BIG DATA ANALYTICS (PE1)

MIT-WPU
॥ विश्वशान्तिर्ध्रुवं ध्रुवा ॥

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(Computer Engineering and Technology)
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UNIT I

Introduction to Big Data

This presentation is for the reference only .You are advised to study from the reference books given on reference slide.

Syllabus

Unit- I : Introduction to Big Data

- **What is Big Data**
- Overview of big data analytics
- Traditional database systems vs. big data systems
- 5 V's of big data
- Importance of big data and real world challenges
- Architecture of big data systems
- Big data applications
- Data analytics life cycle

Motivation For BIG DATA

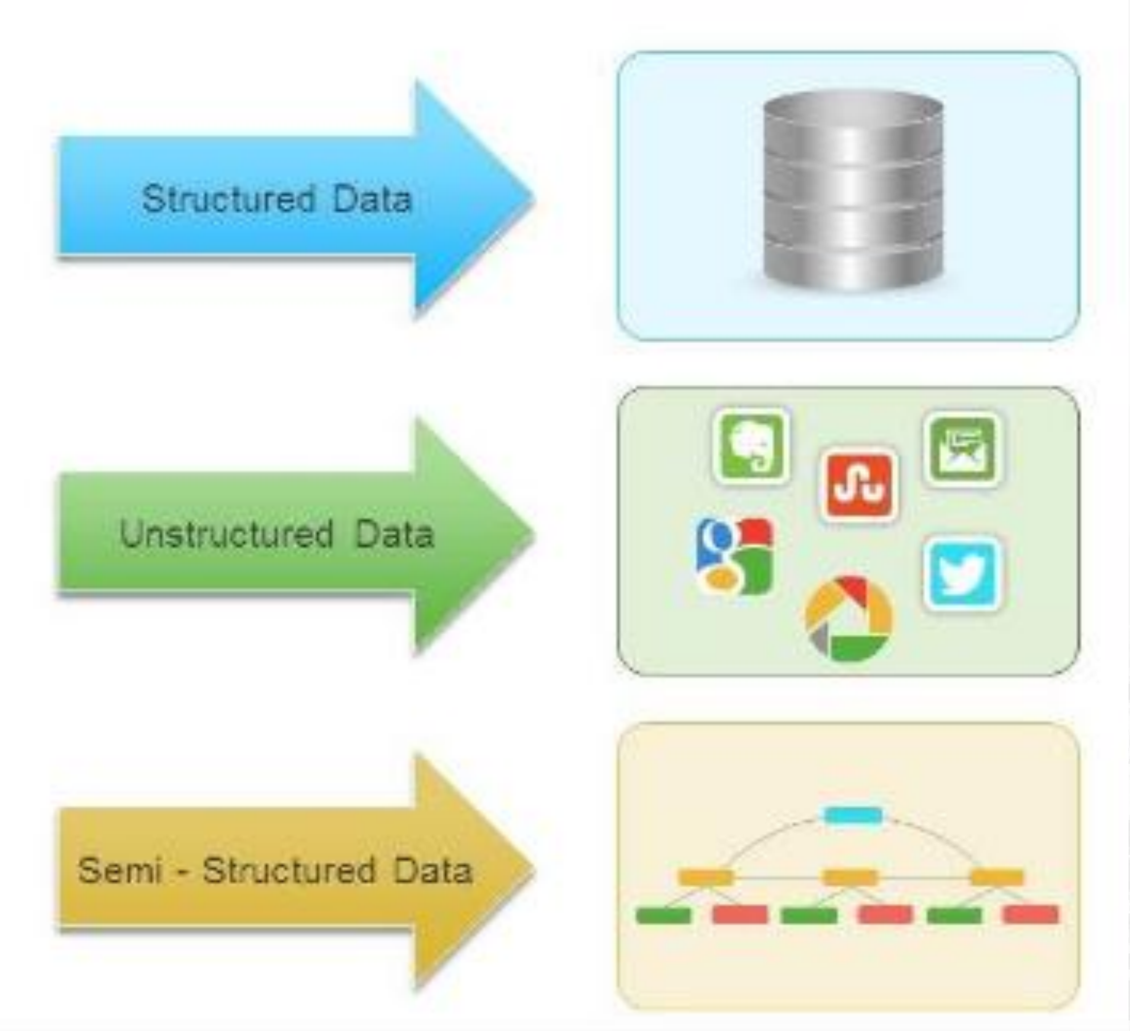
1. Huge volume of data:

Rather than thousands or millions of rows, Big Data can be billions of rows and millions of columns due to different applications like twitter, Facebook, Instagram.

2. Complexity of data types and structures:

Big data can come in multiple forms, including structured and non-structured data such as financial data, text files, multimedia files, and genetic mappings also digital traces being left on the web and other digital repositories for subsequent analysis

Motivation for BIG data Contd..



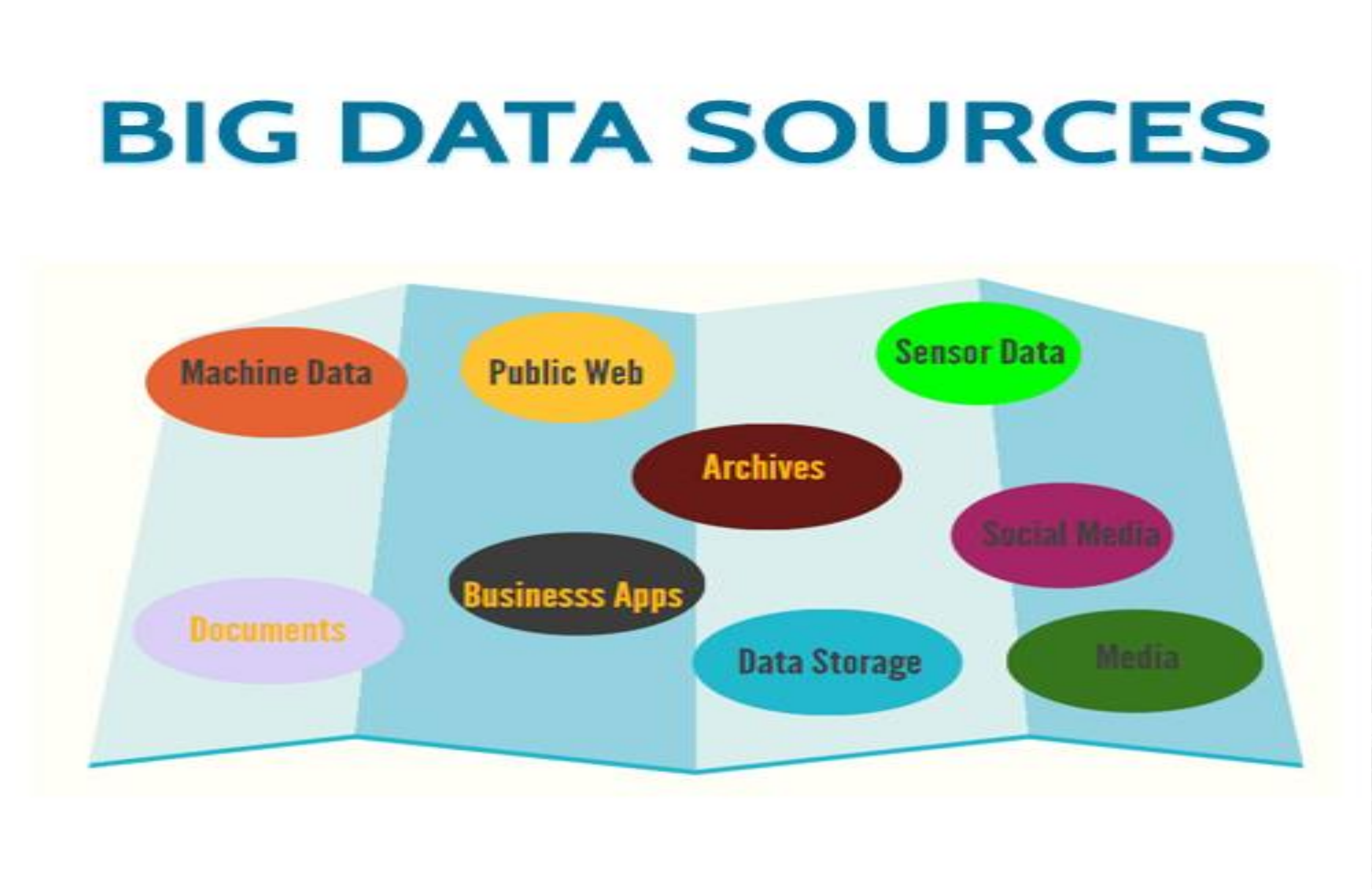
Motivation for BIG data Contd..

3. High Speed of new data creation and growth:

Big Data can describe high velocity data, with rapid data ingestion and near real time analysis.

4. Distributed computing environments and Massively Parallel Processing (MPP) architectures that enable parallelized data ingest and analysis are the preferred approach to process such complex data

Big Data Sources



Big Data Sources Contd..

Data is created constantly, and at an ever-increasing rate:

Sources of Big Data:

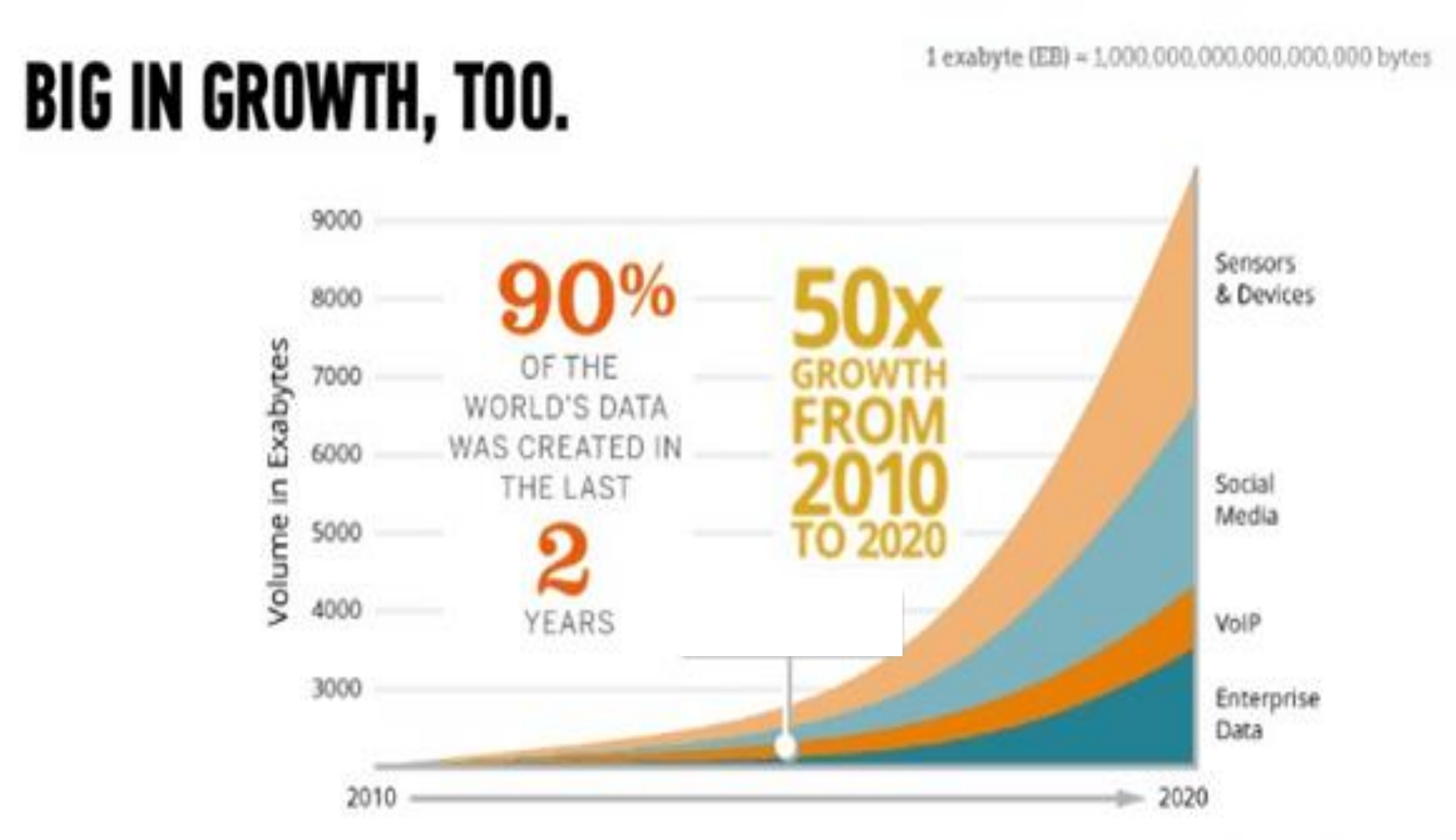
1. Mobile phones, social media, imaging technologies -all these and more create new data, and that must be stored somewhere for some purpose

2.Devices and sensors automatically generate diagnostic information that needs to be stored and processed in real time

Examples of big data

- Photos and video footage uploaded to the World Wide Web.
- Video surveillance, such as the thousands of video cameras spread across a city .
- Mobile devices, which provide geospatial location data of the users, as well as metadata about text messages, phone calls, and application usage on smart phones
- Smart devices, which provide sensor-based collection of information from smart electric grids, smart buildings, and many other public and industry infrastructures

Statistics of big data



DEFINITION OF BIG DATA

Not a single definition…..

- Big data is high volume, high velocity, high variety information assets that require new forms of processing to enable enhanced decision making, insight discovery and process optimization. ---*Doug Laney, Gartner, 2012.*
- Big Data is data whose scale, distribution, diversity, and/or timeliness require the use of new technical architectures and analytics to enable insights that unlock new sources of business value.

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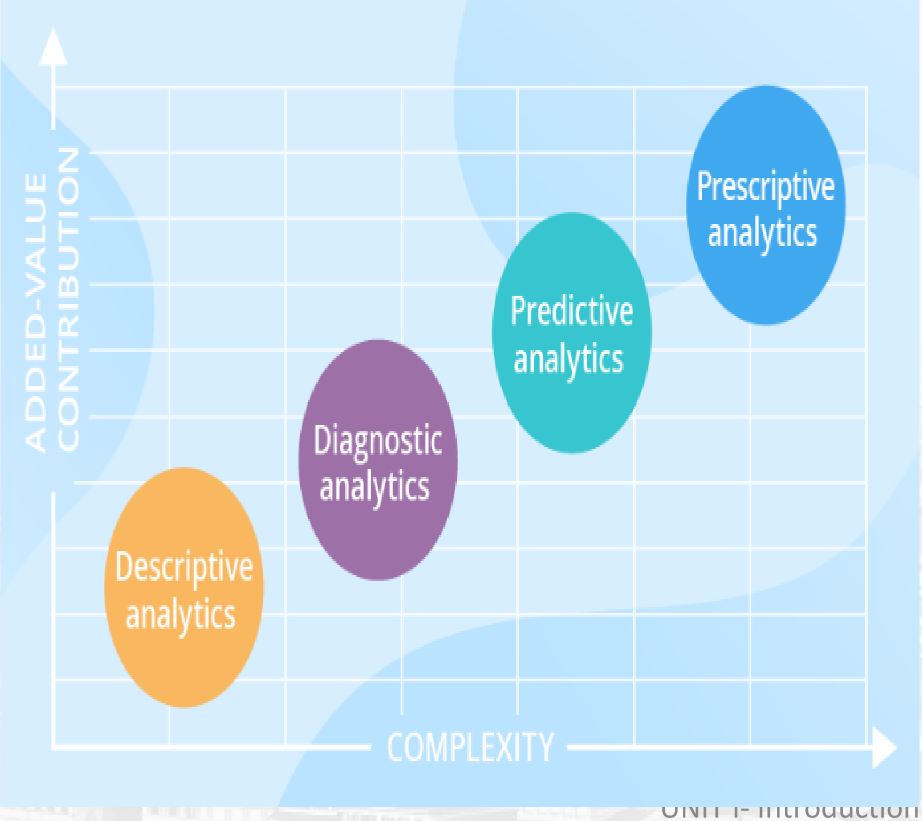
Big Data Analytics..

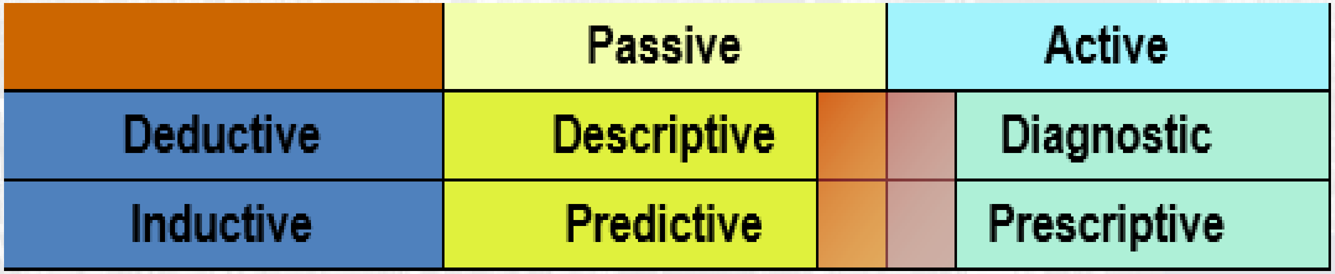
- Big data analytics is a form of advanced analytics, which involves complex applications .
- Following is the type of analytics:



- *Descriptive analytics* answers the question of what happened.
- *Diagnostic Analytics* ,historical data can be measured against other data to answer the question of why something happened.
- *Predictive analytics* tells what is likely to happen.
- The purpose of *prescriptive analytics* is to literally prescribe what action to take to eliminate a future problem or take full advantage of a promising trend.

Types of Analytics

- ***Descriptive***: A set of techniques for reviewing and examining the data set(s) to understand the data and analyze business performance.
- ***Diagnostic***: A set of techniques for determine what has happened and why
- ***Predictive***: A set of techniques that analyze current and historical data to determine what is most likely to (not) happen
- ***Prescriptive***: A set of techniques for computationally developing and analyzing alternatives that can become courses of action – either tactical or strategic – that may discover the unexpected
- ***Decisive***: A set of techniques for visualizing information and recommending courses of action to facilitate human decision-making when presented with a set of alternatives.



	Passive	Active
Deductive	Descriptive	Diagnostic
Inductive	Predictive	Prescriptive

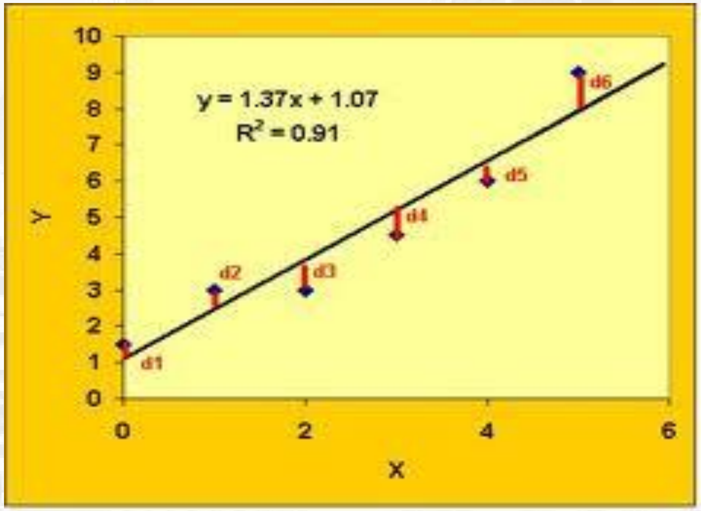
Descriptive Analytics

- **Steps:**
  - Identify the attributes, then assess/evaluate the attributes
  - Estimate the magnitude to correlate the relative contribution of each attribute to the final solution
  - Accumulate more instances of data from the data sources
  - If possible, perform the steps of evaluation, classification and categorization quickly
  - Yield a measure of adaptability within the OODA loop
- At some threshold, crossover into diagnostic and predictive analytics

“Data don’t make any sense, we will have to resort to statistics.”

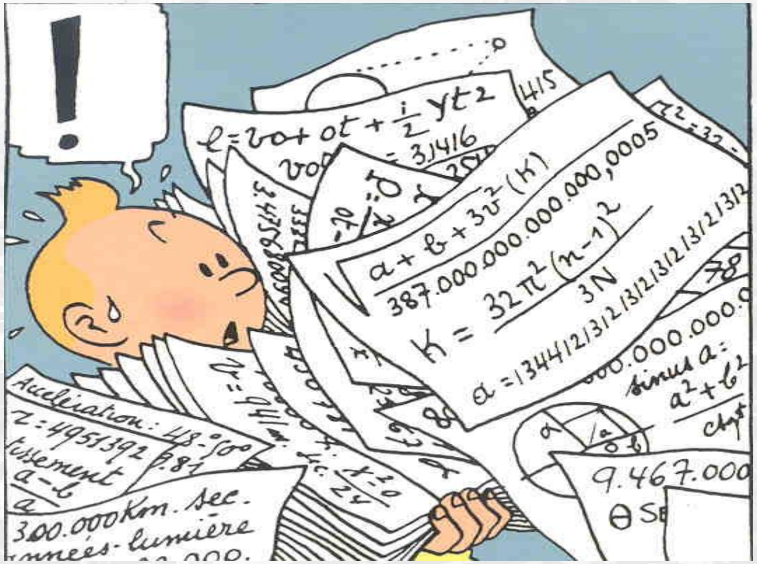
Diagnostic Analytics

- **Steps:**
  - Begin with descriptive analytics
  - Extract patterns from large data quantities via data mining
  - Correlate data types for explanation of near-term behavior – past and present
  - Estimate linear/non-linear behavior not easily identifiable through other approaches.
- Example: by classifying past insurance claims, estimate the number of future claims to flag for investigation with a high probability of being fraudulent.



Predictive Analytics

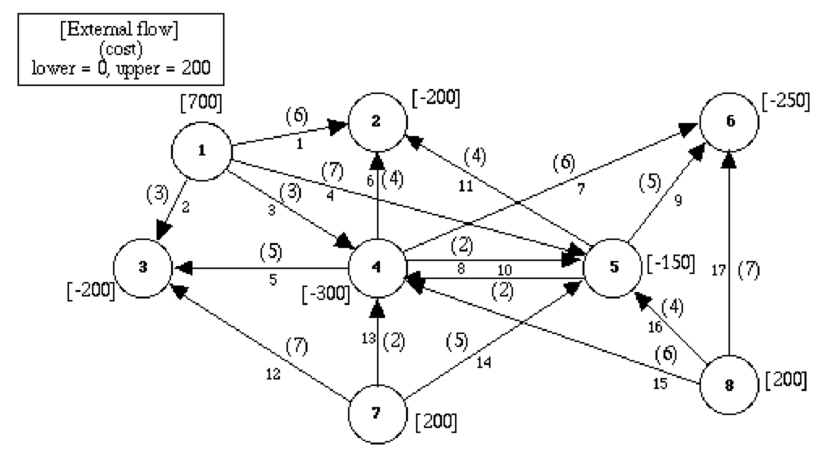
- **Steps:**
  - Begin with descriptive AND diagnostic analytics
  - Choose the right data based on domain knowledge and relationships among variables
  - Choose the right techniques to yield insight into possible outcomes
  - Determine the likelihood of possible outcomes given initial boundary conditions
  - Remember! Data driven analytics is non-linear; do NOT treat like an engineering project



Prescriptive Analytics

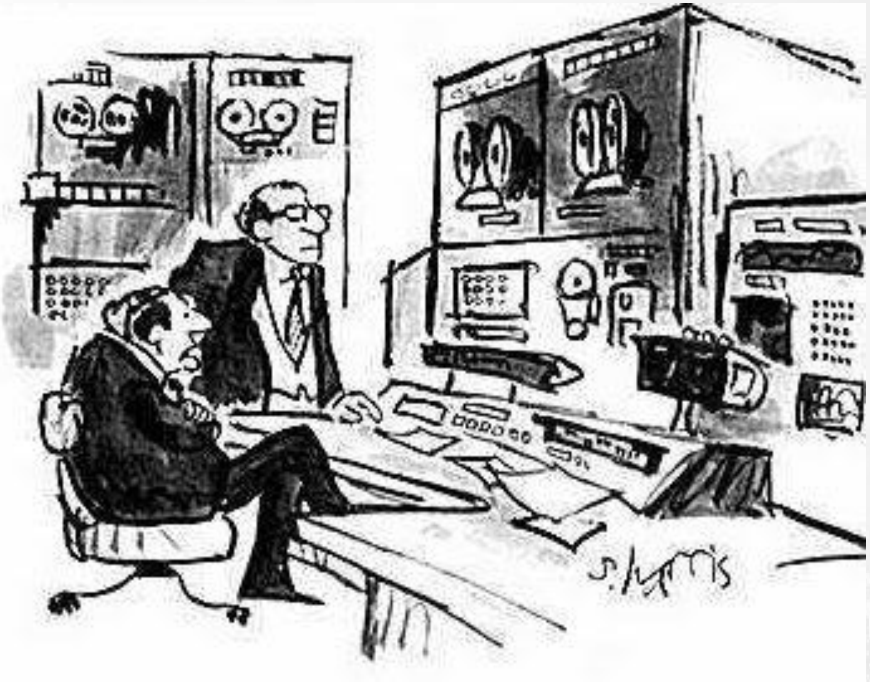
- **Steps:**
  - Begin with predictive analytics
  - Determine what should occur and how to make it so
  - Determine the mitigating factors that lead to desirable/undesirable outcomes
  - "What-if" analysis with local or global optimization

1. Find the best set of prices and advertising frequency to maximize revenue
2. The right set of business moves to make to achieve that goal



Decisive Analytics

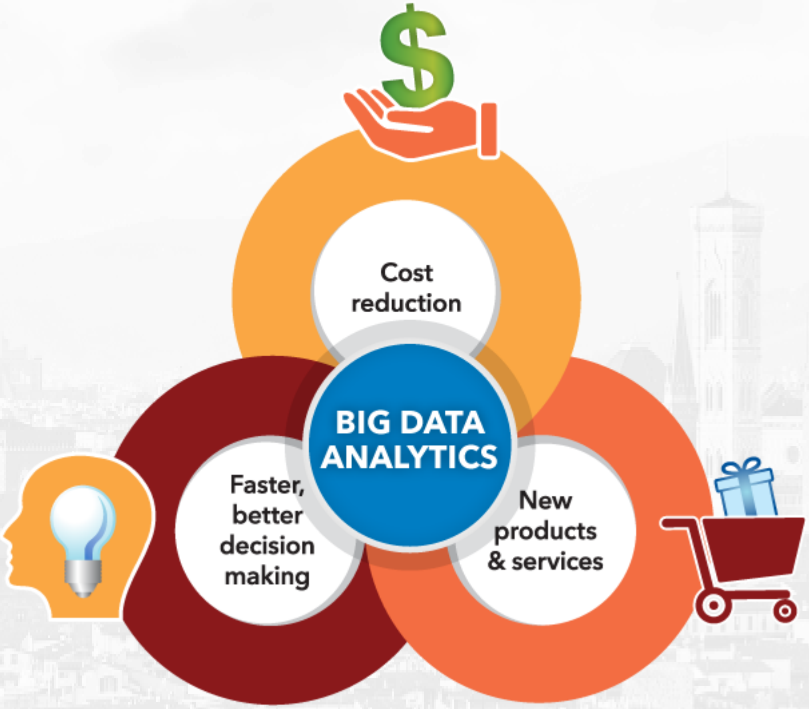
- **Steps:**
  - Given a set of decision alternatives, choose the one course of action to do from possibly many
  - But, it may not be the optimal one.
  - Visualize alternatives – whole or partial subset
  - Perform exploratory analysis – what-if and why
    - How do I get to there from here?
    - How did I get here from there?



"What it comes down to is this thing is capable of telling us a lot more than we really want to know."

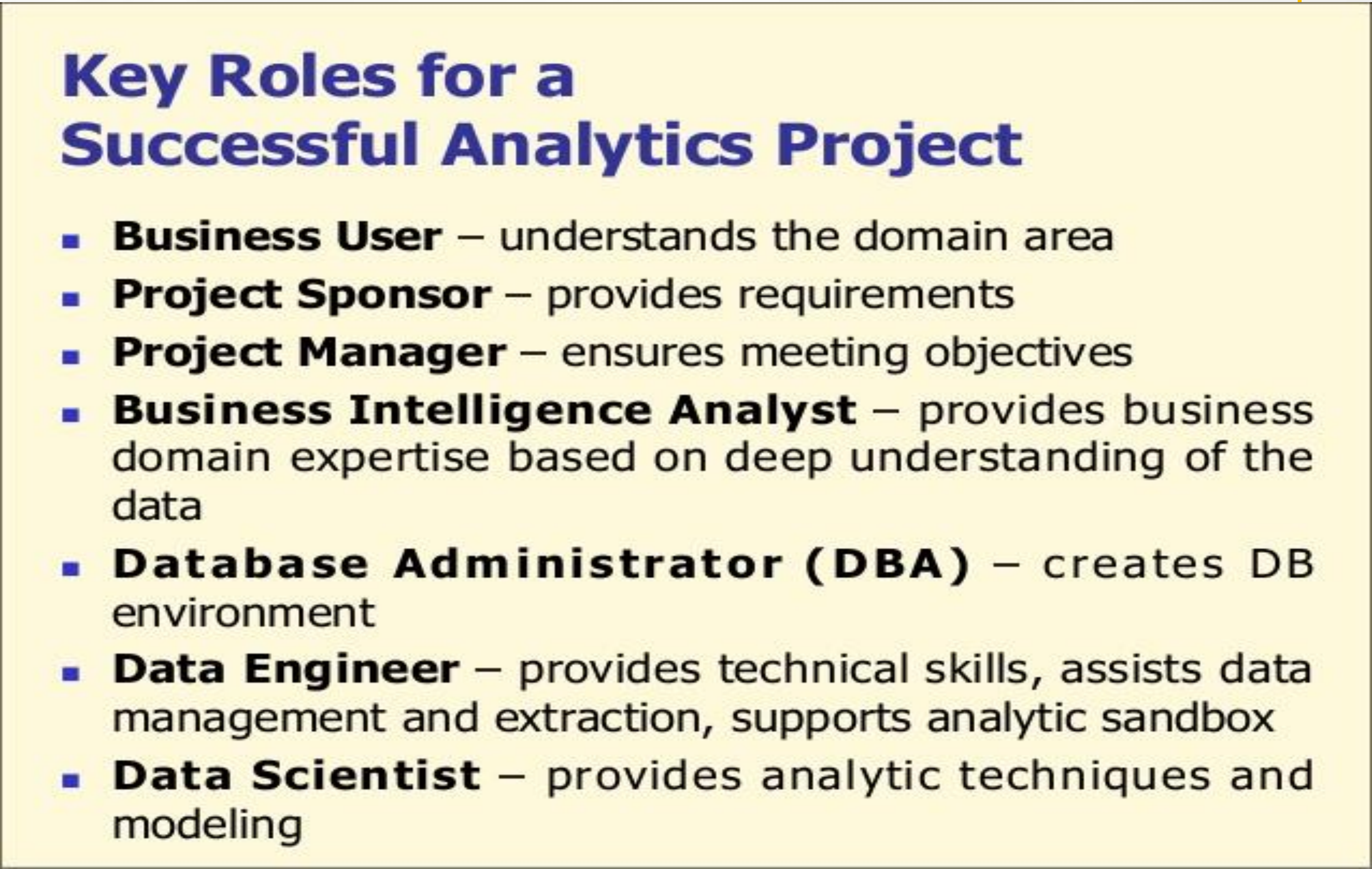
Big data Analytics

- Big data can deliver value in almost any area of business or society:



Report on Big Data in Big Companies

Key Roles For A Successful Analytics Project



Key Roles for a Successful Analytics Project

- **Business User** – understands the domain area
- **Project Sponsor** – provides requirements
- **Project Manager** – ensures meeting objectives
- **Business Intelligence Analyst** – provides business domain expertise based on deep understanding of the data
- **Database Administrator (DBA)** – creates DB environment
- **Data Engineer** – provides technical skills, assists data management and extraction, supports analytic sandbox
- **Data Scientist** – provides analytic techniques and modeling

1. Business User

- Someone who understands the domain area and usually benefits from the results.

- This person can consult and advise the project team on the context of the project, the value of the results, and how the outputs will be operationalized.[put into operation / use]

- Usually a business analyst or subject matter expert in the project domain fulfills this role.

2. Project Sponsor:

- Responsible for the genesis of the project. [origin/ source]

- Provides the impetus and requirements for the project and defines the core business problem. [impulse/stimulus]

- Generally provides the funding and gauges the degree of value from the final outputs of the working team.

- This person sets the priorities for the project and clarifies the desired outputs.

3. Project Manager:

- Ensures that key milestones and objectives are met on time and at the expected quality. [a significant stage/event]

4. Business Intelligence Analyst

- Provides business domain expertise based on :
  - **A deep understanding of the data,**
  - **Key Performance Indicators (KPIs)**
  - **key metrics**
  - **Business intelligence from a reporting perspective**
- Business intelligence analysts generally create dashboards and reports and have knowledge of the data feeds and sources.

KPIs vs Key metrics

- **KPIs** are measurable values that show you how effective you are at achieving business objectives.

- **Metrics** are different in that they simply track the status of a specific business process.

- Thus **KPIs** track whether you hit business objectives/targets, and **metrics** track processes

KPI

- Example of KPI
- Target of teams was to increase sales revenue by 20% this year end (2021)

Team A

Team B

increase in sales = 21%

increase in sales = 18%

KPIs vs Key Metrics (contd…)

- KPI addresses the overall / targeted goal / objectives.

  Metrics do not.

- Key metrics are specific.

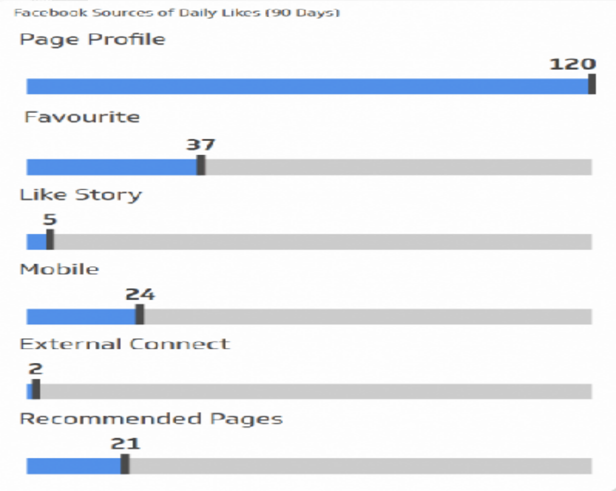
  KPIs are not.

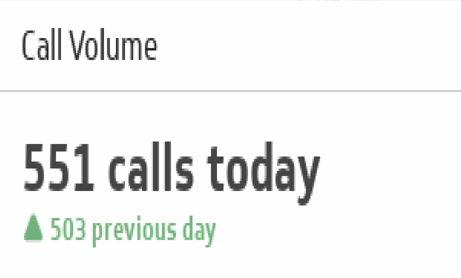
- Accurate tracking of progress (staff to enterprise) needs the use of both – *KPIs and key metrics*.

Example for KPI and Metrics

- **Best Social Media Marketing Metrics**
  - Likes
  - Engagement
  - Followers growth
  - Traffic conversions
  - Social interactions
  - Social sentiment
  - Social visitor goals
  - Social shares
  - Web visitors from social channel
  - Social visitors conversion rates

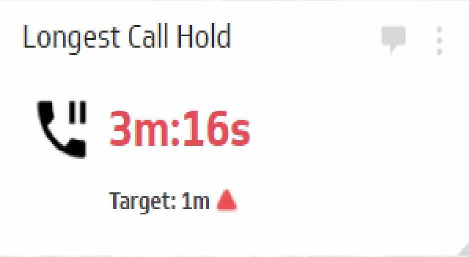
Best call center metrics to monitor
Many industry leading companies track these on TV data walls:
Call completion rate
Agent utilization
First call resolution rate
Speed of answer (SA)
Call handling time
Call drop rate (CDR)
First contact resolution rate
Sales per agent
Lead conversion rate




Call Volume

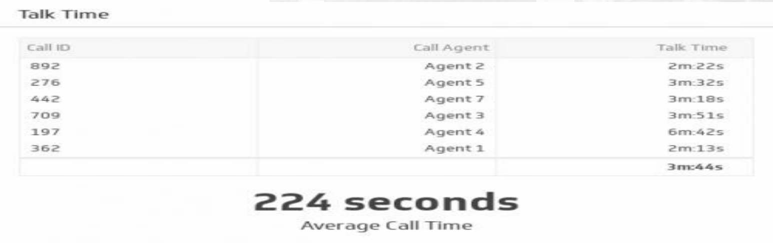
551 calls today

▲ 503 previous day


Longest Call Hold

☎ 3m:16s

Target: 1m ▲


Talk Time

Call ID	Call Agent	Talk Time
892	Agent 2	2m:22s
276	Agent 5	3m:32s
442	Agent 7	3m:18s
709	Agent 3	3m:51s
197	Agent 4	6m:42s
362	Agent 1	2m:13s
		3m:44s

224 seconds
Average Call Time

Business intelligence

- **Business Intelligence (BI)** refers to technologies, applications and practices for the collection, integration, analysis, and presentation of business information.
- The purpose of Business Intelligence is to support better business decision making.
- Business Intelligence Analysts generally create dashboards and reports and have knowledge of the data feeds and sources.

5. Database Administrator (DBA)

- Provisions and configures the database environment to support the analytics needs of the working team.

These responsibilities may include

- providing access to key databases or tables and
- ensuring the appropriate security levels are in place related to the data repositories.

6. Data Engineer

- Leverages deep technical skills to assist with tuning Query Language queries for data management and data extraction, and provides support for data ingestion into the analytic sandbox.
- While the DBA sets up and configures the databases to be used, the data engineer executes the actual data extractions and performs substantial data manipulation to facilitate the analytics.

[Analytics Sandbox]

- An Analytics Sandbox is a separate environment that is part of the architecture, used by multiple users and is maintained with the support of IT.

Key Characteristics

- The environment is controlled by the analyst
  - Allows them to install and use the data tools of their choice
  - Allows them to manage the scheduling and processing of the data assets
- Enables analysts to explore and experiment with internal and external data
- Can hold and process large amounts of data efficiently from many different data sources –

  big data (unstructured),   transactional data (structured),
  web data,   social media data,   documents etc.

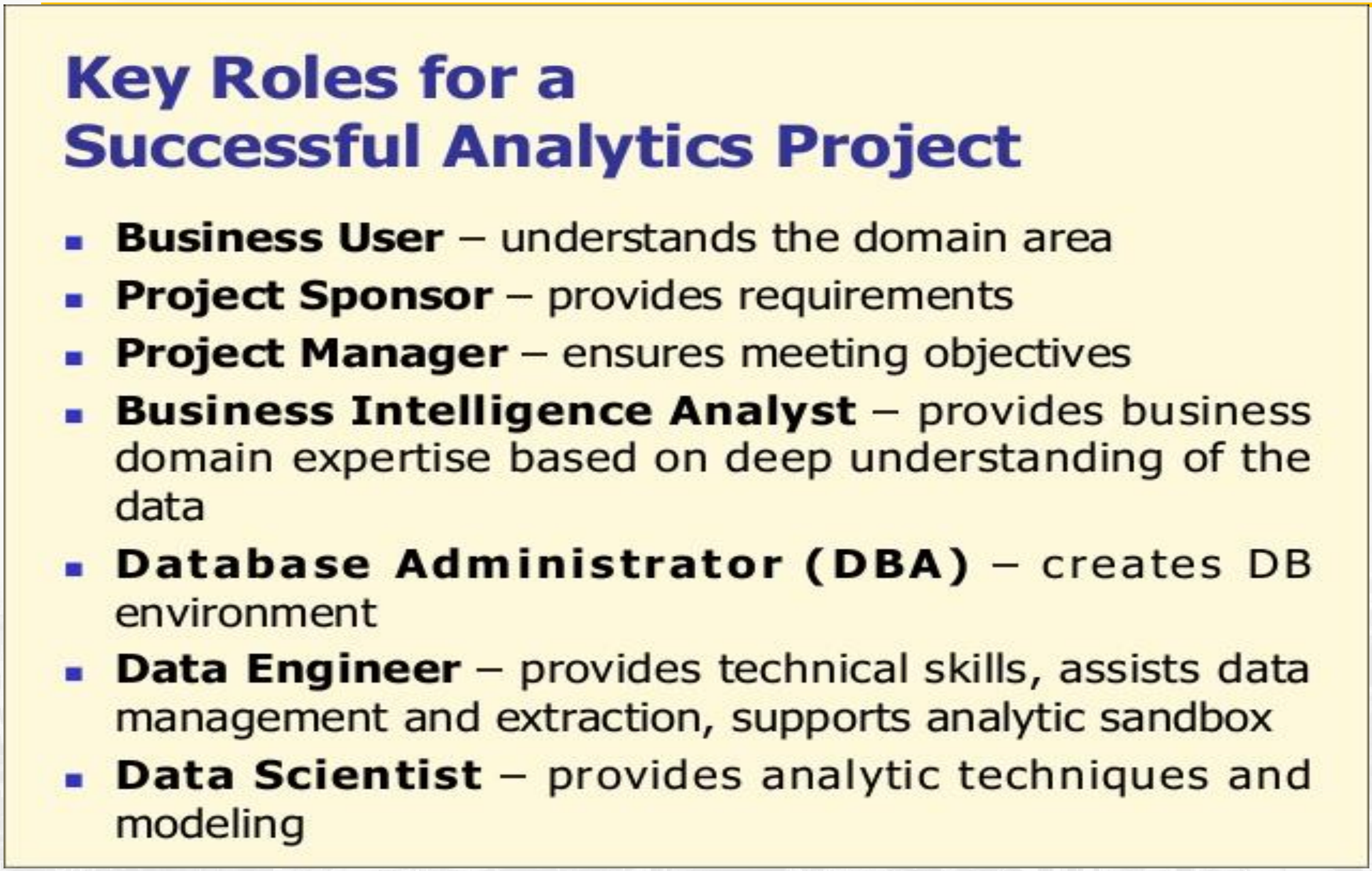
7. Data Scientist

- The data engineer works closely with the data scientist to help shape data in the right ways for analyses.
- Provides subject matter expertise for:
  - analytical techniques,
  - data modeling,
  - applying valid analytical techniques to given business problems.
- Ensures overall analytics objectives are met.
- Designs and executes analytical methods and approaches with the data available to the project.

contd…

- Each role plays a critical part in a successful analytics project.
- Although seven roles are listed, fewer or more people can accomplish the work depending on
    - » the scope of the project,
    - » organizational structure and
    - » the skills of the participants.

SUMMARY



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Syllabus

Introduction to Big Data:

- What is Big Data
- Overview of big data analytics
- Traditional database systems vs. Big Data Systems 👉
- 5 v's of big data
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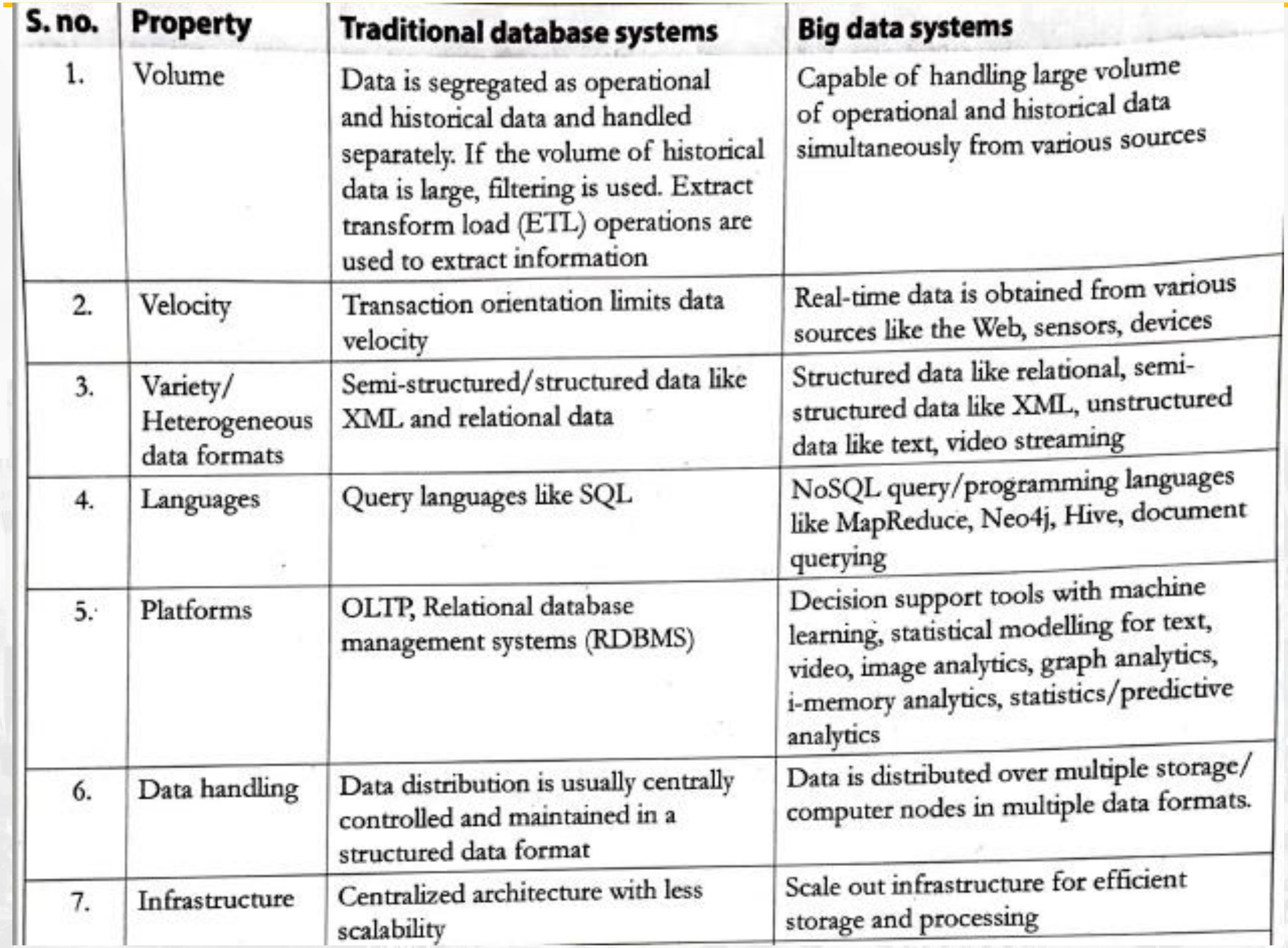
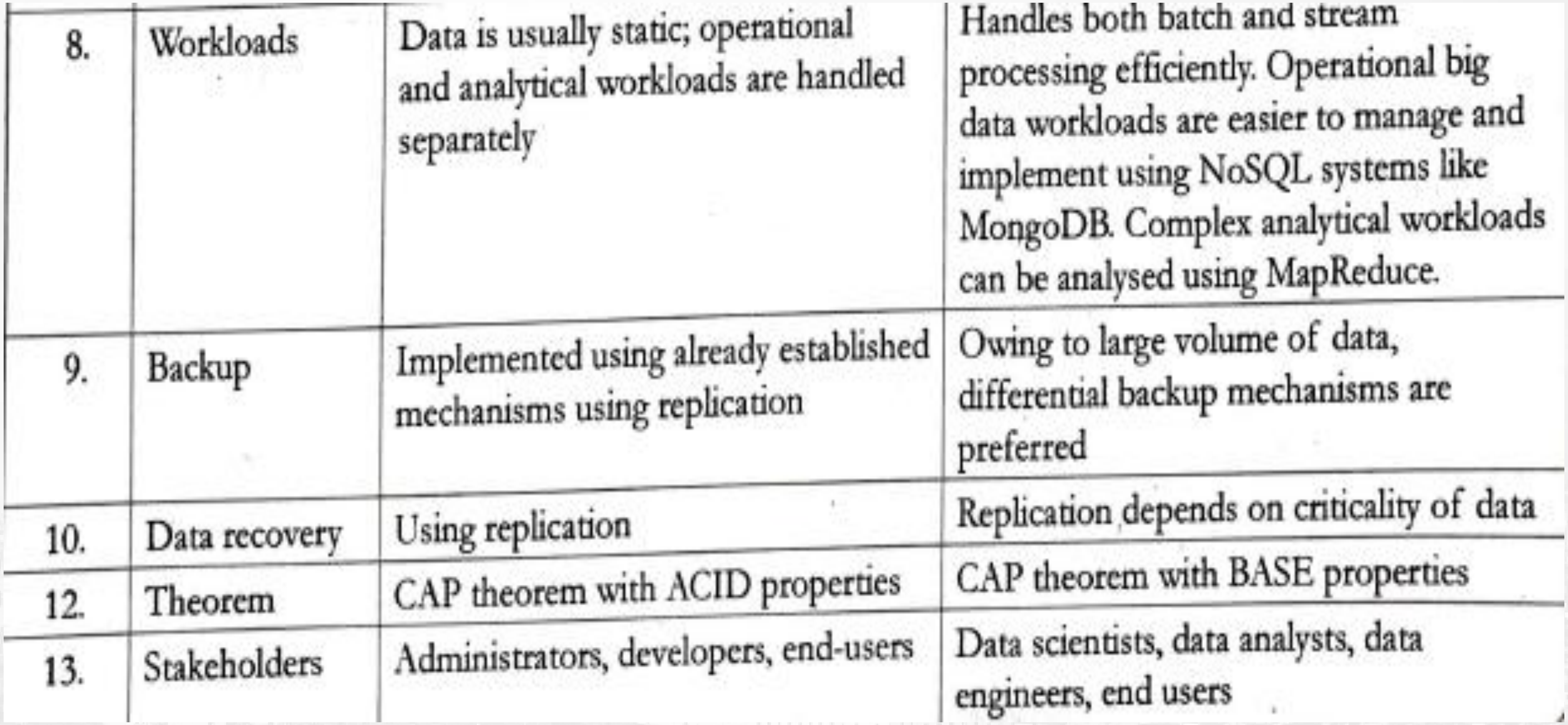
Traditional database systems
vs
Big Data systems



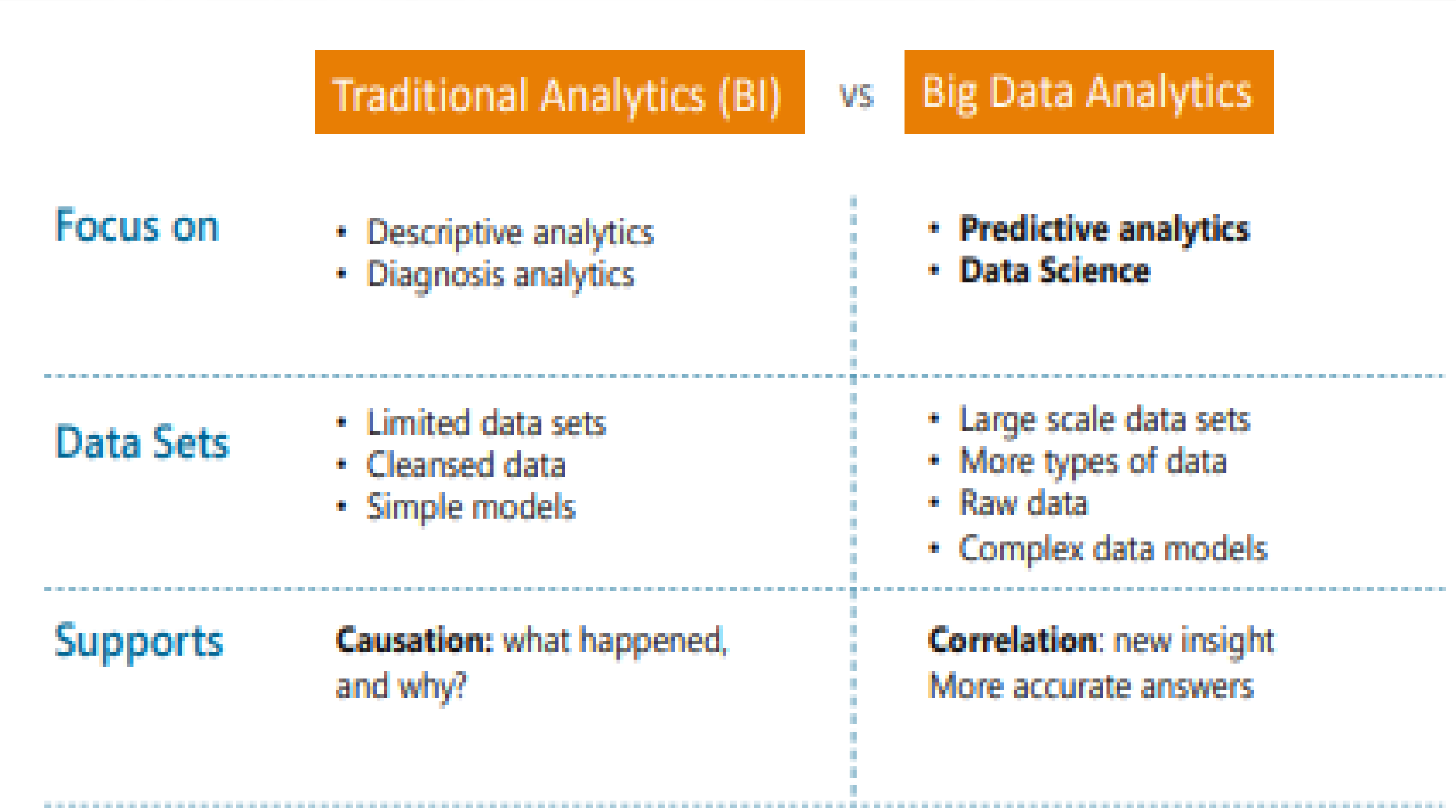
S. no.	Property	Traditional database systems	Big data systems
1.	Volume	Data is segregated as operational and historical data and handled separately. If the volume of historical data is large, filtering is used. Extract transform load (ETL) operations are used to extract information	Capable of handling large volume of operational and historical data simultaneously from various sources
2.	Velocity	Transaction orientation limits data velocity	Real-time data is obtained from various sources like the Web, sensors, devices
3.	Variety/ Heterogeneous data formats	Semi-structured/structured data like XML and relational data	Structured data like relational, semi-structured data like XML, unstructured data like text, video streaming
4.	Languages	Query languages like SQL	NoSQL query/programming languages like MapReduce, Neo4j, Hive, document querying
5.	Platforms	OLTP, Relational database management systems (RDBMS)	Decision support tools with machine learning, statistical modelling for text, video, image analytics, graph analytics, i-memory analytics, statistics/predictive analytics
6.	Data handling	Data distribution is usually centrally controlled and maintained in a structured data format	Data is distributed over multiple storage/ computer nodes in multiple data formats.
7.	Infrastructure	Centralized architecture with less scalability	Scale out infrastructure for efficient storage and processing

Traditional Database systems vs Big Data systems



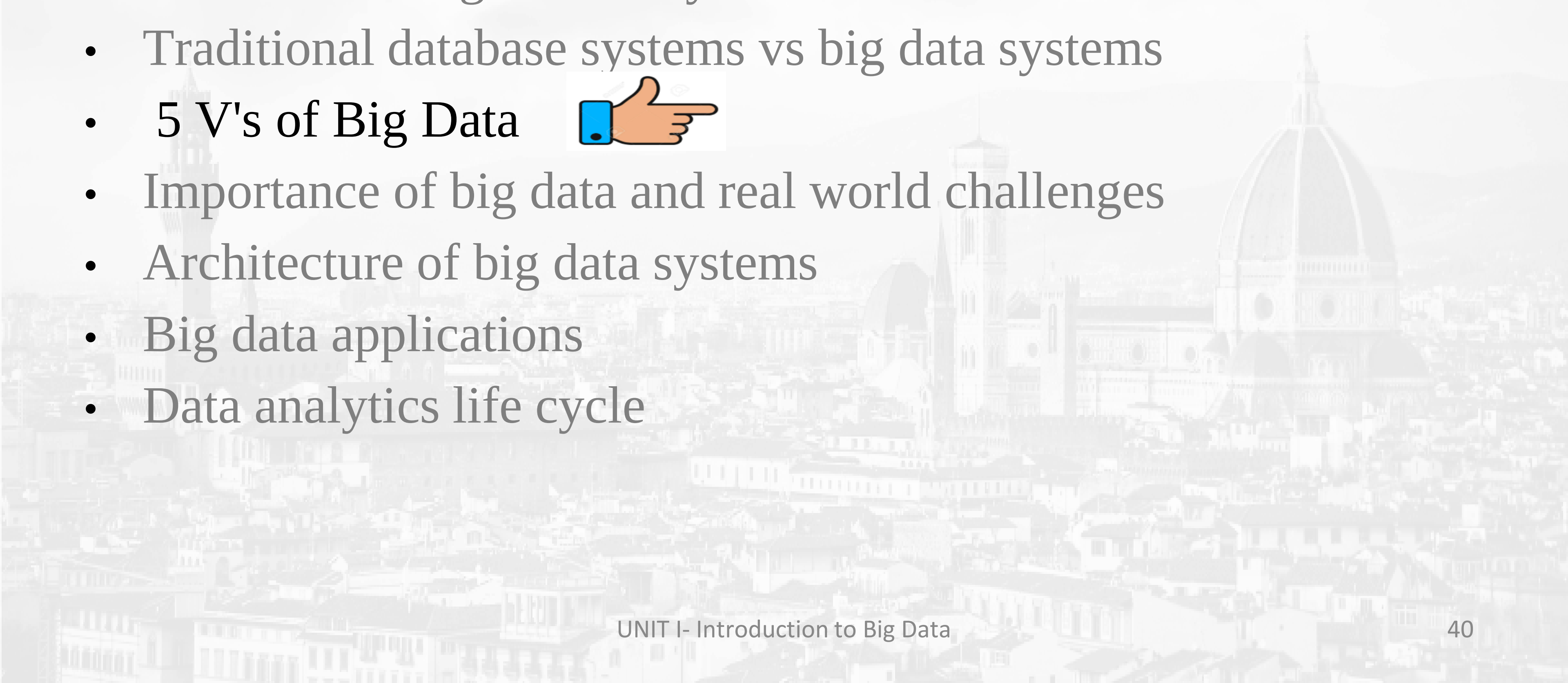
8.	Workloads	Data is usually static; operational and analytical workloads are handled separately	Handles both batch and stream processing efficiently. Operational big data workloads are easier to manage and implement using NoSQL systems like MongoDB. Complex analytical workloads can be analysed using MapReduce.
9.	Backup	Implemented using already established mechanisms using replication	Owing to large volume of data, differential backup mechanisms are preferred
10.	Data recovery	Using replication	Replication depends on criticality of data
12.	Theorem	CAP theorem with ACID properties	CAP theorem with BASE properties
13.	Stakeholders	Administrators, developers, end-users	Data scientists, data analysts, data engineers, end users

Analytics Difference



	Traditional Analytics (BI)	vs	Big Data Analytics
Focus on	- Descriptive analytics - Diagnosis analytics		- **Predictive analytics** - **Data Science**
Data Sets	- Limited data sets - Cleansed data - Simple models		- Large scale data sets - More types of data - Raw data - Complex data models
Supports	**Causation:** what happened, and why?		**Correlation**: new insight More accurate answers

Syllabus



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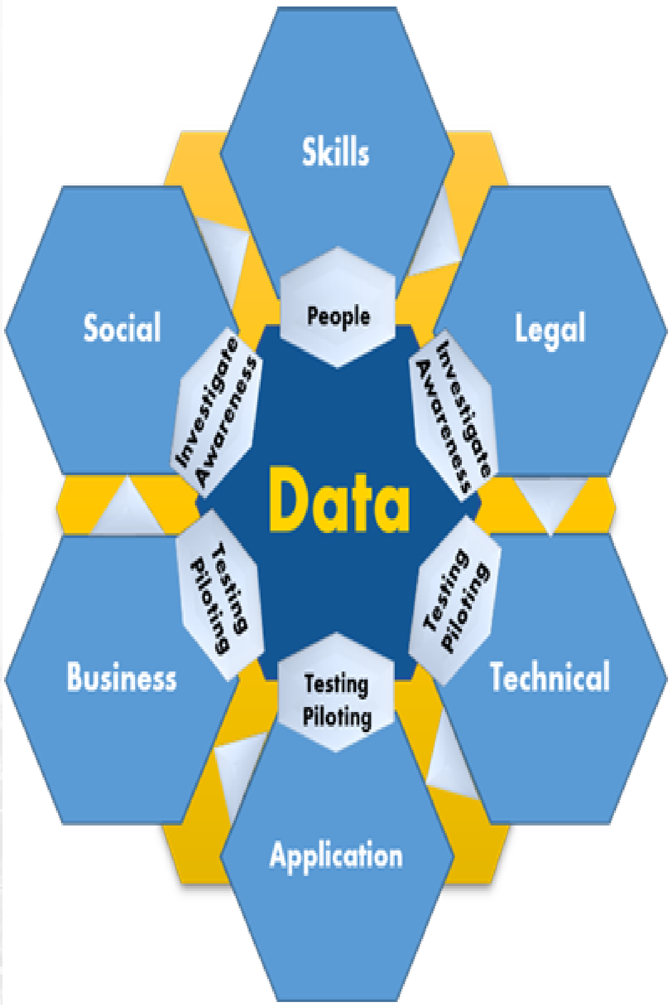
Multiple dimensions of Big Data



- Data Management
- Data Architectures
- Data Analytics
- Data Protection
- Data Visualization

DATA:

- Availability of data and the access to data sources.

- There is a broad range of data types and data sources:

  - ✓ structured and unstructured data
  - ✓ multi-lingual data sources
  - ✓ data generated from machines and sensors
  - ✓ data-at-rest
  - ✓ data–in-motion.

DATA contd…

Value is generated by:

- acquiring data,
- combining data from different sources
- providing access to it while ensuring data integrity and preserving privacy.

- **Value is added by**
- Pre-processing,
- Validating,
- Analyzing
- Augmenting
- Ensuring data integrity and accuracy

1. Skills

- Ensuring the availability of highly and rightly skilled people who have an excellent grasp of the best practices and technologies for delivering Big Data Value within applications and solutions.

- There will be the need for data scientists and engineers who have expertise in :
  - ✓ analytics
  - ✓ statistics
  - ✓ machine learning
  - ✓ data mining
  - ✓ data management.

2. Legal:

- The increased importance of data will intensify the debate on
  - data ownership and usage,
  - data protection and privacy,
  - security,
  - liability,
  - cybercrime,
  - Intellectual Property Rights (IPR)
  - impact of insolvencies on data rights.

3. Technical

- Key aspects including
  - real-time analytics,
  - low latency and scalable data processing,
  - new and rich user interfaces,
  - data interaction
  - linking data, information and content
- All have to be advanced to open up new opportunities and to sustain or develop competitive advantages.

4. Application

- Business and market ready applications need to be a core target to allow activities to have market impact.

- Novel applications and solutions must be developed and validated based on technologies and concepts in ecosystems.

5. Business

- A more efficient use of Big Data and understanding data as an economic asset carries great potential for the economy and society.

- The setup of Big Data Value ecosystems and the development of appropriate business models on top of a strong Big Data Value ecosystem must be supported in order to generate the desired positive impact on economy and employment

6. Social

- Big Data will provide solutions for major societal challenges, such as
  - The improved efficiency in healthcare information processing or
  - Reduced CO2 emissions through climate impact analysis.

- In parallel it is critical for an accelerated adoption of Big Data to increase awareness on the benefits and the Value that Big Data can create for business, the public sector, and the citizen

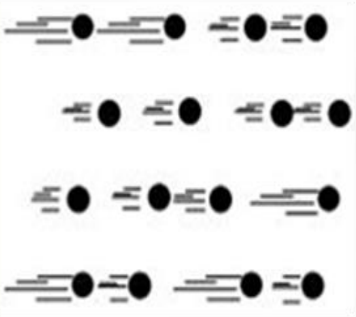
Characteristics of Big Data

Volume

Data at Rest

Terabytes to Exabytes of existing data to process

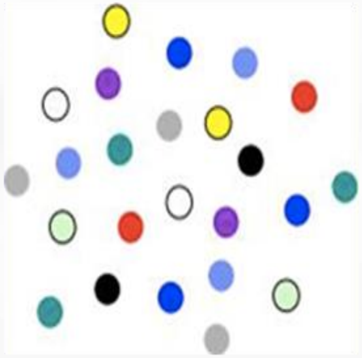
Velocity



Data in Motion

Streaming data, requiring milliseconds to seconds to respond

Variety



Data in Many Forms

Structured, unstructured, text, multimedia,…

Veracity

Data in Doubt

Uncertainty due to data inconsistency & incompleteness, ambiguities, latency, deception, model approximations

Value

Data into Money

Business models can be associated to the data

Adapted by a post of Michael Walker on 28 November 2012

1. **Volume:**

- Big data first and foremost has to be "**big**," and size in this case is measured as volume.

- Example:
- From clinical data associated with lab tests and physician visits, to the administrative data surrounding payments, this well of information is already expanding.

- When that data is coupled with greater use of precision medicine, there will be a big data explosion in health care, especially as genomic and environmental data become more ubiquitous.

2. **Velocity:**

- Velocity in the context of big data refers to two related concepts familiar to anyone in healthcare: the rapidly increasing speed at which new data is being created by technological advances, and the corresponding need for that data to be digested and analyzed in near real-time.

- Example:
- As more and more medical devices are designed to monitor patients and collect data, there is great demand to be able to analyze that data and then to transmit it back to clinicians and others.

- This “internet of things” of healthcare will only lead to increasing velocity of big data in healthcare.

3. **Variety:**

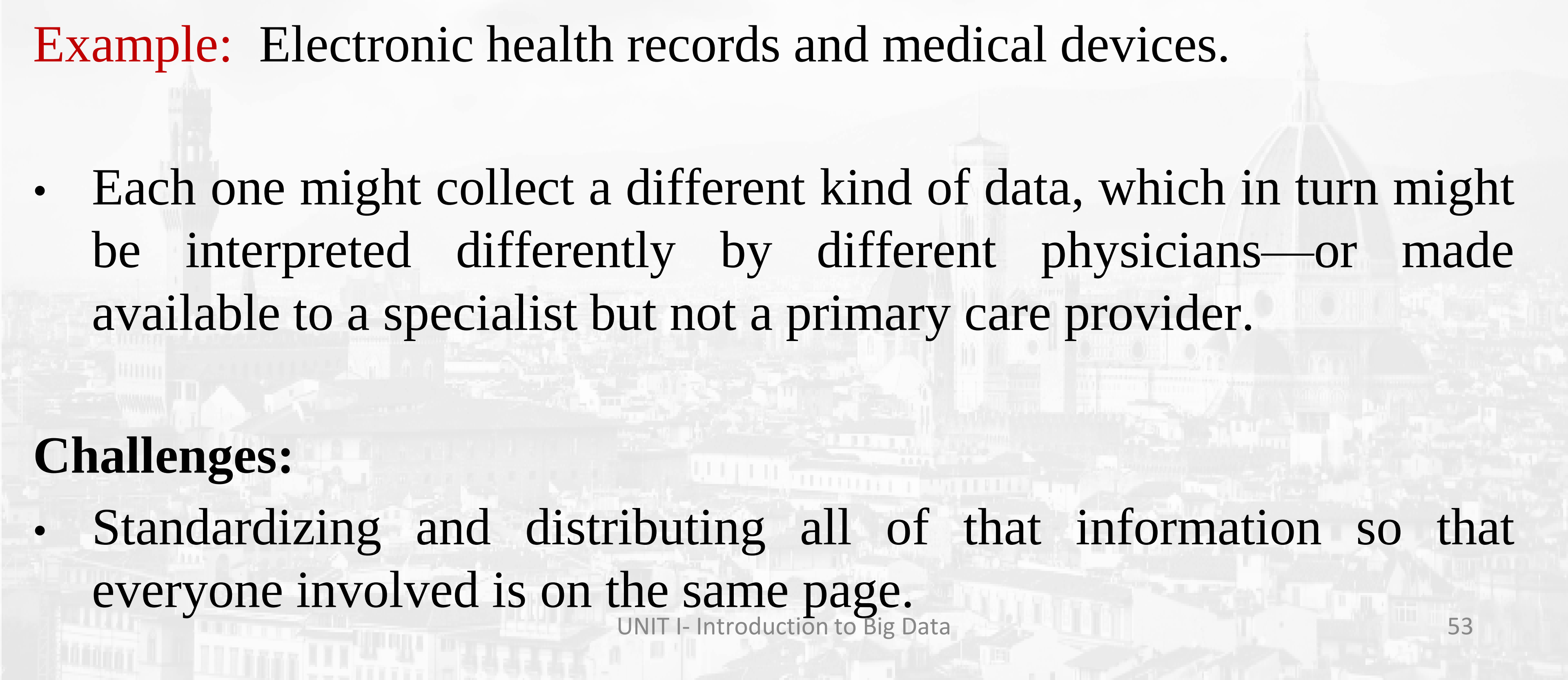
- With increasing volume and velocity comes increasing variety. This third “V” describes just what you’d think: the huge diversity of data types that healthcare organizations see every day.

Example: Electronic health records and medical devices.

- Each one might collect a different kind of data, which in turn might be interpreted differently by different physicians—or made available to a specialist but not a primary care provider.

Challenges:

- Standardizing and distributing all of that information so that everyone involved is on the same page.



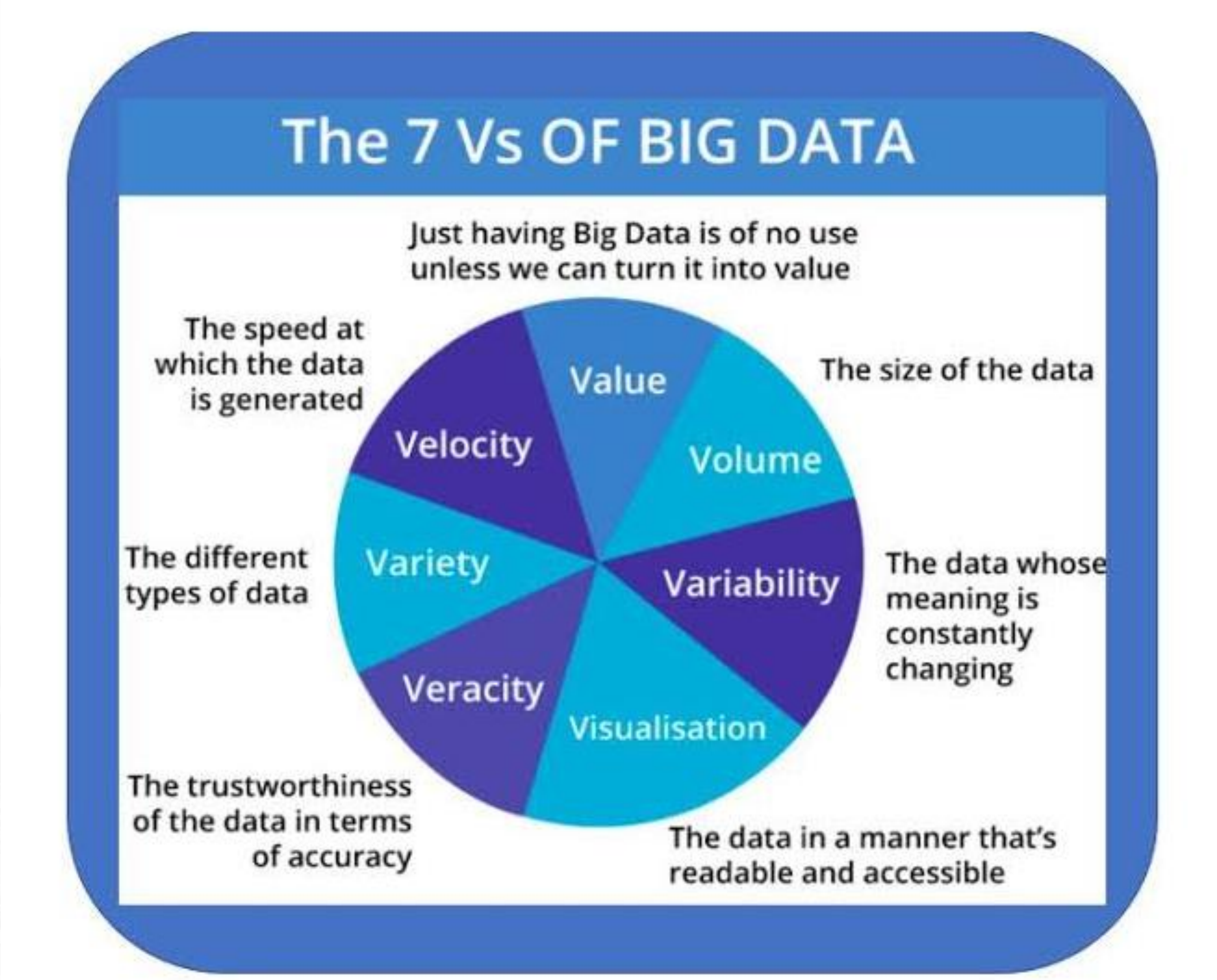
4. Veracity

- Veracity refers to the level of trustiness or messiness of data, and if higher the trustiness of the data, then lower the messiness and vice versa.
- Since the data is collected from multiple sources, we need to check the data for accuracy before using it for business insights.
- It also refers to the assurance of **quality/ integrity/ credibility/ accuracy** of the data.
- Veracity and Value both together define the data quality, which can provide great insights to data scientists..

5. Value

- Last but not least, big data must have value.
- That is, if you’re going to invest in the infrastructure required to collect and interpret data on a system-wide scale, it’s important to ensure that the insights that are generated are based on accurate data and lead to measurable improvements at the end of the day.
- Organizations might use the same tools and technologies for gathering and analyzing the data they have available, but how they then put that data to work is ultimately up to them.
- The technical experts will need to be combined with domain experts with strong industrial knowledge and the ability to apply this know-how within organisations for value creation

Current ‘V’ s of Big Data



The 7 Vs OF BIG DATA

Just having Big Data is of no use unless we can turn it into value

The size of the data

The data whose meaning is constantly changing

The data in a manner that’s readable and accessible

The trustworthiness of the data in terms of accuracy

The different types of data

The speed at which the data is generated

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- Importance of big data and real world challenges
- Architecture of big data systems
- Big data applications
- Data analytics life cycle

Importance of Big Data

- Driven by specialized analytics systems and software, as well as high-powered computing systems, big data analytics offers various business benefits, including:
  - New revenue opportunities
  - More effective marketing
  - Better customer service
  - Improved operational efficiency
  - Competitive advantages over rivals

Importance of Big Data Cont....

1. It helps companies to better understand and serve customers:

- Examples include the recommendations made by Amazon or Netflix., Coca-Cola(Customer Acquisition and Retention)

2. It allows companies to optimize their processes:

- Faster and Better Decision Making
- Example
  - UOB Bank from Singapore use Big Data for Risk Management
  - Uber is able to predict demand, dynamically price journeys and send the closest driver to the customers

Importance of Big Data Cont….

3. It improves our health care:

Government agencies can now predict flu outbreaks and track them in real time and pharmaceutical companies are able to use big data analytics to fast-track drug development.

4. It helps us to improve security:

Government and law enforcement agencies use big data to foil terrorist attacks and detect cyber crime.

5. It allows sport stars to boost their performance:

Sensors in balls, GPS trackers on their clothes allow athletes to analyze and improve upon what they do.

6. Cost Reduction:

Big Data Technologies like Hadoop and Cloud based analytics bring sufficient cost advantages when it come to storing large data

Real world challenges

- Exploiting the opportunities that Big Data presents requires new data architectures, including analytic sandboxes, new ways of working, and people with new skill sets.

- These drivers are causing organizations to set up analytic sandboxes and build Data Science teams.

Real world Challenges contd..

1. Dealing with data Growth

- The most obvious challenge associated with big data is simply storing and analyzing all that information.

2. Recruiting and retaining big data talent

- In order to develop, manage and run applications that generate insights, organizations need professionals with big data skills.
- Potential pitfalls of big data analytics initiatives include a lack of internal analytics skills and the high cost of hiring experienced data scientists and data engineers to fill the gaps.

Active Learning

State Business Goals

- Decreasing expenses through operational cost efficiencies
- Creating new avenues for innovation and disruption
- Accelerating the speed with which new capabilities and services are deployed
- Launching new product and service offerings

Real world Challenges contd..

3. **Generating insights in a timely manner**

- Business goals can be achieved if data scientists can extract insights from Big Data and can act upon on those quickly.
- Although some organizations are fortunate to have data scientists (most may not be), there is a growing talent gap that makes finding and hiring data scientists in a timely manner difficult

Real world Challenges contd..

4. **Integrating disparate data sources**

- The variety associated with big data leads to challenges in data integration.
- Big data comes from a lot of different places — enterprise applications, social media streams, email systems, employee-created documents, etc. Combining all that data and reconciling it so that it can be used to create reports can be incredibly difficult.

Real world Challenges contd..

5. **Validating data**

- Often organizations are getting similar pieces of data from different systems, and the data in those different systems doesn't always agree.
- For example, the ecommerce system may show daily sales at a certain level while the enterprise resource planning (ERP) system has a slightly different number.

Syllabus

Introduction to Big Data:

- What is Big Data
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Architecture of Big Data Systems

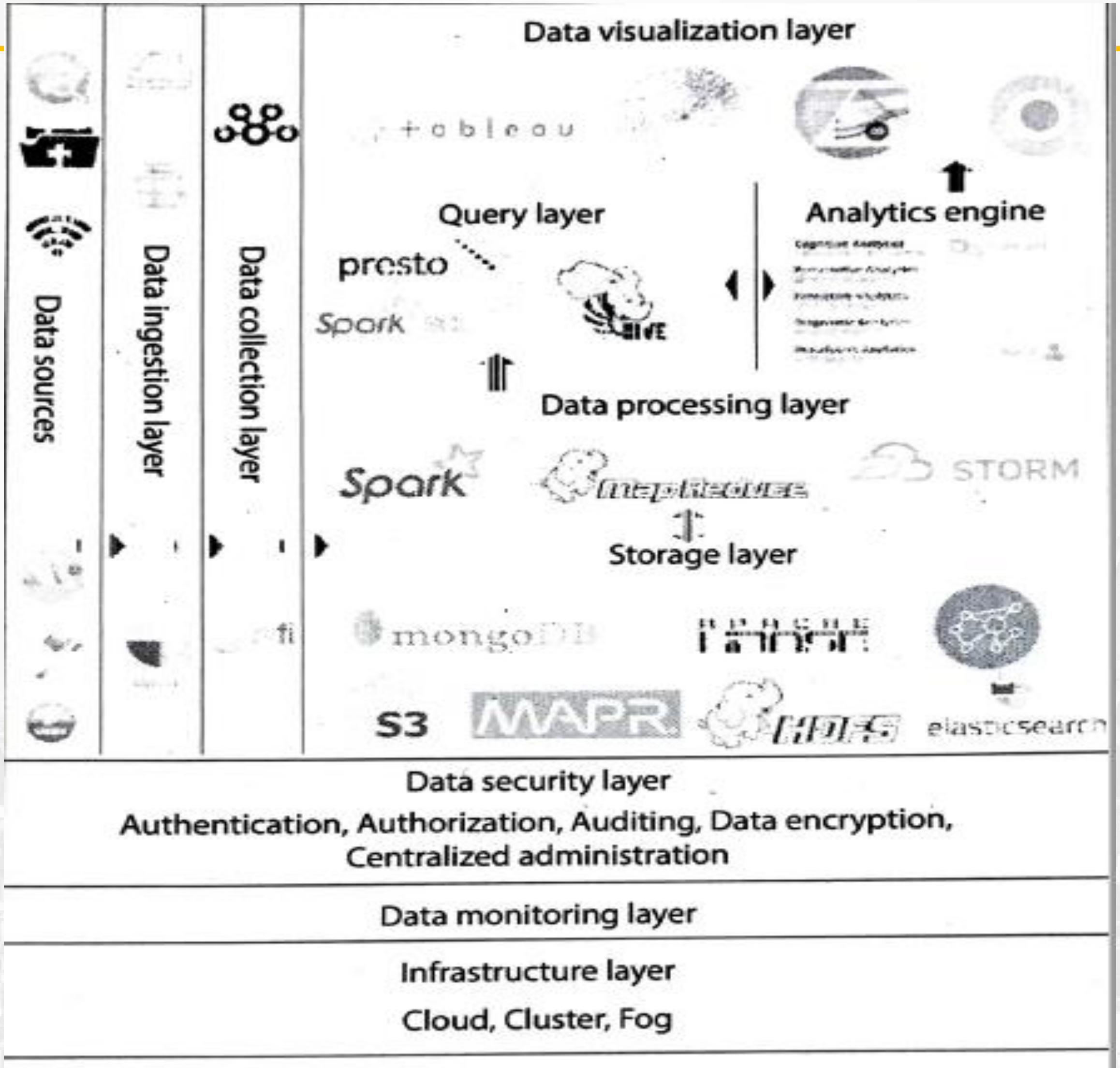

Fig. 1.3 Architecture of big data systems

Architecture of Big data Systems

Traditional Data Systems:

- Physical layer
- Logical layer
- View layer

4 Core Layers of Big Data Systems Architecture:

1. Data Storage layer
2. Data Processing layer
3. Data Query layer
4. Data Visualization layer

Architecture of Big data Systems (Cont….)

1. Data Storage layer:

   - Necessity to handle heterogeneity using different data stores
   - Polyglot persistence: Approach to identify an effective data store for a particular data
   - To store large amount of unstructured data , Hadoop Distributed File System (HDFS) can be used.
   - For Object based storage Simple Storage System(S3) can be used
   - Functionality of this layer is handled by 2 sublayers
     - Physical layer- Handles large volume of heterogeneous real-time data
     - Data layer- Maintains data blocks and the global namespace to access data
       - It also maintains tools to organize, access and retrieve heterogeneous data

Architecture of Big data Systems(Contd…)

2. Data Processing layer:

Data collected in the storage layer is processed in this layer in batch or real-time mode

- Batch Processing is used for offline Analytics
  - E.g. Hadoop is a batch processing system with Map-Reduce programming technique
- Real-time processing is used for online analytics
  - E.g. Apache storm processes streaming data in real time to make the decision
  - Spark is time-efficient, in-memory data processing engine that can execute streaming, machine learning or SQL-workloads
- Along with MapReduce, Spark it also supports tools for statistical modelling, machine Learning

Architecture of Big data Systems (Cont….)

3. Data query layer:

- This layer aims at obtaining data values or valuable insights from the processing layer
- Hive: used by data analysts to query, summarize, explore and analyze unstructured data to obtain actionable business insights
- Analytics Engine- It extends the functionality of the data processing layer with domain specific tools for decision making
- Tools in this layer performs descriptive, predictive, diagnostic analytics

Architecture of Big data Systems (Cont….)

4.Data Visualization layer:

- This layer presents the value of the data in a presentable , understandable formats
- It makes use of Dashboards, Graphs and tables tools for visualization
- E.g. Google Chart-
  - It is a JavaScript based charting library meant to enhance web applications by adding interactive charting capability.
  - Google Charts provides wide variety of charts. For example, line charts, spline charts, area charts, bar charts, pie charts and so on.
- E.g. D3-
  - It is programming tool for visualization
  - User must be knowledgeable on Java Script to visualize the collected data effectively

Architecture of Big data Systems (Cont....)

Following layers offer common services to the core layers also called as *service layers.*

1. Data Ingestion layer:

   - This layer determines the value of information extracted
   - Data coming from different sources is prioritized, validated, categorized and routed to the destination for effective storage and access
   - Data may be ingested in batches periodically or in real time
   - E.g. Sqoop-
     - Supports bulk data transfer between Hadoop and structured stores such as ORACLE, MYSQL
   - E.g. Elastic Logstash-
     - Aggregates data from multiple sources and routes it to Elastic Search Engine
   - E.g. Flume
     - Framework based on the streaming flows to efficiently collect, aggregate large real time data.

Architecture of Big data Systems (Cont….)

2. Data Collector layer:

- This layer transport data from ingestion layer to the rest of the data pipeline
- E.g. Kafka-
  - It is a message oriented middleware used for data collection
  - It collaborates with Storm, Hbase, Spark for real time analysis of data

3. Data Security layer:

- This layer provides authentication, Authorization, audit, data encryption and central administration for big data systems
- E.g. Knox in Hadoop stack, Kerberos, HDFS encryption

Architecture of Big data Systems (Cont….)

4. Data Monitoring layer:

- It includes tools for monitoring the performance at infrastructure, framework analytics engine, data store and application levels

5. Infrastructure layer:

- This layer provides the hardware to host various big data frameworks in cloud infrastructure that is highly scalable and preferable

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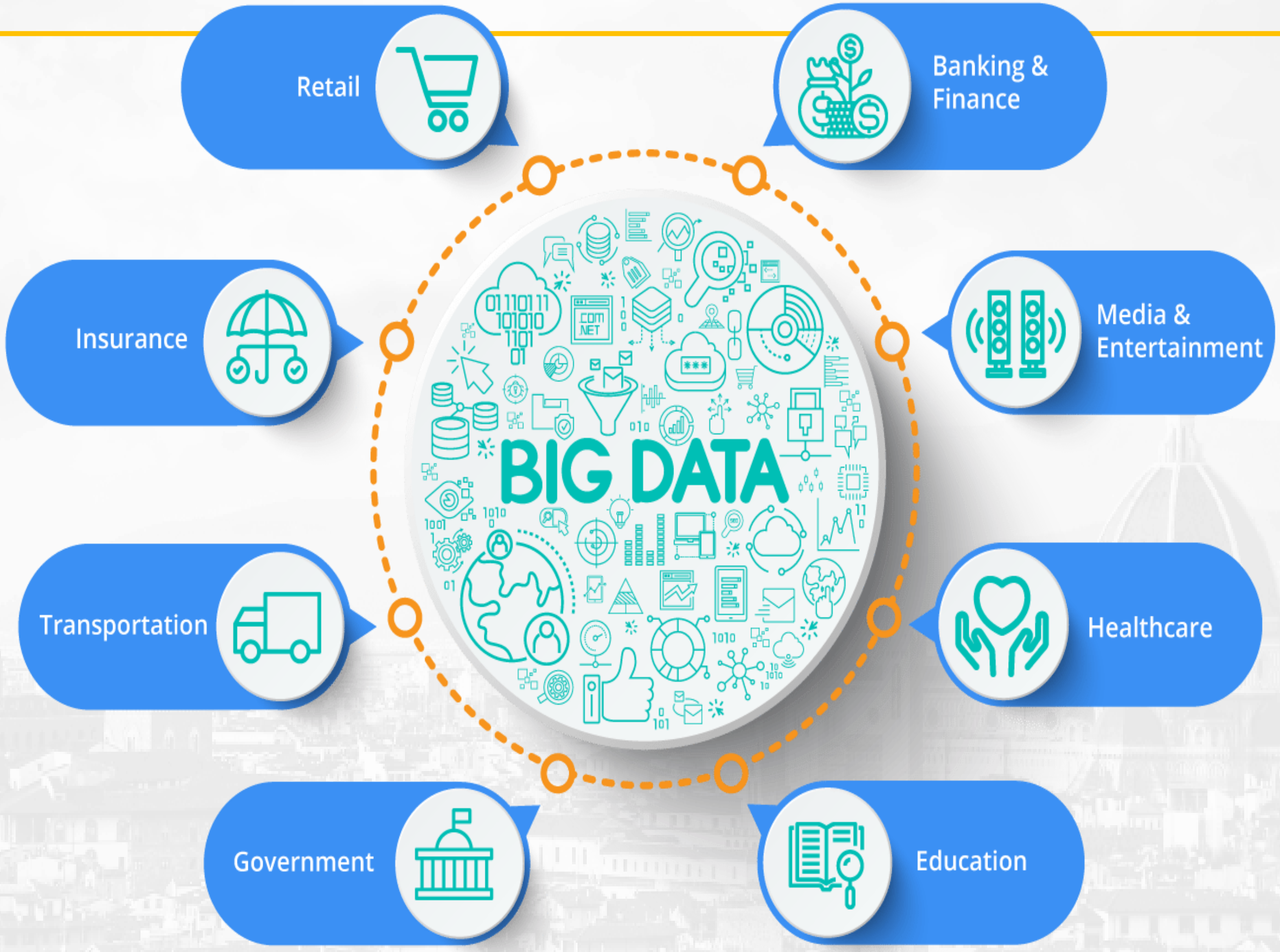
Big Data Applications



BIG DATA

Retail

Banking & Finance

Insurance

Media & Entertainment

Transportation

Healthcare

Government

Education

Big Data Applications

- Sports Domain
  - To understand and study player movement
  - E.g. Nike uses big data for eco-friendly product design
- Sentiment Analysis
  - To understand changing customer interest, identify potential customer
  - E.g. Delta Airlines
- Behavioral Analysis
  - To understand customer behavior
  - E.g. Amazon’s product recommendations , Mc Donald, target leverages, shopping patterns
- Healthcare

Big Data Applications

- Customer Segmentation
  - It is the grouping of similar users on their purchases and recommending suitable items for them based on personal or group interest.
    - e.g. Pandora provides music recommendation based on static profile, related songs, user interest, location.
    - Netflix uses collaborative filtering algo. to recommend the movies.
    - Amazon
- Prediction
  - It is the outcome done on historical information.
- Fraud Detection
  - To detect prevent and eliminate internal and external frauds.
  - Unusual usage pattern of a debit and credit cards can alert a bank of stolen card.
- Personalized Healthcare

Big Data Architecture for personalized Healthcare.

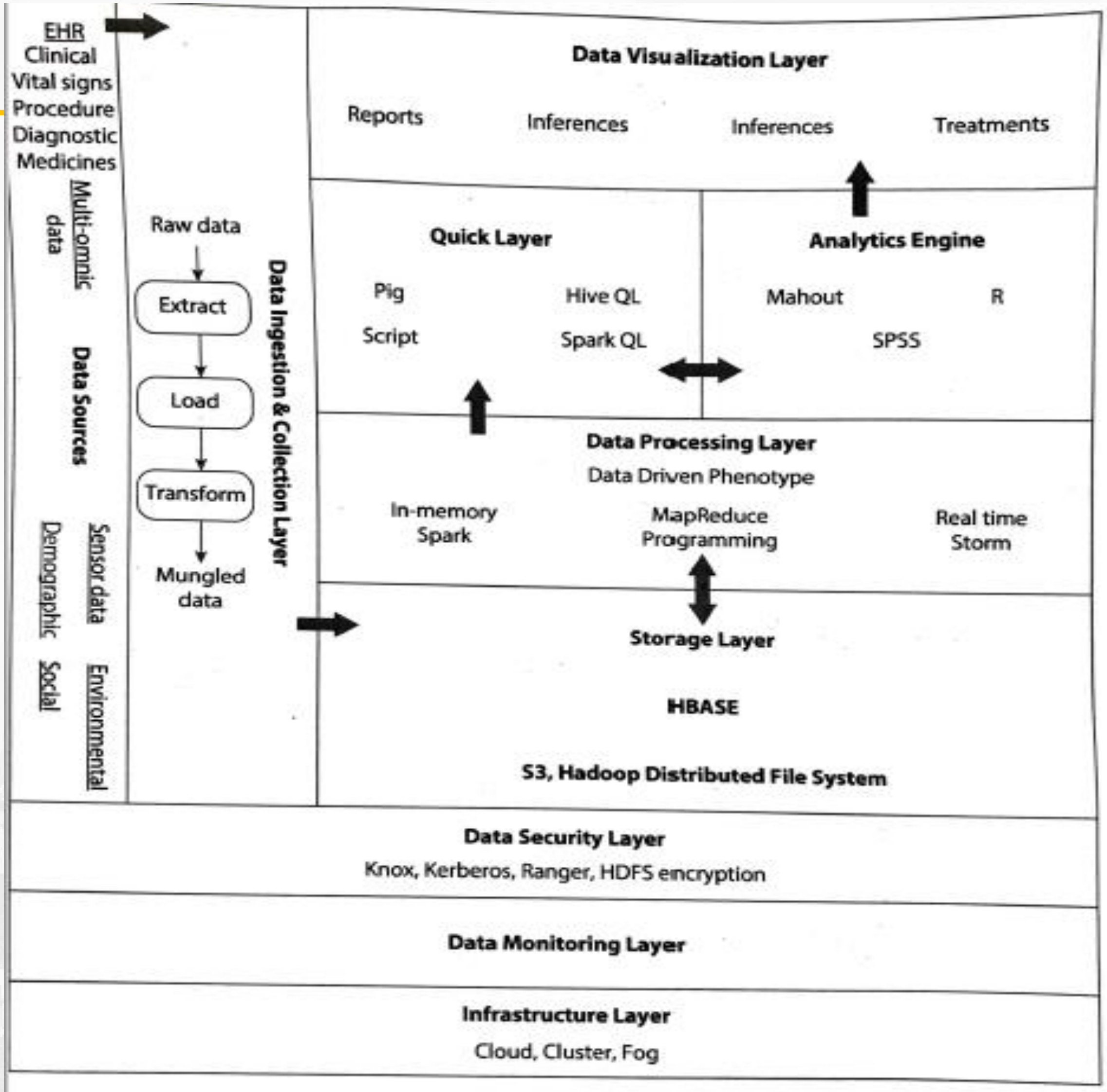


Fig. 1.5 Big data architecture for personalized healthcare

Personal Health Care Cont….

- The data processing layer extracts the Big Data Driven phenotype.
- The analytic layer uses the following:
  - *Descriptive analytics* to evaluate various statistics and visualize them using charts.
  - *Diagnostics analytics* using survival analysis and regression technique to correlate survival rate of patients with heart failure.
  - *Predictive analytics* using classification , clustering and inferential analysis to predict survival rate for a new patient.
  - *Prescriptive analytics* for treatment plan and decision support.

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Data Analytics Life Cycle

- The Data Analytics Lifecycle defines analytics process best practices spanning discovery to project completion.
- The lifecycle draws from established methods in the realm of data analytics and decision science.
- This synthesis was developed after gathering input from data scientists and consulting established approaches that provided input on pieces of the process.
- Traditional projects follows the process centric approach(WAERFALL/ SPIRAL) to develop the project.
- SDLC can *not be applied directly* for the data analytics projects as it is *data centric* projects.
- We have to follow CRISP-DM approach for data oriented projects.

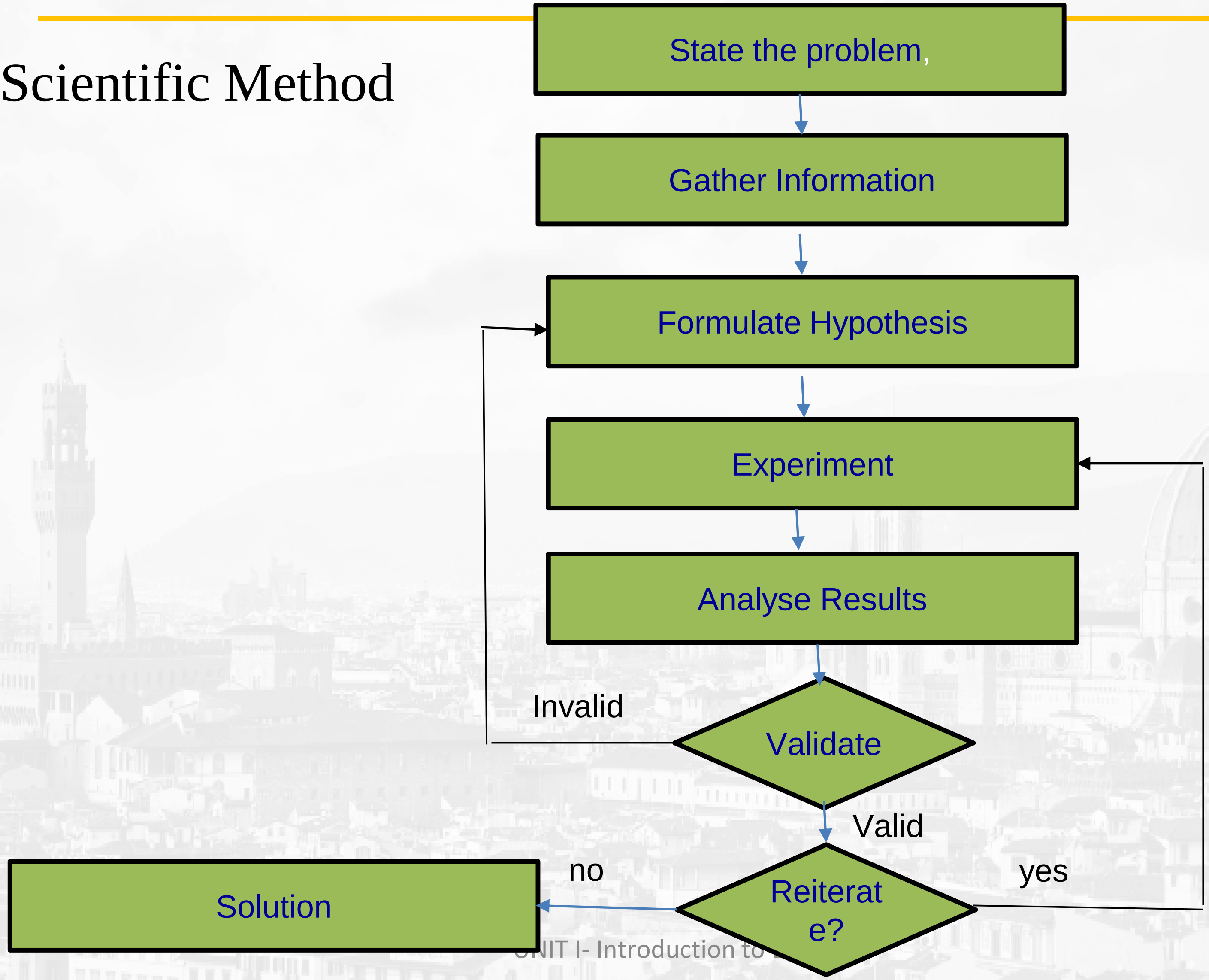
Life Cycle of Data Centric Projects

- Techniques Include:

1. Scientific Method
2. Cross Industry Standard Process for Data Mining (CRISP-DM)
3. Sample, Explore, Modify, Model, Access (SEMMA)
4. DELTA Framework
5. Applied Information Economics(AIE) Approach
6. Magnetic, Agile, Deep Analytic skills

Life Cycle of Data Centric Projects

1. Scientific Method



State the problem,

Gather Information

Formulate Hypothesis

Experiment

Analyse Results

Validate

Invalid

Valid

Reiterate?

yes

no

Solution

Life Cycle of Data Centric Projects

2. CRISP-DM Phases include
    1. Business Understanding
    2. Data Understanding
    3. Data Preparation
    4. Modelling
    5. Evaluation
    6. Deployment

- This approach was incorporated into SPSS .
- This model is highly suitable for data mining projects dealing with traditional business intelligence.

Process Flow in CRISP

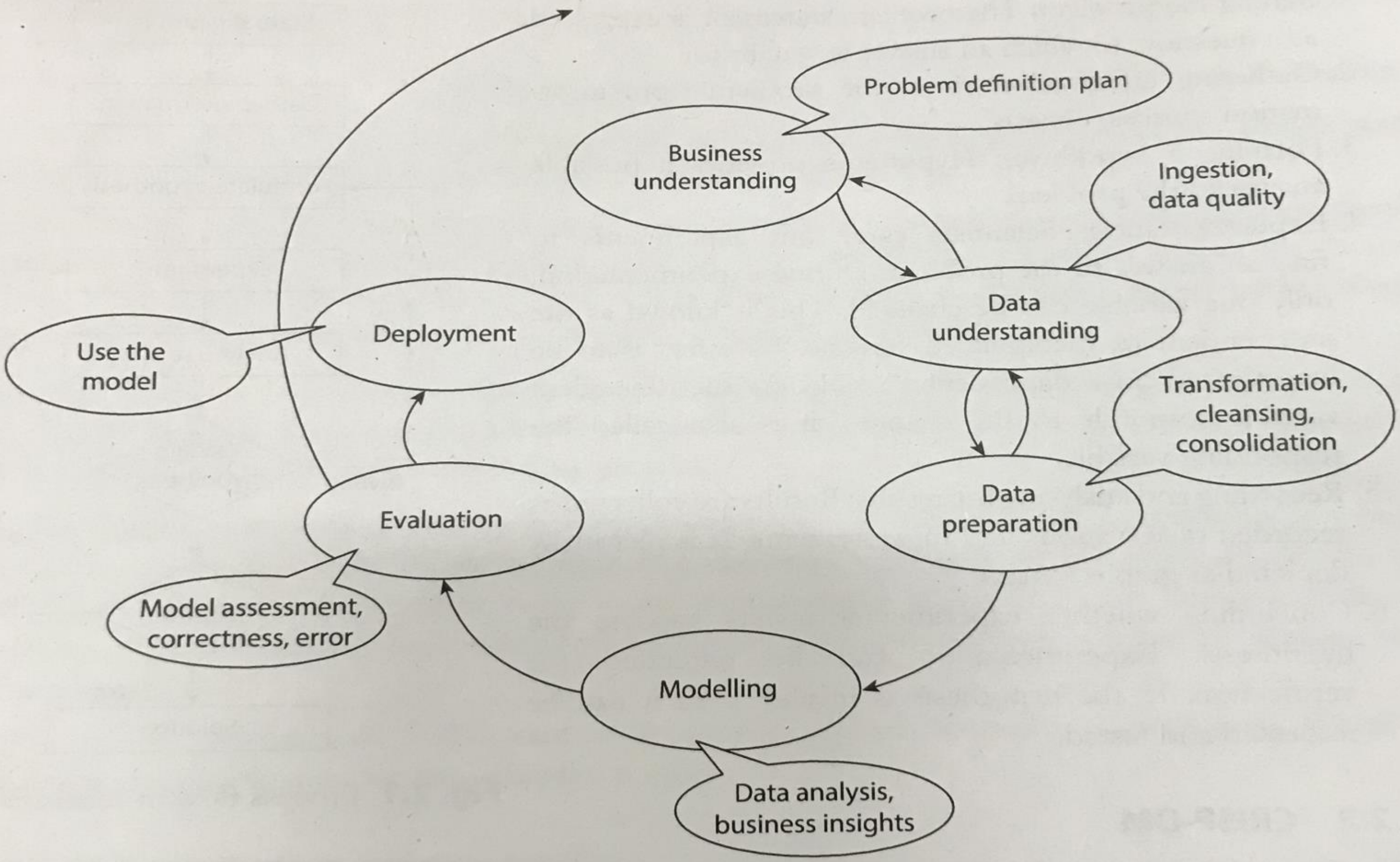


Fig. 2.2 Process flow in CRISP-DM

3. SEMMA Methodology

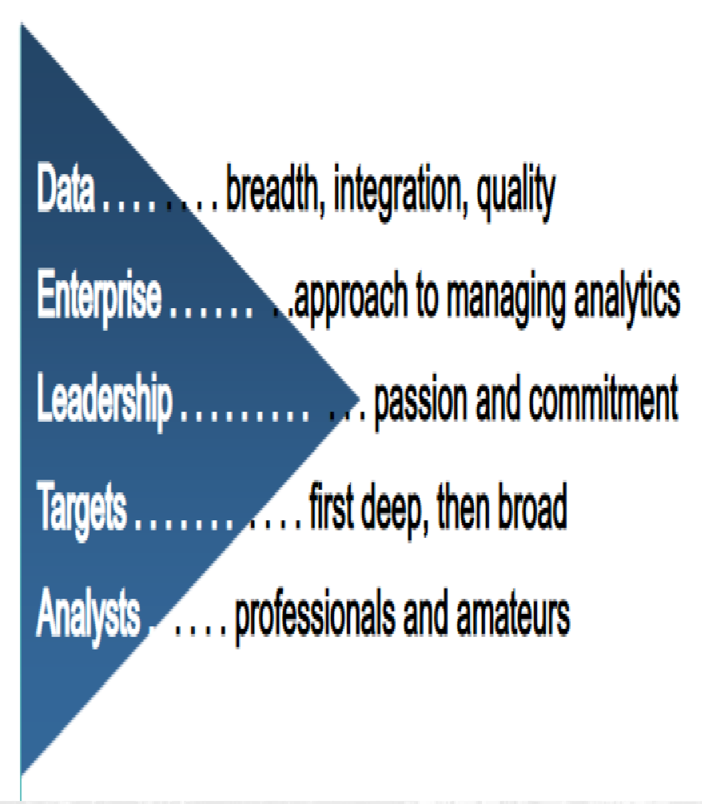
- SEMMA is another methodology developed by SAS for *data mining* modeling.
- It stands for **S**ample, **E**xplore, **M**odify, **M**odel, and **A**ssess. Here is a brief description of its stages −
- **Sample** − The process starts with data sampling, e.g., selecting the dataset for modeling.
  - The dataset should be large enough to contain sufficient information to retrieve, yet small enough to be used efficiently.
  - This phase also deals with data partitioning.
- **Explore** − This phase covers the understanding of the data by discovering anticipated and unanticipated relationships between the variables, and also abnormalities, with the help of data visualization.

SEMMA Methodology cont….

- **Modify** – The Modify phase contains methods to select, create and transform variables in preparation for data modeling.
- **Model** – In the Model phase, the focus is on applying various modeling (data mining) techniques on the prepared variables in order to create models that possibly provide the desired outcome.
- **Assess** – The evaluation of the modeling results shows the reliability and usefulness of the created models.
- Difference between CRISM–DM and SEMMA
  - SEMMA focuses on the *modeling aspect*, whereas CRISP-DM gives more importance *to stages of the cycle prior to modeling* such as understanding the business problem to be solved, understanding and preprocessing the data and deployment phases.
  - Both the models are iterative, adaptive, cyclic.

4. DELTA FRAMEWORK/ model

- Suggested by Davenport.



Data……….breadth, integration, quality

Enterprise…… ..approach to managing analytics

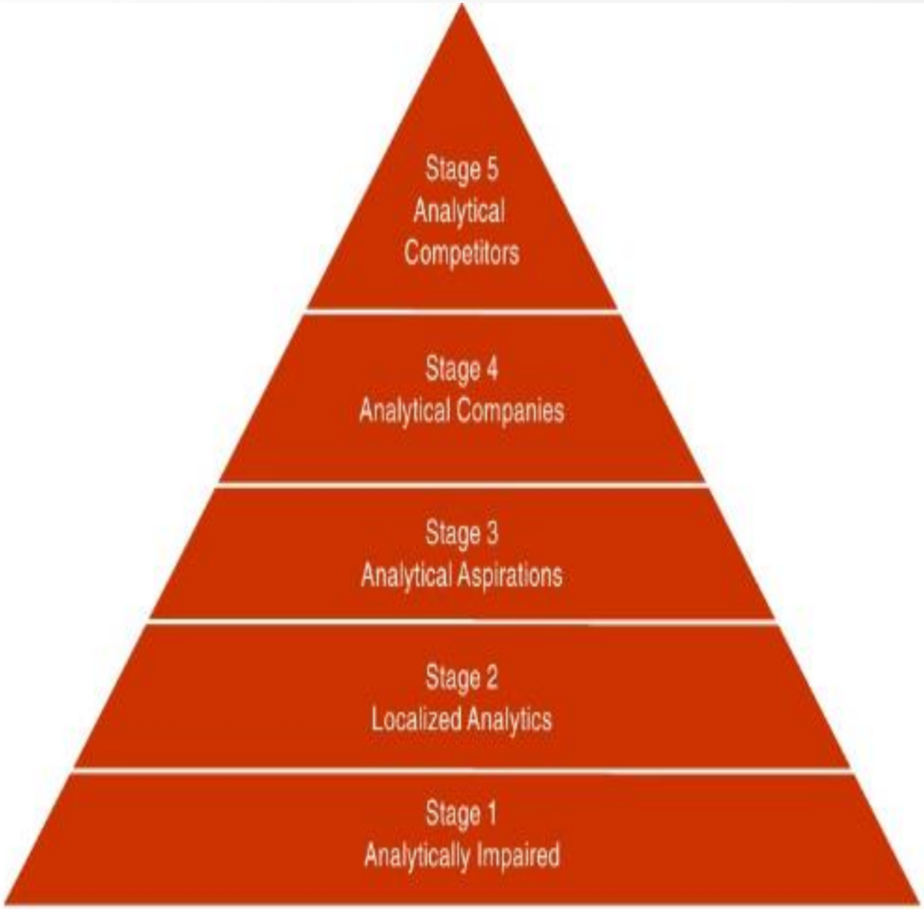
Leadership……… …. passion and commitment

Targets………….first deep, then broad

Analysts…….professionals and amateurs

Analytical DELTA pieces

- Companies can implement the Delta elements into 5 stages



Stage 5
Analytical
Competitors

Stage 4
Analytical Companies

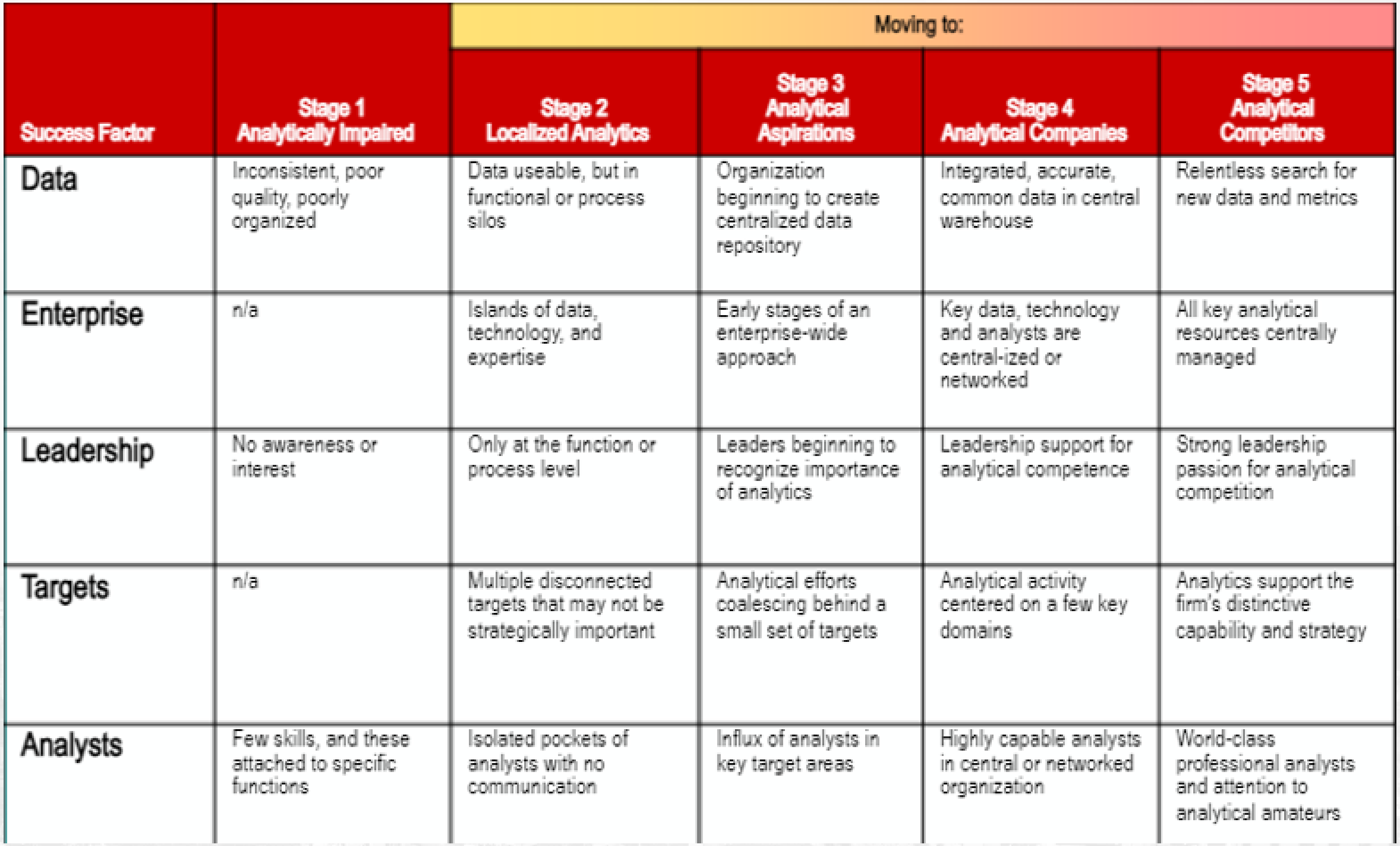
Stage 3
Analytical Aspirations

Stage 2
Localized Analytics

Stage 1
Analytically Impaired

Thomas H. Davenport – Analytics at Work

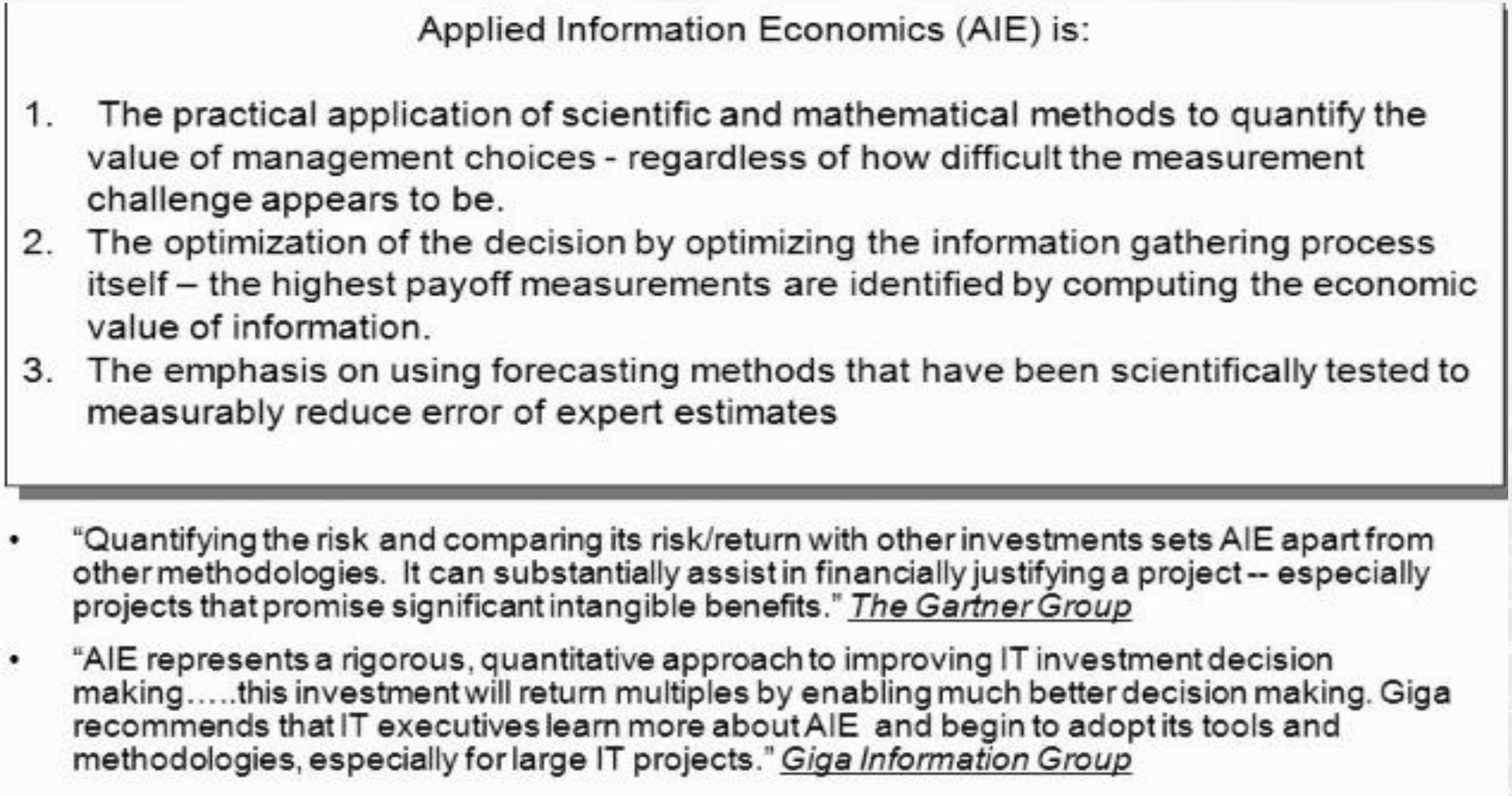
Mapping DELTA elements with organizational analytical maturity



		Moving to:			
Success Factor	Stage 1 Analytically Impaired	Stage 2 Localized Analytics	Stage 3 Analytical Aspirations	Stage 4 Analytical Companies	Stage 5 Analytical Competitors
Data	Inconsistent, poor quality, poorly organized	Data useable, but in functional or process silos	Organization beginning to create centralized data repository	Integrated, accurate, common data in central warehouse	Relentless search for new data and metrics
Enterprise	n/a	Islands of data, technology, and expertise	Early stages of an enterprise-wide approach	Key data, technology and analysts are central-ized or networked	All key analytical resources centrally managed
Leadership	No awareness or interest	Only at the function or process level	Leaders beginning to recognize importance of analytics	Leadership support for analytical competence	Strong leadership passion for analytical competition
Targets	n/a	Multiple disconnected targets that may not be strategically important	Analytical efforts coalescing behind a small set of targets	Analytical activity centered on a few key domains	Analytics support the firm's distinctive capability and strategy
Analysts	Few skills, and these attached to specific functions	Isolated pockets of analysts with no communication	Influx of analysts in key target areas	Highly capable analysts in central or networked organization	World-class professional analysts and attention to analytical amateurs

5. Applied Information Economics Approach(AIE)

- It is a proven method for measuring intangibles, optimizing decisions and avoiding catastrophe.



Applied Information Economics (AIE) is:

1. The practical application of scientific and mathematical methods to quantify the value of management choices - regardless of how difficult the measurement challenge appears to be.
2. The optimization of the decision by optimizing the information gathering process itself – the highest payoff measurements are identified by computing the economic value of information.
3. The emphasis on using forecasting methods that have been scientifically tested to measurably reduce error of expert estimates

- "Quantifying the risk and comparing its risk/return with other investments sets AIE apart from other methodologies. It can substantially assist in financially justifying a project -- especially projects that promise significant intangible benefits." *The Gartner Group*
- "AIE represents a rigorous, quantitative approach to improving IT investment decision making.....this investment will return multiples by enabling much better decision making. Giga recommends that IT executives learn more about AIE and begin to adopt its tools and methodologies, especially for large IT projects." *Giga Information Group*

AIE

Cont…

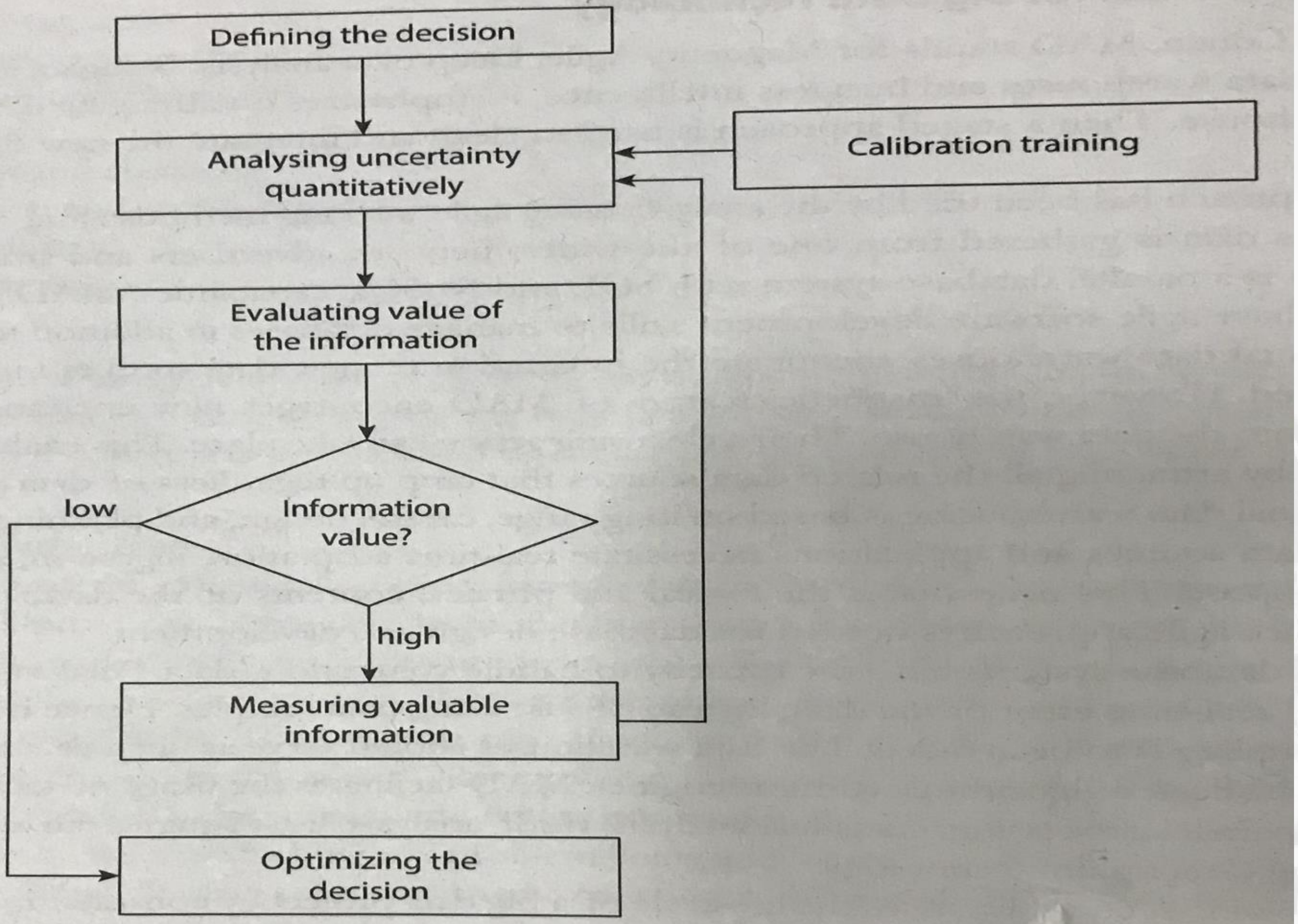

Defining the decision
Analysing uncertainty quantitatively
Calibration training
Evaluating value of the information
Information value?
low
high
Measuring valuable information
Optimizing the decision

Fig. 2.3 Stages in AIE framework

6. Magnetic, Agile, Deep Analytic skills (MAD Technique)

- Magnetic, Agile, Deep Analytic skills.
- It attracts data from different data sources to data warehouse.
- Then a staged approach is used to clean and integrate the new data with the warehouse.
- This approach is used by the analysts using agile working methods along with deep analytics .
  - *E.g. Voluminous data can be collected from one of the widest network advertisers and stored Greenplum.*
  - *Greenplum is a parallel database system with SQL+NoSQL capabilities.*
- MAD encourages Agile software technologies to manage databases with their analytics skills.
- In traditional DW integration takes place after cleaning the data while in magnetic feature of MAD encourages new un-cleaned data sources included in DW.
- MAD technique uses OLAP, datacubes, parallel processing, statistical analysis , tf-idf analysis etc. using Greenplum technology.

Big Data Analytics Life Cycle

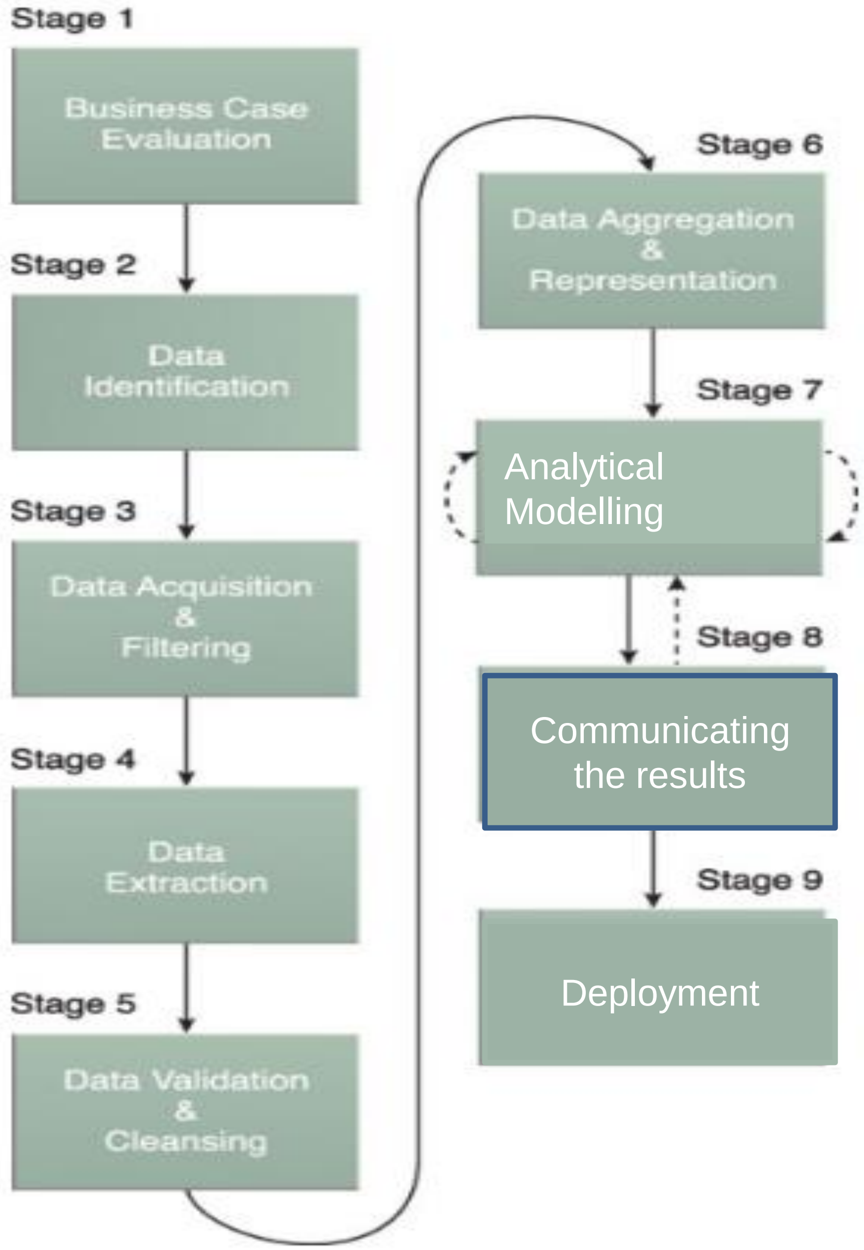


Figure 3.6 The nine stages of the Big Data analytics lifecycle.

1. Business Case Evaluation

- It must begin with a well-defined business case that presents a clear understanding of the justification, motivation and goals of carrying out the analysis.
- An evaluation of a Big Data analytics business case helps decision-makers to understand the business resources which helps business challenges to tackle including KPIs .
- The outcome of this stage is the understand budget (h/w, s/w) required to carry out the analysis project.
- Initial iterations of the Big Data analytics lifecycle will require more up-front investment of Big Data technologies, products and training compared to later iterations

2. Data Identification

- Identifying a wider variety of data sources may increase the probability of finding hidden patterns and correlations.
- Depending on the business scope of the analysis project and nature of the business problems being addressed, the required datasets and their sources can be categorized into 2 types
  - ➢ Internal datasets: such as data marts and operational systems, are typically compiled and matched against a pre-defined dataset specification.
  - ➢ External datasets: publicly available datasets, content-based web sites, blogs.
- Review the raw data
- Evaluating the data structures.
- Decide on the infrastructure requirements.

3. Data Acquisition and Filtering

- The data is gathered from all of the data sources that were identified during the previous stage.

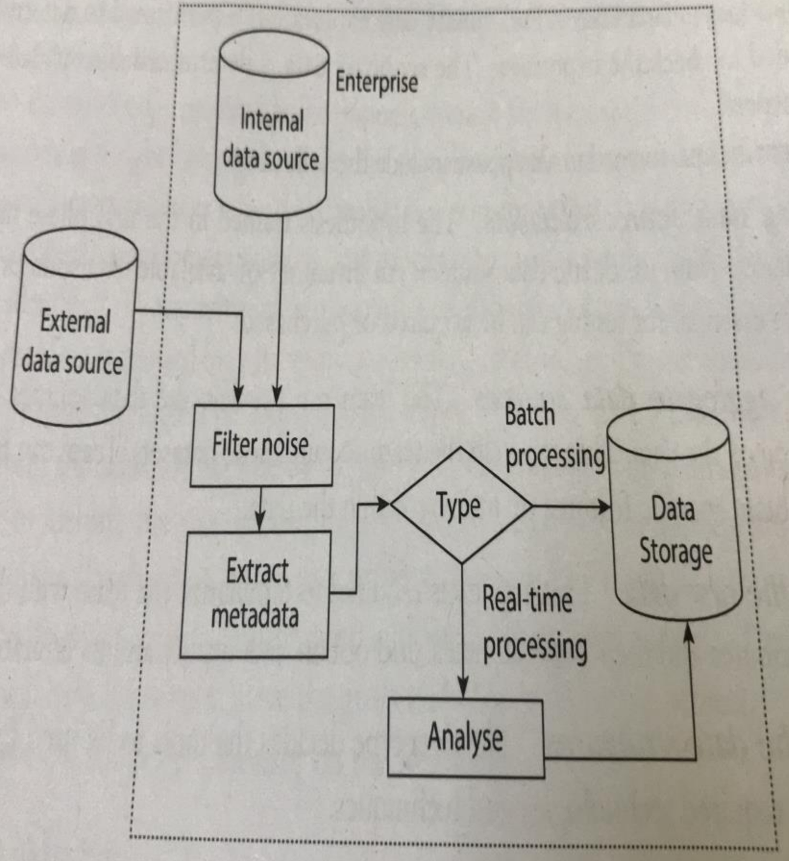


Fig. 2.4 Data acquisition and filtering

4. Data Extraction

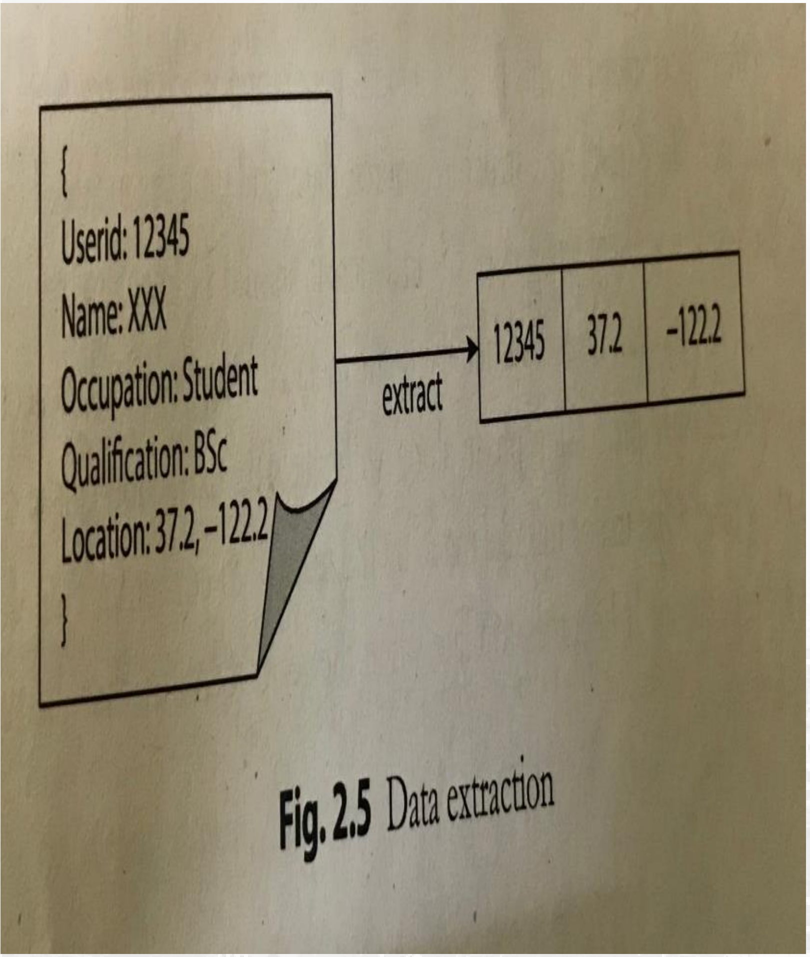
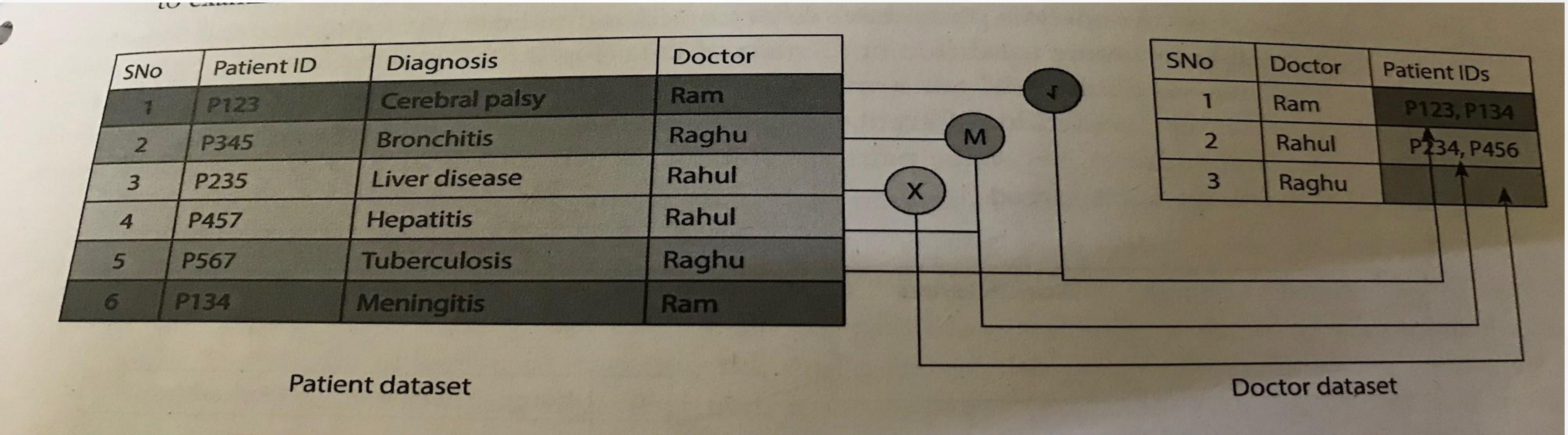


Fig. 2.5 Data extraction

- The extent of extraction and transformation required depends on the types of analytics and capabilities of the Big Data solution.
- E.g., extracting the required fields from delimited textual data, such as with webserver log files.
- Similarly, extracting text for text analytics, which requires scans of whole documents, is simplified if the underlying Big Data solution can directly read the document in its native format.

5.Data Validation and Cleansing



SNo	Patient ID	Diagnosis	Doctor
1	P123	Cerebral palsy	Ram
2	P345	Bronchitis	Raghu
3	P235	Liver disease	Rahul
4	P457	Hepatitis	Rahul
5	P567	Tuberculosis	Raghu
6	P134	Meningitis	Ram

Patient dataset

SNo	Doctor	Patient IDs
1	Ram	P123, P134
2	Rahul	P234, P456
3	Raghu	

Doctor dataset

Fig. 2.6 Data validation

- Examining the cleanliness of the data
- Checking for consistency of data by identifying missing and inconsistent values.
- Assessing the consistency of the data types by checking if values suit the data type.
- Reviewing the contents of the data columns for relevant and consistent values
- Looking for validity of incoming data by checking for extreme or incorrect values.

6. Data Aggregation and Representation

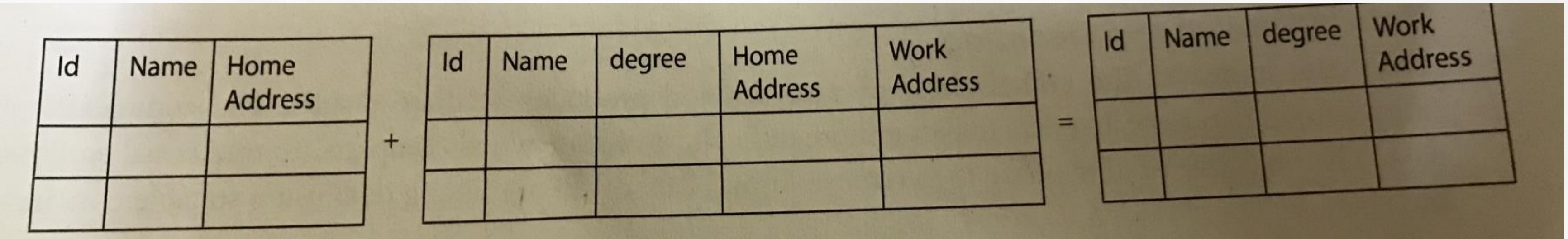


Fig. 2.7 Data aggregation

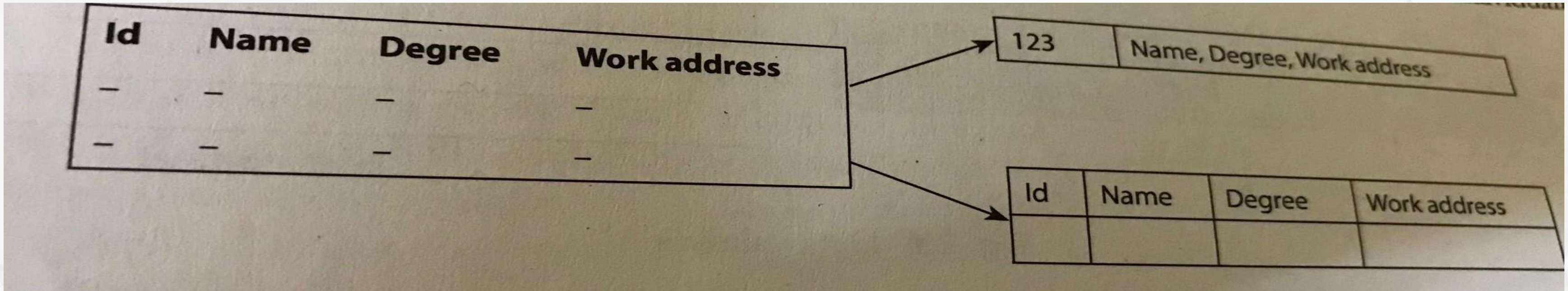


Fig. 2.8 Choice of data storage

- The objective of this phase is to integrate multiple datasets to arrive at unified view.
- The tools for data indigestion, filtering ,extraction, validation ,cleansing and aggregation are Hadoop, open refiner, Alpine miner, Data Wrangler.

7. Analytical Modelling

- The data analysis helps to decide the hypothesis which can be used know the data.
- Analytical modelling includes two sub-phases

1. Model Planning
   1. Data Exploration
      - Helps to clean the data to gain data quality.
   2. Model Selection
      - Commonly used tools are R, SQL Analysis services, SAS/ Access for RDBMS
2. Model Building
   – Develop analytical model that fits on the training data , evaluated against test data which is fitted after several iterations.

8. Communicating the results

- Record all the findings and then select the most significant ones and share with the other stakeholders.
- The team made recommendations for future work or improvements to existing processes.

9. Deployment

- This phase deals with deploying the analytical models in a production environment.
- The output of these models can also be used to prescribe some actions such as:
  - Optimizing business process
  - Creating alerts
  - Extending the functionality of enterprise systems

Summary: Life Cycle of BDA Project

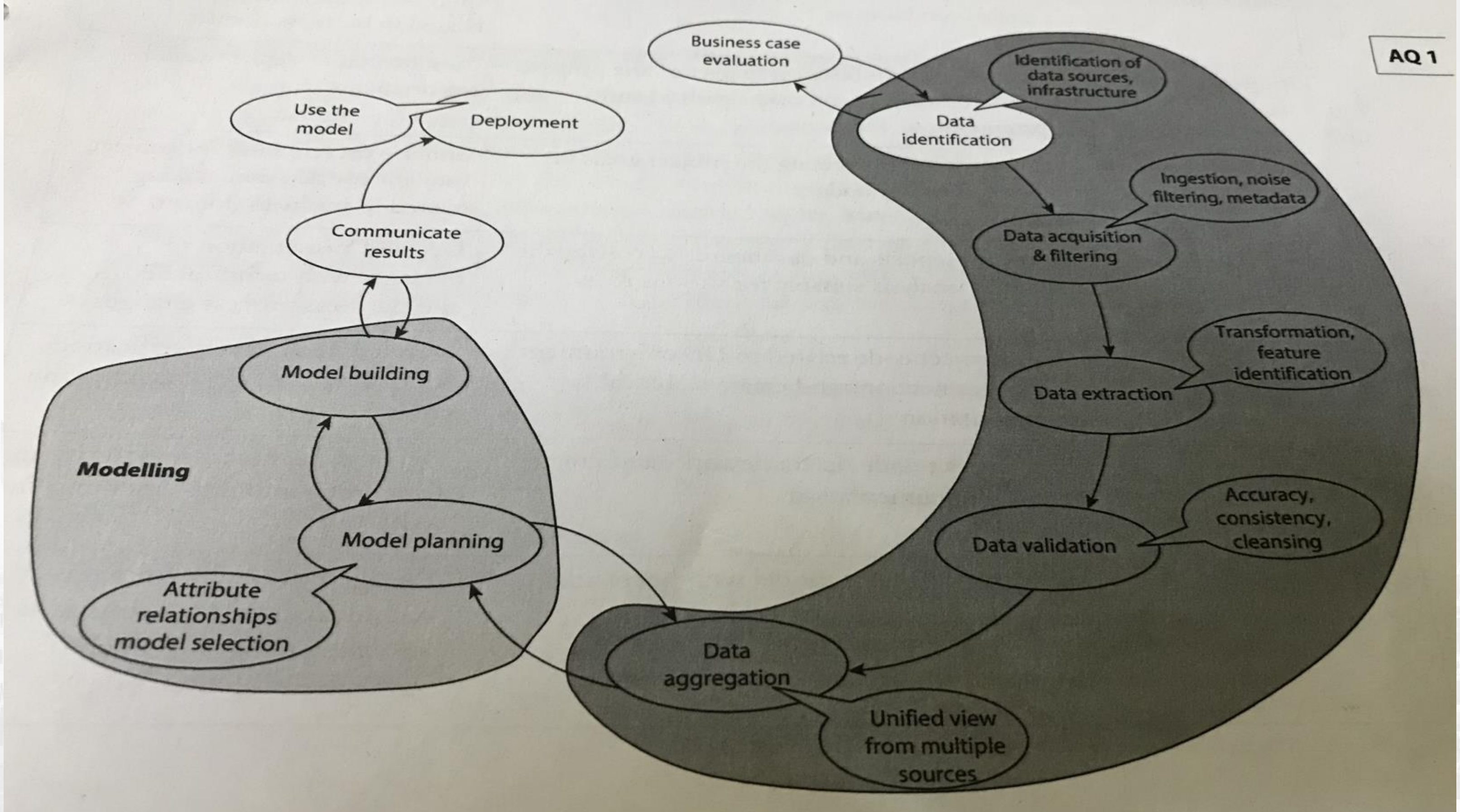

AQ 1
Business case evaluation
Identification of data sources, infrastructure
Data identification
Use the model
Deployment
Ingestion, noise filtering, metadata
Data acquisition & filtering
Communicate results
Transformation, feature identification
Data extraction
Model building
Modelling
Accuracy, consistency, cleansing
Data validation
Model planning
Attribute relationships model selection
Data aggregation
Unified view from multiple sources

Fig. 2.9 Life cycle of a big data analytics project

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- *https://https://www.dezyre.com/article/types-of-analytics-descriptive-predictive-prescriptive-analytics/209 [image]*
- *https://informationcatalyst.com [image]*
- *https://www.slideshare.net/hktripathy/lecture2-big-data-life-cycle[image]*