Chapter 1: Introduction to Analytics

Contents:- Introduction to Business analytics, Types of Analytics : predictive models, descriptive models, prescriptive models, Applications, Analytical techniques

Introduction to Business analytics

- Business analytics refers to new skills, naive practices, marketing, new technologies, and business tools algorithms for **continuous iterative exploration**.
- It is used for deep investigation of past business performance of the respective company and also the competitors of that company in the market to gain its own insight and of its competitors i.e **what they do, how they do, what mistakes they do so far, what are the false commitments they do with their clients or consumer.**
- This data is quite useful for an organization during market enhancement and drive the whole business planning in an effective way.
- Data Analytics, etc. which can also be the **part of a skilled Business Analyst**. Business Analytics makes large use of **statistical analysis** in a modern way.
- It also includes **explanatory and predictive modelling** methods, fact-based management, and fixed data/information driven based management to drive decision making in an effective manner.
- It is therefore very closely related to management science, data science, and data analytics. Analytics used as input for driven human decisions or may drive fully automated decisions.

Types of Analytics

1. Descriptive:

Descriptive analytics is the **application of earlier and simple statistical techniques** that are used from the earlier period and also describe what is contained in a data set or database. *Example:* An age bar chart which is used to depict customers for a Gaming company who wants to target the customers for new game production by age.

2. Diagnostic:

Diagnostic analytics is the successor of the Descriptive analytics which allows an analyst to **dig deeper into a problem or issue to arrive at the source of the problem**. It is generally characterized by techniques like data discovery, drill-down, data mining, etc.

3. Predictive:

Predictive analytics is an application of advanced statistical techniques and tools, methods, informatics software, we can also consider all the operations research methods **to identify predictive variables and also which are used to build predictive models** which are used in real time **to identify trends and relationships** which are not readily observed in a descriptive analysis. *Example:* Multiple regression is used to show the relationship between working hours, work type, qualifications on hiring someone on payroll.

4. Prescriptive:

Prescriptive analysis is actually an application of **decision science, management science, and operational research methodologies** (which are also applied mathematical techniques) to make the best use of allocatable resources. *Example:* A startup which has a limited advertising budget and who wants to advertise to target customers only. So the Linear programming models of prescriptive analysis can be used here to optimally allocate the budget of various advertising media for the company focusing on the Target Customer only.

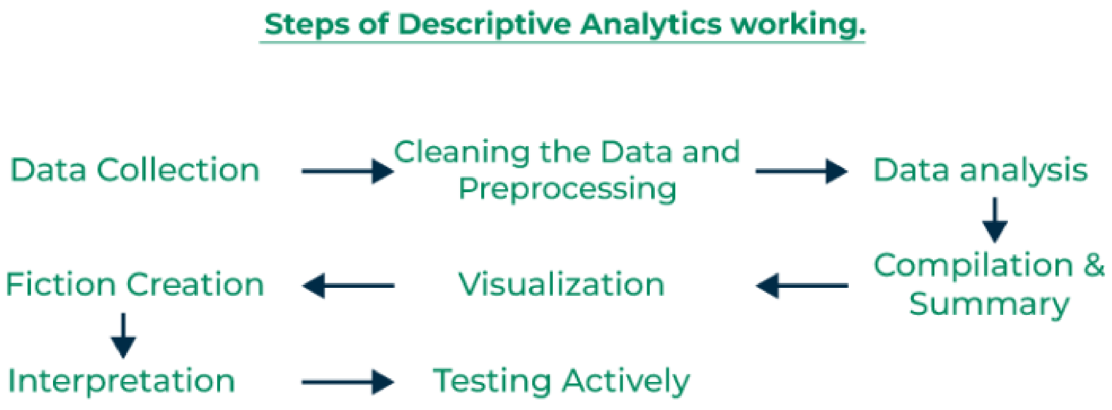
Data analytics can be divided into four key types:

- **Descriptive Analytics:** What happened? (Summarizes past and current data)
- **Diagnostic Analytics:** Why did this happen? (Drills down to identify causes)
- **Predictive Analytics:** What might happen in the future? (Uses trends to forecast future events)
- **Prescriptive Analytics:** What should we do next? (Recommends actions based on predictions)

Descriptive analytics

It uses statistical summaries and data visualization techniques to condense and describe historical data. It helps identify patterns, trends, and relationships within the data, clearly showing **"what happened"** and **"what is currently happening."** Think of it as the foundation for further analysis - it sets the stage for understanding past performance and current trends.

A type of descriptive analytics involves analysing and simplifying historical data to provide insights into previous events, trends, and patterns. It is much closer to reporting than to what most people think of as analytics.



Working of Descriptive analyis

Steps for Descriptive Analytics Work:

1. **Data Collection:** Collecting useful information is the initial stage in the descriptive analytics process. By using multiple resources such as databases, spreadsheets, and other data repositories. All of these provide this data. Since they directly affect how accurate the descriptive analytics is, the accuracy and standard of the data are extremely important.
2. **Cleaning the Data and Preprocessing:** The obtained data usually needs to be cleaned and pre-processed before analysis can start. This includes converting data into a uniform structure, standardizing formats, and handling missing or incorrect values. Clean and well-pre-processed data ensures that the subsequent analytics is reliable.
3. **Data analysis:** It provides an understanding of the structure and features of the dataset. Here EDA (***exploratory data analysis***) methods helps to find the patterns, trends, and possible outliers in the data. These methods include making histograms, scatter plots, and summary statistics.
4. **Compilation and Summary:** The goal of descriptive analytics is to offer an overview of the data at a high level. To get important metrics and statistics, such as mean, median, mode, range, and standard deviation, this frequently requires combining the data.
5. **Visualization:** In descriptive analytics, visualizations are extremely useful tools. It helps us to communicate complex information with a variety of charts, graphs, and other visual representations are employed. Data patterns and trends can be highlighted with the use of visualization, which also makes it easier to convey insights to a wide range of audiences.
6. **Fiction Creation:** Descriptive analytics can include the creation of descriptions that offer a logical and contextualized explanation of the data, in addition to visuals. When communicating findings to those in the audience who might not be familiar with the complexities of the data, this can be especially helpful.
7. **Interpretation:** To obtain significant knowledge, analysts interpret the outcomes of descriptive analytics. This involves knowing the effects of the trends and patterns seen in the data. While interpretation provides the foundation for more in-depth analyses that investigate "why" and "what might happen in the future," descriptive analytics concentrates on the "**what happened**" topic.
8. **Testing Actively:** The process of descriptive analytics is not one-time. Organizations continually repeat the descriptive analytics when new data becomes available in order to keep informed about the latest developments and patterns. This way, people making decisions get the newest information.

Applications of Descriptive Analytics

- **Social Networking Analytics:** In order to analyze user involvement, content performance, and audience demographics, descriptive analytics is used in social media. It assists businesses in customizing their social media plans according on past performance.

- **Crime and Fraud Detection:** Pattern in previous crime data is investigated by law enforcement and security agencies in order to do descriptive analysis which is one of the types of analytics. It is applied by financial organizations to make discoveries of market fluctuations and anomalies that can prevent or can be used to fight them.
- **Crypto Market Analysis:** Cryptocurrency markets are a great source of information for investors, as historical price data, market volumes aggregates, and market trends can be used to analyze the behavior of Bitcoin traders. These algorithms, mood patterns in the market, and possible factors may affect the price fluctuation of Bitcoin can all been fancy with the help of a descriptive analytics.
- **Human Resources Management:** HR uses descriptive analytics to analyze their staff. It aids businesses in the analysis of previous information on worker performance, turnover rates, training effectiveness, and other HR indicators.
- **Risk Assessment and Management:** To identify and analyze historical risk factors, descriptive analytics is used in risk assessment. Organizations need to know this information. This information is really important for companies in areas like banking and insurance to create plans that help reduce and handle risks better.

Advantages of Descriptive Analytics

- **Data-driven decision making:** It provides well-informed decision-making based on facts rather than gut instincts by evaluating and simplifying data.
- **Presents data clearly:** Descriptive analytics simplifies complex data, making it easy to understand through reports and visualizations like charts and graphs.
- **Convenient to Realize:** Data that has been summarized and graphically represented is easier to clarify and evaluate for a larger audience.
- **Identifies Relevant Data Points:** It offers straightforward metrics that give an accurate estimation of important data points.
- **Simple and cost-effective:** Descriptive analytics is simple to use and just requires basic arithmetic knowledge for execution.
- **Efficient with tools:** With the aid of tools like Python or MS Excel, which make things fast and easy.

Disadvantages of Descriptive Analytics

- **Inability of Cause Analysis:** The main goal of descriptive analytics is to explain historical events. It doesn't explore the root causes or reasons for the patterns that are seen.
- **Analysis Simplicity:** The reach of descriptive analytics is restricted to basic analyses that look at the relationships between a small number of variables.
- **Doesn't Explain Why:** History offers lessons for future generations, by offering facts, but causes and predictions are not provided to the readers.
- **Inappropriate for Making Decisions in Real Time:** Normally, descriptive analytics involves getting summary information at intervals intervals and this might not be the best option for decision- making when the time matter. In many situations, fast responsiveness is vital, therefore, sometimes only relying on the descriptive analytics might drag you behind.
- **Lack of ability to handle unstructured data:** Structured and well-organized datasets are better suited for descriptive analytics. while analyzing semi-structured or unstructured data, such as text, photos, or multimedia, it could make challenging to offer insightful analysis.

Diagnostic Analytics

The primary purpose of diagnostic analytics is to uncover the root causes behind trends, anomalies, or issues identified through data analysis. It goes beyond simply describing what's happening (descriptive analytics) to understanding why it's happening.

Key Steps in Diagnostic Analytics

Key steps in Diagnostic Analytics that are followed are as followed:

1. **Identify the Anomaly:** The first step is pinpointing the deviation from the norm. Is it a sudden drop in sales, a spike in customer complaints, or an unexpected equipment failure?
2. **Data Collection:** Begin by gathering relevant data from various sources, ensuring a comprehensive dataset. Compile relevant data from various sources – website logs, customer surveys, sensor readings, financial records – to build a comprehensive picture.
3. **Data Exploration:** Dive into the data to uncover hidden insights and anomalies through statistical analysis and visualization.
4. **Pattern Identification:** Employ advanced algorithms to identify patterns and trends in the data. Analyze the data using techniques like drill-down, data mining, and correlation analysis. This involves sifting through layers of information, identifying patterns, and spotting hidden relationships.

5. **Root Cause Analysis:** Drill down into the data to understand the underlying factors contributing to specific outcomes. Based on your analysis, narrow down the possible causes. Was it a competitor's new campaign? A faulty software update? A change in supplier quality?

6. **Testing and Confirmation:** Design and implement tests to validate your hypothesis. Did the website redesign cause the traffic dip? Did the new marketing campaign trigger customer churn?

Importance of Diagnostic Analytics

- **Informed Decision-Making:** Diagnostic Analytics equips organizations with the information needed to understand why certain events occurred, facilitating strategic decision-making.

- **Performance Evaluation:** Businesses can assess the effectiveness of past strategies and operations, enabling continuous improvement.

- **Root Cause Analysis:** One of the primary goals of diagnostic analytics is to perform root cause analysis. This involves investigating the underlying factors that contribute to a particular outcome, allowing organizations to address fundamental issues rather than just symptoms.

- **Optimizing Processes:** Diagnostic analytics helps organizations optimize their processes by identifying inefficiencies and bottlenecks. Understanding the factors that impact performance enables businesses to streamline operations, improve resource allocation, and enhance overall efficiency.

Benefit of Diagnostic Analytics

By diagnostic analytics, the sectors which can be disrupted are given a range of opportunities, such as versatility, that can be game-changing for organizations. Here are some key advantages:

- **Deeper Insights:** With detection of reasoning behind "what" to "why," diagnostics analytics provide a profound information about data. It serves to expose the reasons, patterns, and problems behind the trends, deviations, and phenomena, hence, you can make sound decisions based on data which backs a case, not an assumption.

- **Improved Problem-Solving:** Diagnostics analytics gives you the capacity of pinning down the real reasons behind what you perceive as a problem. Thus, you have a possibility for directed actions aimed at preventing the root of problems, what, in turn, brings about the sensible solutions and sustainable improvements.

- **Process Optimization:** Diagnostic analysis-driven insights may shed light on the presence of bottlenecks and efficiencies in work flows. The knowledge on how operations fail can help you in adopting improved techniques, boosting productivity and lowering waste.

- **Enhanced Decision-Making:** Diagnostic analytics provides you with a predictive mode of causation and exposition from your data. It enables evidence-based decision making so managers will have tactical strategic choices and we will see a performance improvement.
- **Risk Reduction:** Via detecting issues while they are still small, the diagnostic analytics avoids the development of a crisis and helps in the further mitigation of risks. What it does is increase efficiency by cutting down the time, money and resources your organization spends on unnecessary things.
- **Increased Customer Satisfaction:** Also, retail industries can take advantage of such analytics to uncover the peculiarities about buyer habits and preferences. This in turn enables the businesses to engage in accurate and tailored marketing campaigns which ultimately culminate to personalized experiences and better product offerings, again increased customer satisfaction.
- **Competitive Advantage:** Through the application of diagnostic analytics in performance improvement, coming up with new opportunities and statistically optimizing decisions, you can achieve a great victory over your aging competitors who only depend on intuition and bare-bone data procedures.

Sectors that use Diagnostic Analysis/Applications

diagnostic analytics plays a crucial role in uncovering the "why" behind things across various industries. Here are some real-world examples categorized by field:

1. Business

- **E-commerce:** An online retailer analyzes a dip in sales and profitability for a specific product category (like smart speakers) compared to overall sales goals. Diagnostic analytics might reveal a pricing issue, lack of targeted advertising, or negative customer reviews, allowing for corrective actions.
- **Marketing:** A marketing team sees a decline in website traffic after launching a new ad campaign. Diagnostic analytics can pinpoint which demographics are less engaged, what content isn't resonating, or if there are technical glitches preventing conversions.

2. Healthcare

- **Patient care:** A hospital examines readmission rates for a particular type of surgery. Diagnostic analytics might identify factors like inadequate post-surgical care instructions, lack of follow-up appointments, or specific patient demographics at higher risk.
- **Drug development:** A pharmaceutical company analyzes clinical trial data for a new drug and discovers higher-than-expected side effects in a specific patient subgroup. Diagnostic analytics can help identify the cause and potentially refine the drug's target audience.

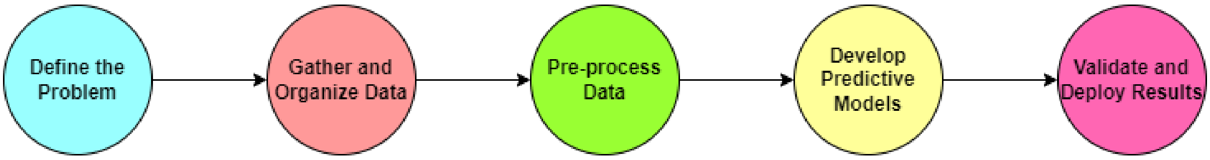
3. Other Applications

- **Website optimization:** A website owner sees a high bounce rate (users leaving quickly). Diagnostic analytics can pinpoint which pages have usability issues, slow loading times, or confusing navigation, allowing for website improvements.
- **Social media engagement:** A social media influencer experiences a sudden drop in audience engagement. Diagnostic analytics can reveal changes in audience demographics, content type fatigue, or negative audience sentiment towards recent posts.

<u>Predictive Analytics</u>

Predictive analytics is a branch of data science that leverages statistical techniques, machine learning algorithms, and historical data to make data-driven predictions about future outcomes.

How Predictive Analytics Modeling works/ steps of Predictive Analytics Model



1. Define a Problem:

- Firstly data scientists or data analysts define the problem.
- Defining the problem means clearly expressing the challenge that the organization aims to focus using data analysis.
- A well- defined problem statement helps determine the appropriate predictive analytics approach to employ.

2. Gather and Organize Data:

- Once you define a problem statement it is important to acquire and organize data properly.
- Acquiring data for predictive analytics means collecting and preparing relevant information and data from various sources like databases, data warehouses,

external data providers, APIs, logs, surveys, and more that can be used to build and train predictive models.

3. Pre-process Data:

- Now after collecting and organizing the data, we need to pre-process data.
- Raw data collected from different sources is rarely in an ideal state for analysis. So, before developing a predictive models, data need to be pre-processed properly.
- Pre-processing involves cleaning the data to remove any kind of anomalies, handling missing data points and addressing outliers that could be caused by errors or input or transforming the data , which can be used for further analysis.
- Pre-processing ensures that data is of high quality and now the data is ready for model development.

4. Develop Predictive Models:

- Data scientists or data analysts leverage a range of tools or techniques to develop a predictive models based on the problem statement and the nature of the datasets.
- Now techniques like machine learning algorithms, regression models , decisions trees, neural networks are much among the common techniques for this.
- These models are trained on the prepared data to identify correlations and patterns that can be used for making predictions.

5. Validate and Deploy Results:

- After building the predictive model, validation is the critical steps to assess the accuracy and reliability of predictions.
- Data scientists rigorously evaluate the model's performance against known outcomes or test datasets.
- If required, modifications are implemented to improve the accuracy of the model.
- Once the model achieve satisfactory outcomes it can be deployed to deliver predictions to stakeholders.
- This can be done through applications, websites or data dashboards, making the insights easily accessible to decision makers or stakeholders.

Predictive Analytics Techniques:

Predictive analytical models leverage historical data to anticipate future events or outcomes, employing several distinct types:

- **Classification Models**: These predict categorical outcomes or categorize data into predefined groups. Examples include Logistic Regression, Decision Trees, Random Forest, and Support Vector Machine.
- **Regression Models**: Used to forecast continuous outcome variables based on one or more independent variables. Examples include Linear Regression, Multiple Regression, and Polynomial Regression.
- **Clustering Models**: These group similar data points together based on shared characteristics or patterns. Examples comprise K-Means Clustering and Hierarchical Clustering.
- **Time Series Models**: Designed to predict future values by analyzing patterns in historical time-dependent data. Examples include Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing Models.
- **Neural Networks Models**: Advanced predictive models capable of discerning complex data patterns and relationships. Examples encompass Feed Forward Neural Networks, Recurrent Neural Networks, and Convolutional Neural Networks.

Benefits of Using Predictive Analytics/ Advantages:

- **Improved Decision Making:** Predictive analytics enables businesses to make informed decisions by analyzing trends and patterns in historical data. This allows organizations to develop market strategies tailored to the insights gained from data analysis, leading to more effective decision-making processes.
- **Enhanced Efficiency and Resource Allocation**: By leveraging predictive analytics, businesses can optimize their operational processes and allocate resources more efficiently. This leads to cost savings, improved productivity, and better utilization of available resources.
- **Enhanced Customer Experience:** Predictive analytics enables businesses to enhance the customer experience by providing personalized product recommendations based on user behaviour. By analyzing customer data, businesses can understand individual preferences and tailor their offerings accordingly, leading to increased customer satisfaction and loyalty.

Applications of Predictive Analytics

Predictive analytics has a vast range of applications across different industries. Here are some key examples:

Applications of Predictive Analytics in Business

- **Customer Relationship Management (CRM):** Predicting customer churn (customer leaving), recommending products based on past purchases, and personalizing marketing campaigns.

- **Supply Chain Management:** Forecasting demand for products, optimizing inventory levels, and predicting potential disruptions in the supply chain.
- **Fraud Detection:** Identifying fraudulent transactions in real-time for financial institutions and e-commerce platforms.

Applications of Predictive Analytics in Finance

- **Credit Risk Assessment:** Predicting the likelihood of loan defaults to make informed lending decisions.
- **Stock Market Analysis:** Identifying trends and patterns in stock prices to inform investment strategies.
- **Algorithmic Trading:** Using models to automate trading decisions based on real-time market data.

Applications of Predictive Analytics in Healthcare

- **Disease Outbreak Prediction:** Identifying potential outbreaks of infectious diseases to enable early intervention.
- **Personalized Medicine:** Tailoring treatment plans to individual patients based on their genetic makeup and medical history.
- **Readmission Risk Prediction:** Identifying patients at high risk of being readmitted to the hospital to improve patient care and reduce costs.

Applications of Predictive Analytics in Other Industries

- **Manufacturing:** Predicting equipment failures for preventive maintenance, optimizing production processes, and improving product quality.
- **Insurance:** Tailoring insurance premiums based on individual risk profiles and predicting potential claims.
- **Government:** Predicting crime rates for better resource allocation and crime prevention strategies.

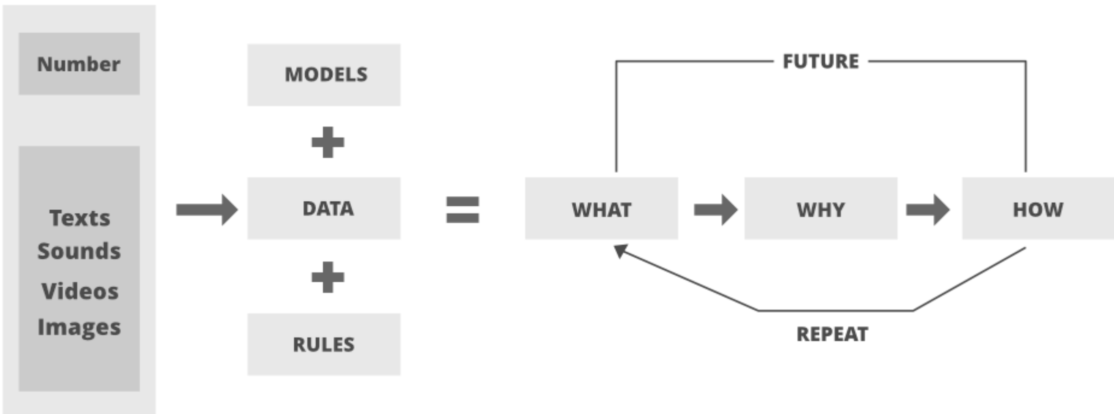
Practical example: https://medium.com/@caulilabs/descriptive-diagnostic-predictive-analytics-project-python-1440b1230fbe

Prescriptive Analytics

Prescriptive Analytics is the area of Business Analytics dedicated to searching out the best solution for day-to-day occurring problems. It is directly related to the other two comparable processes, i.e. *Descriptive and Predictive Analytics*. *Prescriptive Analytics* can be defined as a type of data analytics that uses algorithms and analysis of raw data to achieve better and more effective decisions for a long and short span of time. It suggests strategy over possible scenarios, accumulated statistics, and past/present databases collected through the consumer community.

Example

Google's Self-driving car, **Waymo** is a preferred example showing prescriptive analytics. It showcases millions of calculations on every trip. The car makes its own decision to turn in whichever direction, to slow/speed up and even when and where to change lanes- these acts are every day like any human being's decision-making process while driving a car.



Prescriptive Analytics Approach

Step 1 Data Collection: Gather data for a customer's locations, their requirement, company warehouses, and transportation

Step 2 Mathematical Modeling: We will create mathematical models that will handle supply chain data like customer location, time, warehouse location, and routes, we will also finalize an optimization function that will minimize company cost and delivery time

Step 3 Optimization: We will use an optimization approach like linear programming or differential calculus to solve mathematical models and find optimal locations.

Step 4 Scenario Analysis: We will perform a scenario analysis for our assumptions variables about the models.

Step 5 Decision Support: Based on our data modeling and business knowledge that we got from the raw data we will create dashboards and visualization graphs that will stakeholders in taking decisions.

Step 5 Implementation: The Final and most important part after doing all the five steps is to implement it with changes that maximizes the company's revenues

Advantages of Prescriptive Analytics

- Effortlessly map Business analysis to declare out steps necessary to avoid failure and achieve success.
- An accurate and Comprehensive form of data aggregation and analysis also reduces human error and bias.
- Helping in decision-making threads related to problems rather than jumping to unreliable conclusions based on instincts.
- Removing immediate uncertainties helps in the prevention of fraud, limits risk, increases efficiency, and creates logical customers.

Descriptive vs. Predictive vs. Prescriptive Analytics

Difference between Descriptive vs. Predictive vs. Prescriptive Analytics can be described as follows:

Feature	Descriptive Analytics	Predictive Analytics	Prescriptive Analytics
Purpose	Understand what happened in the past.	Forecast what might happen in the future.	Recommend actions to achieve desired outcomes.
Focus	Historical data analysis.	Future trends and patterns.	Decision-making and optimization.
Time Frame	Past events and trends.	Future events and probabilities.	Future actions and recommendations.
Examples	Summarizing sales data from the previous month.	Predicting future sales based on market trends and historical data.	Recommending product pricing strategies to maximize profits.

Feature	Descriptive Analytics	Predictive Analytics	Prescriptive Analytics
Tools	Reporting tools, dashboards, data visualization.	Statistical models, machine learning algorithms.	Optimization algorithms, decision support systems.
Key Metrics	Descriptive statistics: mean, median, mode, etc.	Predictive accuracy metrics: RMSE, MAE, etc.	Prescriptive performance metrics: ROI, cost-benefit analysis, etc.
Decision Support	Provides insights for informed decision-making.	Guides future actions and strategies.	Offers actionable recommendations to achieve specific goals.
Example Application	Analyzing website traffic to understand user behavior.	Predicting customer churn to anticipate and prevent losses.	Suggesting personalized marketing campaigns based on customer segmentation.
Objective	Historical understanding and trend analysis.	Future prediction and risk assessment.	Optimal decision-making and performance improvement.
Impact	Historical insights for strategy refinement.	Anticipating future scenarios for proactive decision-making.	Maximizing outcomes and efficiency through informed actions.
Data Requirements	Historical data sets.	Historical data sets, future predictors.	Historical data sets, future predictors, decision variables.