and preferences, making it an invaluable resource for businesses. 5. Media: Digital images, audio, video, MP3, and other forms of media represent a significant portion of unstructured data, offering opportunities for businesses to gain valuable insights into their customers' needs. In order to fully realize the benefits of unstructured data, organizations must develop strategies to analyze and utilize this type of information. By doing so, they can unlock new avenues for customer engagement, sales growth, and improved business performance. Images are considered unstructured information because they require processing to understand their meaning, unlike structured formats like digital photos stored in JPG and PNG. This logic applies to audio and video files as well. Unstructured Data: Unlocking the Secrets to Your Business Success Your business strategy and success are deeply connected to how you manage and analyze your unstructured data. For deeper insights, check out the Organization for the Advancement of Structured Information Standards (OASIS) and its Unstructured Information Management Architecture (UIMA) standard. Silvia Valcheva is a seasoned digital marketer with extensive experience in crafting content for the tech industry. She's passionate about writing about emerging technologies like big data, AI, IoT, process automation, and more. Unstructured Data: The Challenge of Organizing Complex Information Unstructured data refers to information without a predefined format or structure, making it hard to organize, process, and analyze. Unlike structured data, which is organized in tables and columns, unstructured data comes in various forms, such as text documents, images, audio files, videos, and social media posts. Characteristics of Unstructured Data Lack of Format: Unstructured data doesn't fit neatly into tables or databases. It can be textual or non-textual, making categorization and organization challenging. Variety: This type of data includes a wide range of formats, such as text documents, multimedia files, social media content, web pages, and blogs. Volume: Unstructured data represents a significant portion of the data generated today, often larger in volume compared to structured data. Diverse Sources: It can originate from various sources, including user-generated content, sensor data, customer interactions, and more. Advantages of Unstructured Data Supports data without proper format or sequence Data is not constrained by a fixed schema Very flexible due to the absence of schema Data is portable Scalable Deals easily with heterogeneity of sources Business Intelligence and Analytics Applications: Unstructured Data Offers Variety These types of data have various business intelligence and analytics applications. Given article text here Update, delete, and search for unstructured data are challenging due to high storage costs compared to structured data. Indexing unstructured data is difficult because it lacks a fixed schema. To overcome this, solutions like content-addressable storage systems (CAS) can be used to store data based on its metadata and unique names. CAS stores data in XML format or relational databases that support BLOBs, making it easier to retrieve data based on content rather than location. Additionally, using taxonomies or classification can help organize data in a hierarchical structure, making search processes easier. Virtual repositories like Documentum can automatically tag and store data, while application platforms like XOLAP can extract information from e-mails and XML-based documents. Data mining tools can also be used to analyze unstructured data. The majority of data is becoming unstructured, driving innovation in storing and processing information. While it presents challenges, solutions like CAS, virtual repositories, and data mining tools help businesses leverage unstructured data for better decision-making. Unstructured data's major challenge lies in its lack of identifiable structure, making it difficult to store, manage, and extract meaningful insights. However, using content-addressable storage systems, XML formats, or relational databases that support BLOBs can help store unstructured data. It is possible to convert unstructured data into structured formats using tools like taxonomies, virtual repositories, and data mining platforms. Common sources of unstructured data include web pages, images, videos from social media platforms, memos, reports, surveys, and presentations. Structured and unstructured data differ in their format and schema rules or lack thereof. Structured data has a fixed schema and fits neatly into rows and columns, while unstructured data has no fixed schema and can have a complex format. Storage systems for structured data often have rigid schemas, such as those in relational databases or data warehouses. Organizations store native-format data in non-relational databases or data lakes for various uses. Both structured and unstructured data are used across AI and analytics cases. Structured data fuels ML algorithms, while unstructured data is utilized in NLP and gen AI models. Structured data is more straightforward to analyze with traditional tools due to its organized format. Structured data's standardized nature makes it easily decipherable by various tools and human users. This type of data includes quantitative (prices, revenue) and qualitative (dates, names, addresses) information. A financial report with organized rows and columns exemplifies structured data. It is typically stored in tabular formats like Excel or relational databases. Users can efficiently input, search, and manipulate structured data using SQL within a RDBMS. Structured query language was developed by IBM in 1974 to manage this type of data. Machine learning applications often process structured data more easily due to its organized architecture. Accessing and interpreting structured data does not require extensive data science knowledge. Many tools are available for working with structured data, such as OLAP, SQLite, MySQL, and PostgreSQL. However, the limitations of structured data include inflexibility in usage and storage options. The predefined data model limits flexibility and usability, requiring modifications or additional data to mine more insights. Changing data requirements necessitates updating all structured data, which can be time-consuming. Unstructured data lacks a predefined format, setting it apart from its structured counterpart. Big Data and Unstructured Data: A Growing Enterprise Challenge The majority of enterprise-generated data, comprising over 90%, is large in volume and often classified as big data. This complex dataset arises from the internet and other connected technologies, leading to unstructured data containing various types of information. Unstructured Data: Textual and Nontextual Sources Examples of textual unstructured data include emails, text documents, social media posts, call transcripts, and message files. On the other hand, nontextual examples encompass image files, multimedia files, video files, and sensor data from Internet of Things (IoT) devices. Handling Unstructured Data Due to its lack of a predefined data model, unstructured data is difficult to process and analyze using conventional tools and methods. Consequently, it is often stored in nonrelational or NoSQL databases or data lakes, which are designed to handle massive amounts of raw data in various formats. Insights from Unstructured Data Machine learning, advanced analytics, and natural language processing (NLP) are frequently employed to extract valuable insights from unstructured data. Real-world applications include the use of machine learning algorithms to find patterns within large datasets. Benefits of Unstructured Data The benefits of unstructured data lie in its flexibility, speed, and storage advantages. It allows for flexible file format preservation, enabling data scientists to utilize data across multiple scenarios. Moreover, unstructured data accumulates at a rate three times faster than structured data, making it ideal for generative AI and large language model (LLM) fine-tuning. Storage and Scalability Unstructured data offers more storage options compared to structured data, thanks to file systems or data lakes with pay-as-you-use pricing. This reduces costs and eases scalability. Challenges of Unstructured Data The primary challenges stem from the requirement of specialized expertise and available resources. Data science skills are necessary for preparing and analyzing unstructured data, which may alienate business users unfamiliar with these topics. Specialized tools like MongoDB, DynamoDB, Hadoop, and Azure are often required to manage unstructured data. Data Quality and AI The large volume and heterogeneous structure of unstructured data can introduce inconsistencies and inaccuracies. Data cleansing prior to processing is essential, particularly with the aid of AI's ability to quickly process massive amounts of data. Machine learning algorithms can sift through unstructured data to find patterns, make real-time predictions, or provide recommendations, ultimately transforming raw data into actionable insights for organizations. Semi-structured data acts as a bridge between structured and unstructured information, enabling automation of decision-making processes by integrating with existing dashboards and APIs. It facilitates web scraping and data integration, while metadata plays a crucial role in identifying data characteristics and scaling it into records and preset fields. Examples of semi-structured data include JSON, CSV, and XML files. Email data is another common example, where standardized formats are used for headers and subject lines, but unstructured content remains within those sections. Semi-structured data is characterized by its blend of features from both structured and unstructured data types. Structured data adheres to a predetermined schema, presenting itself in organized formats such as Excel spreadsheets or relational databases. Unstructured data lacks a clear framework, instead relying on free-form content like web pages, call transcripts, or media files. Semi-structured data is distinguished by its presence of metadata and accompanying markers that facilitate indexing and analysis, yet it diverges from the structured database paradigm. This data form dominates corporate output, encompassing diversity and flexibility while hiding valuable insights, which might not be present in structured datasets. As a crucial component for modern AI systems, unstructured data plays a pivotal role in shaping the performance of deep learning models. By leveraging this vast repository of untapped information, enterprises can unlock various use cases such as generative AI development, sentiment analysis, predictive analytics, and chatbot optimization. Fine-tuning a large language model (LLM) is an essential step in adapting it to a specific use case or task, but it requires high-quality, structured data. On the other hand, retrieval augmented generation (RAG) can be more effective by incorporating unstructured data, gathering relevant information and feeding it to the model to improve response quality. Using RAG ensures timely and accurate outcomes as it constantly retrieves the latest information during response generation. Unlike fine-tuning, which may struggle with outdated or general data, RAG helps transform AI initiatives from generic to customized and impactful. Proper data governance and management are crucial for unstructured data, including classification, assessment, filtering for personally identifiable information (PII), and deduplication. With the right tools and even AI assistance, businesses can make their unstructured data usable. Unstructured data storage environments include object storage, which stores data in self-contained repositories with metadata and unique identifiers. Cloud-based object storage is often used to optimize costs and data usage of AI workloads. Data lakes handle large amounts of raw data in any format, using cloud computing for scalability and affordability. Data lakehouses combine the best parts of data lakes and data warehouses, offering fast, low-cost storage with flexibility for data analytics and AI/ML workloads. They also support real-time data ingestion, critical for timely decision-making. Structured query language (SQL) is being replaced by other programming languages like NoSQL, which doesn't require a schema to store data. MongoDB, Redis, and HBase are examples of this type of database. After storing unstructured data, it needs processing to be used in various use cases such as business intelligence or analytics. Some organizations use open-source frameworks like Apache Hadoop to process large datasets. Another framework is Apache Spark which uses in-memory processing making it suitable for machine learning and AI applications. There are also modern data integration platforms that can handle both structured and unstructured data automatically. These tools reduce the manual work of data science teams and provide insights from unstructured data using AI analytics. structured data can be accessed through SaaS on IBM Cloud or as a self-hosted solution. IBM Consulting offers various analytics services to transform enterprise data into valuable insights, enabling organizations to gain a competitive edge. By structuring data, businesses can improve transaction speeds, ensure continuous availability, and enhance security. IBM Db2 is an AI-driven database that streamlines decision-making, reduces costs by utilizing a single engine, and protects business data with robust security measures.