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DATA EPISTEME

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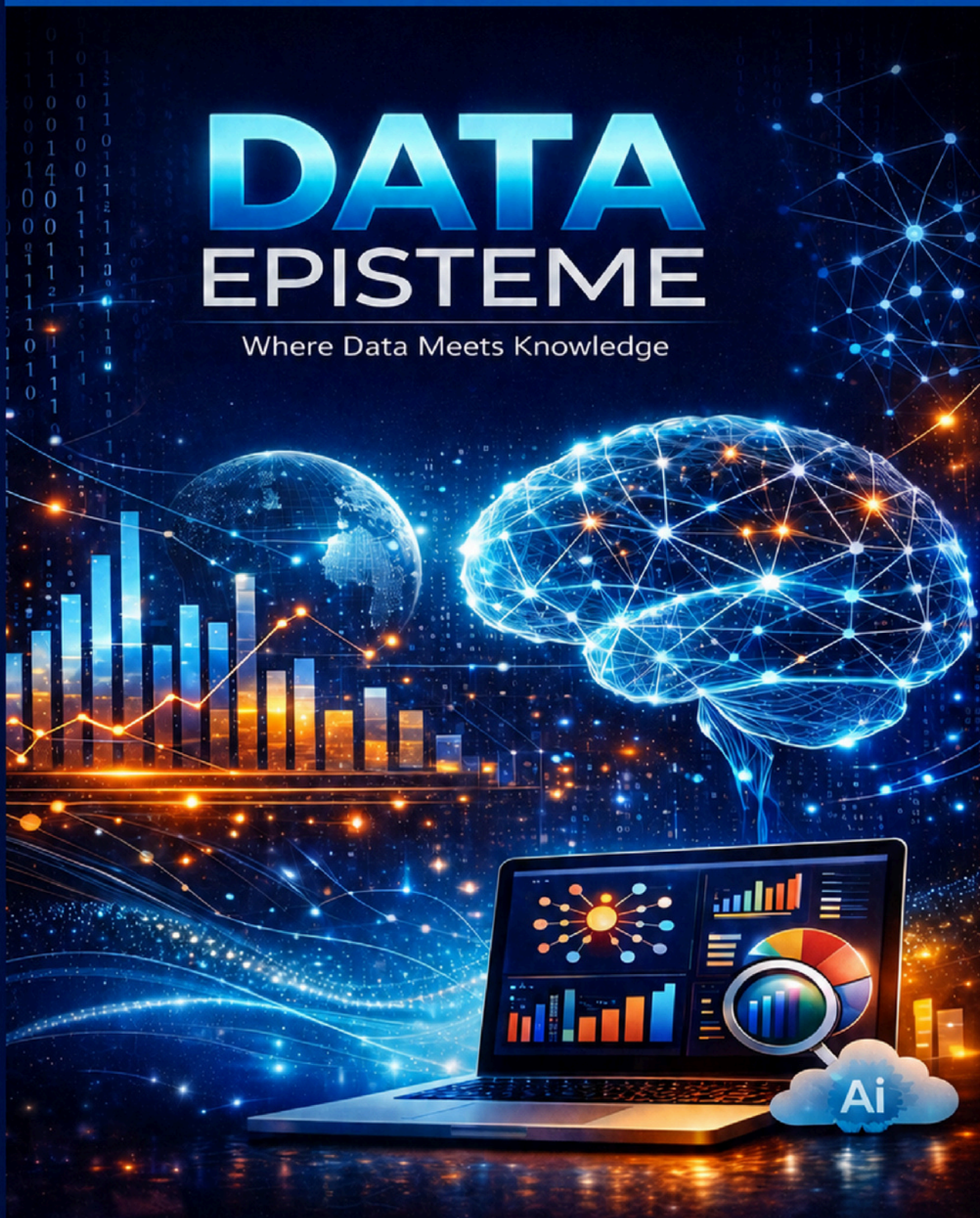
DATA EPISTEME

Where Data Meets Knowledge



DEPARTMENT OF **DATA SCIENCE (UG)**

2026 EDITION

"Data science is about asking the right questions not just having the right data".

PRINCIPAL'S MESSAGE

Dr. J. Paul Jayakar,
PRINCIPAL & SECRETARY.

Data Science continues to stand at the forefront of innovation as an inherently interdisciplinary field, drawing strength from mathematics, statistics, artificial intelligence, and computer science. In today's rapidly evolving digital landscape, the ability to adapt, upskill, and stay technologically relevant has become not just an advantage but a necessity. The increasing reliance on data-driven decision-making across industries has further amplified the importance of strong computational and analytical skills.

At the heart of academic and professional excellence lies the ability to think critically, creatively, and computationally. In this era, creativity must be complemented by technical competence. The power to analyze data, interpret patterns, and derive meaningful insights is transforming the way we understand the world. I urge our students to actively engage in upskilling themselves—especially in computer skills and Data Science—so that they are well-equipped to meet the demands of the future. Let learning be continuous, curiosity-driven, and purpose-oriented.

The Department of Data Science remains committed to fostering innovation, academic rigour, and a forward-looking vision. It strives to equip students not only with theoretical knowledge but also with practical, industry-relevant skills. The enthusiasm and proactive engagement of our students reflect the department's growing significance and its impact in shaping competent professionals for a data-centric world.

I commend the Data Science Club and the Department for the successful release of Volume 6 of DATA EPISTEME, the official departmental newsletter. This publication captures a vibrant spectrum of departmental initiatives, academic pursuits, skill-development activities, and co-curricular achievements. It also highlights the continuous efforts made towards enhancing digital literacy and technical proficiency among students.

The 2025–2026 edition of DATA EPISTEME underscores the department's sustained commitment to empowering students through upskilling, particularly in emerging technologies, programming, and data analytics. The newsletter stands as a testament to the department's progress, adaptability, and vision for the future.

Congratulations to the entire editorial team for presenting this volume with insight, creativity, and thoughtful design. Your dedication in showcasing the spirit of learning and innovation is truly commendable.

May God bless you all

EDITORIAL MESSAGE

Welcome to Data Episteme

It gives us immense pleasure to present the inaugural edition of **"DATA EPISTEME,"** the premier magazine of the Department of Data Science.

In a world increasingly driven by numbers and algorithms, this magazine is intended to bridge the gap between technical prowess and creative expression. It serves as a vital platform to bring out the hidden literary talents of our students, sharpening not only their technical writing skills but also their organizational and collaborative abilities.

Moreover, Data Episteme is a true reflection of our students' boundless creativity, intellectual curiosity, and their multifariousness. Within these pages, you will find a vibrant tapestry of ideas, insights, and unique perspectives that showcase the diverse capabilities of our academic community.

Finally, we are indeed proud of this new venture. We extend our heartfelt gratitude to everyone who contributed to making this vision a reality, and we hope this publication inspires a passion for lifelong learning and discovery.

Happy Reading!

— The Editorial Board

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Ink & Ideas

WHAT IS DATA SCIENCE AND WHY ITS MATTERS TODAY ?

Data science is a multidisciplinary field that combines mathematics, statistics, computer science, and domain expertise to extract meaningful insights and knowledge from large volumes of structured and unstructured data. It involves a structured life cycle —often called the OSEMN process—which includes obtaining, scrubbing, exploring, modeling, and interpreting data to drive informed decision-making.

Why Data Science Matters Today ?

In a world where data is generated at an unprecedented rate, data science has become a critical business tool for several reasons:

- Informed Decision-Making: It replaces intuition-based "gut feelings" with empirical evidence and statistical analysis, allowing leaders for more strategic approach.
- Predicting Future Trends: Using historical data, organizations can forecast market fluctuations, customer demand, and potential risks before they escalate.
- Operational Efficiency: It identifies bottlenecks in supply chains, optimizes delivery routes for logistics, and predicts equipment failures in manufacturing.
- Societal Impact: In healthcare, it is used for early disease detection and personalized treatment plans; in public safety, it helps allocate resources to prevent crime.

Key Skills and Careers

- The field is one of the fastest-growing today, with the U.S. Bureau of Labor Statistics projecting a 36% increase in employment for data scientists from 2021 to 2031.

- Essential Tools: Professionals primarily use Python and R for analysis, SQL for database management, and visualization tools like Tableau or Power BI.

- Data Scientist: Builds predictive models and answers complex business questions.

ROLE OF STATISTICS IN MODERN DATA SCIENCE

Role of Statistics in Data Science

Data science is based on statistics. It is a mathematical framework that collects, analyzes and performs data. This framework plays a crucial role in turning raw information into useful insights.

Statistics is a vital tool in the field of data science, revealing patterns, trends, and relationships among large, complex rows. In data science, statistics is important because it can reveal insights and empower informed decision-making. Statistics are also integral in preprocessing data, hypothesis testing, and model validation.

In their ability to make accurate inferences and predictions, and provide actionable insights, statistics and data sciences have a symbiotic partnership. This collaboration increases the efficiency of data-driven solutions and shapes a future in which data is used to its full potential.
Statistics and data science are essential to provide the best information. They create a path to a more insightful future.

Fundamentals of Statistical Methods in Data Analysis

Understanding fundamental statistical methods in data analysis is essential for gaining meaningful insights. A cornerstone of data analysis is hypothesis testing. This involves forming and evaluating hypotheses based on sampled data. This step is crucial for data analysts who can then make well-informed decisions and draw conclusions. Random variables are integral to statistical models and represent unreliable quantities. They also play an important role in the probability theory.

The use of statistical tools—ranging from simple descriptive measures to advanced analytical models—is essential for extracting meaningful insights from data. By examining measures of central tendency, variability, and distribution shapes, analysts can more easily uncover hidden patterns and better understand the underlying structure of a dataset. Exploring correlations further reveals how variables relate to one another, setting the foundation for deeper analysis.

Regression analysis, in particular, plays a crucial role in identifying and quantifying relationships between variables, enabling analysts to make informed predictions and interpret trends with greater confidence. These statistical concepts are indispensable for data analysts who aim to generate accurate forecasts, support data-driven decisions, and communicate findings effectively.
Statistics and Data Visualization

Combining data visualization with statistical analysis will help you extract meaningful insights from large datasets. Visualization is a powerful way to convey patterns, trends, and relationships in data. It enhances comprehension. By using statistical methods, data are no longer isolated values. They become part of a larger narrative.

Charts and graphs are visual representations that make complex statistical information more accessible. Visualization facilitates a better understanding of data structures by identifying outliers and highlighting distributions. This collaboration between data visualization and statistical analyses allows decision makers to gain actionable insights that will enable them to develop informed strategies and plan.

Combining visualization with statistical interpretation can transform raw data into an engaging visual story. This helps to foster a better understanding of data patterns, and more effective communication during the data-driven decision making process.

Big Data Analytics and Statistics

Data Scaling and Sampling: Statistics allows for efficient handling of large datasets through strategic sampling.

Anomaly detection: Statistics can help identify irregularities and outliers that may indicate potential problems.

Predictive modeling: This allows you to predict future trends based on past patterns.

Data Quality Assurance: Statistics assures data reliability through assessment and maintenance of quality.

The Role of statistics in data analytics:

Data analytics reveals patterns and extracts insights from statistics.

Decision Support, Performance measurement, Trend Analysis,

Amazon, for example, can provide personalized product recommendations through collaborative big data filters and other statistical techniques. This will enhance the user's shopping experience. This real-time application highlights the importance of statistics for extracting actionable insight, ultimately driving customer happiness and optimizing business strategy in the competitive ecommerce landscape.
Important Data Science Tools
Programming Languages

- Python – Most popular language for Data Science.
- Libraries: NumPy, Pandas, Matplotlib, Seaborn, Scikit-learn
- R – Specialized for statistical analysis and visualization.
- SQL – Used to query and manage databases.

DATA COLLECTION METHOD DIGITAL ERA

Data collection is the process of gathering information or data from various sources to analyze and draw information. It is an essential component of research and allows researchers to collect accurate and reliable data that can be used to answer research questions, test hypotheses, and make informed decisions.

There are various data collection techniques for collecting data, and the choice of method depends on the research question, the nature of the data, and the available resources. The most common methods of data collection are surveys, interviews, observations, and experiments.

Data collection tools and techniques have also evolved over time. In addition to traditional methods such as paper surveys and face-to-face interviews, researchers can now use digital tools to collect data which the big market research firms are already using. For example, online surveys, mobile surveys, and social media listening tools are widely used for data collection.

Types of Data Collection

Primary data is the data that is collected directly from the source. It is original data that has not been previously collected or published and is collected by researchers themselves or by hired research firms. Primary data can be collected through various methods, such as surveys, interviews, observations, and experiments.

Secondary data, on the other hand, has already been collected and published by someone else. Data has been gathered for a different purpose or by a different entity than the one currently using it. Secondary data can be obtained from various sources, such as government agencies, research firms, academic institutions, and libraries.

Both types of data have their advantages and limitations, and the choice of which type to use depends on the research question, available resources, and the purpose of the study.
Methods of Data Collection

1. Surveys
Most popular methods of data collection
Can be conducted in person, via email, phone, or online Ideal for collecting quantitative data

2. Interviews
Great way to collect in-depth information
Can be conducted in person, via phone, or online
Ideal for collecting qualitative data.

3. Observation

Involves watching and recording people's behaviours and interactions in natural settings. Can be conducted in person or via video recording provide insights into how people behave.

4. Experiments

Collecting data by manipulating variables and observing the effects Conducted in a controlled environment Ideal for collecting quantitative data Provides insights into cause-and-effect relationships between variables

5. Secondary data

Data that has already been collected by someone else.
Includes government reports, academic research, and industry publications.

Useful for providing context and background information
Key Data Collection Methods in the Digital Era:

- Online Surveys & Questionnaires: Digital tools like Google Forms and SurveyMonkey facilitate rapid, cost-effective data gathering from diverse populations.
- Social Media Monitoring: Analysing trends, sentiments, and user-generated content on platforms such as Twitter/X, Instagram, and LinkedIn.

- Web Scraping & Digital Mining: Using automated software (e.g., Python with libraries like Beautiful Soup) to extract data from websites, competitive analysis, and public records.

- Transactional Tracking: Recording digital purchases, website interactions, and clickstream data to understand consumer behaviour and preferences.

- IoT and Sensor Data: Collecting real-time data from connected devices, wearables, and machinery for behavioural or performance analysis.

- Remote Interviews & Virtual Focus Groups: Conducting qualitative research through video platforms like Zoom, allowing for global participation.

- Mobile Data Collection Apps: Using tools like ODK or Kobo Toolbox for offline or online field data collection.

DATA CLEANING: THE MOST CRITICAL STEP IN ANALYSIS

WHAT IS DATA CLEANING?

Data cleaning is also known as data cleansing or data scrubbing, is a process where information is organized and optimized in ways that support an organization's objectives, often with the goal of creating consistency in the data as presented. This can be many forms. Common task in data cleaning include:

- Handling Missing Data: Strategies include removing records with missing values, imputing values based on statistical methods, or using algorithms to predict missing data
- Removing Duplicates: Identifying and eliminating duplicate records to ensure each data point is unique.
- Correcting Inaccuracies: Identifying and fixing errors in data entries, such as typos or incorrect values.
- Standardizing Formats: Ensuring consisting in data formats, such as dates and phone numbers, to facilitate analysis.
- Dealing with Outliers: Identifying and managing outliers that can skew analysis results.

***EXAMPLE*:**

Data can be naturally fall out of data over time, because contact information changes, because people change jobs or people move during the early days of pandemic.

BENEFITS OF DATA CLEANING:

Improved accuracy: Removes errors, inconsistencies, and duplicates, ensuring reliable insights and decision making.

Better performance: Enhance the quality of models and analytics, leading to more actionable results.

Informed decisions: Ensures data aligns with business goals for strategic planning.
Efficiency: Saves time by reducing manual corrections during analysis

Trustworthy data: Builds confidence among stakeholders in the result derived from cleaning data

WHY IS DATA CLEANING SO IMPORTANT?

Real-word data is noisy and contains a lot of errors. They are not in their best format. So, it becomes important that these data points need to be fixed.

It is estimated that data scientists spend between 80 to 90 percent of their time in data cleaning

DATA CLEANING CYCLE:

1. Importing data
2. Merging data set
3. Rebuilding missing data
4. Standardization
5. Normalization
6. De-duplication
7. Verification & enrichment
8. Exporting data

DATA CLEANING TECHNIQUES:

Data Validation: Ensure data accuracy and consistency through validation rules

Data Profiling: Help analyse data to identify anomalies & patterns

Data Standardization: Ensure data consistency by converting into a common format

Deduplication: Help identify & remove duplicate records

Conclusion:

Data cleaning is a foundation step analysis and management. By ensuring that data is accurate, complete, and consistent, organizations can make better decisions, improve operational efficiency, and leverage data for competitive advantage. Regular data cleaning practices are essential to maintain data quality throughout the data lifecycle

ETHICS BIAS RESPONSIBILITY IN DATA SCIENCE

The Importance of Ethics in Data Science

All of this tends to come back to whether data was equally collected and if its interpretation is fair, hoping that no decision at any point in time was ethically problematic. Nevertheless, here is the challenge: data collection is often affected by bias, and we know how badly things can go if we do not acknowledge and control that.

For example, consider an AI system used in healthcare that makes decisions based on historical data. If the information it is fed fails to account for certain demographics, its decisions will be flawed, and lives could be put at risk. This is where data science ethics comes in—it is fundamentally about recognizing and preventing such bias from seeping into our models.

T***he Professional's Duty:*** UNESCO underlines the need for inclusive approaches in AI governance, transparency, explainability, open education, civic engagement, digital skills development, and ethics training. It is your job to ensure that your systems and models work well for everyone, and not just for the majority of users in your dataset.

The Hidden Bias in Algorithms

Bias in AI and data science is not always straightforward. It lies in the datasets, in the code, and sometimes even embedded within the very questions we ask. Data bias exists when the data used to train AI systems is not entirely representative of the population it is designed to serve.

A clear illustrative case of algorithmic bias is facial recognition software, which notoriously fails to identify people of color with high accuracy.

To counter these biases, researchers have been creating frameworks like FAT (Fairness, Accountability, and Transparency) to help data scientists structure more responsible solutions. However, researchers are not alone in this responsibility. These ethical nuances need to be core lessons for future leaders regardless of whether they are in marketing, social work, management, or tech.

Responsibilities for Future Data Professionals

How do you make sure you are building ethical AI systems? It begins with a growth mindset and the courage to challenge the prevailing order. As you design models, always ask yourself:

- “What is the real-world outcome of what I am doing?”
- “Who gains, and who loses?”

This is where specialized, interdisciplinary training equips you to make a substantial impact. For example, an MBA specializing in supply chain management could use data science to maximize logistics processes. But if those models are built on flawed data, they might further marginalize smaller suppliers. True leadership means ensuring that your models contribute to more equitable supply chains built on fairness. Those who can bridge the technical and ethical sides of data management will own the future.

Looking ahead, it is critical to stay attuned to burgeoning global trends and international regulations attempting to set norms for responsible AI usage. Key global initiatives like the UNESCO AI Guidelines advocate for transparency, explainability, and inclusive governance training, while the Global Partnership on AI (GPAI) bridges theory and practice to ensure AI deployment actively serves human well-being. Structurally, robust regional regulations like the European Union's GDPR (General Data Protection Regulation) set strict legal standards for data privacy, transparency, and user data processing. Concurrently, academic and industry researchers rely on standard frameworks like FAT (Fairness, Accountability, and Transparency) to embed these principles directly into daily model building, ensuring global compliance translates into fair algorithmic design.

The Future of Data Science is Ethical Leadership

In the end, data science for social good goes beyond simply avoiding bias—it is about creating systems that actively benefit society. From healthcare and education to climate action and beyond, the models you create today are going to decide what kind of world we build tomorrow.

The road to the future holds a delicate balance between ingenuity and ethics. Uniting your technical talent with ethical leadership will make you the most powerful driver of real change.

UNDERSTANDING BIG DATA VOLUME VELOCITY AND VARIETY

Predictive models in healthcare use Machine Learning (ML), Artificial Intelligence (AI), and historical patient data to forecast potential health risks, disease onset, and patient outcomes. By identifying patterns, these models enable earlier interventions, reduce mortality, minimize readmissions, and optimize resource utilization. Key applications include disease diagnosis (e.g., cancer), risk stratification, and personalized treatment planning

.

Key Aspects of Predictive Models in Healthcare

- Data Sources: Models analyze electronic health records (EHRs), medical imaging, genetic data, and, increasingly, wearable IoT devices.
- Methodologies: Common techniques include logistic regression, Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests (RF), and CNNs for image-based analysis.
- Disease Detection & Prediction:
- Chronic Diseases: Predicting diabetes, hypertension, and heart disease risks.
- Cancer: Early detection of lung, breast, and other cancers through imaging.
  Infectious Disease: Modeling outbreak patterns and COVID-19 risk factors.

Benefits:

- Early Intervention: Identifying high-risk patients before conditions become critical.
- Improved Efficiency: Optimizing hospital resource allocation, such as bed management and staffing.
- Personalized Care: Tailoring treatment plans to individual patient data.
- Challenges: Key limitations include data bias, where models may not represent diverse populations, and the need for high-quality, actionable data.

Examples of Use Cases

- Hospital Readmission Risk: Forecasting which patients are likely to return shortly after discharge.
- Lung Cancer Detection: Using algorithms to analyze patient data (e.g., Mayo Clinic model).
- Sepsis Prediction: Early warning systems to detect deteriorating patient conditions.

Predictive analytics is transforming healthcare from a reactive, one-size-fits-all approach to a proactive, personalized system, ultimately enhancing the quality of care.

BIG DATA IN GOVERNMENT AND PUBLIC POLICY

Big data revolutionizes government and public policy by replacing traditional, slow decision-making with real-time, evidence-based insights, significantly enhancing efficiency in areas like taxation, health, and urban planning. By leveraging AI and massive datasets—from sensors, social media, and administrative records—governments can detect anomalies, forecast trends, target services, and combat fraud.

Key Applications in Government & Public Policy:

- Predictive Policy Making: Governments use analytics to anticipate issues, such as using data to target areas for opioid-avoidance programs or predicting traffic patterns for infrastructure planning.
- Improved Service Delivery: Programs like India's Aadhaar-based Direct Benefit Transfer (DBT) ensure welfare schemes reach beneficiaries without leakages.
- Real-time Decision Making: During crises, such as the COVID-19 pandemic, data from platforms like CoWIN allowed for rapid, informed, and responsive policy adjustments.
- Citizen Engagement: Governments analyze public feedback and social media sentiment to refine policies and improve perceived legitimacy.

Challenges and Considerations:

- Data Privacy & Security: Protecting sensitive citizen data remains a critical concern, necessitating robust data governance frameworks.
- Algorithmic Bias: Automated systems must be audited to prevent reinforcing existing inequalities.
- Data Sovereignty: Ensuring data remains within national borders is essential for national security.

ROLE OF BIG DATA IN ECONOMIC AND MARKET ANALYSIS

Big data drives economic and market analysis by analyzing vast, real-time datasets—including social media, IoT, and transaction records—to enhance forecasting, optimize consumer targeting, and mitigate risk. It transforms traditional analysis by enabling high-frequency, granular insights into market trends, allowing businesses to adapt quickly to shifting demand.

Key Roles of Big Data in Economic & Market Analysis

- Market Trend Forecasting: Analyzes social media trends, news, and industry reports to identify emerging opportunities and anticipate market shifts.
- Consumer Behavior Insights: Enables companies to understand "who, where, and what" customers want by analyzing behavioral, sentiment, and purchasing data, enhancing personalization.
- Real-Time Economic Monitoring: Replaces or supplements traditional surveys with scanner data and online price tracking for faster, more accurate macroeconomic indicators.
- Supply Chain & Inventory Optimization: Predicts demand fluctuations to optimize stock levels and improve operational efficiency.
- Risk Management & Competitive Analysis: Provides tools to assess competitive landscapes, predict financial distress, and detect fraud.

Data Sources & Techniques

Sources: Social media, website clickstreams, mobile applications, IoT sensors, and transaction histories.
Techniques: Machine learning algorithms, sentiment analysis, and time-series analysis.

By integrating these diverse data streams, firms and policymakers can make more proactive, informed, and strategic decisions in a dynamic economic environment

SOCIAL MEDIA AND BIG DATA TREND ANALYSIS

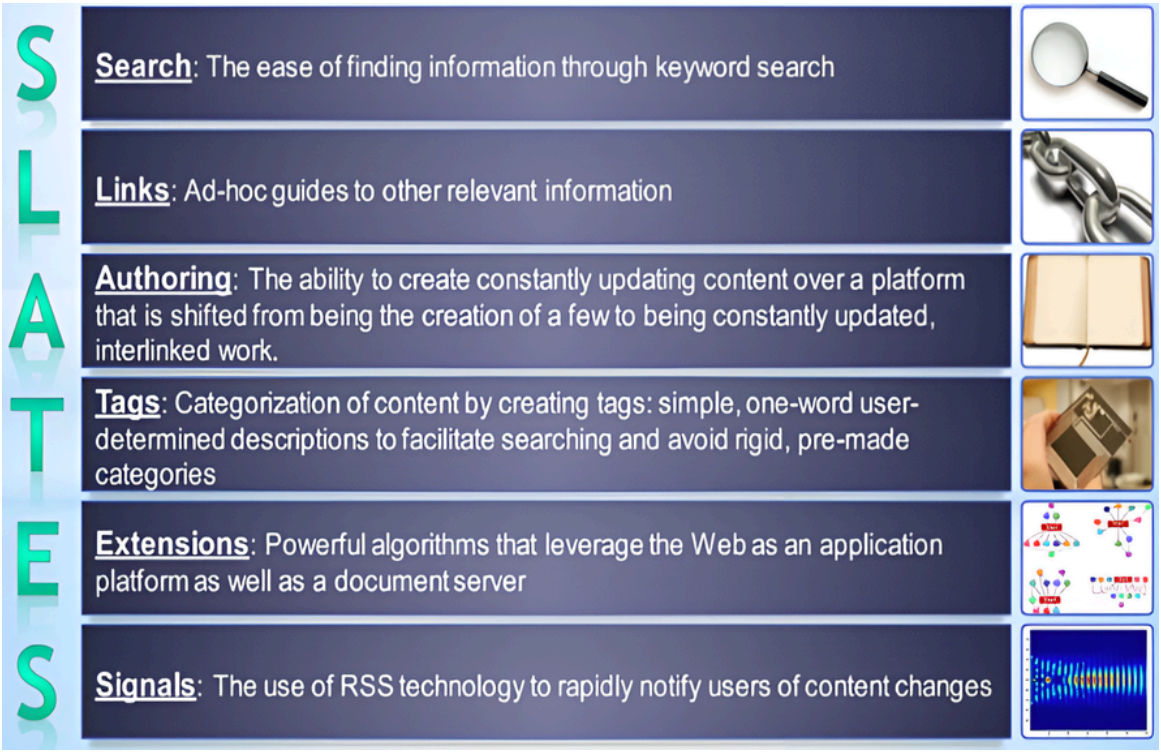
Web 2.0 & Social Media

Web 2.0 is defined as a complex, organic online conversation.

- Core Technologies: Websites typically include features and techniques summarized by the acronym SLATES (Search, Links, Authoring, Tags, Extensions, Signals).

- Powered By: Social networks, news and bookmarking, blogs, microblogging, video/photo-sharing, message boards, wikis, virtual reality, social gaming, podcasts, RSS (Real Simple Syndication), and social media press.

Social Media serves as the umbrella term for the platforms and activities that integrate this technology with social interaction, allowing users to construct and share words, pictures, videos, and audio.



Big Data

Big Data refers to data whose scale, diversity, and complexity require new architectural techniques, algorithms, and analytics to manage and extract hidden knowledge.

The Big Data Equation: Technologies + Specialists

- *Technologies: Systems capable of working with data within consistent timeframes using distributed environments or cloud-based services (e.g., NoSQL, Cloud).*
- *Specialists: Technical experts capable of understanding business goals and improving processes by analyzing diverse, distributed, and massive data volumes using both SQL and NoSQL tools.*

The 5 Vs of Big Data

Big Data is traditionally described using five dimensions:

1. *Volume: The vast amounts of data generated every second (measured in Zettabytes or Brontobytes, rather than just Terabytes).*
2. *Velocity: The speed at which new data is generated and moves around (e.g., a social media message going viral in seconds).*
3. *Variety: The different types of data available today. While past analysis focused on structured financial data in relational databases, 80% of the world's data is now unstructured (text, images, video, voice).*
4. *Veracity: The "messiness" or trustworthiness of the data. Quality and accuracy are less controllable in Big Data, requiring advanced technology to process it reliably.*
5. *Value: The ability for companies to generate actionable, amazing value and insights from their data.*

Sentiment Analysis & Research

Sentiment Analysis is the process of analyzing people's sentiments, opinions, appraisals, attitudes, evaluations, and emotions as presented online via text, video, and other communications.

- *Targets: Entities such as organizations, products, services, individuals, topics, issues, events, and their attributes.*
- *Categories: Communications are classified into three broad categories: Positive, Neutral, or Negative.*
- *Levels of Analysis: Conducted at the word, clause, or sentence level.*

Application: Social Media Meme Research

A practical application of Big Data and Sentiment Analysis is studying how memes spread on social media.

- *Definition: A meme is a transmissible unit of information, such as a hashtag, phrase, or link.*
- *Outputs: Research projects tracking these spread patterns often yield visualizations, analytical tools, and broader data resources to demonstrate the impact of digital information sharing.*

BIG DATA ANALYTICS FOR NATIONAL DEVELOPMENT

Big Data

The world is rapidly advancing towards becoming a fully digital society. At a global level, the amount of data is projected to increase more than fivefold, rising from 33 zettabytes in 2018 to 175 zettabytes by 2025. Of this, 49 percent is expected to be stored in the public cloud, and the number of devices connected through the Internet of Things (IoT) is anticipated to reach approximately 75 billion, which is ten times the world population by 2025.

However, the digital divide—both between and within developed and developing countries—continues to widen. This gap particularly affects developing nations, especially in Africa, Least Developed Countries (LDCs), and Small Island Developing States (SIDS), hindering their ability to integrate into the global economy and benefit from it.

The Data Revolution

The data revolution -- which encompasses the open data movement, the rise of crowdsourcing, new ICTs for data collection, and the explosion in the availability of big data, together with the emergence of artificial intelligence and the Internet of Things -- is already transforming society. Advances in computing and data science now make it possible to process and analyze big data in real time. New insights gleaned from such data mining can complement official statistics and survey data, adding depth and nuance to information on human behaviors and experiences. The integration of this new data with traditional data should produce high-quality information that is more detailed, timely, and relevant.

Opportunities

Data is the lifeblood of decision-making and the raw material for accountability. Today, in the private sector, analysis of big data is commonplace, with consumer profiling, personalized services, and predictive analysis being used for marketing, advertising, and management. Similar techniques could be adopted to gain real-time insights into people's wellbeing and to target aid interventions in vulnerable groups. New sources of data - such as satellite data -, new technologies, and new analytical approaches, if applied responsibly, can enable more agile, efficient and evidence-based decision-making and can better measure progress on the Sustainable Development Goals (SDGs) in a way that is both inclusive and fair.

Risks

Fundamental elements of human rights must be safeguarded to realize the opportunities presented by big data: privacy, ethics and respect for data sovereignty require us to assess the rights of individuals along with the benefits of the collective. Much new data is collected passively – from the 'digital footprints' people leave behind and from sensor-enabled objects – or is inferred via algorithms. Because big data is the product of unique patterns of behavior of individuals, removal of explicit personal information may not fully protect privacy. Combining multiple datasets may lead to the re-identification of individuals or groups of individuals, subjecting them to potential harms. Proper data protection measures must be put in place to prevent data misuse or mishandling.

There is also a risk of growing inequality and bias. Major gaps are already opening up between the data haves and have-nots. Without action, a whole new inequality frontier will split the world between those who know, and those who do not. Many people are excluded from the new world of data and information by language, poverty, lack of education, lack of technology infrastructure, remoteness or prejudice and discrimination.

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Big Data for Development and Humanitarian Action

In 2015, the world embarked on a new development agenda underpinned by the Sustainable Development Goals (SDGs). Achieving these goals requires integrated action on social, environmental, and economic challenges, with a focus on inclusive, participatory development that leaves no one behind.

Critical data for global, regional and national development policymaking is still lacking. Many governments still do not have access to adequate data on their entire population. This is particularly true for the poorest and most marginalized, the very people that leaders will need to focus on if they are to achieve zero extreme poverty and zero emissions by 2030, and to 'leave no one behind' in the process.

Big data can shed light on disparities in society that were previously hidden. For example, women and girls, who often work in the informal sector or at home, suffer social constraints on their mobility, and are marginalized in both private and public decision-making

INTRODUCTION TO MACHINE LEARNING

Machine learning (ML) allows computers to learn and make decisions without being explicitly programmed. It involves feeding data into algorithms to identify patterns and make predictions on new data. It is used in various applications like image recognition, speech processing, language translation, recommender systems, etc. In this article, we will see more about ML and its core concepts.

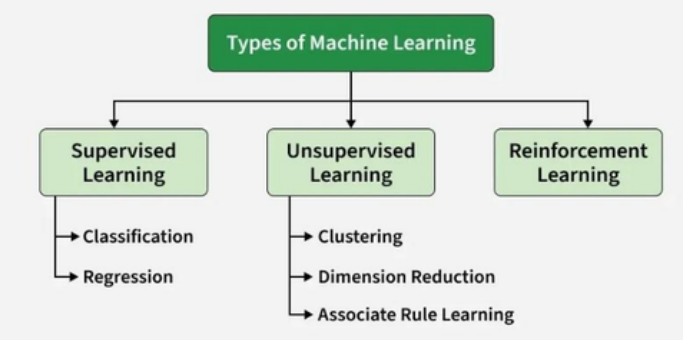
Machine learning definition

Machine learning is a subfield of artificial intelligence (AI) that uses algorithms trained on data sets to create self-learning models capable of predicting outcomes and classifying information without human intervention. Machine learning is used today for a wide range of commercial purposes, including suggesting products to consumers based on their past purchases, predicting stock market fluctuations, and translating text from one language to another.

Types of Machine Learning

There are several types of machine learning, each with special characteristics and applications. Some of the main types of machine learning algorithms are as follows:

- Supervised Machine Learning
- Unsupervised Machine Learning
- Reinforcement Learning



1. Supervised machine learning

In supervised learning, algorithms are trained on labeled data sets that include tags describing each piece of data. In other words, the algorithms are fed data that includes an “answer key” describing how it should be interpreted. For example, an algorithm may be fed images of flowers that include tags for each flower type so that it will be able to identify the flower better again when fed a new photograph. Supervised learning is often used to create machine learning models used for prediction and classification purposes.

2. ***Unsupervised machine learning***

Unsupervised learning uses unlabeled data sets to train algorithms. In this process, the algorithm is fed data that doesn't include tags, which requires it to uncover patterns on its own without any outside guidance. For instance, an algorithm may be fed a large amount of unlabeled user data culled from a social media site in order to identify behavioral trends on the platform.Unsupervised machine learning is often used by researchers and data scientists to identify patterns within large, unlabeled data sets quickly and efficiently

3.***Semi-supervised machine learning***

Semi-supervised learning uses both unlabeled and labeled data sets to train algorithms. Generally, during semi-supervised learning, algorithms are first fed a small amount of labeled data to help direct their development and then fed much larger quantities of unlabeled data to complete the model. For example, an algorithm may be fed a smaller quantity of labeled speech data and then trained on a much larger set of unlabeled speech data in order to create a model capable of speech recognition. Semi-supervised learning is often employed to train algorithms for classification and prediction purposes when large volumes of labeled data are unavailable

MACHINE LEARNING IN ELECTION AND OPINION ANALYSIS

Elections are a vital component of democracy because they allow citizens to exercise their right to vote and choose representatives at all levels of government. The exponential growth of social media platforms has facilitated more accessible communication between political parties, politicians, and voters, disseminating distinctive political messages. Twitter, one of the most liked social media platforms, has become a valuable source for real-time public opinion. The proposed work uses sentiment analysis to predict electoral outcomes. Through analyzing the sentiment expressed in tweets regarding political candidates or parties, the machine learning algorithm, Long Short-Term Memory (LSTM), can be trained to identify patterns and correlations between sentiment and election results. The work examines the efficacy of the suggested approach by analyzing two large datasets of tweets during a specific election period. The proposed work presents a hybrid multimodal framework that incorporates emojis and multilingual text, including Hindi, English, and Hinglish (tweets containing both Hindi and English). The model is validated on datasets containing these multilingual elements and additionally tested on English-language tweets to evaluate its performance across different linguistic contexts. The results demonstrate the predictive capability of sentiment analysis on Twitter activity, shedding light on its potential as a supplementary tool for election forecasting. The outcome of the proposed method overviews Rahul Gandhi and Narendra Modi's polarity and subjectivity values. The accuracy of the proposed work is 87.65%, which outperforms the Twitter dataset used in state-of-artwork.

Our strategy chooses a high-impact political event and collects related Twitter messages. The event is usually unique. It brings difficulty directly apply existing trained models for analyzing messages related to this event, because these models were trained based on cases unrelated to this event. Our strategy suggests selecting some messages and manually annotating them. These annotated messages can be used to train computational models. In practice, we classify each word into five categories, which are very negative, negative, neutral, positive, and very positive. Similarly, we also classify each sentence and message into these five categories. Computational model selection is also important for Twitter message analysis. Here, we use the Stanford CoreNLP toolkit. It applies deep learning in sentiment analysis. This is a Recursive Neural Tensor Network (RNTN). This model applies to a binary tree to organize all words. The root node represents the whole sentence or message. Each word or sentence is annotated with a sentiment score. We use 0, 0.25, 0.5, 0.75, and 1 to very negative, negative, neutral, positive, and very positive, respectively. After the model is trained by our manually annotated data, this model classifies all Twitter sentences into five categories. The weighted sentiment score can be used to predict the overall election result. Fig. 1 describes the whole working flow of our strategy. This strategy gives users the flexibility of selecting events. It is worth noting that the selected event should happen closely before the election. Otherwise, the analysis results cannot correctly reflect the election situation. Here, we suggest selecting events with less than two months to the election. If an event is politically controversial, people from all sides are likely to express their political opinions.

BIAS AND FAIRNESS ISSUES IN MACHINE LEARNING

Bias and fairness issues in Machine Learning (ML) have become central concerns as ML systems are increasingly used in high-stakes decision-making domains such as hiring, lending, policing, healthcare, and criminal justice. Machine learning models learn patterns from historical data, and when that data reflects existing societal inequalities, the models can reproduce and even amplify those inequalities. Bias in ML refers to systematic and unfair discrimination against certain individuals or groups, particularly those defined by sensitive attributes such as race, gender, age, disability, or socioeconomic status. Importantly, bias is not always intentional; it often emerges from the data collection process, model design choices, or evaluation practices. However, unintentional bias can still produce harmful and discriminatory outcomes, making fairness a critical technical, ethical, and social challenge.

One of the primary sources of bias in ML systems is data bias. Since models rely heavily on training data, any imbalance or distortion in that data can directly affect predictions. Historical bias occurs when the data reflects past discrimination or unequal treatment, such as historical hiring data that favored men over women. Representation bias arises when certain groups are underrepresented in the dataset, leading the model to perform poorly for them. Measurement bias occurs when variables or labels are recorded differently across groups, and sampling bias happens when data is collected from a population that does not accurately represent the broader community. For example, early facial recognition systems developed by companies like IBM were found to perform less accurately on women and people with darker skin tones due to imbalanced training datasets. These examples highlight how biased data can lead to unequal system performance

Bias can also arise from algorithmic design choices. Even when sensitive attributes such as race or gender are removed from the dataset, models may rely on proxy variables that indirectly encode the same information. For instance, ZIP codes can act as proxies for race or socioeconomic status. Additionally, many models are optimized primarily for overall accuracy, which can result in better performance for majority groups while minority groups experience higher error rates. Imbalanced class distributions further exacerbate this issue, as models tend to favor patterns that occur more frequently in the training data. Thus, algorithmic bias is not only about the data itself but also about how objectives, features, and optimization strategies are chosen.

Evaluation practices also play a significant role in fairness concerns. Many ML systems are assessed using aggregate metrics such as overall accuracy, precision, or recall. However, high overall performance can mask disparities across demographic groups. A well-known example involves a healthcare risk prediction system analyzed by researchers at the University of Chicago, which used healthcare spending as a proxy for medical need. Because historically less money was spent on Black patients due to unequal access to care, the model underestimated their health needs, resulting in racial bias. This case illustrates how evaluation metrics and proxy variables can unintentionally disadvantage certain populations. Fairness in ML is complex because it can be defined in multiple, sometimes conflicting ways.

Demographic parity requires that outcomes be independent of protected attributes, such as ensuring equal loan approval rates across genders. Equalized odds demands that error rates, including false positives and false negatives, be equal across groups. Equal opportunity focuses specifically on equal true positive rates, while individual fairness requires that similar individuals receive similar outcomes. Research has shown that it is often mathematically impossible to satisfy all fairness definitions simultaneously, forcing practitioners to make trade-offs depending on the application and ethical priorities.

Real-world examples demonstrate the seriousness of these concerns. Hiring algorithms have been shown to disadvantage women when trained on historically male-dominated data. Predictive policing tools can disproportionately target minority communities, creating feedback loops where increased policing leads to more recorded incidents, reinforcing the model's biased predictions. In criminal justice, the recidivism prediction tool COMPAS sparked significant debate over racial fairness after investigations suggested disparities in error rates between racial groups. These cases underscore how biased ML systems can influence life-altering decisions.

Addressing bias requires interventions throughout the ML lifecycle. Pre-processing techniques include rebalancing datasets, reweighting samples, and carefully analyzing feature selection. In-processing methods involve modifying learning algorithms to incorporate fairness constraints or adversarial debiasing strategies. Post-processing approaches adjust decision thresholds or recalibrate predictions to reduce disparities. However, improving fairness may involve trade-offs with accuracy, complexity, or interpretability. Moreover, fairness is not purely a technical issue; it also requires ethical reflection, regulatory compliance, transparency, and accountability. Organizations such as Partnership on AI and AI Now Institute actively research and promote best practices in responsible AI development. In conclusion, bias and fairness issues in machine learning are deeply intertwined with social structures, historical inequalities, and technical design decisions. As ML systems continue to influence critical aspects of society, ensuring fairness is not optional but essential. It requires careful data collection, transparent modeling practices, rigorous evaluation across demographic groups, and ongoing monitoring after deployment. Ultimately, achieving fairness in ML demands collaboration between technologists, policymakers, ethicists, and communities to ensure that AI systems serve all members of society equitably and responsibly.

FUTURE OF MACHINE LEARNING IN PUBLIC DECISION MAKING

The future of Machine Learning (ML) in public decision making is expected to significantly transform the way government's function and deliver services to citizens. Machine learning, a branch of artificial intelligence, enables systems to analyze large amounts of data, identify patterns, and make predictions with minimal human intervention. In recent years, governments across the world have started integrating ML into their administrative processes to improve efficiency, transparency, and evidence-based governance. As public institutions collect vast amounts of data related to population demographics, healthcare, education, environment, and economic activities, ML provides powerful tools to convert this raw data into meaningful insights that support better policy formulation and implementation

One of the most important applications of ML in public decision making is smarter policy design. Traditionally, policies were often based on limited data and expert opinion. However, with machine learning, governments can simulate and predict the outcomes of policies before implementing them. By analyzing historical trends and real-time datasets, ML models can identify vulnerable populations, forecast economic growth, and estimate the social impact of proposed initiatives. Such data-driven approaches reduce uncertainty and help policymakers make informed decisions that are more aligned with citizens' needs.

Another significant area where ML is shaping the future is data-driven governance. Governments increasingly rely on real-time data analysis to monitor economic indicators, track public health trends, and detect irregularities in welfare distribution. Machine learning algorithms can quickly analyze large datasets, enabling authorities to respond faster and more accurately. ML systems are also used to detect fraud in tax systems and public welfare schemes, ensuring that resources reach the intended beneficiaries and reducing financial losses

Machine learning also plays a crucial role in public safety and smart city initiatives. By analyzing crime data, ML models can identify crime hotspots and help law enforcement agencies allocate resources more effectively. Traffic management systems use data analytics to optimize traffic signals, reduce congestion, and improve emergency response times. In disaster management, ML models can predict floods, earthquakes, and extreme weather events by studying environmental patterns. This allows governments to take preventive measures, issue early warnings, and minimize damage to life and property.

In the field of healthcare and social welfare, ML is transforming service delivery and planning. Predictive analytics can forecast disease outbreaks, estimate hospital admission rates, and optimize the distribution of medical supplies. Machine learning can also help identify eligible beneficiaries for social programs by analyzing socioeconomic data, thereby improving the fairness and effectiveness of welfare distribution.

PYTHON IS THE BACKBONE OF DATA SCIENCE

1. Introduction to Data Science

Data Science is a multidisciplinary field that uses scientific methods, processes, algorithms, and systems to extract knowledge and insights from structured and unstructured data. It combines statistics, mathematics, programming, and domain knowledge.

2. Introduction to Python

Python is a high-level, interpreted programming language known for its simplicity and readability. It supports multiple programming paradigms such as procedural, object-oriented, and functional programming.

3. Why Python is the Backbone of Data Science

Simple and Easy Syntax – Python code is easy to read and write.
Large Ecosystem – Thousands of libraries support data-related tasks.

4. Important Python Libraries

NumPy
Provides support for large, multi-dimensional arrays and mathematical functions.
Pandas
Provides powerful data structures like DataFrame for data manipulation.
Matplotlib
Used for basic plotting and visualization.

Seaborn
Advanced visualization built on Matplotlib.
Scikit-learn
Provides machine learning algorithms for classification, regression, clustering.
TensorFlow
Used for deep learning and neural networks.
Keras
High-level neural networks API running on TensorFlow.

5. ***Data Science Lifecycle Using Python***

- Data Collection – Using APIs, Web Scraping, Databases.
- Data Cleaning – Handling missing values and duplicates.
- Data Exploration – Using statistics and visualization.
- Feature Engineering – Selecting important variables.
- Model Building – Applying ML algorithms.
- Model Evaluation – Checking accuracy and performance.
- Deployment – Deploying model into real-time applications.

6. ***Advantages of Python in Data Science***

- Open Source and Free
- Easy Integration with Cloud Platforms
- Supports Automation
- Powerful Visualization Tools
- Large Job Market Demand
- Rapid Development and Prototyping

7. ***Conclusion***

Python is considered the backbone of Data Science because it supports every stage of the data science lifecycle. From data preprocessing to advanced machine learning and deployment, Python provides flexibility, scalability, and powerful tools. Its simplicity and strong ecosystem ensure its dominance in the future of Data Science.

ROLE OF SQL IN DATA ANALYSIS AND GOVERNANCE

SQL (Structured Query Language) is the universal language for querying, transforming, and governing relational data. From exploratory analysis to enterprise-scale compliance, it remains the backbone of the modern data stack

1. SQL as the Backbone of Data Analysis

a. Efficient Data Retrieval

SQL allows analysts to query massive datasets efficiently. Using commands like SELECT, JOIN, GROUP BY, and ORDER BY, analysts can extract relevant information from multiple tables. This makes SQL ideal for generating insights, dashboards, and reports.

b. Data Transformation and Cleaning

Data rarely comes in a ready-to-use form. SQL helps analysts clean, filter, and reshape raw datasets through operations such as:

- Removing duplicates (DISTINCT)
- Handling missing values using CASE WHEN
- Creating new calculated fields
- Filtering noisy or irrelevant data

These capabilities ensure high-quality, analysis-ready datasets.

c. Aggregations for Business Insights

SQL's aggregate functions—such as SUM, COUNT, AVG, and MAX—enable analysts to perform descriptive analytics quickly. This supports decision-making in areas like sales performance, customer behavior, and operational efficiency.

d. Integration With Analytics Tools

Because SQL is universally supported, it integrates seamlessly with BI and data tools like:

- Tableau
- Power BI
- Python (via libraries like SQLAlchemy)
- R
- Excel

This enables smooth workflows between raw data extraction and advanced analytics or visualization.

2. SQL's Role in Data Governance

Data governance focuses on ensuring that corporate data is accurate, secure, and reliable. SQL plays a major role in enforcing these standards.

a. Ensuring Data Quality

SQL databases enforce rules that maintain data consistency, such as:

- Constraints (PRIMARY KEY, FOREIGN KEY, CHECK)
- Data types that prevent invalid entries
- Triggers for automated validations

SQL enables fine-grained access control through:

User roles
Permissions (GRANT, REVOKE)
Authentication mechanisms
This ensures that only authorized individuals can view or modify sensitive data, supporting compliance with regulations like GDPR and HIPAA.

a. Audit Trails and Accountability
Many SQL-based systems maintain logs that track:

- Who accessed data
- When changes were made
- What queries were executed

Such logs are essential for audits, security investigations, and compliance monitoring.

b. Metadata Management
SQL systems often include tools for managing metadata—information about the data itself. This helps organizations understand:

- Data origins
- Transformation history
- Current usage
- Good metadata practices strengthen data transparency and governance frameworks.

Conclusion
SQL remains a cornerstone of modern data ecosystems. Its power in data analysis helps analysts derive meaningful insights efficiently, while its strong capabilities in data governance ensure that data is accurate, compliant, and secure. As organizations continue to grow their data assets, SQL will continue to be a critical tool in maintaining quality and extracting value.

DATA VISUALIZATION TOOLS FOR PUBLIC COMMUNICATION

Data visualization plays a critical role in helping the public understand complex information quickly and accurately. By converting raw data into clear charts, maps, and interactive dashboards, organizations can communicate insights in a transparent and engaging manner.

Why Data Visualization Matters

1. Simplifies Complex Data

Visuals make it easier for people with little technical background to understand trends, comparisons, and patterns.

2. Builds Transparency and Trust

Clear visual reporting helps governments, media, and institutions communicate openly, increasing public confidence.

3. Enhances Public Engagement

Interactive dashboards and visually appealing graphics encourage exploration and deeper engagement with issues.

4. Supports Timely Decision-Making

Visual tools help the public and policymakers interpret data quickly during emergencies, elections, or health crises.

Popular Tools Used in Public Communication

- Tableau: Interactive dashboards and storytelling visuals.
- Power BI: Easy-to-share reports for government and corporate communication.
- Google Looker Studio: Free and ideal for online public reporting.
- Flourish: Media-friendly interactive charts and scrollytelling.
- Datawrapper: Clean charts and maps used widely in journalism.
- Infogram: Infographics suitable for social media and awareness campaigns.

Key Features That Make These Tools Effective

Interactivity: Filters, clickable maps, and dynamic charts.
Accessibility: Mobile-friendly and color-blind–aware designs.
Ease of Sharing: Embed visuals in websites or share via links.
Custom Storytelling: Templates and layouts for clear narrative flow.

Conclusion

Data visualization tools help bridge the gap between complex data and public understanding. By presenting information in a clear, engaging, and accessible form, these tools strengthen transparency, support informed decision-making, and enhance public communication across sectors.

CLOUD COMPUTING AND DATA SCIENCE WORKFLOWS

Cloud computing has become a foundational technology for modern data science, enabling organizations to store, process, and analyze massive volumes of data with unprecedented scalability and flexibility. As data continues to grow exponentially, traditional on-premise systems often struggle with limitations in storage, computing power, and cost. Cloud platforms—such as AWS, Google Cloud, and Microsoft Azure—address these challenges by offering on-demand resources, advanced analytics tools, and seamless integration for end-to-end data science workflows.

A typical data science workflow includes several key stages: data collection, storage, processing, modeling, and deployment. Cloud computing enhances each of these stages through its distributed architecture. For data collection, cloud services provide scalable ingestion tools that can capture structured and unstructured data from multiple sources in real time. Storage solutions like object stores and managed databases offer virtually unlimited capacity with high durability, allowing data scientists to access and organize large datasets efficiently.

Data processing is one of the areas where the cloud demonstrates its greatest strengths. Using distributed computing frameworks—such as Apache Spark, Hadoop, or cloud-native serverless functions—large datasets can be processed in parallel, significantly reducing computation time. This scalability makes it possible to experiment with complex machine learning models that require intensive computation.

Once the data is prepared, cloud-based machine learning services streamline model development. Platforms such as Google Vertex AI, AWS SageMaker, and Azure Machine Learning provide tools for automated model training, hyperparameter tuning, experiment tracking, and version control. They also allow data scientists to work collaboratively and share resources through managed notebooks and integrated pipelines.

Model deployment—often one of the most challenging steps—becomes more efficient with the cloud. Models can be deployed as APIs, serverless functions, or edge services with auto-scaling capabilities. This ensures that applications remain responsive even under high user demand. Cloud monitoring tools also help track performance, detect anomalies, and manage model updates in production environments.
Overall, cloud computing transforms the data science workflow into a highly agile, scalable, and cost-effective operation. By reducing infrastructure constraints and offering advanced capabilities, the cloud empowers organizations to accelerate innovation and make data-driven decisions with greater accuracy and speed. As data science continues to evolve, cloud technologies will remain central to building robust, efficient, and future-ready analytics systems.

OPEN-SOURCE TOOLS TRANSFORMING DATA SCIENCE

Open-source tools have become the backbone of modern data science, reshaping how professionals analyze data, build models, and deploy intelligent solutions. Unlike proprietary software, open-source tools provide transparency, flexibility, and community-driven innovation—making them indispensable for both beginners and advanced practitioners.

At the heart of this transformation is Python, now the most widely used programming language in data science. Its open-source libraries—such as NumPy, Pandas, and Matplotlib—enable efficient data manipulation, statistical analysis, and visualization. These tools reduce the complexity of working with large datasets and allow users to build custom workflows with ease. The open nature of Python fosters continuous improvement, with new features and community contributions rapidly expanding its capabilities.

Another key category is machine learning frameworks. Scikit-learn has simplified classical machine learning through its intuitive API and collection of supervised and unsupervised algorithms. For deep learning, TensorFlow and PyTorch dominate the ecosystem. Both are open source and provide powerful tools for building neural networks, computer vision models, and natural language systems. Their flexibility and active communities make cutting-edge research easily accessible to practitioners worldwide.

In recent years, open-source tools for big data have also gained prominence. Apache Spark enables distributed processing of huge datasets, dramatically reducing computation time compared to traditional single-machine methods. Paired with Hadoop and other components of the Apache ecosystem, Spark supports large-scale analytics and real-time data streaming—crucial for enterprise applications.
Data visualization and dashboarding have been revolutionized as well. Tools like Plotly, Bokeh, and Apache Superset allow teams to create interactive visualizations and dashboards without relying on expensive commercial software. These tools bring clarity to complex data and make insights more accessible to decision-makers.

Open-source tools also play a pivotal role in workflow automation and reproducible research. Jupyter Notebooks enable interactive coding and documentation, while Git and GitHub support version control and collaboration. In addition, platforms like Airflow, Luigi, and Prefect help automate pipelines so data scientists can operationalize projects more efficiently.

Ultimately, open-source tools are democratizing data science. They empower individuals and organizations—regardless of budget—to explore data, build models, and deploy scalable solutions. As communities continue to innovate, open-source technologies will remain at the forefront of advancing data science and shaping its future.

Empirical Studies

PREDICTIVE MODELS IN HEALTHCARE AND DISEASES DETECTION

Predictive models in healthcare use AI, machine learning, and historical data to forecast patient outcomes, detect diseases early, and optimize treatment, shifting care from reactive to proactive. These models analyze patient records, imaging, and lifestyle data to identify high-risk individuals, reducing mortality, readmissions, and operational costs.

Key Applications in Disease Detection & Management

- Chronic Disease Risk: Models predict the likelihood of diabetes, cardiovascular diseases (heart attacks/strokes), and kidney failure based on patient vitals and health history.
- Early Diagnosis: AI algorithms detect patterns in medical imaging or genomic data for early cancer detection, such as lung cancer recognition.
- Patient Deterioration: Real-time monitoring of, for example, in-patient data to identify potential infections or sudden health deterioration before symptoms become critical.
- Preventive Care: Identification of high-risk patients allows clinicians to intervene with personalized, preventative measures, reducing long-term costs.
- Common Methodologies and Techniques
- Machine Learning (ML): Algorithms such as XGBoost, Decision Trees, and Random Forests are used to classify patient data and predict outcomes.
- Deep Learning (DL): Neural networks, including Convolutional Neural Networks (CNNs), are employed for analyzing complex data like medical images.
- Data Sources: Models rely on EHR (Electronic Health Records), IoT wearables, genomic, and imaging data.

Limitations and Challenges

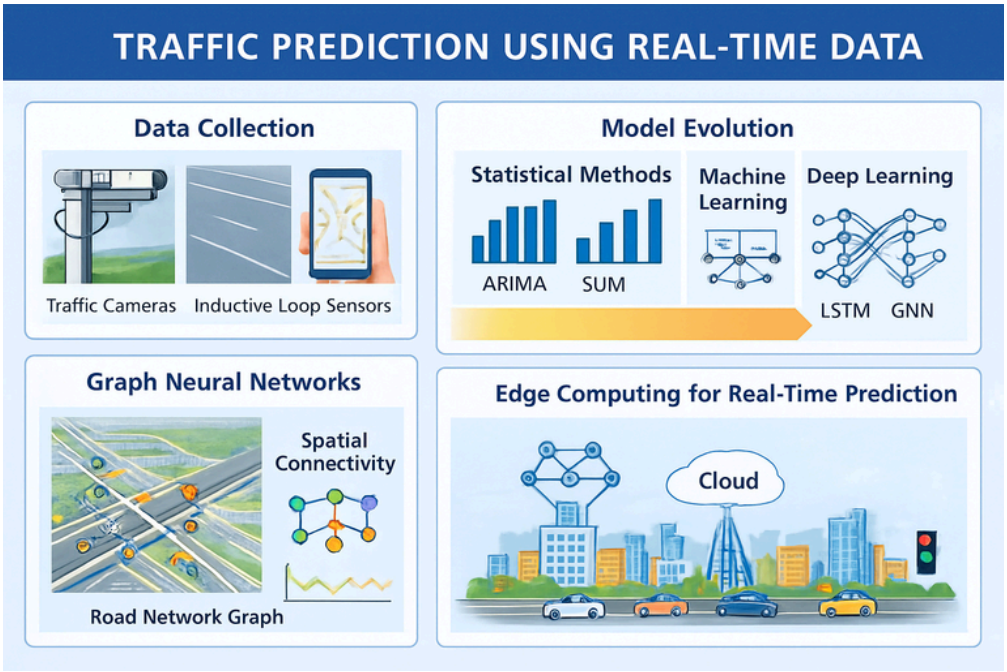
- Data Bias: Models may inherit biases from non-representative training data, potentially leading to inequitable care.
- Data Privacy: Ensuring patient data security during model development is critical, requiring strict compliance with protocols.

Future Outlook

The integration of federated learning allows for training robust models across different institutions without sharing sensitive patient data directly. This approach promises to improve personalized medicine and overall healthcare efficiency.

TRAFFIC PREDICTION USING REAL TIME DATA

Traffic prediction is a deal in computer science. It is about using new data from sensors and phones to guess what the traffic will be like in the future. This is a part of making smart roads. It helps to keep the traffic moving reduce jams make travel times shorter use fuel and make it easier for emergency services to get around. As more people move to cities and there are cars on the road traffic is becoming a huge problem all over the world. We really need to be able to predict the traffic so that cities can keep moving.



Traffic prediction is mainly about working out how fast the cars are going, how cars there are, how closely they are packed and how long it takes to get from one place to another.. Traffic is really hard to predict because it changes all the time and is affected by lots of things. These things include where you are, what time it is, the weather, accidents and big events.

The data we get about traffic is also very complicated. A time ago people used special math models like Autoregressive Integrated Moving Average to predict the traffic. These models are good for short-term predictions. Help us understand how traffic works.. They do not take into account how different roads are connected.

We get traffic data from lots of places. We have sensors in the road, cameras, radar and LIDAR. We also get data from phones, GPS and special platforms that collect data from lots of people. We can even use weather forecasts and information about events to make our predictions better. But the data is not always perfect so we have to clean it up and make it better before we can use it. This means getting rid of data making sure it is all in the same format and combining it with other data.

Now that computers are faster and we have data we are using machine learning and deep learning to predict the traffic. These methods are better than the math models. We use models like Support Vector Machines, Random Forests and k-nearest neighbors. These models are good. We have to be careful about how we prepare the data. Deep learning models are even better at working out what the data means. Some models, like Recurrent Neural Networks are good at understanding how things change over time. Others, like Convolutional Neural Networks are good at understanding how things are connected.

Recently we have started using something called Graph Neural Networks. These models are like maps of the roads. They help us understand how the traffic is connected. They are really good at working out patterns in the data. We can even combine models to make them work better.

Predicting the traffic in time is hard because we have to deal with delays it costs a lot to process the data and it has to work for a lot of people.. If we use something called edge computing we can process the data closer to where it is needed and it makes the predictions faster and more efficient. This is especially good when we use it with learning.

FRAUD DETECTION IN DIGITAL PAYMENTS

Problem Statement

A leading digital payment company faced rising cases of fraudulent transactions, resulting in financial losses and declining customer trust. Traditional rule-based systems were ineffective against evolving fraud patterns, as fraudsters continuously adapted their techniques to bypass static rules.

Data Collection and Features

The system collected large volumes of transactional data, including:

- Transaction amount and frequency
- User location and device information
- Time of transaction
- Merchant category
- Historical user behavior patterns

These features helped in identifying anomalies and suspicious activities.

Approach and Methodology

The company implemented a machine learning-based fraud detection system. The workflow included:

- Data Preprocessing: Cleaning and handling imbalanced data (since fraud cases are rare). Techniques like oversampling (SMOTE) were used.
- Feature Engineering: Creating new variables such as transaction velocity and deviation from normal behavior.
- Model Selection: Algorithms like Logistic Regression, Random Forest, and Gradient Boosting were tested.
- Advanced Techniques: Deep learning models and anomaly detection methods (e.g., Autoencoders) were introduced for better accuracy.

Real-Time Detection System

A real-time pipeline was deployed using streaming technologies. Each transaction was analyzed instantly, and a fraud score was generated. If the score exceeded a threshold, the transaction was flagged or blocked, and the user was notified.

Results and Impact

- Fraud detection accuracy improved significantly
- False positives (legitimate transactions flagged as fraud) were reduced
- Real-time alerts increased customer trust and satisfaction
- Financial losses due to fraud decreased

Challenges

- Handling highly imbalanced datasets
- Maintaining low latency for real-time decisions
- Ensuring data privacy and regulatory compliance
- Adapting to new and sophisticated fraud techniques.

CLIMATE DATA AND DISASTER FORECASTING

1. Background

Climate change has increased the frequency and intensity of natural disasters such as floods, cyclones, droughts, and heatwaves. Accurate forecasting using climate data has become critical to reduce damage and save lives.

This case study examines how climate data analytics helped forecast and manage Cyclone Fani (India, 2019).

2. Problem Statement

India's eastern coast is highly vulnerable to cyclones.

Before 2019, disaster response systems faced challenges:

Limited early warning accuracy
Delayed evacuation planning
High casualty rates
Poor coordination between agencies

The need was to use climate data for precise and early disaster forecasting.

3. Data Sources Used

Meteorological agencies collected massive datasets, including:

Satellite Data – cloud movement, sea surface temperature
Ocean Buoy Data – wave height, wind speed, pressure
Historical Climate Data – past cyclone patterns
Radar Systems – real-time storm tracking
Numerical Weather Prediction (NWP) Models

4. Methodology

a. Data Collection

Real-time and historical data were gathered from:

- Indian Meteorological Department (IMD)
- NASA and NOAA satellites

b. Data Processing

Cleaning and integrating multi-source data
Using machine learning models to detect patterns

c. Forecasting Models

Cyclone track prediction models
Intensity prediction algorithms
Storm surge simulation models

d. Visualization

GIS maps showing cyclone path
Risk zone mapping

5. Implementation

- IMD issued accurate forecasts 4–5 days in advance
- Government used predictions to:
  - Evacuate over 1 million people
  - Pre-position relief materials
  - Shut down transport systems
  - Alert fishermen and coastal communities

6. Results

- Significant reduction in casualties compared to past cyclones
- Improved accuracy in cyclone path prediction
- Faster response and coordination
- Economic losses were minimized

7. Key Technologies Used

- Big Data Analytics
- Machine Learning
- Remote Sensing
- Geographic Information Systems (GIS)
- Cloud Computing

8. Challenges

- Data gaps in rural/coastal regions
- High computational cost
- Model uncertainties
- Communication barriers in remote areas

9. Lessons Learned

Early warning systems save lives
Integration of multiple data sources improves accuracy
Government preparedness is as important as forecasting
Public awareness is critical

10. Conclusion

Climate data-driven disaster forecasting has transformed disaster management. The Cyclone Fani case shows how data science and climate analytics can significantly reduce human and economic losses, making forecasting systems essential for climate resilience.

Brain Teasers

QUIZ

1.Which of the following is NOT a step in the Data Science process?

(a) Data Collection
(b) Data Cleaning
(c) Data Visualization
(d) Data Guessing

2.Which programming language is most widely used in Data Science?

(a) Python
(b) C++
(c) Java
(d) PHP

3.What does PCA (Principal Component Analysis) primarily do?

(a) Classification
(b) Dimensionality Reduction
(c) Regression
(d) Clustering

4.Which metric is best for evaluating classification models with imbalanced datasets?

(a) Accuracy
(b) Precision
(c) Recall
(d) F1-Score

5.Which algorithm is commonly used for clustering?

(a) Decision trees
(b) Linear Regression
(c) K-Means
(d) Naive Bayes

6.Which type of learning uses labeled data?

(a) Supervised Learning
(b) Unsupervised Learning
(c) Reinforcement Learning
(d) Semi-supervised Learning

7.Which of the following is a measure of model overfitting?

(a) Low training accuracy but low test accuracy
(b) High training accuracy and high test accuracy
(c) Equal training and test accuracy
(d) None of the above

8.Which library is most popular for deep learning in Python?

(a) NumPy
(b) Pandas
(c) Tensor flow
(d) Matplotlib

9.Which visualization is best for showing correlation between two variables?

(a) Bar Chart
(b) Scatter Plot
(c) Pie Chart
(d) Line Chart

10.Which SQL command is used to retrieve data?

(a) SELECT
(b) UPDATE
(c) DELETE
(d) INSERT

11.Which distribution is often assumed in statistical modeling?

(a) Uniform Distribution
(b) Normal Distribution
(c) Poisson Distribution
(d) Exponential Distribution

12.Which evaluation metric is used for regression models?

(a) Mean Squared Error (MSE)
(b) Accuracy
(c) F1-Score
(d) ROC Curve

13.Which algorithm is used for recommendation systems?

(a) Collaborative Filtering
(b) K-Means
(c) Logistic Regression
(d) Random Forest

14.Which of the following is a feature scaling technique?

(a) Regression
(b) Classification
(c) Normalization
(d) Clustering

15.Which type of bias occurs when training data does not represent the real-world population?

(a) Sampling Bias
(b) Measurement Bias
(c) Confirmation Bias
(d) None

16.Which algorithm is best for text classification?

(a) K-Means
(b) Naïve Bayes
(c) PCA
(d) Linear Regression

17.Which Python library is used for data manipulation and analysis?

(a) Pandas
(b) Matplotlib
(c) Seaborn
(d) Scikit-learn

18.Which metric is used to evaluate clustering performance?

(a) Silhouette Score
(b) Accuracy
(c) Precision
(d) Recall

19.Which algorithm is commonly used for decision-making in reinforcement learning?

(a) Q-Learning
(b) K-Means
(c) Logistic Regression
(d) PCA

20.Which of the following is a Big Data framework?

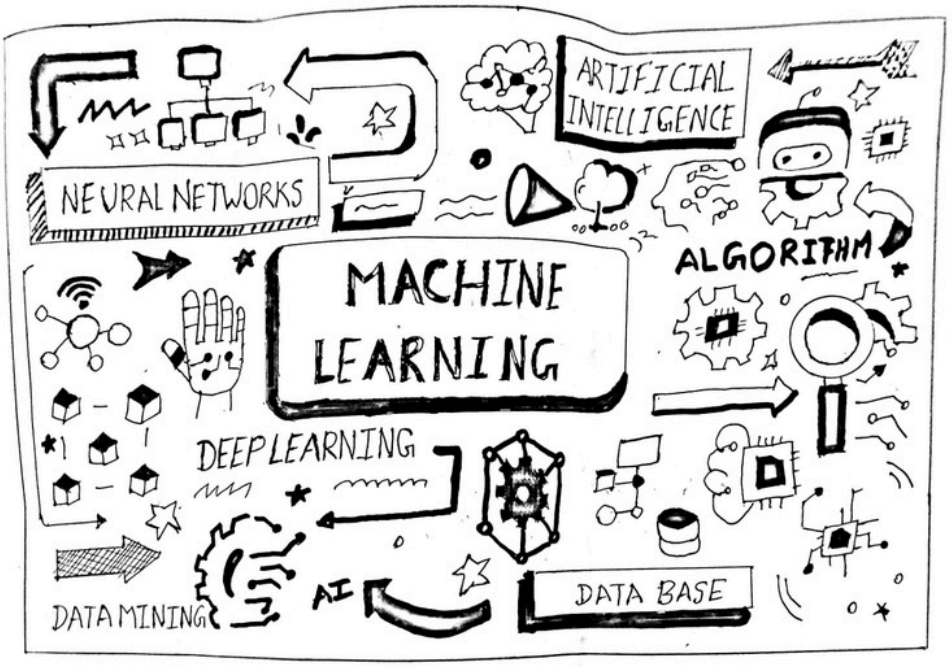
(a) Hadoop
(b) NumPy
(c) Pandas
(d) Matplotlib

Answers

1)D	***6)A***	***11)B***	***16)B***
2)A	***7)B***	***12)A***	***17)A***
3)B	***8)A***	***13)A***	***18)A***
4)D	***9)C***	***14)C***	***19)A***
5)C	***10)A***	***15)A***	***20)A***

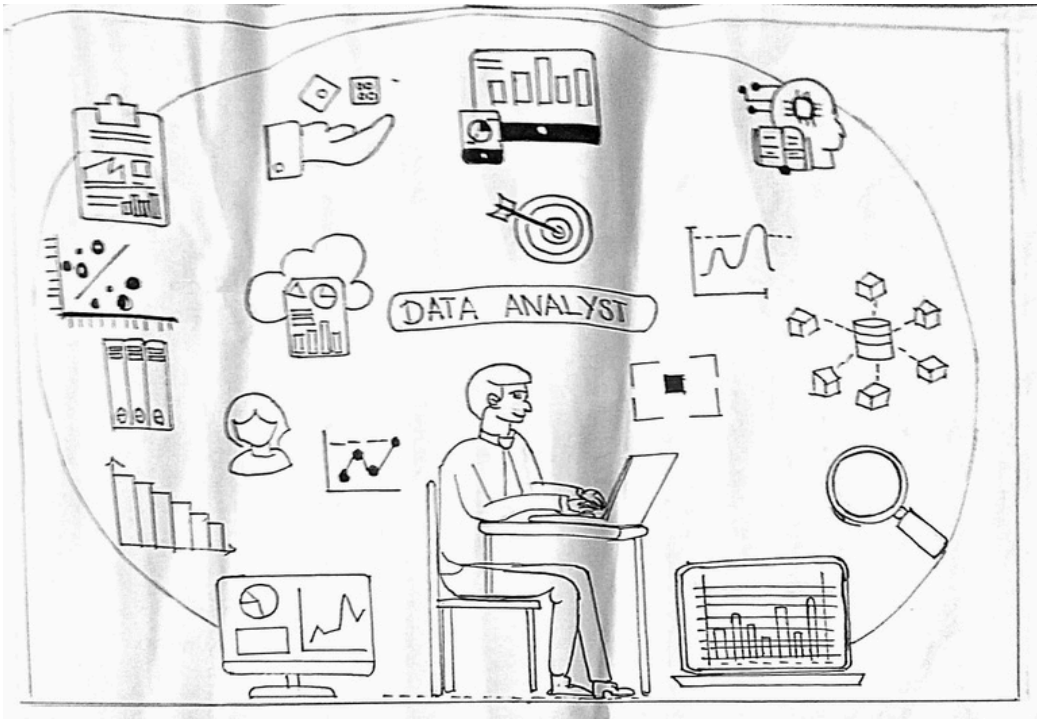
Visual Vibes

Components of Machine learning



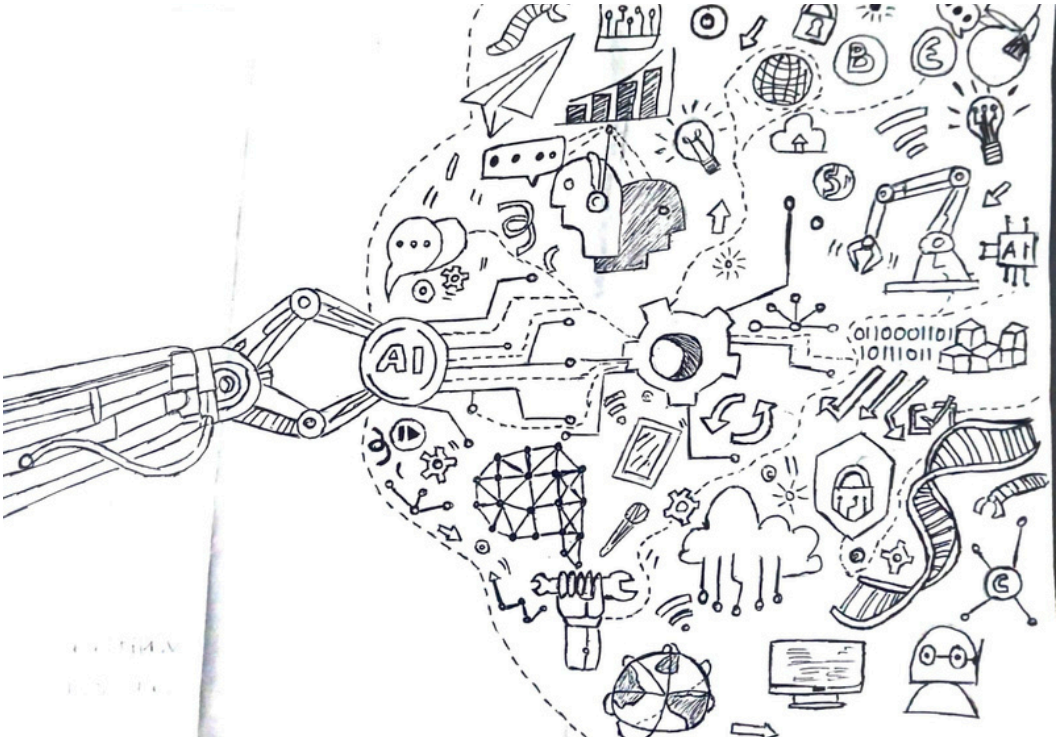
24DSC221
S.ASWIN

The World Inside Machine Learning



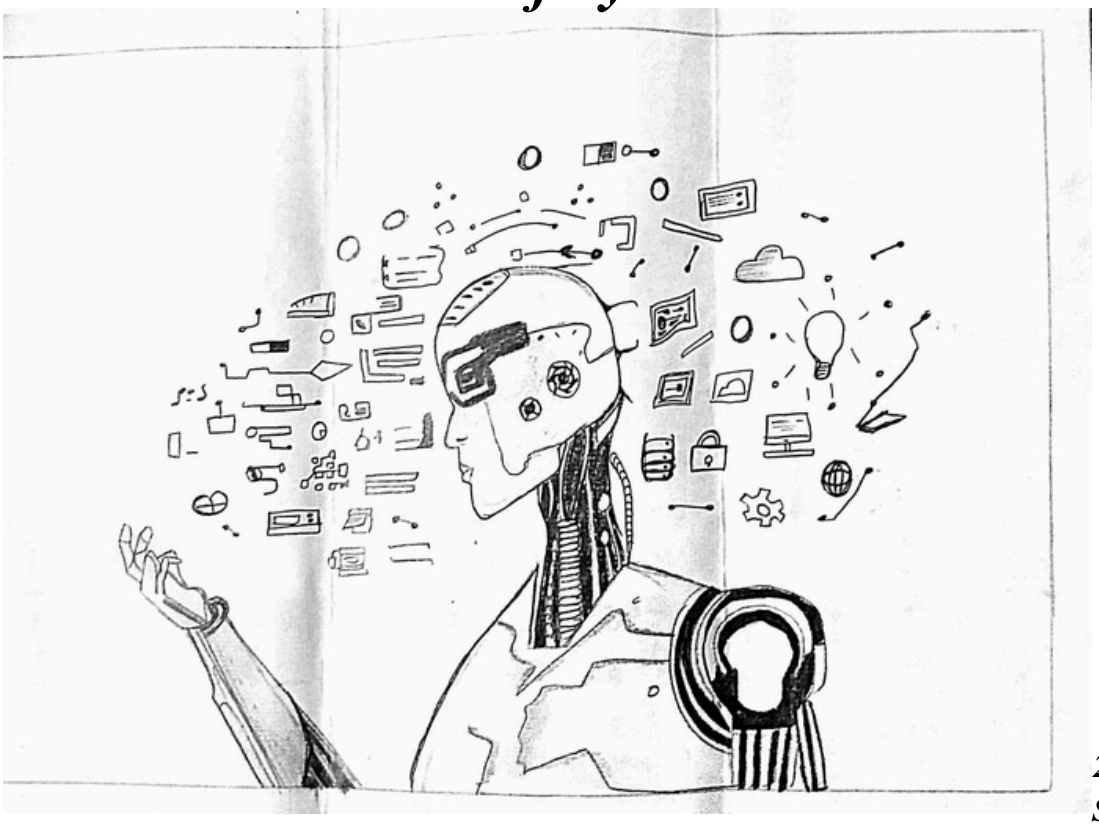
24DSC202
K.ABINAYA

The Engine of Innovation:



24DSC217
V.NITHISH

Architect of Synthesis



24DSC214
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