Introduction

Lecture BigData Analytics

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Disclaimer: Big Data software is constantly updated, code samples may be outdated.

Outline

1 Introduction

2 BigData Challenges

3 Analytical Workflow

4 Use Cases

5 Programming

6 Summary

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 focussing 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 accessable 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

Excercise

- Weekly delivery, processing time about 8 hours / per week estimated
- Teamwork of two people (groups are important to keep the time limit)
- Supported by: Hans Ole Hatzel

[1] If available

Idea of BigData

Methods of obtaining knowledge (Erkenntnissprozess)

- Scientific method: question, hypothesis, prediction, testing, analysis

1. Explorative: start theory with empirical observations of phenomena and experimentation
2. Constructivism: starts with axioms and reason implications (other theoretical approaches)
3. Computational science and simulation

The Fourth Paradigm

- (Big) Data + Analytics $\Rightarrow$ Insight (prediction of the future)
  - For industry: insight = business advantage and money...
- Analytics: follow an explorative approach and study the data
  - To infer knowledge, use statistics / machine learning
- Construct a theory (model) and validate it with the data

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

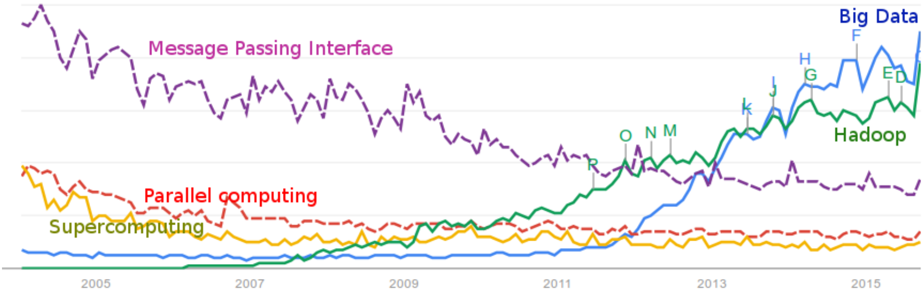
- You may develop and rely on complex models of physics
- Or use a simple model for a particular day; e.g., expect it to be similar to the weather of the typical day over the last X years
  - Used by humans: rule of thumb for farmers

Preferences of Humans

- Identify a set of people which liked items you like
- Predict you like also the items those people like (items you haven't rated so far)

Relevance of Big Data

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



Google Search Trends, relative searches

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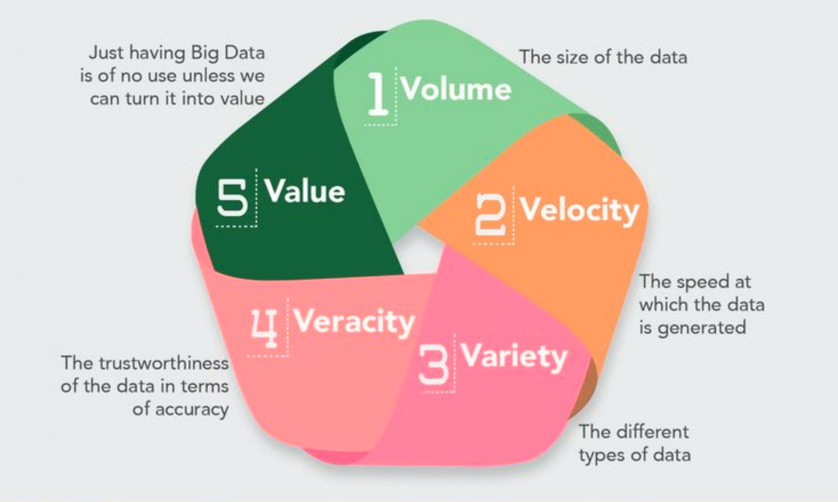
BigData Challenges & Characteristics



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

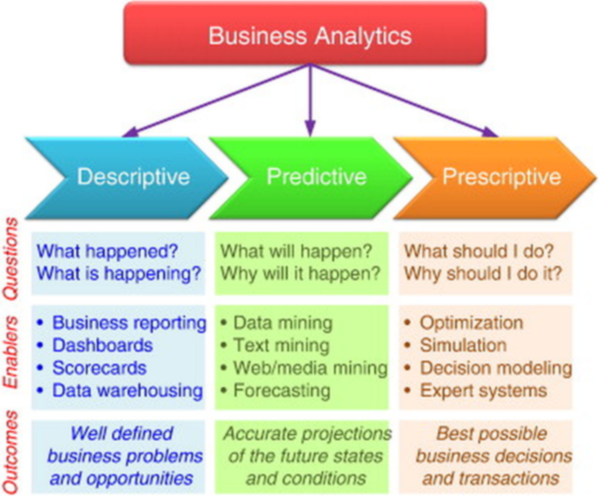
- Raw data of Big Data is of low value
  - For example, single observations
- Analytics and theory about the data increases the value
  - Analytics transform big data into smart (valuable) data!

Types of Data Analytics and Value of Data

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

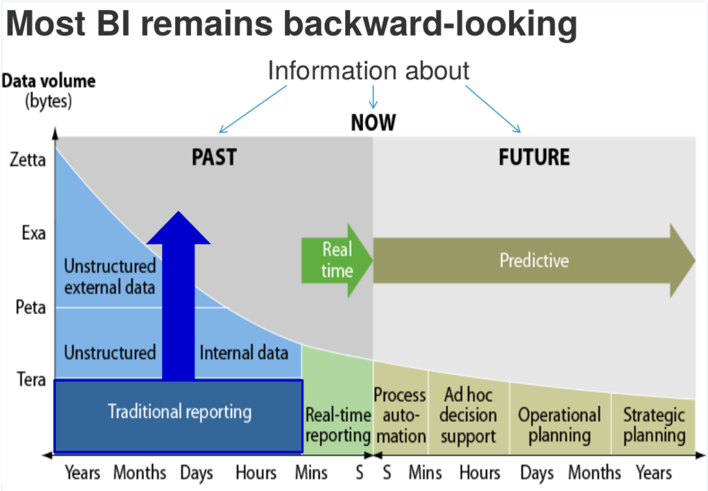
The level of insight and value of data increases from Step 1 to 4

The Value of Data (alternative view)



Source: Dursun Delen, Haluk Demirkan [9]

The Value of Data (alternative view)



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

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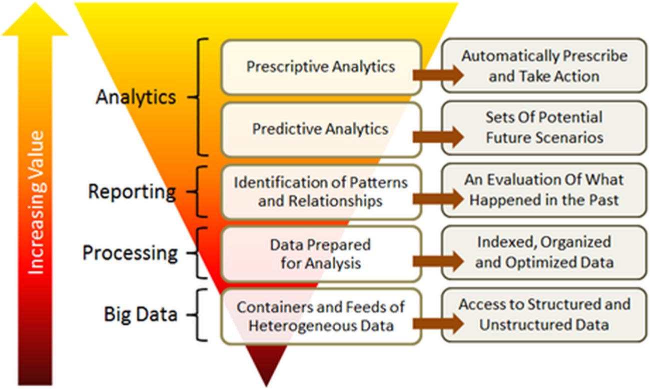
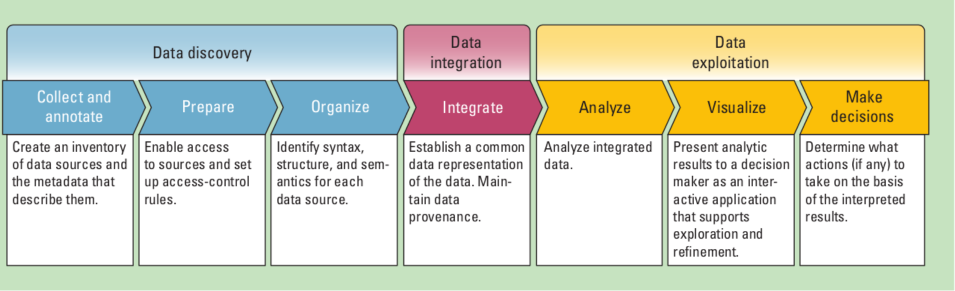
Big Data Analytics Value Chain

- There are many visualizations of the processing and value chain



Source: Andrew Stein [8]

Big Data Analytics Value Chain (2)



Source: Miller and Mork [7]

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

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”

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 data, both raw sources over extended periods of time as well as any 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: enable multiple data access patterns across a shared infrastructure: batch, interactive, online, search, and others

Privacy

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

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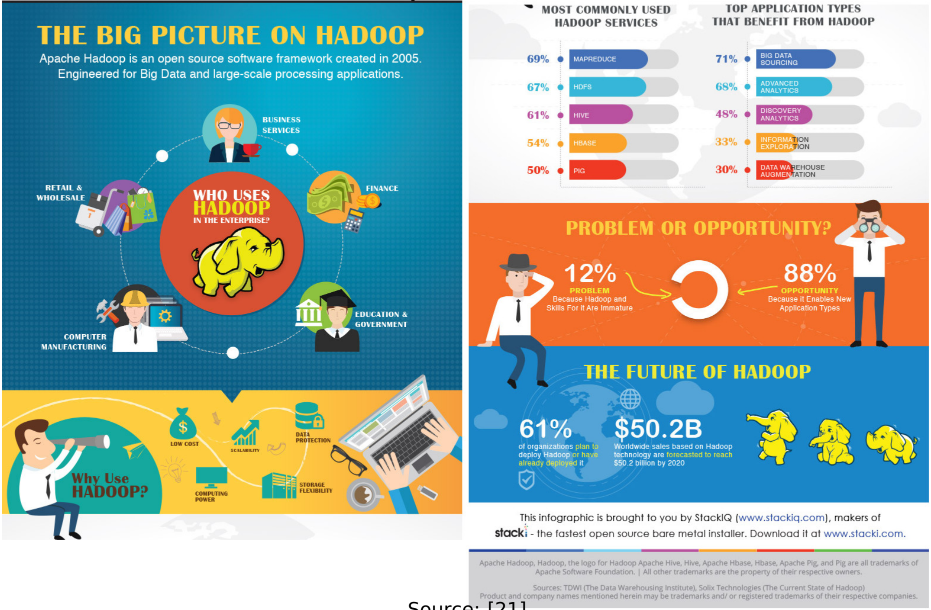
Advertisement for a Big Data Platform



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
- Supply chain management

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

Big Data in Industry

INDUSTRY	USE CASE	Sensor	Server Logs	Text	Social	Geographic	Machine	Clickstream	Structured	Unstructured
Financial Services	New Account Risk Screens		✔	✔						
	Trading Risk		✔							
	Insurance Underwriting	✔		✔		✔				
Telecom	Call Detail Records (CDR)					✔	✔			
	Infrastructure Investment		✔				✔			
	Real-time Bandwidth Allocation		✔	✔	✔					
Retail	360° View of the Customer			✔				✔		
	Localized, Personalized Promotions					✔				
	Website Optimization							✔		
Manufacturing	Supply Chain and Logistics	✔								
	Assembly Line Quality Assurance	✔								
	Crowd-sourced Quality Assurance				✔					
Healthcare	Use Genomic Data in Medial Trials	✔							✔	
	Monitor Patient Vitals in Real-Time									
Pharmaceuticals	Recruit and Retain Patients for Drug Trials				✔			✔		
	Improve Prescription Adherence				✔	✔				✔
Oil & Gas	Unify Exploration & Production Data	✔				✔				✔
	Monitor Rig Safety in Real-Time	✔								✔
Government	ETL Offloaded Response to Federal Budgetary Pressures								✔	
	Sentiment Analysis for Government Programs				✔					

Source: [20]

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"

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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

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

```
#!/bin/env python
import re # use the module 're'

# function reading a file
def readFile(filename):
   with open(filename, 'r') as f:
      data = f.readlines()
      f.close()
      return data
   return [] # return an empty array/list

# the main function
if __name__ == "__main__":
   data = readFile('intro.py')
   # iterate over the array
   for x in data:
      # extract imports from a python file using a regex
      m = re.match("import[ \t]+(?P<WHAT>[^# ]*)", x)
      if m:
         print(m.group("WHAT"))
         # dictionary (key value pair)
         dic = m.groupdict()
         dic.update( {"FILE" : 'intro.py'}) # append a new dict. with one key
         # use format string with dictionary
         print("Found import '%(WHAT)s' in file %(FILE)s" % dic )
         # 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

```
# 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 $\Rightarrow$byte code $\Rightarrow$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

```java
import java.util.Scanner;
import java.io.FileReader;
import java.io.FileNotFoundException;
// compile with javac program.java
// run with java program
public class program{
   // the main method is part of a class
   public static void main(String [ ] args) throws FileNotFoundException{
      try{
         // read from file "program.java" and create simple tokens
         Scanner data = new Scanner(new FileReader("program.java"));
         while(data.hasNext()){
            System.out.println(data.next());
         }
      }catch(Exception e){
         // handle error here, we'll just rethrow the error
         throw(e);
      }
   }
}
```

Example Java Classes

```
// Run: javac classes1.java and java Rabbit
// An abstract class is not completely implemented
abstract class Animal{
   // instance member
   private float weight;
   // not-implemented instance function
   public abstract String name();
   // constructor
   public Animal(float weight){ this.weight = weight; }
   public String toString(){ return "I'm a " + name() + " with " +
      weight + " kg"; }
}

class Rabbit extends Animal{
   // invoke the constructor of the parent
   public String name(){ return "Rabbit"; }
   public Rabbit(){ super(2.5f); }

   // the main method is part of a class
   public static void main(String [ ] args){
      Animal a = new Rabbit();
      System.out.println(a); // I'm a Rabbit with 2.5 kg
   }
}
```

Summary

- Big data analytics
  - Explore data and model causalities to gain knowledge & value
- Challenges: 5 Vs – Volume, velocity, variety, veracity, value
- Data sources: Enterprise, humans, Exp./Observational data (EOD)
- Types of data: Structured, unstructured and semi-structured
- Levels of analytics: Descriptive, predictive and prescriptive
- Roles in big data business: Data scientist and engineer
- Data science != business intelligence

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