Big Data Analytics

Lecture BigData Analytics

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Disclaimer: Big Data software is constantly updated, code samples may be outdated.

Outline

About DKRZ

German Climate Computing Center (DKRZ)

Partner for Climate Research

Maximum Compute Performance.

Sophisticated Data Management.

Competent Service.

Scientific Computing

- Research Group of Prof. Ludwig at the University of Hamburg
- Embedded into DKRZ

Research

- Analysis of parallel I/O
- I/O & energy tracing tools
- Middleware optimization
- Alternative I/O interfaces
- Data reduction techniques
- Cost & energy efficiency

Lecture

Concept of the lecture

- The lecture is focusing on applying technology and some theory
- Theory
  - Data models and data processing
  - Statistics and machine learning
  - System architectures
  - Algorithms and data structures
- Applying technology
  - Learning about various state-of-the art technology
  - Hands-on for understanding the key concepts
  - Languages: R and Python, (Java is important but not used)
- The domain of big data is overwhelming, especially technology
- It is a crash course for several topics such as statistics and databases

$\Rightarrow$ it is not the goal to learn and understand every aspect in this lecture

Lecture (2)

Slides

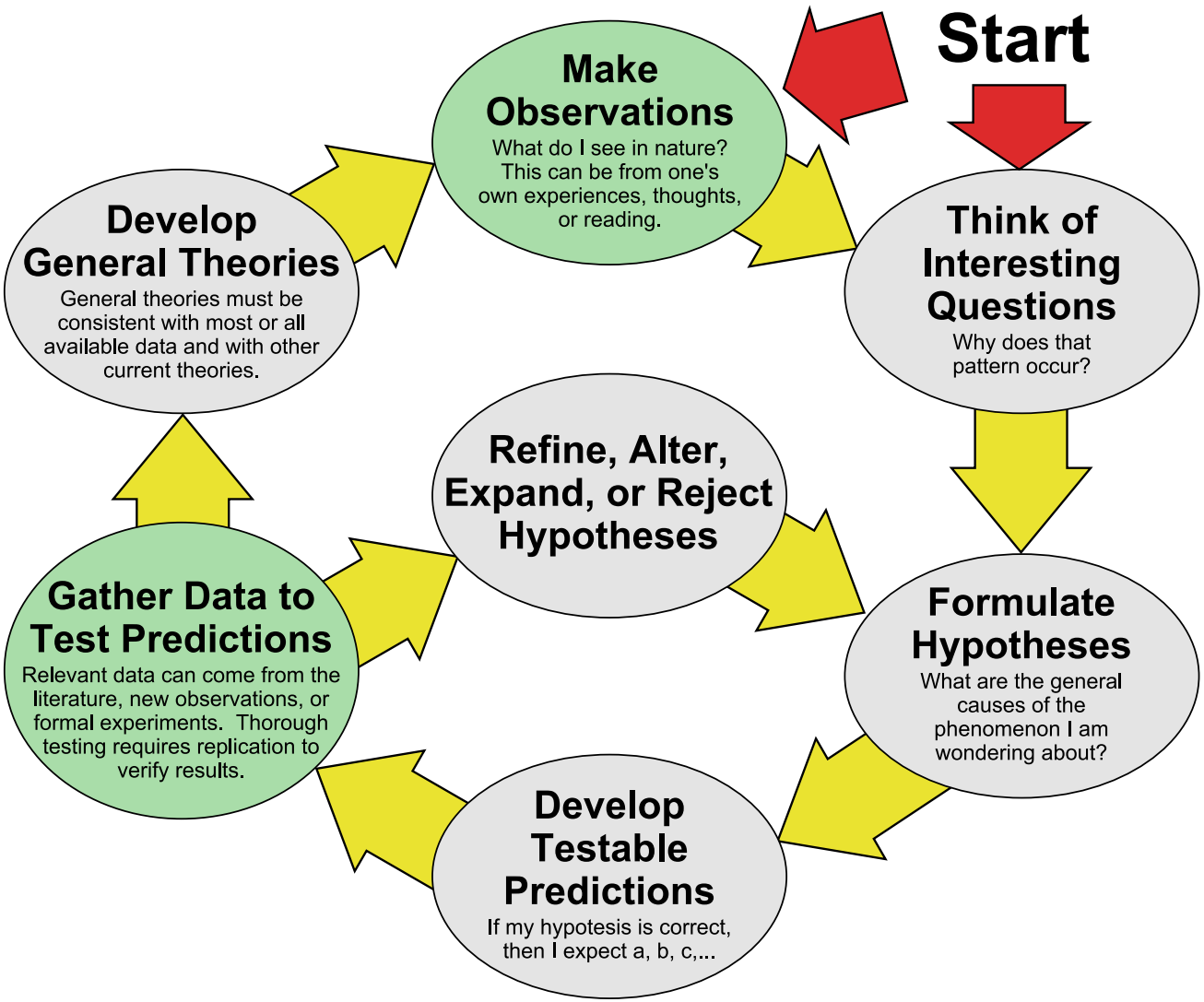
- Many openly accessible sources have been used
  - They are cited by a number
  - The reference slide provides the link to the sources
- For figures, a reference is indicated by *Source: [Author]*[1] *[title]*[1] *[ref]*
- In the title, an [ref] means that this reference has been used for the slide, some text may be taken literally

Exercise

- Unfortunately no student assistant found so corrections during exercise...
- Weekly delivery, processing time about 8 hours / per week estimated
- Teamwork of two people (groups are important to keep the time limit)

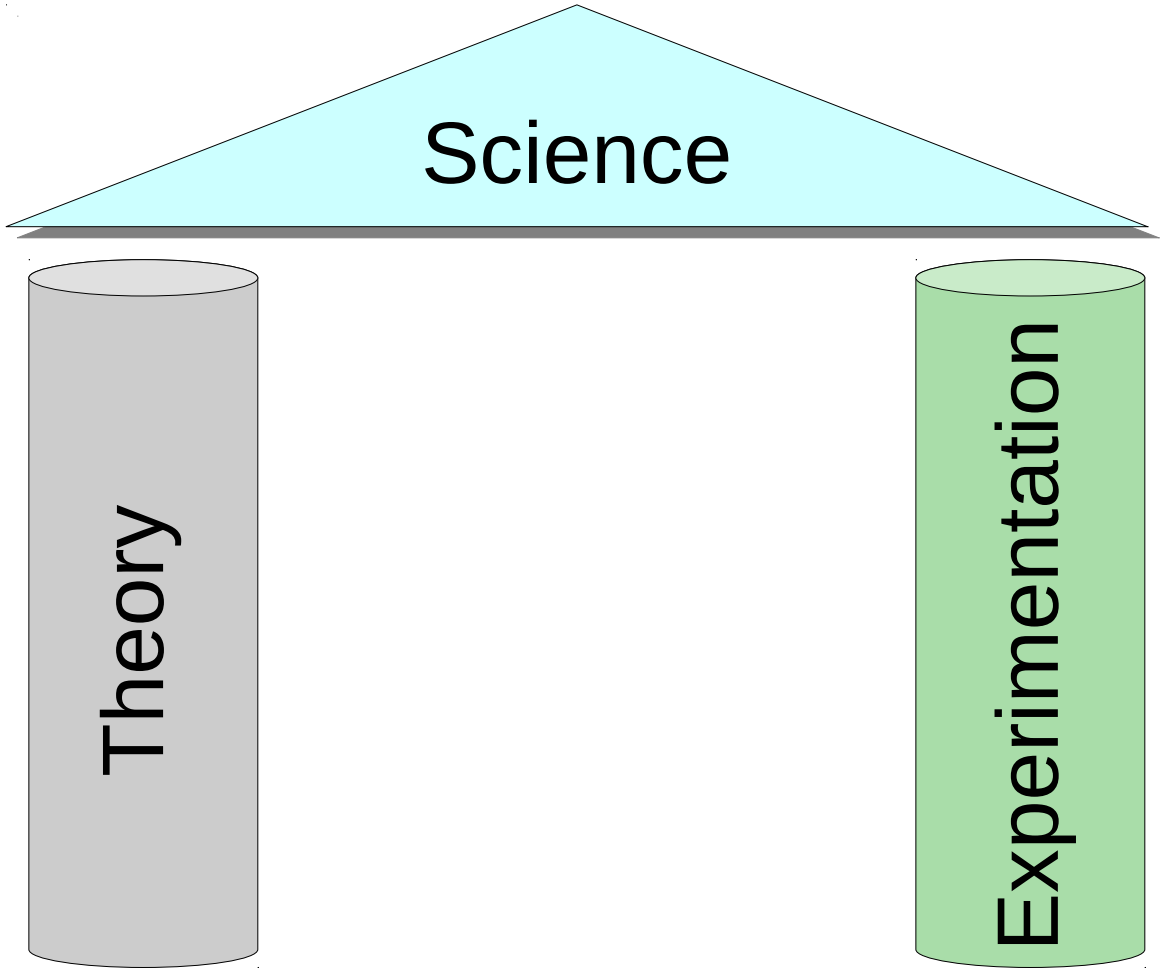
[1] If available

Scientific Method

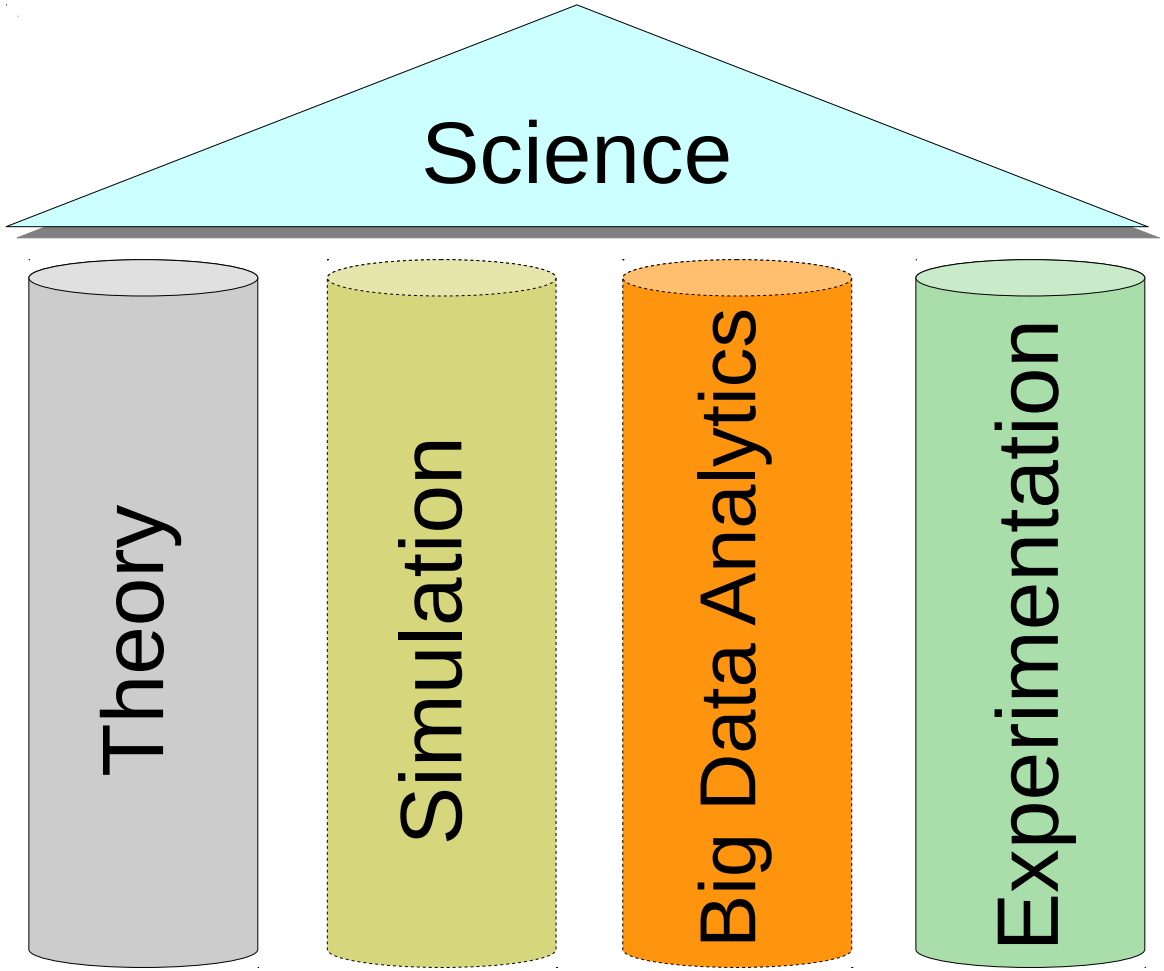


Based on: The Scientific Method as an Ongoing Process, ArchonMagnus[22]

Pillars of the Scientific Method



Pillars of Science: **Modern Perspective**



Idea of Big Data Analytics

Big Data

- Vast amounts of data are available
- Many heterogene data sources
- Raw data is of low value (fine grained)

Analytics

- Analyzing data $\Rightarrow$ Insight == value
  - For academia: knowledge
  - For industry: business advantage and money
- Levels of insight – primary abstraction levels of analytics
  - **Exploration**: study data and identify properties of (subsets) of data
  - **Induction/Inference**: infer properties of the full population
- Big data tools allow to construct a theory/model and validate it with data
  - **Statistics** and **machine learning** provide **algorithms and models**
  - Visual methods support data exploration and analysis

Example Models

Similarity is a (very) simplistic model and predictor for the world

- Humans use this approach in their cognitive process
- Uses the advantage of BigData

Weather prediction

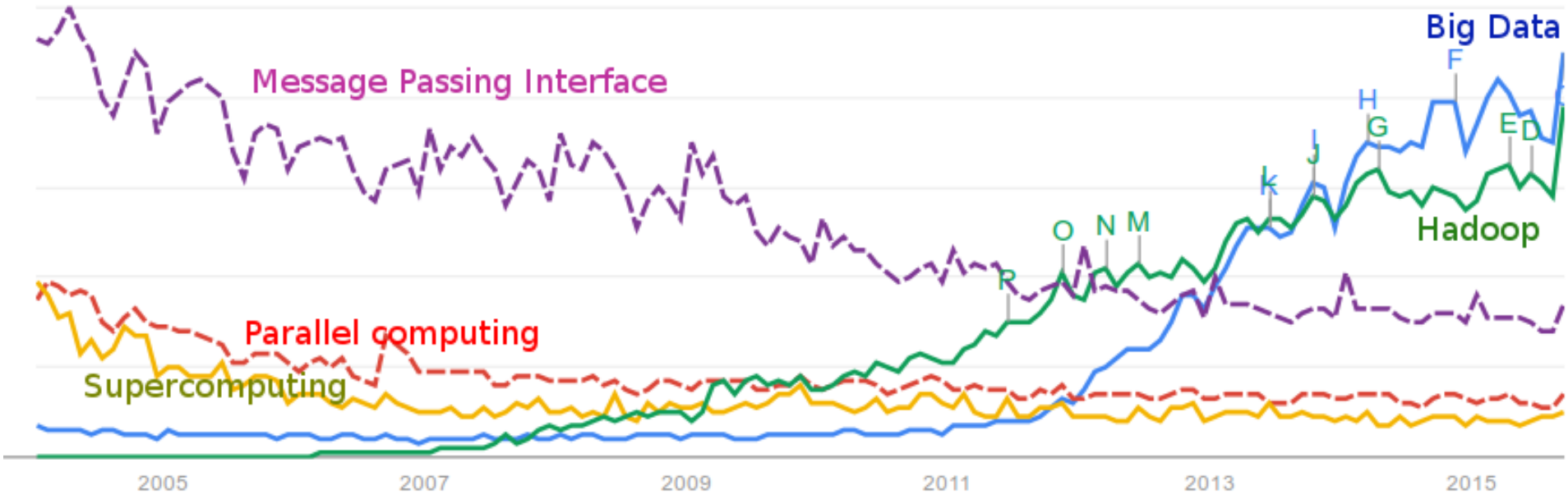
- You may develop and rely on complex models of physics
- Or use a simple model for a particular day; e.g., expect it to be similar to the weather of the typical day over the last X years
  - Used by humans: rule of thumb for farmers

Preferences of Humans

- Identify a set of people which liked items you like
- Predict you like also the items those people like but haven't rated

Relevance of Big Data

- Big Data Analytics is emerging
- Relevance increases compared to supercomputing



Google Search Trends, relative searches

Roles in the Big Data Business

Data scientist

Data science is a systematic method dedicated to knowledge discovery via data analysis [1]

- In business, optimize organizational processes for efficiency
- In science, analyze experimental/observational data to derive results

Data engineer

Data engineering is the domain that develops and provides systems for managing and analyzing big data

- Build modular and scalable data platforms for data scientists
- Deploy big data solutions

Typical Skills

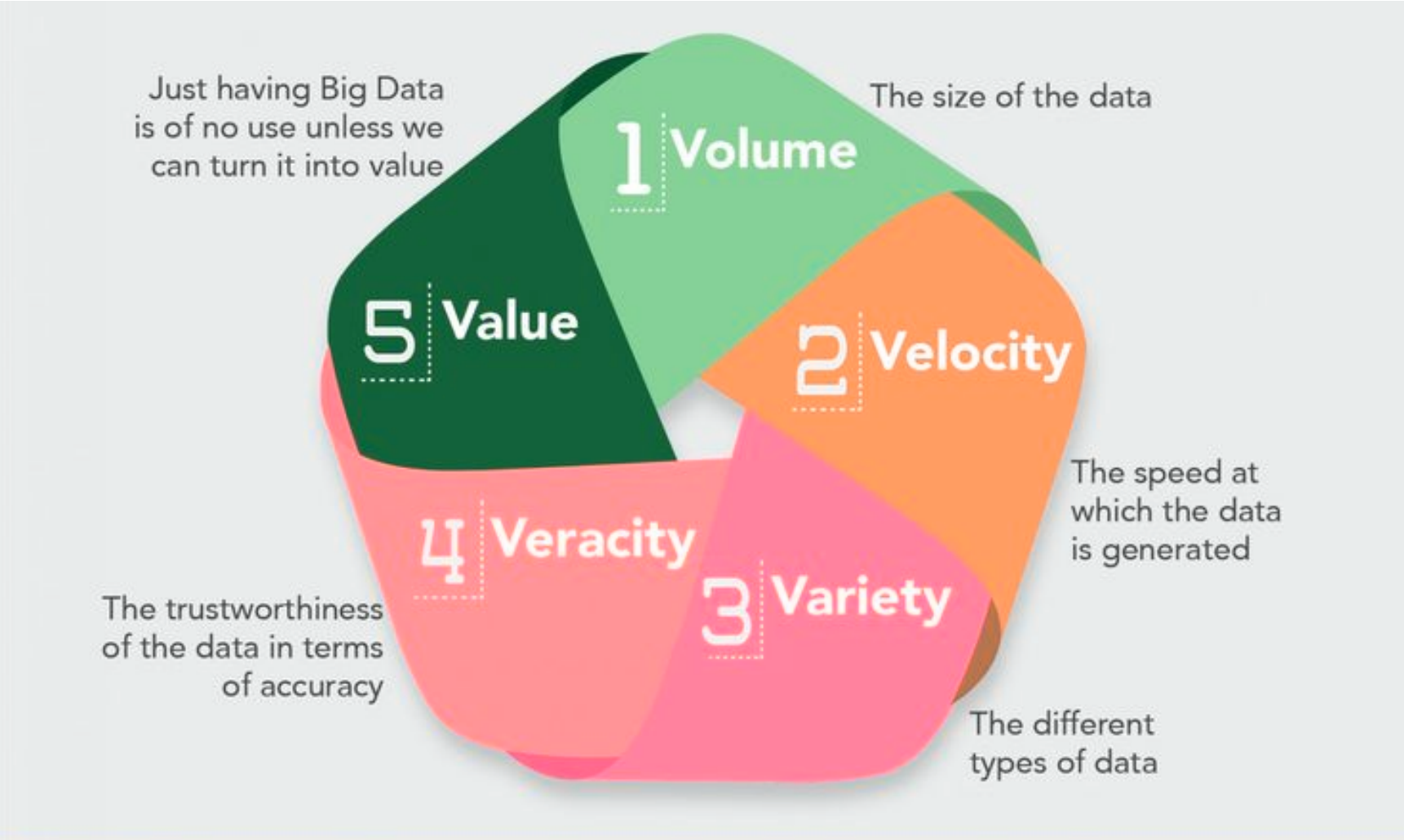
Data scientist

- Statistics + (mathematics) background
- Computer science
  - Programming, e.g.: R, (SAS,) Java, Scala, Python
  - Machine learning
- Some domain knowledge for the problem to solve

Data engineer

- Computer science background
  - Databases
  - Software engineering
  - Massively parallel processing
  - Real-time processing
- Languages: C++, Java, (Scala,) Python
- Understand performance factors and limitations of systems

BigData Challenges & Characteristics



Source: MarianVesper [4]

Volume: The size of the Data

What is Big Data

Terrabytes to 10s of petabytes

What is not Big Data

A few gigabytes

Examples

- Wikipedia corpus with history ca. 10 TByte
- Wikimedia commons ca. 23 TByte
- Google search index ca. 46 Gigawebpages[2]
- YouTube per year 76 PByte (2012[3])

[2] http://www.worldwidewebsize.com/

[3] https://sumanrs.wordpress.com/2012/04/14/youtube-yearly-costs-for-storagenetworking-estimate/

Velocity: Data Volume per Time

What is Big Data

30 KiB to 30 GiB per second
(902 GiB/year to 902 PiB/year)

What is not Big Data

A never changing data set

Examples

- LHC (Cern) with all experiments about 25 GB/s [4]
- Square Kilometre Array 700 TB/s (in 2018) [5]
- 50k Google searches per s [6]
- Facebook 30 Billion content pieces shared per month [7]

[4] http://home.web.cern.ch/about/computing/processing-what-record
[5] http://venturebeat.com/2014/10/05/how-big-data-is-fueling-a-new-age-in-space-exploration/
[6] http://www.internetlivestats.com/google-search-statistics/
[7] https://blog.kissmetrics.com/facebook-statistics/

Data Sources

Enterprise data

- Serves business objectives, well defined
- Customer information
- Transactions, e.g., purchases

Experimental/Observational data (EOD)

- Created by machines from sensors/devices
- Trading systems, satellites
- Microscopes, video streams, smart meters

Social media

- Created by humans
- Messages, posts, blogs, Wikis

Variety: Types of Data

- Structured data
  - Like tables with fixed attributes
  - Traditionally handled by relational databases
- Unstructured data
  - Usually generated by humans
  - Examples: natural language, voice, Wikipedia, Twitter posts
  - Must be processed into (semi-structured) data to gain value
- Semi-structured data
  - Has some structure in tags but it changes with documents
  - Examples: HTML, XML, JSON files, server logs

What is Big Data

- Use data from multiple sources and in multiple forms
- Involve unstructured and semi-structured data

Veracity: Trustworthiness of Data

What is Big Data

- Data involves some uncertainty and ambiguities
- Mistakes can be introduced by humans and machines
- Examples
  - People sharing accounts
  - Like sth. today, dislike it tomorrorw
  - Wrong system timestamps

Data Quality is vital!

Analytics and conclusions rely on good data quality

- Garbage data + perfect model => garbage results
- Perfect data + garbage model => garbage results

GIGO paradigm: *Garbage In – Garbage Out*

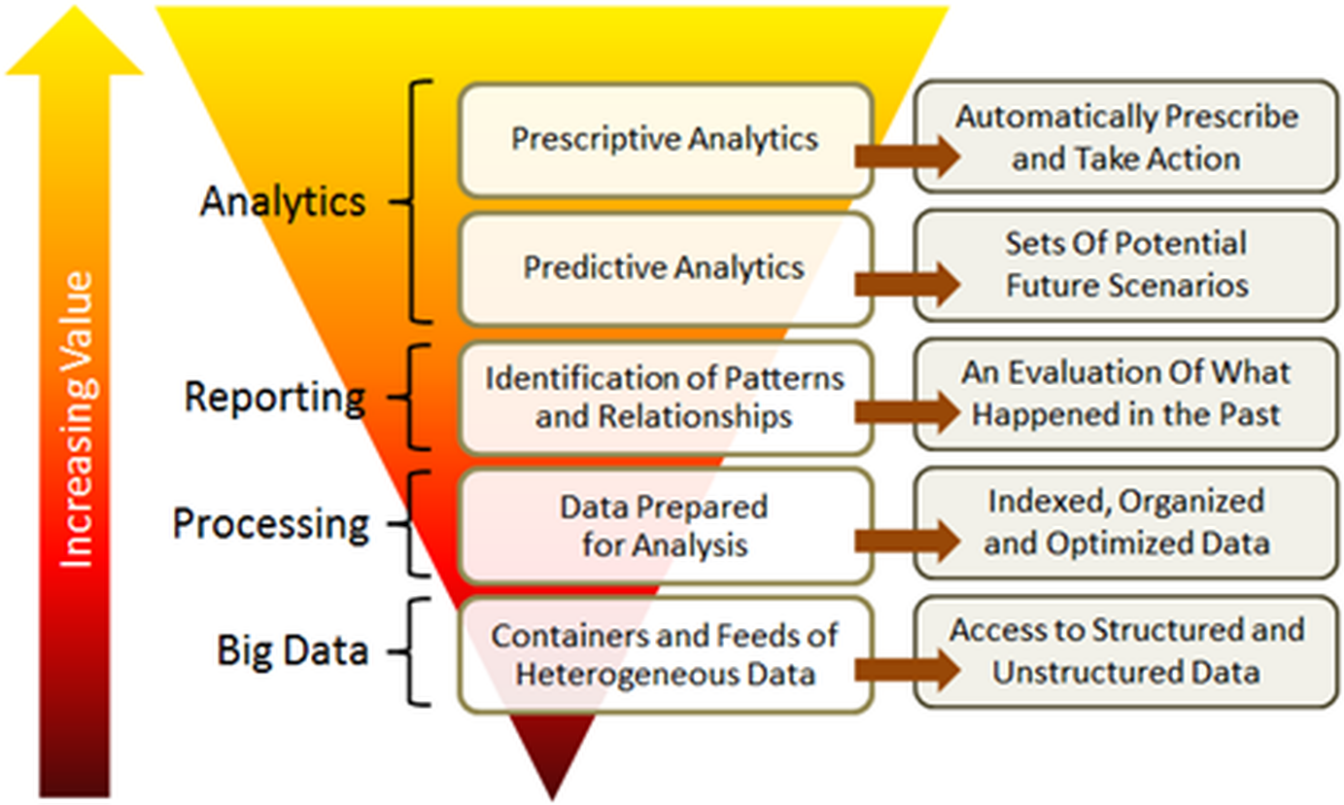
Value of Data

What is Big Data

- Raw data of Big Data is of low value
  - For example, single observations
- Analytics and theory about the data increases the value
  - Analytics transform big data into smart (valuable) data!

Big Data Analytics Value Chain

- There are many visualizations of the processing and value chain



Source: Andrew Stein [8]

From Big Data to the Data Lake [20]

- With cheap storage costs, people promote the concept of the data lake
- Combines data from many sources and of any type
- Allows for conducting future analysis and not miss any opportunity

Attributes of the data lake

- Collect everything: all time all data: raw sources and processed data
  - Decide during analysis which data is important, e.g., no “schema“ until read
- Dive in anywhere: enable users across multiple business units to
  - Refine, explore and enrich data on their terms
- Flexible access: shared infrastructure supports various patterns
  - Batch, interactive, online, search

Data Science vs. Business Intelligence (BI)

Characteristics of BI

- Provides pre-created dashboards for management
  - Repeated visualization of well known analysis steps
- Deals with structured data
- Typically data is generated within the organization
- Central data storage (vs. multiple data silos)
- Handeled well by specialized database techniques

Typical types of questions and insight

- Customer service data: “what business causes customer wait times”
- Sales and marketing data: “which marketing is most effective”
- Operational data: “efficiency of the help desk”
- Employee performance data: “who is most/least productive”

Privacy

- Privacy is a challenge for the big data business
- Be aware of privacy issues if you deal with personal/private information
- German privacy laws are more strict than those of other countries

Ziel des Datenschutzes

Recht auf informationelle **Selbstbestimmung**

- Schutz des Einzelnen vor beeinträchtigung des Persönlichkeitsrechts durch den Umgang mit seinen personenbezogenen[8] Daten
- Besonderer Schutz für Daten über Gesundheit, ethnische Herkunft, religiöse, gewerkschaftschliche oder sexuelle Orientierung

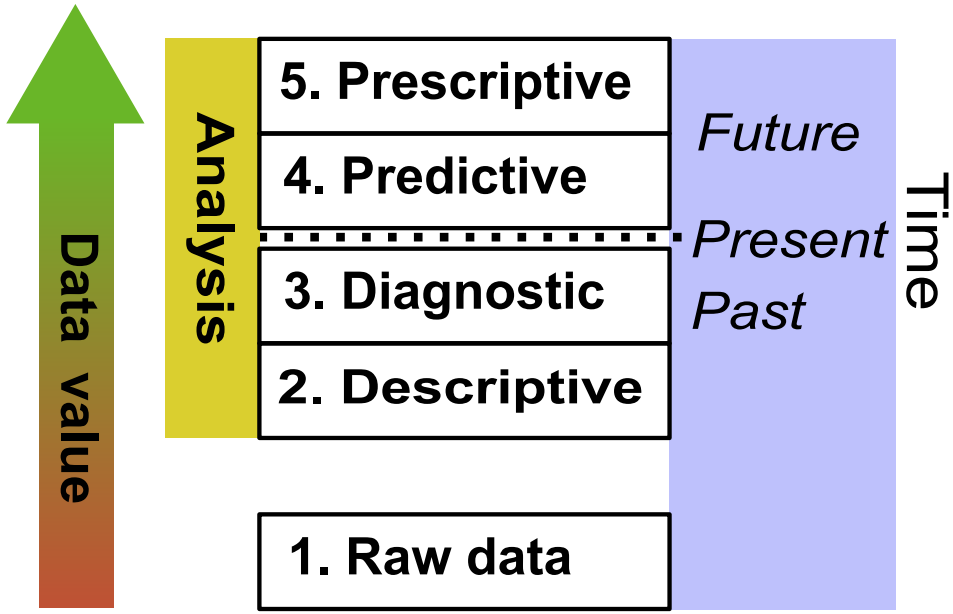
[8] §3 BDSG, Einzelangaben über persönliche oder sachliche Verhältnisse einer bestimmten oder bestimmbaren natürlichen Person

Wichtige Grundsätze des Gesetzes [10]

- Verbotsprinzip mit Erlaubsnisvorbehalt
  - Erhebung, Verarbeitung, Nutzung und Weitergabe von personenbezogenen Daten sind verboten
  - Nutzung nur mit Rechtsgrundlage oder mit Zustimmung der Person
- Unternehmen mit 10 Personen benötigen Datenschutzbeauftragten
- Verfahren zur automatischen Verarbeitung sind vom Datenschutzbeauftragten zu prüfen und anzeigepflichtig
- Sitz der verantwortlichen Stelle maßgeblich
  - Bei einer Niederlassung in D gilt BDSG
- Prinzipien: Datenvermeidung, -sparsamkeit
- Schutz vor Zugriffen, Änderungen und Weitergabe
- Betroffene haben Recht auf Auskunft, Löschung oder Sperrung
- Anonymisierung/Pseudonymisierung: Ist die Zuordnung zu Einzelpersonen (nahezu) ausgeschlossen, so können Daten verabeitet werden

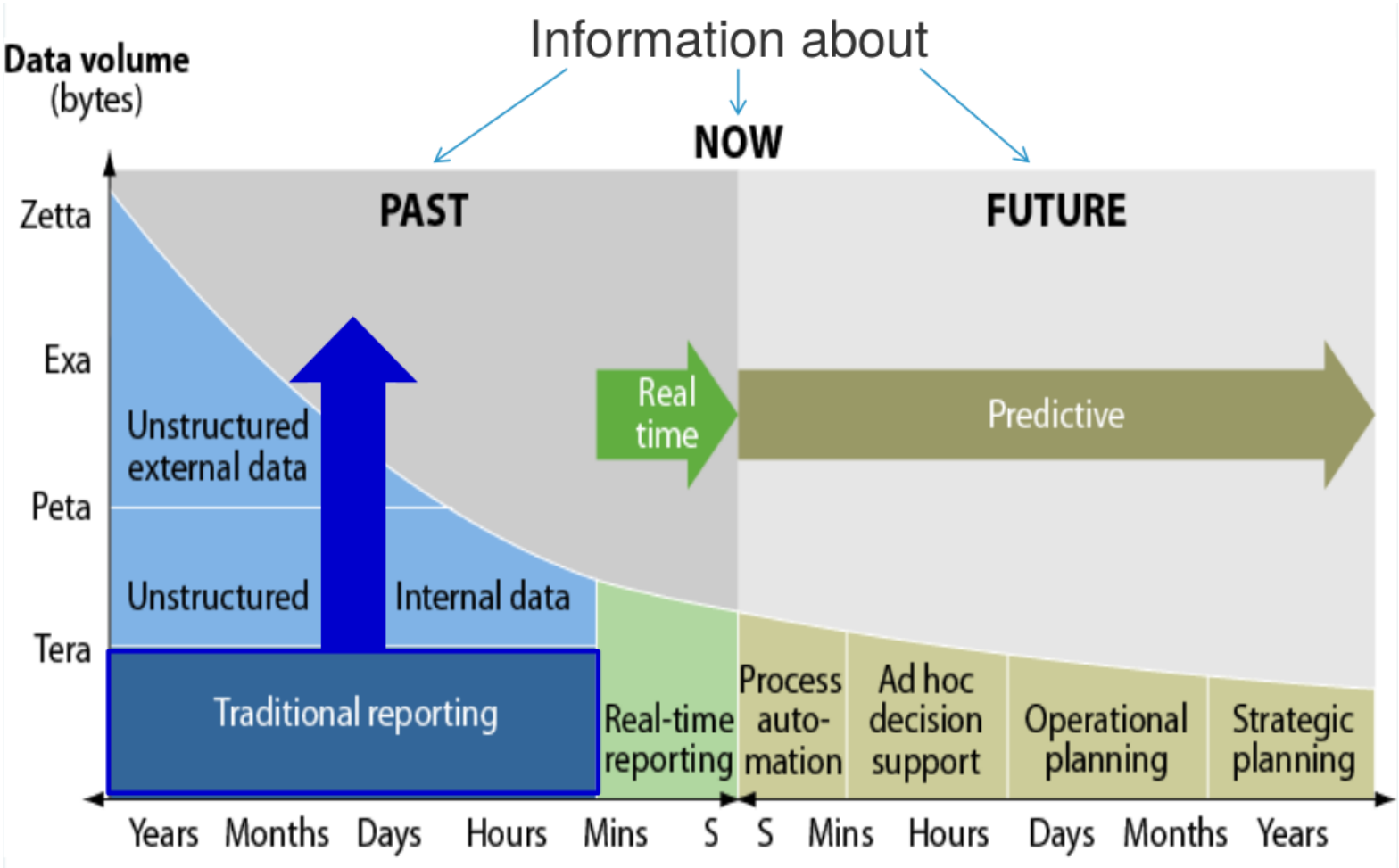
Abstraction Levels of Analytics and the Value of Data

1. Prescriptive analytics *(Empfehlen)*
   - "What should we do and why?"
2. Predictive analytics *(Vorhersagen)*
   - "What will happen?"
3. Diagnostic analytics
   - "What went wrong?"
   - "Why did this happen"
4. Descriptive analytics *(Beschreiben)*
   - "What happened?"
5. Raw (observed) data



For me, descriptive and diagnostic analysis is forensics!

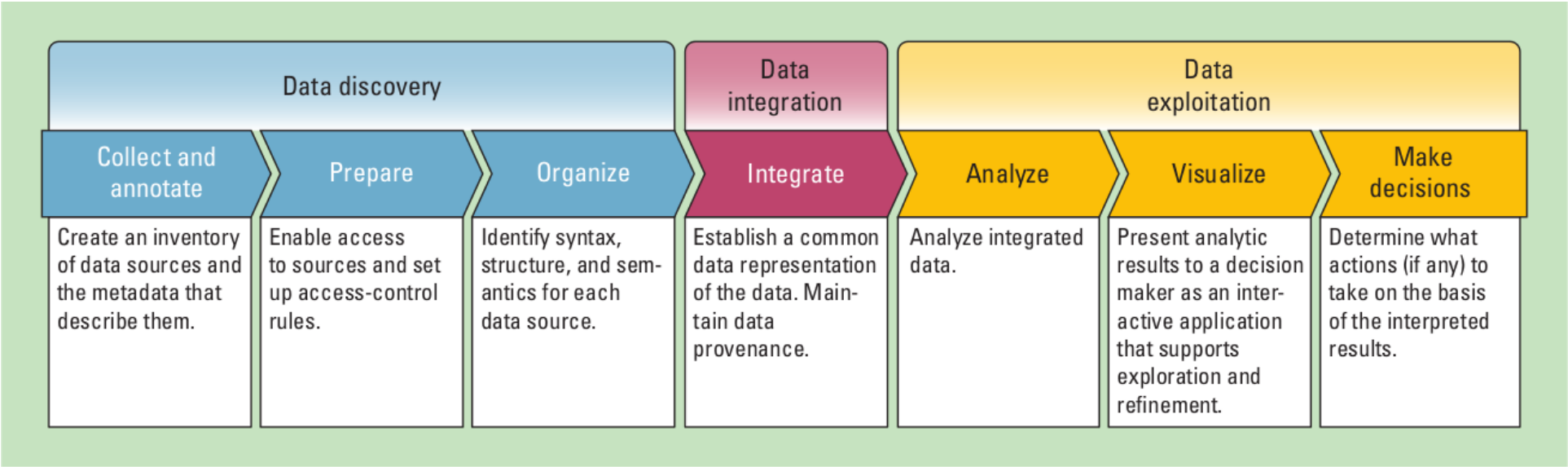
Analytics Abstraction Level



Source: Forrester report. Understanding The Business Intelligence Growth Opportunity. 20-08-2011

Data Analysis Workflow

The traditional approach proceeds in phases:



Source: Gilbert Miller, Peter Mork From Data to Decisions: A Value Chain for Big Data.

- Analysis tools: machine learning, statistics, interactive visualization
- Limitation: Interactivity by browsing through prepared results
- Indirect feedback between visualization and analysis

Exploratory Data Analysis (EDA) [23]

Definition

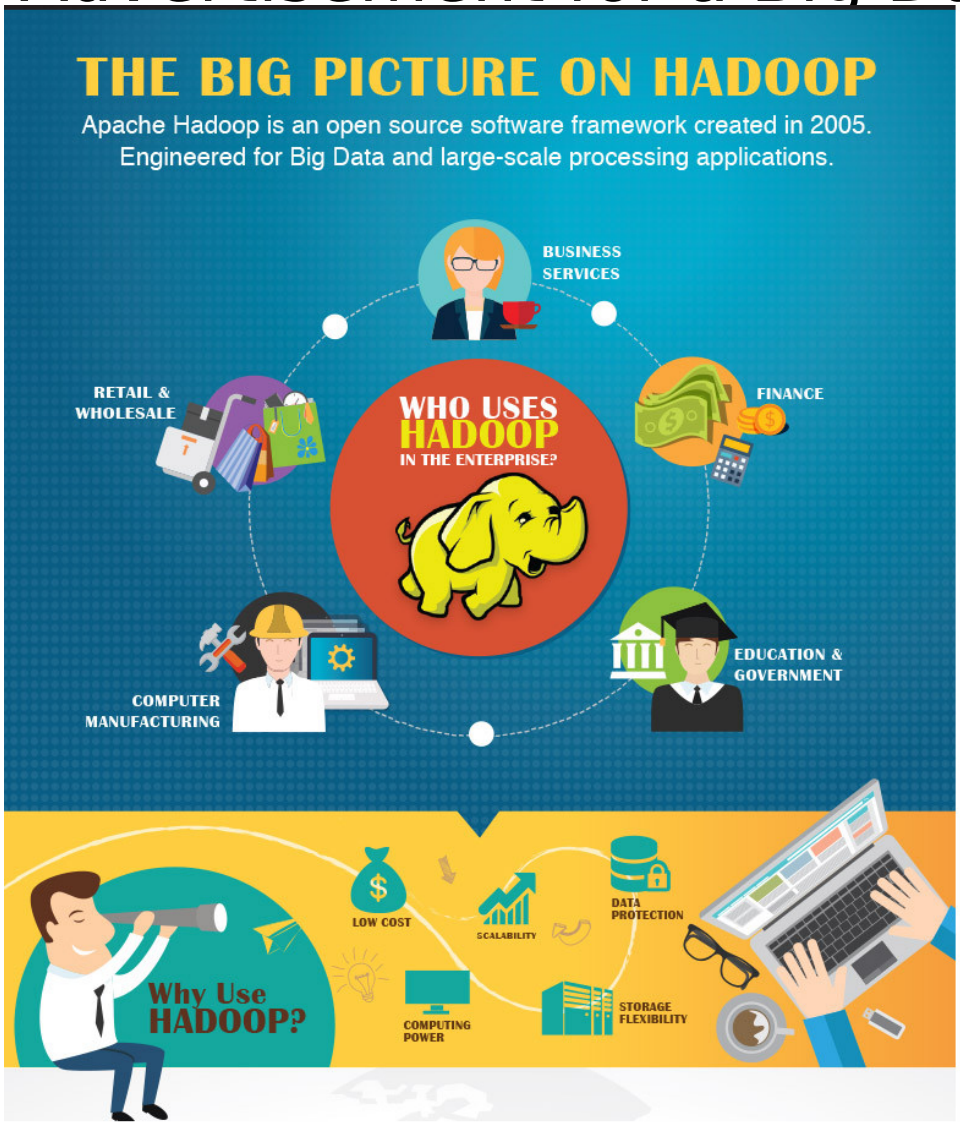
The approach of analyzing data sets to **summarize** their main **characteristic**, often with visual methods

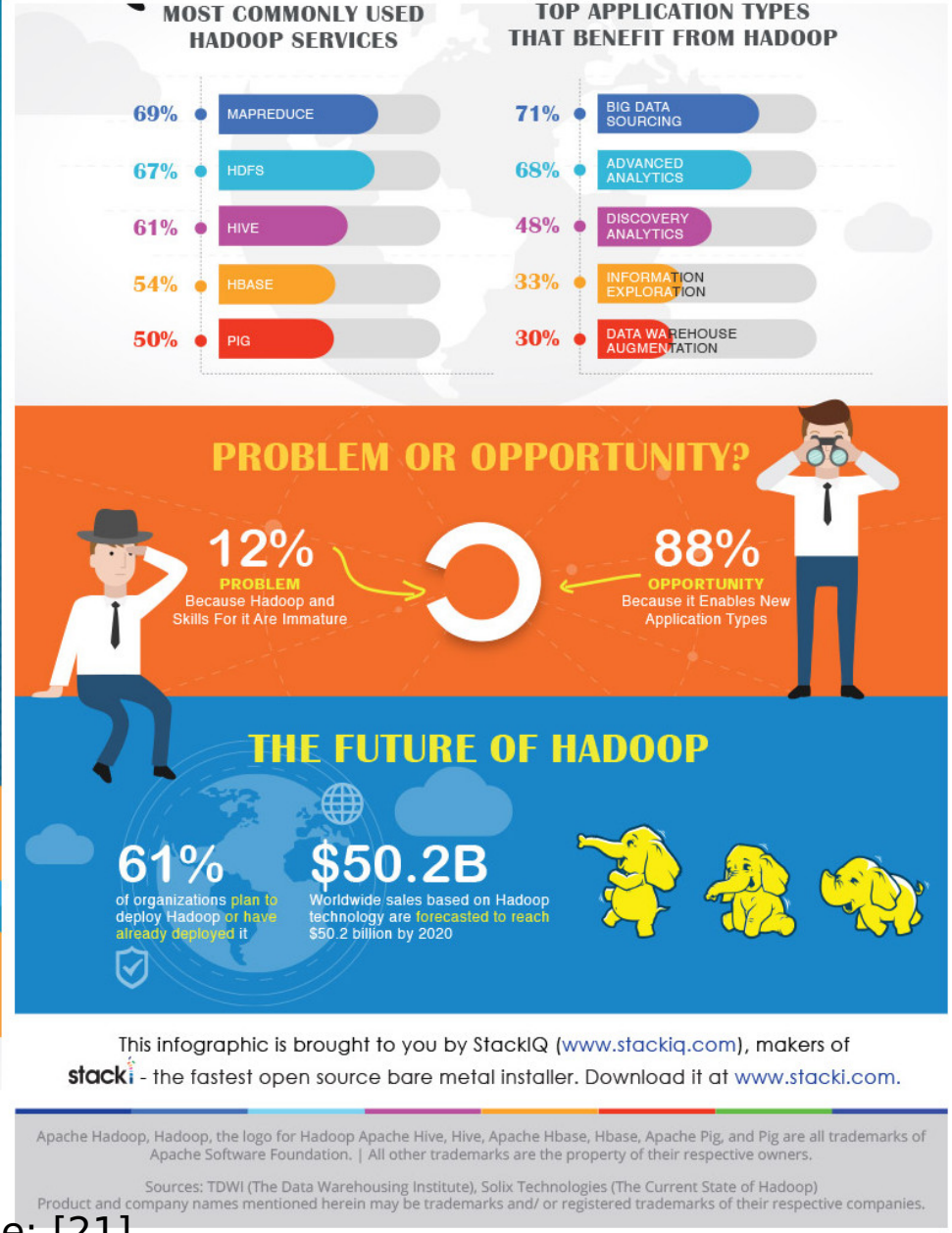
Objectives

- Suggest hypotheses about the causes of observed phenomena
- Identify assumptions about the data to drive statistical inference
- Support selection of appropriate statistical tools and techniques
- Provide a basis for further data collection through surveys or experiments

Methods from EDA can also be used for analyzing model results / outliers

Advertisement for a Big Data Platform





Source: [21]

Use Cases for BigData Analytics

Increase efficiency of processes and systems

- Advertisement: Optimize for target audience
- Product: Acceptance (like/dislike) of buyer, dynamic pricing
- Decrease financial risks: fraud detection, account takeover
- Insurance policies: Modeling of catastrophes
- Recommendation engine: Stimulate purchase/consume
- Systems: Fault prediction and anomaly detection
- Monetization: Extract money from gamers [27]

Science

- Epidemiology research: Google searches indicate Flu spread
- Personalized Healthcare: Recommend good treatment
- Physics: Finding the Higgs-Boson, analyze telescope data
- Enabler for social sciences: Analyze people's mood

Example Use Case: Deutschland Card [2]

Goals

- Customer bonus card which tracks purchases
- Increase scalability and flexibility
- Previous solution based on OLAP

Big Data Characteristics

- Volume: O(10) TB
- Variety: mostly structured data, schemes are extended steadily
- Velocity: data growth rate O(100) GB / month

Results

- Much better scalability of the solution
- From dashboards to ad-hoc analysis within minutes

Example Use Case: DM [2]

Goals

- Predict required number of employees per day and store
- Prevent staff changes on short-notice

Big Data Characteristics

- Input data: Opening hours, incoming goods, empl. preferences, holidays, weather ...
- Model: NeuroBayes (Bayes + neuronal networks)
- Predictions: Sales, employee planning
- 450.000 predictions per week

Results

- Daily updated sales per store
- Reliable predictions for staff planning
- Customer and employee satisfaction

Example Use Case: OTTO [2]

Goals

Optimize inventory and prevent out-of-stock situations

Big Data Characteristics

- Input data: product characteristics, advertisement
- Volume/Velocity: 135 GB/week, 300 million records
- Model: NeuroBayes (Bayes + neuronal networks)
- 1 billion predictions per year

Results

- Better prognostics of product sales (up to 40%)
- Real time data analytics

Example Use Case: Smarter Cities (by KTH) [2]

Goals

- Improve traffic management in Stockholm
- Prediction of alternative routes

Big Data Characteristics

- Input data: Traffic videos/sensors, weather, GPS
- Volume/Velocity: 250k GPS-data/s + other data sources

Results

- 20% less traffic
- 50% reduction in travel time
- 20% less emissions

Example Facebook Studies

“Insight” from [11] by exploring posts

- Young narcissists tweet more likely.
  Middle-aged narcissists update their status
- US students post more problematic information than German students
- US Government checks tweets/facebook messages for several reasons
- Human communication graph has an average diameter of 4.74

Manipulation of news feeds [13]

- News feeds have been changed to analysis people’s behavior in subsequent posts
- Paper: “Experimental evidence of massive-scale emotional contagion through social networks”

Learning Behavior

Games

- DeepMind playing atari games [29]
- AlphaGo wins vs. humans in playing Go [26]
- AI beating world's best gamer in Dota 2 [28]

Motion

- Learning hand motion by human training [30]
- Robots learning to pick up items [31]

Systems: Fault Prediction and Anomaly Detection

Smart buildings [24]

- Predicting faults of heating and ventilation of an hospital
- Predicted 76 of 124 real faults and 41 of 44 exceptional temperatures
- May consider weather to control systems automatically

Google DeepMind AI [25]

- Controlling 120 variables in the data center (fans, ...)
- Saves 15% energy of the overall bill

Automatize Classification

Analysis of multimedia

- Voice, face, biometric recognition
- Speech recognition
- Counting (animal) species on pictures / videos
- Finding patterns on satellite images (e.g., damn, thunderstorms)
- Anomalies in behavior (depressed people)
- Anomalies in structures (operational condition)

Programming BigData Analytics

High-level concepts

- SQL and derivatives
- Domain-specific languages (Cypher, PigLatin)

Programming languages

- Java interfaces are widely available but low-level
- Scala language increases productivity over Java
- Python and R have connectors to popular BigData solutions

In the exercises, we'll learn and use Python and R

Tools for Data Exploration

Mandatory features

- Interactive
- Rich set: visualization, data manipulations, algorithms
- Real-time processing of big data

Requirements

- Usability
- Flexible
- Performance

Tools (excerpt)

- Closed source: SAS, Spotfire, Domo, Tableau
- Open source: **R, Python/Jupyter**/Bokeh, GoogleVis
- Other open source tools, see [19]

Productivity

Productivity is a very important metric for Big Data tools

Development environments

1. Text editor; workflow: edit, save, (compile), run on a server
   - Notepad, gedit
2. Interactive shell; type code and execute it
   - Python, SQL frontent
3. IDE; optimized workflow of the text editor, may run code on a server
   - NetBeans, Eclipse, VisualStudio
4. Interactive lab notebook; type code and store it together with results
   - Examples: Jupyter, Apache Zeppelin
   - Embedded in GitHub:
     https://github.com/jakevdp/PythonDataScienceHandbook/blob/master/code_listings/03.11-Working-with-Time-Series.ipynb
5. Lab notebook + IDE;
   - Examples: Spyder

Introduction to Python

- Open source
- Position 5 on TIOBE index
- Interpreted language
- Weak type system (errors at runtime)
- Development tools: any editor, interactive shell, Spyder
- Many useful libraries: matplotlib[9], NumPy, SciPy, Pandas
- *Note: Use and learn Python 3*

Specialties

- Strong text processing
- Simple to use
- Support for object oriented programming
- Indentation is relevant for code blocks

[9] http://matplotlib.org/gallery.html

Example Python Program

```
1  #!/bin/env python
2  import re # use the module 're'
3
4  # function reading a file
5  def readFile(filename):
6     with open(filename, 'r') as f:
7        data = f.readlines()
8        f.close()
9        return data
10    return [] # return an empty array/list
11
12 # the main function
13 if __name__ == "__main__":
14    data = readFile('intro.py')
15    # iterate over the array
16    for x in data:
17       # extract imports from a python file using a regex
18       m = re.match("import[ \t]+(?P<WHAT>[^# ]*)", x)
19       if m:
20          print(m.group("WHAT"))
21          # dictionary (key value pair)
22          dic = m.groupdict()
23          dic.update( {"FILE" : 'intro.py'}) # append a new dict. with one key
24          # use format string with dictionary
25          print("Found import '%(WHAT)s' in file %(FILE)s" % dic )
26          # Prints: Found import 're' in file intro.py
```

Example Python Classes

```python
from abc import abstractmethod

class Animal():
    # constructor, self are instance methods, else class methods
    def __init__(self, weight):
        self.__weight = weight # private variables start with __

    # decorator
    @abstractmethod
    def name(self):
        return self.__class__.__name__ # reflection like

    def __str__(self):
        return "I'm a %s with weight %f" % (self.name(), self.__weight)

class Rabbit(Animal):
    def __init__(self):
        # super() is available with python 3
        super().__init__(2.5)

    def name(self):
        return "Small Rabbit" # override name

if __name__ == "__main__":
    r = Rabbit()
    print(r) # print: I'm a Small Rabbit with weight 2.500000
```

Introduction to R

- Based on S language for statisticians
- Open source
- Position 19 on TIOBE index (but rising)
- Interpreter with C modules (packages)
- Libraries: Easy installation of packages via CRAN[10]
- Popular language for data analytics
- Development tools: RStudio (or any editor), interactive shell
- Recommended plotting library: ggplot2[11]

Specialties

- Vector/matrix operations. *Note: Loops are slow, so avoid them*
- Table data structure (data frames)

[10] Comprehensive R Archive Network
[11] http://docs.ggplot2.org/current/

Course for Learning R Programming

```r
# Run with "Rscript intro.R" or run "R" and copy&paste into interactive shell
# Installing a new package is as easy as:
install.packages("swirl")
# Note: sometimes packages are not available on all mirrors!
library(swirl) # load the package

help(swirl) # read help about the function swirl

swirl() # start an interactive course to learn R

# a simple for loop
for (x in 1:10){
   if (x < 5){
      print(x)
   }else{
      print(x * 2)
   }
}
```

Example R Program

```r
# create an array
x = c(1, 2, 10:12)

# apply an operator on the full vector and output it
print( x*2 ) # prints: 2  4 20 22 24

# slice arrays, i.e., create subsets based on row numbers/names
print ( x[3:5] ) # prints: 10 11 12
print( x[c(1,4,8)] ) # prints: 1 11 NA

r = runif(100, min=0, max=100) # create array with random numbers
m = matrix(r, ncol=4, byrow = TRUE) # create a matrix

# slice matrix rows "m[row(s), column(s)]"
print( m[10:12, ] ) # Output:
#          [,1]      [,2]       [,3]      [,4]
#[1,] 85.46609 60.749703 10.5062183  7.449173
#[2,] 79.76042 52.199321 96.9699856 97.877946
#[3,] 37.34286  8.266282  0.3398741  1.957607

# slice rows & columns
print ( m[10, c(1,4)]  ) # Output: [1] 85.466085  7.449173

# subset the 2D table based on a mask
set = m[ (m[,1] < 20 & m[,2] > 2) , ]
```

Accessing CSV Files with R

```r
# function to create a table (data frame) and fill it with random data
createTable = function (size){
   tbl = read.table(text="", col.names = c("Type", "Time"))
   tbl[1:size, ] = 0  # initialize size times a full rows
   tbl$Time = runif(size, min=0, max=100) # address by column name
   # create random types, factor() for nominal data and
   # ordered() for ordinal data
   tbl$Type = factor(round(runif(size, min=0.5, max=3.49)),
      levels=1:3, # three categories
      labels=c("unknown", "good", "bad"))
   tbl$Type[size] = "bad" # assign last element to be bad
   return (tbl)
}
# change column names
colnames(tbl) = c("Typ", "Duration")

d = createTable(5)
# Assign the column with the name
print( d )
print( summary (d) ) # some statistics about d
# Write CSV incl. header
write.table(d, file = "mydata.csv", sep=",", row.names=FALSE)
# reread table
d =  read.table("mydata.csv", header = TRUE, sep = ",")
```

Introduction to Java

- Developed by Sun Microsystems in 1995
- Object oriented programming language
- OpenJDK implementation is open source
- Source code ⇒byte code ⇒just-in-time compiler
  - Byte code is portable & platform independent
  - Virtual machine abstracts from systems
- Strong and static type system
- Popular language for Enterprise & Big Data applications
  - Most popular programming language (Pos. 1 on the TIOBE index)
- Development tools: Eclipse

Specialties

- Good runtime and compile time error reporting
- Generic data types (vs. templates of C++)
- Introspection via. Reflection

Example Java Program

```
1  import java.util.Scanner;
2  import java.io.FileReader;
3  import java.io.FileNotFoundException;
4  // compile with javac program.java
5  // run with java program
6  public class program{
7     // the main method is part of a class
8     public static void main(String [ ] args) throws FileNotFoundException{
9        try{
10          // read from file "program.java" and create simple tokens
11          Scanner data = new Scanner(new FileReader("program.java"));
12          while(data.hasNext()){
13             System.out.println(data.next());
14          }
15       }catch(Exception e){
16          // handle error here, we'll just rethrow the error
17          throw(e);
18       }
19    }
20 }
```

Example Java Classes

```
1  // Run: javac classes1.java and java Rabbit
2  // An abstract class is not completely implemented
3  abstract class Animal{
4     // instance member
5     private float weight;
6     // not-implemented instance function
7     public abstract String name();
8     // constructor
9     public Animal(float weight){ this.weight = weight; }
10    public String toString(){ return "I'm a " + name() + " with " +
11       weight + " kg"; }
12 }
13
14 class Rabbit extends Animal{
15    // invoke the constructor of the parent
16    public String name(){ return "Rabbit"; }
17    public Rabbit(){ super(2.5f); }
18
19    // the main method is part of a class
20    public static void main(String [ ] args){
21       Animal a = new Rabbit();
22       System.out.println(a); // I'm a Rabbit with 2.5 kg
23    }
24 }
25
26
```

Summary

- Big data analytics is a pillar of science
  - Supports building of hypothesis and experimentation
  - Challenges: 5 Vs – Volume, velocity, variety, veracity, value
- Data sources: Enterprise, humans, Exp./Observational data (EOD)
- Types of data: Structured, unstructured and semi-structured
- Roles in big data business: Data scientist and engineer
- Data science != business intelligence
- Analytics: Descriptive, diagnostic; predictive, prescriptive

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