1. Intro to Data and Data Science

1 The Different Data Science Fields

1: "The Different Data Science Fields"

• Importance of Data:

- Foundation for business success in the modern era.
- Key for entrepreneurs to gain a competitive edge.

• Professional Evolution:

• Statisticians from 25 years ago can seamlessly integrate into diverse fields with modern technologies.

2: "Analysis vs Analytics"

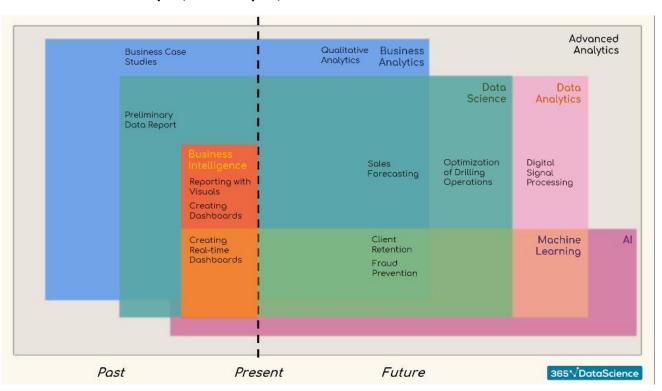
Analysis:

• Examining past data, explaining 'how' and 'why' something happened.

Analytics:

- Focuses on the future, identifying patterns through logical and computational reasoning.
- Qualitative (intuition, experience) vs Quantitative (formulas, algorithms) analytics.

3: "Intro to Business Analytics, Data Analytics, and Data Science"



• Data-Driven vs Subjective Activities:

• Business activities vary from data-driven to subjective/experience-driven.

• Data Science vs Business Analytics:

• Data science relies on data, incorporating complex tools. Business analytics doesn't solely rely on data.

4: "Adding BI, Machine Learning, and AI"

Business Intelligence (BI):

- Analyzing and reporting historical business data.
- Preliminary step for predictive analytics.

• Machine Learning (ML):

• Machines predict outcomes without explicit programming.

Artificial Intelligence (AI):

- Simulates human knowledge and decision-making.
- Includes machine and deep learning.

5: "Overview of 365 Data Science Infographic"

• Infographic Overview:

- 5 columns represent stages in solving a business task.
- Rows answer key questions: When, Why, What techniques, Where applicable, How implemented, Who does it.

Columns:

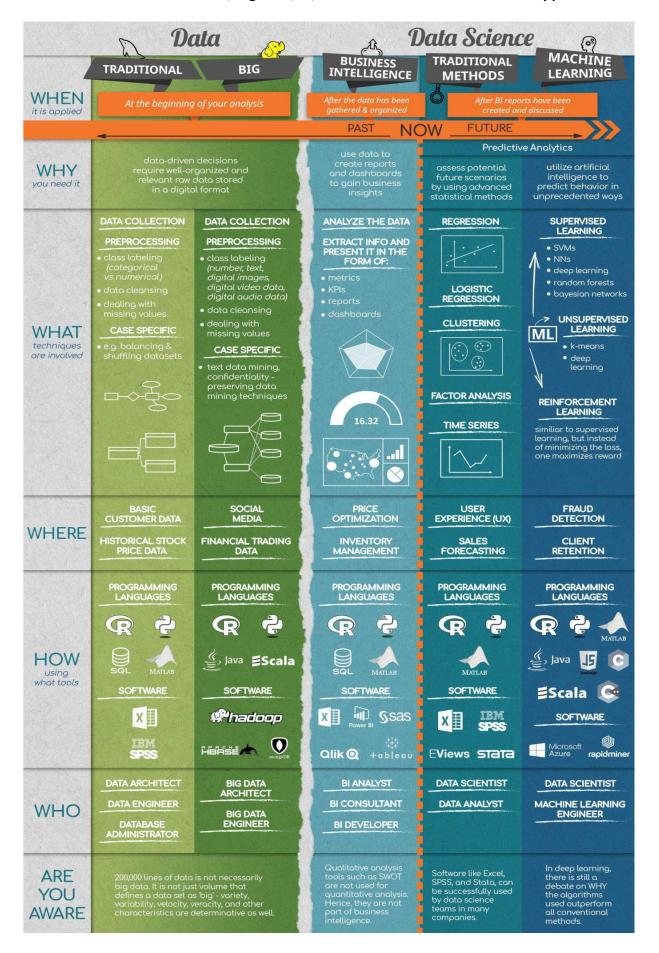
- 1. Working with traditional data
- 2. Working with big data
- 3. Doing business intelligence
- 4. Applying traditional data science techniques
- 5. Using ML techniques

Infographic Purpose:

- Essential guide for a data scientist.
- Covers practical aspects of solving business tasks.

2. The relationship between different data science fields

1: "When are Traditional data, Big Data, BI, Traditional Data Science and ML applied"



• **Data Definition:** Information in digital format, the basis for analysis and decision-making.

Types of Data:

- *Traditional Data:* Structured tables with numeric or text values stored in databases.
- *Big Data:* Extremely large, characterized by volume, variety, and velocity (3 Vs).

Data Science Overview:

 Broad, interdisciplinary field combining statistical, mathematical, programming, problem-solving, and data-management tools.

Segments of Data Science:

- Business Intelligence: Analyzing past data for decision-making.
- Traditional Methods: Derived from statistics, adapted for business.
- Machine Learning: Creating algorithms for accurate predictions.

Example Explanation:

• Think of traditional data as a neatly organized Excel sheet and big data as a vast, rapidly updating stream of information. Data science combines these through Business Intelligence, traditional methods, and machine learning to extract valuable insights.

3. What is the Purpose of Each Data Science Field

1. Why do we need each of disciplines

• Key Points:

- Data as Foundation: Data is the foundation for data-driven decisions.
- **Segments of Data Science:** Business Intelligence, Traditional Methods, and Machine Learning.
- **Traditional Methods vs. Machine Learning:** Both aim for predictive insights but differ in the era of technology.

• Example Explanation:

• Think of data as the raw material, and Business Intelligence, Traditional Methods, and Machine Learning as different tools extracting valuable insights from that material.

4: Common Data Science Techniques -

1. Traditional Data Techniques

Data Collection Basics:

- Raw Data Definition: Unanalyzed data stored on servers.
- **Collection Methods:** Surveys, automatic (e.g., cookies) for diverse data sources.
- **Data Preprocessing:** Operations to convert raw data into a more understandable format.

• Data Preprocessing Operations:

- Class Labelling: Assigning correct data types or arranging data by category.
- Data Cleansing: Handling inconsistent data, like correcting misspelled names.
- **Data Balancing:** Equalizing sample priority for balanced representation.
- **Data Shuffling:** Randomizing dataset observations to eliminate unwanted patterns.

ER Diagrams, Relational Tables

Example: Analyzing survey responses about product preferences using various data sources.

2. Big Data Techniques

- Diverse Data Handling:
 - **Big Data Examples:** Text, digital images, videos, audio, etc.
 - Cleansing Methods: Various techniques for diverse data types.
 - **Text Data Mining:** Deriving valuable, unstructured data from text.
 - **Data Masking:** Concealing original data with false information to preserve confidentiality.

Example: Extracting insights from vast social media text data for sentiment analysis.

3. Business Intelligence Techniques

- Analyzing Past Performance:
 - BI Analyst Role: Explaining past business performance through data analysis.

- **Metrics and Measures:** Evaluating business performance with meaningful values.
- **KPIs Importance:** Focusing on essential metrics aligned with business objectives.

Reports, Dashboards(KPI)

Example: Using BI tools to analyze historical sales data and optimize future strategies.

4. Traditional Methods Techniques

- Predictive Analytics Overview:
 - Regression Model: Quantifying causal relationships among variables.
 - **Clustering and Time Series:** Grouping data for meaningful patterns, tracking values over time.

Example: Predicting future sales trends using time series data and regression models.

5. Machine Learning Techniques

- Algorithmic Model Building:
 - **Machine Learning Process:** Creating algorithms for accurate predictions through trial-and-error.
 - Four Ingredients: Data, model, objective function, optimization algorithm.

Example: Developing a machine learning algorithm to predict customer churn in a subscription service.

6. Machine Learning Types

- Diverse Learning Approaches:
 - **Supervised Learning:** Teacher-supervised model using labeled data for feedback.
 - Unsupervised Learning: Self-training model categorizing unlabeled data into groups.
 - **Reinforcement Learning:** Introducing a reward system to maximize an objective function.
 - **Deep Learning:** State-of-the-art neural network approach, applicable to both supervised and unsupervised learning.

Example: Training a model to recognize handwritten digits in images using supervised learning.

5. Common Data Science Tools

1. Programming Languages & Software Employed in Data Science – All the tools you need

Programming Languages vs. Software:

- *Programming Languages:* Enable program development for specific operations; Python and R are popular for general-purpose programming.
- *Software:* Tools like Excel, SPSS, and specialized software address domain-specific challenges.
- Limitations: Python and R might not suffice for certain domains, e.g., relational database management systems; SQL is preferred.

Example: Using Python for statistical computations and SQL for relational database queries in data science projects.

6. Data Science Career Paths

1. What do they involve & What to look out for

1. Data Architect:

• Responsibility: Designs the structure for data retrieval, processing, and consumption.

2. Data Engineer:

Responsibility: Processes obtained data to ensure readiness for analysis.

3. Database Administrator:

• Responsibility: Controls and manages data, specializing in traditional data.

4. BI Analyst (Business Intelligence):

Responsibility: Analyzes and reports past historical data for business insights.

5. BI Consultant:

Responsibility: External BI analyst offering consulting services.

6. BI Developer:

• Responsibility: Conducts analyses tailored to the company's specific needs.

7. Data Scientist:

• Responsibility: Utilizes traditional statistical methods or unconventional ML techniques for predictions.

8. Data Analyst:

• Responsibility: Prepares advanced analyses for data-driven decision-making.

9. Machine Learning Engineer:

• Responsibility: Applies state-of-the-art ML techniques for model development.

Example: A Data Engineer processing raw customer data for a Data Scientist to build a predictive model.

7. Dispelling Common Misconceptions

1. Big Data Volume Misconception:

• *Correction:* Big Data involves variety, variability, velocity, veracity, and other characteristics, not just sheer volume.

2. Qualitative Analysis in Business Intelligence:

• *Clarification:* Qualitative methods like SWOT are not quantitative but play a crucial role in business strategy.

3. Excel, SPSS, Stata in Data Science:

• Reality Check: These tools are successfully used in many companies by data science teams.

4. Debate on Deep Learning Superiority:

• Fact Check: There is an ongoing debate on why deep learning algorithms outperform conventional methods.

Example: Understanding that Big Data is more than just a large volume and recognizing the role of qualitative analysis in business intelligence.