Lecture Notes for PMDS604L
Exploratory Data Analysis

Contents

Module 1 Introduction to Exploratory Data Analysis

1.1 Overview of Data Analysis

Data analysis refers to the process of inspecting, cleaning, transforming, and modeling data to discover useful information, inform conclusions, and support decision-making. It is an essential step in extracting insights from raw data.

Key Steps in Data Analysis:

1. **Data Collection**: Gathering data from various sources, including databases, APIs, surveys, or experiments.
2. **Data Cleaning**: Handling missing values, removing duplicates, correcting errors, and ensuring consistency.
3. **Exploratory Analysis**: Using statistical techniques to summarize and understand data characteristics.
4. **Modeling**: Applying machine learning or statistical models to make predictions or understand relationships.
5. **Interpretation**: Drawing actionable conclusions based on the analysis.

Example: Suppose we have a dataset of sales records for a retail company. The data analysis process might involve:

- Identifying trends in sales over time.
- Exploring relationships between product pricing and sales volume.
- Determining the most profitable product categories.

1.2 Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) is the process of analyzing datasets to summarize their main characteristics, often with visual methods. It helps to identify patterns, spot anomalies, and test hypotheses.

Objectives of EDA:

- Understand the data structure.
- Detect outliers and anomalies.
- Identify relationships and dependencies among variables.
- Provide a foundation for selecting appropriate statistical tools or models.

Techniques Used in EDA:

- Descriptive statistics (mean, median, mode, variance, etc.).
- Data visualization (histograms, scatter plots, box plots, etc.).
- Correlation analysis to measure relationships between variables.

Example: Using a dataset of student grades, EDA might involve:

- Visualizing grade distributions using a histogram.
- Analyzing correlations between study hours and grades using a scatter plot.

1.3 The Data Science Process

The data science process outlines the steps to solve complex data problems systematically. It often includes:

1. **Define the Problem**: Identify the business or research problem to address.
2. **Collect Data**: Gather relevant datasets.
3. **Clean Data**: Prepare the data for analysis by removing inconsistencies.
4. **Explore Data**: Perform EDA to understand the data.
5. **Model the Data**: Apply statistical or machine learning models.
6. **Evaluate the Results**: Measure model performance and interpret findings.
7. **Communicate Insights**: Present results to stakeholders with actionable recommendations.

Example: For a customer churn analysis:

- **Problem Definition**: Predict which customers are likely to leave.
- **Data Collection**: Customer demographic and transaction data.
- **EDA**: Analyze patterns in churned and retained customers.
- **Modeling**: Train a machine learning model to predict churn.
- **Insights**: Suggest retention strategies based on customer profiles.

1.4 Responsibilities of a Data Analyst

Data analysts play a crucial role in converting data into actionable insights. Their responsibilities include:

- Collecting, cleaning, and preparing data.
- Performing EDA to understand data characteristics.
- Creating visualizations to summarize findings.

- Developing reports to communicate insights effectively.
- Collaborating with stakeholders to understand business needs.
- Ensuring data integrity and security.

Example: In a marketing team, a data analyst might:

- Analyze the performance of recent campaigns.
- Provide recommendations for improving customer targeting.
- Track key metrics such as ROI and customer engagement.

1.5 Data Analytics vs. Data Analysis

Data Analysis:

- Focuses on inspecting and interpreting raw data.
- Often involves statistical and visual techniques.
- Aims to answer specific questions based on existing data.

Data Analytics:

- Encompasses a broader scope, including predictive and prescriptive analytics.
- Uses advanced tools like machine learning for insights.
- Focuses on actionable outcomes and strategy development.

Comparison Example:

- **Data Analysis**: Summarizing last quarter's sales data.
- **Data Analytics**: Building a model to predict future sales trends.

1.6 Types of Data

Understanding the different types of data is essential for effective analysis. Data can be broadly classified as follows:

1. Structured Data:

- Organized in a predefined format, such as rows and columns.
- Stored in relational databases or spreadsheets.
- Examples: Customer information (name, age, address), sales data.

2. Unstructured Data:

- Does not have a predefined format or organization.
- Includes text, images, videos, and social media content.
- Examples: Emails, social media posts, audio recordings.

3. Semi-Structured Data:

- Combines elements of structured and unstructured data.
- Often stored in hierarchical or graph-based formats.
- Examples: JSON files, XML files, sensor data logs.

4. Time-Series Data:

- Collected at consistent intervals over time.
- Used to analyze trends and patterns.
- Examples: Stock prices, weather data, sensor readings.

5. Categorical vs. Numerical Data:

- **Categorical Data:** Represents categories or groups (e.g., gender, product type).
- **Numerical Data:** Represents numbers and can be:
  - **Discrete:** Whole numbers (e.g., number of sales).
  - **Continuous:** Any value within a range (e.g., temperature, revenue).

Example: A dataset of student records might include:

- Structured data: Student IDs, grades.
- Categorical data: Gender, major.
- Numerical data: GPA, age.

1.7 Understanding Different Types of File Formats

Data is stored in various formats depending on its use case. Common file formats include:

1. Text-Based Formats:

- **CSV (Comma-Separated Values):**
  - Stores tabular data as plain text.
  - Widely used due to its simplicity.
- **JSON (JavaScript Object Notation):**
  - Stores structured data in key-value pairs.
  - Commonly used in APIs and web applications.
- **XML (eXtensible Markup Language):**
  - Stores hierarchical data.
  - Often used in configuration files and data exchange.

2. Binary Formats:

- **Excel (XLS, XLSX):**
  - Used for spreadsheets with complex data.
  - Supports formulas, charts, and formatting.
- **Parquet:**
  - Columnar storage format optimized for analytics.
  - Used in big data frameworks like Apache Spark.

3. Multimedia Formats:

- Images: JPEG, PNG.
- Videos: MP4, AVI.
- Audio: MP3, WAV.

Example: A retail company might use:

- CSV for sales data.
- JSON for storing customer preferences.
- Images (PNG) for product photos.

1.8 Languages for Data Professionals

Proficiency in programming languages is critical for data professionals. Commonly used languages include:

1. Python:

- Popular for its simplicity and versatility.
- Extensive libraries for data manipulation (`pandas`), visualization (`matplotlib`, `seaborn`), and machine learning (`scikit-learn`).

2. R:

- Specialized for statistical analysis and visualization.
- Commonly used in academia and research.

3. SQL:

- Essential for querying and managing relational databases.

4. **Other Languages:**
   - **Java/Scala:** Used in big data tools like Apache Spark.
   - **Julia:** High-performance computing and numerical analysis.

   Example: A data scientist might use:
   - SQL to extract data from a database.
   - Python for cleaning and modeling data.
   - R to create detailed visualizations.

1.9 Overview of Data Repositories

Data repositories store and share datasets for analysis. Key types include:

1. **Public Repositories:**
   - **Kaggle:** A platform for datasets, competitions, and community discussions.
   - **UCI Machine Learning Repository:** A collection of datasets for machine learning research.
2. **Institutional Repositories:**
   - Hosted by universities or research institutions.
   - Examples: NOAA (climate data), WHO (health statistics).
3. **Cloud-Based Repositories:**
   - Provide scalable storage and access.
   - Examples: AWS S3, Google BigQuery, Azure Data Lake.
4. **Domain-Specific Repositories:**
   - Tailored for specific industries or research fields.
   - Examples: GenBank (genomics), IMDB (movies).

   Example: For a project on global warming:
   - Use NOAA for historical climate data.
   - Use Kaggle for preprocessed datasets on CO_2 emissions.

1.10 Data Marts

A **data mart** is a subset of a data warehouse focused on a specific business area or department, such as marketing, sales, or finance. It provides targeted data to specific users, improving access and performance.

Key Characteristics of Data Marts:

- Smaller in scope compared to a data warehouse.
- Optimized for specific queries and reporting.
- Often tailored for a single department or business unit.

Types of Data Marts:

- **Dependent Data Marts:** Extracted from a centralized data warehouse.
- **Independent Data Marts:** Created directly from operational systems without a data warehouse.
- **Hybrid Data Marts:** Combine data from a warehouse and operational systems.

Example: A retail company might use:

- A **sales data mart** to analyze revenue trends and sales performance.
- A **marketing data mart** to track customer segmentation and campaign success.

1.11 Data Lakes

A **data lake** is a centralized repository that stores all types of data in their raw format, whether structured, semi-structured, or unstructured. It allows scalable storage and flexible access.

Key Features of Data Lakes:

- Stores raw data as-is without a predefined schema.
- Supports high-volume data from diverse sources.
- Used for big data analytics, machine learning, and real-time analysis.

Advantages of Data Lakes:

- Scalability for handling vast amounts of data.
- Flexibility in supporting diverse data types.
- Cost-efficient storage using cloud-based solutions.

Example: A streaming platform might use a data lake to:

- Store raw video viewing logs for later analysis.
- Support machine learning algorithms for personalized recommendations.

1.12 ETL and Data Pipelines

ETL (Extract, Transform, Load): ETL refers to the process of moving data from various sources to a destination (e.g., a data warehouse) after transforming it into a suitable format.

1. **Extract:** Gather data from multiple sources (databases, files, APIs).
2. **Transform:** Cleanse and convert data into the desired format.
3. **Load:** Store the transformed data into a target system.

Example: A financial institution might:

- Extract data from customer databases and transaction logs.
- Transform it by aggregating and converting currencies.
- Load it into a centralized financial data warehouse.

Data Pipelines: A data pipeline is a broader concept that includes ETL and other processes to move and process data. It may handle both batch and real-time data streams.

Components of a Data Pipeline:

- **Source:** Data input from databases, sensors, or files.
- **Processing:** Transformation, filtering, and aggregation.
- **Destination:** Storage systems, dashboards, or machine learning models.

Example: A data pipeline for e-commerce might:

- Extract clickstream data from a website.
- Filter sessions with abandoned carts.
- Load the data into a dashboard for marketing analysis.

1.13 Foundations of Big Data

Big Data refers to data that is too large, fast, or complex for traditional data processing tools. It is characterized by the **5 Vs**:

1. **Volume:** Huge amounts of data generated every second.
2. **Velocity:** High-speed data generation and processing.
3. **Variety:** Different types of data (structured, unstructured, semi-structured).
4. **Veracity:** Ensuring data accuracy and trustworthiness.
5. **Value:** Extracting actionable insights from data.

Big Data Tools:

- **Hadoop:** Open-source framework for distributed storage and processing.

- **Spark:** Fast data processing engine for large-scale analytics.
- **NoSQL Databases:** MongoDB, Cassandra for handling unstructured data.

Example: A social media platform processes big data to:

- Analyze user behavior in real time.
- Detect trending topics and hashtags.
- Improve ad targeting through machine learning.

1.14 Identifying Data for Analysis

Choosing the right data is critical for successful analysis. The process involves:

1. Define the Objective:

- Clearly understand the goals of the analysis.
- Identify key questions to be answered.

2. Identify Relevant Sources:

- Determine data availability and accessibility.
- Sources include databases, public repositories, APIs, and surveys.

3. Assess Data Quality:

- Ensure data is accurate, complete, and relevant.
- Check for missing values and inconsistencies.

4. Evaluate Data Suitability:

- Confirm that the data aligns with the analysis requirements.
- Validate its granularity and coverage.

Example: For a customer segmentation project:

- **Objective:** Group customers based on purchasing behavior.
- **Data Sources:** Transaction history, demographic details.
- **Quality Assessment:** Check for missing age or purchase records.
- **Suitability:** Ensure data covers all customer segments.

Module 2 Data Wrangling

2.1 Data Sources

Data can be sourced from various platforms, systems, and repositories. Common data sources include:

1. **Databases:**
   - Relational Databases: MySQL, PostgreSQL.
   - NoSQL Databases: MongoDB, Cassandra.
2. **Files:**
   - Text files (CSV, JSON, XML).
   - Binary files (Parquet, HDF5).
3. **APIs:**
   - RESTful APIs for accessing web services.
   - Examples: OpenWeatherMap API, Twitter API.
4. **Web Pages:**
   - Extract data using web scraping.
   - Tools: BeautifulSoup, Selenium.
5. **Streaming Data:**
   - Real-time data sources like IoT devices or social media.
   - Tools: Apache Kafka, Spark Streaming.

2.2 Data Loading, Storage, and File Formats

Understanding file formats and methods to load/store data is essential for efficient analysis.

1. **Text Formats:**
   - CSV: Comma-separated values for tabular data.
   - JSON: Key-value format for structured data.
   - XML: Hierarchical markup-based format.
2. **Binary Formats:**
   - Parquet: Columnar storage optimized for big data.
   - HDF5: Hierarchical data storage for large numerical datasets.

3. Relational Databases:

- Store structured data in tables.
- Access via SQL queries.

Example:

- Load a CSV file with pandas:

```
import pandas as pd
data = pd.read_csv('file.csv')
```

- Write data to a Parquet file:

```
data.to_parquet('file.parquet')
```

2.3 Reading and Writing Data in Text Format

Reading Data:

- **CSV Files:**

```
pd.read_csv('file.csv')
```

- **JSON Files:**

```
pd.read_json('file.json')
```

Writing Data:

- **CSV:**

```
data.to_csv('output.csv', index=False)
```

- **JSON:**

```
data.to_json('output.json')
```

2.4 Web Scraping

Overview: Web scraping involves extracting data from web pages. It is useful for gathering public data for analysis.

Tools:

- **BeautifulSoup:** For parsing HTML and XML.
- **Selenium:** For automating web browsers.

Example:

```
from bs4 import BeautifulSoup
import requests

url = "https://example.com"
response = requests.get(url)
soup = BeautifulSoup(response.text, 'html.parser')
print(soup.title.text)
```

2.5 Binary Data Formats

Binary formats are optimized for storage and speed, especially for large datasets.

1. Parquet:

- Columnar format for efficient compression and analytics.

2. HDF5:

- Supports hierarchical data storage and fast I/O operations.

2.6 Interacting with Web APIs

APIs (Application Programming Interfaces) provide a structured way to access web-based data.

Steps for API Interaction:

1. Obtain API key or credentials.
2. Use HTTP methods (GET, POST) to interact with the API.
3. Parse the JSON/XML response.

Example:

```
import requests

url = "https://api.example.com/data"
params = {"key": "API_KEY"}
response = requests.get(url, params=params)
data = response.json()
print(data)
```

2.7 Interacting with Databases

Relational Databases: Use SQL to query structured data from relational databases.
Example:

```
import sqlite3

conn = sqlite3.connect('example.db')
query = "SELECT * FROM table_name"
data = pd.read_sql_query(query, conn)
```

NoSQL Databases: Handle unstructured data using tools like MongoDB.
Example:

```
from pymongo import MongoClient

client = MongoClient('localhost', 27017)
db = client['database_name']
collection = db['collection_name']
data = collection.find({})
```

2.8 Data Wrangling

Data wrangling is the process of transforming raw data into a clean and usable format.

1. Hierarchical Indexing:

- Allows handling of multi-indexed data.

Example:

```
data = pd.DataFrame({'key1': [1, 2], 'key2': [3, 4]})
data.set_index(['key1', 'key2'], inplace=True)
```

2. Combining and Merging Datasets:

- Use `merge` for combining datasets based on keys.

Example:

```
merged = pd.merge(df1, df2, on='key')
```

3. Reshaping and Pivoting:

- Reshape data using `melt`.
- Create summaries using `pivot_table`.

Example:

```
reshaped = data.melt(id_vars='key', value_vars=['col1', 'col2'])
pivoted = data.pivot_table(values='value', index='key1', columns='key2')
```

2.9 Tools for Data Wrangling

Data wrangling requires tools and libraries that facilitate efficient manipulation, cleaning, and preparation of data. Common tools include:

1. Python Libraries:

- **pandas**: Powerful library for data manipulation and analysis.
- **numpy**: Provides support for numerical computations.
- **OpenPyXL and xlrd**: For handling Excel files.

2. R Packages:

- **dplyr**: Used for data manipulation.
- **tidyr**: Simplifies reshaping and cleaning data.

3. SQL:

- Structured Query Language (SQL) for working with relational databases.

4. Visualization Tools:

- Tools like Tableau or Power BI can identify patterns or anomalies in data.

Example: To load and clean data using pandas in Python:

```
import pandas as pd
data = pd.read_csv('file.csv')
cleaned_data = data.drop_duplicates()
```

2.10 Data Cleaning and Preparation

Data cleaning and preparation involve ensuring the dataset is accurate, consistent, and ready for analysis.

1. Common Tasks:

- Removing duplicates.
- Standardizing data formats (e.g., dates, numbers).
- Resolving inconsistencies in naming or labeling.

Example: Standardizing column names:

```
data.columns = data.columns.str.lower().str.replace(' ', '_')
```

2.11 Handling Missing Data

Missing data can skew analysis and must be handled appropriately.

1. Identifying Missing Data:

- Use functions to detect missing values.

Example:

```
import pandas as pd
data = pd.read_csv('file.csv')
print(data.isnull().sum())  # Count missing values in each column
```

2. Strategies for Handling Missing Data:

- **Removing Rows or Columns:** Drop rows/columns with excessive missing values.

  ```
  data.dropna(axis=0, inplace=True)  # Drop rows with missing values
  ```

- **Imputation:** Replace missing values with a calculated value (mean, median, mode).

  ```
  data['column_name'].fillna(data['column_name'].mean(), inplace=True)
  ```

2.12 Data Transformation

Data transformation involves converting data into a suitable format or structure for analysis.

1. Scaling and Normalization:

- Adjusting data ranges for compatibility in analysis.

Example: Normalize data to a 0-1 range:

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
data_scaled = scaler.fit_transform(data)
```

2. Encoding Categorical Variables:

- Convert categorical data into numerical form.

Example: Using one-hot encoding in pandas:

```
data = pd.get_dummies(data, columns=['category_column'])
```

2.13 String Manipulation

String manipulation involves cleaning and transforming text data.

1. Common Operations:

- **Lowercasing/Uppercasing:**

  ```
  data['text_column'] = data['text_column'].str.lower()
  ```

- **Stripping Whitespace:**

  ```
  data['text_column'] = data['text_column'].str.strip()
  ```

- **Replacing Text:**

  ```
  data['text_column'] = data['text_column'].str.replace('old', 'new')
  ```

- **Extracting Substrings:**

  ```
  data['extracted'] = data['text_column'].str.extract('pattern')
  ```

2. Handling Complex Text Patterns:

- Use regular expressions (regex) for advanced text processing.

Example: Extract email domains from email addresses:

```
data['domain'] = data['email'].str.extract('@(.*)$')
```

Module 3 Data Analysis

3.1 Statistical Summary Measures

Statistical summary measures provide insights into the central tendency, spread, and shape of the data distribution.

1. Measures of Central Tendency:

- **Mean:** Average of the data values.

$$\text{Mean} = \frac{\sum_{i=1}^{n} x_i}{n}$$

- **Median:** Middle value of sorted data.
- **Mode:** Most frequently occurring value.

2. Measures of Dispersion:

- **Range:** Difference between the maximum and minimum values.
- **Variance:** Average squared deviation from the mean.

$$\text{Variance} = \frac{\sum_{i=1}^{n} (x_i - \mu)^2}{n}$$

- **Standard Deviation:** Square root of variance.

3. Shape of Distribution:

- **Skewness:** Measures asymmetry of the data distribution.
- **Kurtosis:** Describes the peakedness or flatness of the distribution.

Example in Python:

```
import pandas as pd
data = pd.DataFrame({'values': [1, 2, 3, 4, 5]})
print(data['values'].mean())  # Mean
print(data['values'].median())  # Median
```

3.2 Data Elaboration

Data elaboration involves organizing and transforming raw data to make it suitable for analysis.

Key Techniques:

- Grouping data by categories.
- Aggregating data using functions like sum, mean, or count.
- Filtering data based on specific conditions.

Example: Grouping data by categories and calculating the mean:

```
grouped = data.groupby('category')['values'].mean()
```

3.3 1D Statistical Data Analysis

1D statistical analysis involves analyzing data with a single variable.

1. Univariate Analysis:

- Summarize data using central tendency and dispersion measures.
- Visualize data using histograms, box plots, or density plots.

Example: Creating a histogram in Python:

```
import matplotlib.pyplot as plt
plt.hist(data['values'], bins=10)
plt.show()
```

3.4 2D Statistical Data Analysis

2D statistical analysis focuses on analyzing relationships between two variables.

1. Bivariate Analysis:

- **Scatter Plots:** Visualize relationships between two variables.
- **Correlation Coefficient:** Measures the strength and direction of linear relationships.

$$\text{Correlation} = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y}$$

Example: Calculating correlation in Python:

```
correlation = data['x'].corr(data['y'])
print(correlation)
```

3.5 Contingency Tables

Contingency tables summarize the relationship between two categorical variables.

Structure of Contingency Tables:

	Category 1	Category 2	Total
Row 1	a	b	$a+b$
Row 2	c	d	$c+d$
Total	$a+c$	$b+d$	N

Analysis Techniques:

- Calculate row and column percentages.
- Use chi-square tests to measure independence.

Example in Python:

```
import pandas as pd
pd.crosstab(data['category1'], data['category2'])
```

3.6 n-D Statistical Data Analysis

n-D statistical analysis involves analyzing datasets with three or more variables.

1. Multivariate Analysis:

- Explore relationships among multiple variables simultaneously.
- Use techniques like multiple regression or principal component analysis (PCA).

Techniques:

- **Pair Plots:** Visualize relationships between all variable pairs.
- **Heatmaps:** Show correlations among multiple variables.

Example in Python: Creating a heatmap:

```
import seaborn as sns
sns.heatmap(data.corr(), annot=True, cmap='coolwarm')
```

3.7 Summary

Statistical data analysis encompasses a range of techniques for understanding and exploring datasets, from simple univariate summaries to complex multivariate methods. Key steps involve summarizing data, identifying relationships, and testing hypotheses to uncover meaningful insights.

Module 4 Outlier Analysis

4.1 Outliers and Outlier Analysis

An **outlier** is a data point that significantly deviates from the majority of data. It may indicate variability in measurements, experimental errors, or novel insights.

Key Characteristics of Outliers:

- Unusual deviation from the normal data distribution.
- May affect statistical analysis and model performance.
- Requires investigation to determine if it is a data error or a meaningful observation.

Causes of Outliers:

- Measurement errors.
- Data entry errors.
- Natural variability in data.
- Novel or rare phenomena.

Example: In a dataset of employee ages, a recorded value of 200 years is likely an outlier due to data entry errors.

4.2 Outlier Detection Methods

Outlier detection involves identifying data points that deviate significantly from the norm. Common methods include:

1. Statistical Methods:

- Use measures such as z-scores or the interquartile range (IQR).
- **Z-Score Method:** A data point is considered an outlier if its z-score is greater than a threshold (e.g., 3).

$$Z = \frac{x - \mu}{\sigma}$$

- **IQR Method:** Outliers lie outside:

$$[Q1 - 1.5 \times IQR, Q3 + 1.5 \times IQR]$$

2. Model-Based Methods:

- Use machine learning models to identify anomalies, e.g., Isolation Forest, One-Class SVM.

3. Proximity-Based Methods:

- Analyze distances between data points to detect outliers.

4.3 Proximity-Based Approaches

Proximity-based methods rely on measuring distances between data points. Common approaches include:

1. k-Nearest Neighbors (k-NN):

- Outliers are identified based on their distance to the k-nearest neighbors.
- Larger distances indicate potential outliers.

2. Density-Based Methods:

- Use density estimations to find regions with low data density.
- **DBSCAN (Density-Based Spatial Clustering of Applications with Noise):** Clusters points based on density and labels points in low-density regions as outliers.

Example: Using Python's scikit-learn library for k-NN outlier detection:

```
from sklearn.neighbors import LocalOutlierFactor

lof = LocalOutlierFactor(n_neighbors=20)
outliers = lof.fit_predict(data)
```

4.4 Distance Metrics

Distance metrics are essential for proximity-based outlier detection methods.

1. Euclidean Distance:

$$d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

2. Manhattan Distance:

$$d(x, y) = \sum_{i=1}^{n} |x_i - y_i|$$

3. Cosine Similarity: Measures the angle between two vectors:

$$\text{Cosine Similarity} = \frac{x \cdot y}{\|x\| \|y\|}$$

4.5 Mahalanobis Distance

The **Mahalanobis Distance** accounts for correlations between variables and scales data appropriately. It is used for detecting multivariate outliers.

$$d_M(x) = \sqrt{(x - \mu)^T \Sigma^{-1} (x - \mu)}$$

Key Features:

- Accounts for variable correlations.
- Robust to scaling issues.

Example in Python:

```
import numpy as np
from scipy.spatial.distance import mahalanobis

mean = np.mean(data, axis=0)
cov = np.cov(data.T)
inv_cov = np.linalg.inv(cov)
distances = [mahalanobis(x, mean, inv_cov) for x in data]
```

4.6 Outlier Detection in High-Dimensional Data

High-dimensional data poses challenges for outlier detection due to the **curse of dimensionality**:

- Data points tend to appear equidistant in high dimensions.
- Noise increases with the number of dimensions.

Approaches to Handle High-Dimensional Data:

- **Dimensionality Reduction:** Techniques like PCA (Principal Component Analysis) reduce data dimensions while retaining variance.

```
from sklearn.decomposition import PCA

pca = PCA(n_components=2)
reduced_data = pca.fit_transform(data)
```

- **Subspace-Based Methods:** Identify outliers in low-dimensional subspaces.
- **Feature Selection:** Select the most informative features to reduce dimensionality.

Advanced Outlier Detection: Use algorithms designed for high-dimensional data, such as:

- Isolation Forest.
- One-Class SVM.

Example in Python:

```
from sklearn.ensemble import IsolationForest

iso_forest = IsolationForest(n_estimators=100)
outliers = iso_forest.fit_predict(data)
```

4.7 Summary

Outlier analysis is crucial for identifying anomalies that could indicate data errors or novel phenomena. Techniques range from simple statistical methods to advanced algorithms suited for high-dimensional data.

Module 5 Data Visualization

5.1 Introduction to Data Visualization

Data Visualization is the graphical representation of information and data. It uses visual elements like charts, graphs, and maps to provide an accessible way to understand patterns, trends, and insights.

Importance of Data Visualization:

- Makes data easier to understand.
- Identifies trends, outliers, and patterns.
- Communicates results effectively to stakeholders.
- Enhances decision-making processes.

Example: Visualizing sales trends using a line chart can show seasonal variations.

5.2 Visualization Tools

There are several tools available for creating impactful visualizations:

- **Tableau:** User-friendly tool for creating interactive dashboards.
- **Power BI:** Microsoft's tool for business intelligence and reporting.
- **Matplotlib/Seaborn (Python):** Libraries for creating static, animated, and interactive plots.
- **Excel:** Widely used for basic visualizations.
- **D3.js:** A JavaScript library for creating dynamic, interactive visualizations.

5.3 Getting Started with Tableau Desktop

Tableau Desktop is a data visualization tool that helps create interactive visualizations and dashboards.

Key Features:

- Drag-and-drop interface for creating visualizations.
- Connects to various data sources (Excel, SQL, cloud platforms).
- Offers interactivity through filters, actions, and tooltips.

5.4 Connecting to the Dataset

Steps to Connect to a Dataset in Tableau:

1. Open Tableau Desktop and select **Connect to Data**.
2. Choose the data source type (e.g., Excel, SQL, Cloud).
3. Load the dataset into Tableau's workspace.

Example: Connect to a sales dataset in Excel:

- Select **Microsoft Excel** in the Connect pane.
- Browse and upload the file.

5.5 Creating Charts

Tableau supports various types of charts for data visualization. Some common types include:

- **Bar Charts:** Compare categorical data.
- **Line Charts:** Show trends over time.
- **Pie Charts:** Represent proportions.
- **Scatter Plots:** Explore relationships between two variables.

Steps to Create a Chart:

1. Drag the desired fields onto the Rows and Columns shelves.
2. Use the **Show Me** panel to select the chart type.
3. Customize the chart using filters, colors, and labels.

5.6 Creating Common Visualizations

1. Bar Chart:

- Drag a categorical field to Rows and a numerical field to Columns.

2. Line Chart:

- Drag a date field to Columns and a numerical field to Rows.

Example: Visualize monthly sales with a line chart:

1. Place **Order Date** on Columns.
2. Place **Sales** on Rows.
3. Select Line Chart from **Show Me**.

5.7 Filtering and Sorting Data

Filters and sorting refine the visualization to focus on relevant information.

Steps to Apply Filters:

1. Drag a field to the Filters shelf.
2. Specify the filtering criteria (e.g., range, categories).

Steps to Sort Data:

1. Click the sort icon on the axis or in the Marks card.
2. Sort data alphabetically, by field values, or manually.

5.8 Adding Titles, Labels, and Descriptions

Annotations enhance the readability and interpretability of visualizations.

Steps:

1. Double-click the title area to edit chart titles.
2. Drag fields to the Label option in the Marks card to add data labels.
3. Add descriptions using annotations (**Right-click** on a data point $\rightarrow$ **Annotate**).

5.9 Publishing Work to Tableau Cloud

Tableau Cloud allows users to share visualizations and dashboards online.

Steps to Publish:

1. Click on **File** → **Publish to Tableau Cloud**.
2. Select a project and provide a name for the workbook.
3. Configure permissions for users to view or edit.

5.10 Interactivity with Text and Visual Tooltips

Tooltips display additional details when hovering over data points.

Steps to Customize Tooltips:

1. Click on the Tooltip card in the Marks pane.
2. Add fields and customize the text or style.

5.11 Interactivity with Actions

Actions enable users to interact dynamically with the visualization.

Types of Actions:

- **Filter Action:** Filters data in one view based on selection in another.
- **Highlight Action:** Highlights specific data points across views.
- **URL Action:** Opens a URL in response to user interaction.

Steps to Add Actions:

1. Go to **Dashboard** → **Actions**.
2. Choose the type of action and configure the settings.

5.12 Assembling Dashboards from Multiple Charts

Dashboards combine multiple visualizations into a single view.

Steps to Create a Dashboard:

1. Click **New Dashboard**.
2. Drag individual sheets (charts) into the dashboard workspace.
3. Arrange and resize charts to fit.
4. Add interactive elements like filters or navigation buttons.

Example: Assemble a dashboard for sales performance:

- Add a bar chart for product categories.
- Add a line chart for monthly sales trends.
- Use a filter to select specific regions.

Module 6 Exploratory Visualization Techniques

6.1 Introduction to Data Visualization Libraries

Data visualization libraries provide tools to create visualizations programmatically. Each library has unique features catering to different visualization needs.

1. Python Libraries:

- **Matplotlib:**
  - Foundation for static plots.
  - Highly customizable but requires detailed coding.
- **Seaborn:**
  - Built on top of Matplotlib.
  - Simplifies statistical plotting and supports themes.
- **Plotly:**
  - Enables interactive visualizations.
  - Supports 3D plotting and real-time interaction.
- **Geopandas:**
  - Extends pandas for geographic data plotting.

2. R Libraries:

- **ggplot2:** Based on the grammar of graphics for creating professional-quality plots.
- **leaflet:** Designed for interactive maps.

Example in Python: Creating a scatter plot with Seaborn:

```
import seaborn as sns
import matplotlib.pyplot as plt

sns.scatterplot(x='age', y='income', data=dataset)
plt.show()
```

6.2 Customizing Plots for Effective Communication

Effective visualization involves tailoring plots to highlight key insights and ensure clarity.

Key Customization Techniques:

- **Color Schemes:**
  - Use contrasting colors for better visibility.
  - Ensure colorblind-friendly palettes.
- **Annotations:**
  - Add text annotations to emphasize critical points.
- **Axis Labels and Titles:**
  - Clearly label axes and provide a meaningful title.
- **Legends:**
  - Position legends to avoid overlapping with data points.

Example in Python: Customizing a line plot:

```
plt.plot(x, y, label='Revenue', color='blue', linestyle='--')
plt.title('Monthly Revenue')
plt.xlabel('Month')
plt.ylabel('Revenue ($)')
plt.legend(loc='upper left')
plt.show()
```

6.3 Interactive Visualization Tools

Interactive visualizations allow users to explore data dynamically, providing deeper insights.

Popular Interactive Tools:

- **Plotly:**
  - Supports dynamic zooming, panning, and tooltips.
- **Dash:**
  - Framework for building interactive dashboards.
- **Tableau:**
  - Drag-and-drop functionality for interactivity.
- **Bokeh:**
  - Python library for creating browser-based interactive visualizations.

Example with Plotly: Creating an interactive scatter plot:

```
import plotly.express as px

fig = px.scatter(dataset, x='age', y='income', color='category')
fig.show()
```

6.4 Geographic Visualization

Geographic visualizations map data points to geographical locations, providing spatial insights.

Tools for Geographic Visualization:

- **Geopandas:**
  - Python library for spatial operations and visualizations.
- **Folium:**
  - Builds interactive maps with markers, popups, and layers.
- **Tableau:**
  - Supports maps and geocoding for location-based data.

Example in Python: Creating a map of sales regions:

```
import geopandas as gpd
import matplotlib.pyplot as plt

world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))
data = gpd.GeoDataFrame(dataset, geometry=gpd.points_from_xy(dataset.lon,
 dataset.lat))
world.plot()
data.plot(ax=world.plot(), color='red')
plt.show()
```

6.5 Text and Sentiment Analysis

Text visualization involves processing unstructured textual data to uncover patterns and trends, while sentiment analysis determines the sentiment polarity of text.

Steps for Text Analysis:

1. Tokenization: Split text into individual words or phrases.
2. Removing stop words: Eliminate common but uninformative words.
3. Stemming/Lemmatization: Reduce words to their base forms.
4. Word frequency analysis: Identify common words.

Visualization Techniques:

- **Word Clouds:** Highlight frequent words with varying font sizes.
- **Bar Charts:** Show word frequency counts.

Sentiment Analysis:

- Classifies text into categories like positive, negative, or neutral.
- Common tools: VADER, TextBlob, and Hugging Face Transformers.

Example in Python: Creating a word cloud:

```
from wordcloud import WordCloud
import matplotlib.pyplot as plt

text = " ".join(dataset['text_column'])
wordcloud = WordCloud().generate(text)

plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.show()
```

Performing sentiment analysis:

```
from textblob import TextBlob

dataset['sentiment'] = dataset['text_column'].apply(lambda x:
TextBlob(x).sentiment.polarity)
```

Module 7 Insights of Data Visualization

7.1 Introduction to Power BI

Power BI is a business intelligence and data visualization tool developed by Microsoft. It allows users to create interactive reports and dashboards to gain insights from their data.

Key Features of Power BI:

- Connects to a wide variety of data sources.
- Provides drag-and-drop functionality for designing visuals.
- Supports advanced analytics using DAX (Data Analysis Expressions).
- Enables sharing of reports via Power BI Service (Cloud).

Components of Power BI:

- **Power BI Desktop:** For creating reports and dashboards.
- **Power BI Service:** Cloud platform for sharing and collaboration.
- **Power BI Mobile:** Access and interact with reports on mobile devices.

7.2 Understanding Power BI Desktop

Power BI Desktop is the primary tool for creating Power BI reports. It integrates:

- **Data Pane:** For managing datasets and fields.
- **Visualizations Pane:** Contains chart types and formatting options.
- **Report Canvas:** Workspace for designing reports.

Steps to Install Power BI Desktop:

1. Download Power BI Desktop from the official Microsoft website.
2. Install the software and launch it.

7.3 Understanding Power BI Report Designer

The Report Designer in Power BI Desktop allows users to create interactive reports by combining datasets with various visualizations.

Key Features:

- Drag-and-drop fields into the report canvas.
- Customize visuals with filters and slicers.
- Add interactivity through drill-through options.

7.4 Report Canvas and Report Pages

Report Canvas: The workspace in Power BI where visuals and data elements are placed.

Report Pages: Multiple pages can be created within a report to organize visualizations logically.

Steps to Create and Rename Report Pages:

1. Click the + icon at the bottom to add a new page.
2. Double-click the page name to rename it.

Advantages:

- Organizes insights by themes or categories.
- Enhances navigation for viewers.

7.5 Report Visuals, Fields, and UI Options

Power BI offers various visuals to represent data effectively.

Types of Report Visuals:

- Bar Charts, Line Charts, and Pie Charts.
- Maps for geographic data.
- KPI Cards for highlighting metrics.
- Matrix and Table visuals for detailed views.

Fields Pane:

- Contains datasets and their respective columns.
- Drag fields into the canvas or filters to add them to visuals.

UI Options:

- Formatting options for changing colors, fonts, and labels.
- Tooltips for adding additional context to visuals.
- Interaction settings for controlling how visuals respond to clicks.

7.6 Experimenting with Visual Interactions

Visual interactions allow interactivity between report visuals.

Steps to Experiment with Visual Interactions:

1. Select a visual and go to **Format** → **Edit Interactions**.
2. Configure how other visuals respond to interactions (filter, highlight, or none).

Advantages:

- Enables dynamic filtering and drilling down into details.
- Provides a seamless user experience for report viewers.

7.7 Reports with Multiple Pages and Advantages

Creating Multiple Pages:

1. Use the + icon at the bottom of the report canvas.
2. Add specific visuals to each page based on themes or KPIs.

Advantages:

- Organizes complex data into manageable sections.
- Provides a logical flow for storytelling in reports.

7.8 Pages with Multiple Visualizations

Each report page can include multiple visuals to provide comprehensive insights.

Guidelines:

- Ensure proper spacing to avoid visual clutter.
- Use complementary visuals to convey related insights (e.g., bar chart + line chart).
- Group related visuals using titles or background shapes.

7.9 PUBLISH Options and Report Verification in Cloud

Power BI reports can be published to the Power BI Service for sharing and collaboration.

Steps to Publish:

1. Click on **Publish** in Power BI Desktop.
2. Log in to your Power BI account.
3. Select a workspace in the Power BI Service to upload the report.

Report Verification:

- Open the published report in the Power BI Service.
- Test visual interactions and filters.
- Verify data accuracy and completeness.

7.10 Adding Report Titles

Steps to Add Titles:

1. Select **Text Box** from the Home ribbon.
2. Type the title and customize its font, size, and color.
3. Place the text box at the top of the canvas.

7.11 Report Format Options

Power BI offers extensive formatting options to enhance the appearance of reports.

Key Formatting Options:

- **Background Colors:** Add custom colors or images to the canvas.
- **Data Labels:** Enable and customize data labels for better clarity.
- **Gridlines:** Adjust gridline settings for tables and charts.
- **Themes:** Apply predefined themes for consistent styling.

Example: Formatting a bar chart:

1. Select the bar chart.
2. Go to the **Format** pane and modify:
    - Bar colors.
    - Axis titles and gridlines.
    - Tooltip information.

Module 8 Contemporary Issues

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