Big Data Analytics and Visualization DS5008 Big Data Analytics CS6011 Data Analysis and Visualization

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Syllabus

- Overview
 - Industry
 - This Course
- 2 Analytics
 - Preparedness
 - Big Data Stack

- R Overview
- Data Analytics
- 3 Hadoop
 - HDFS
 - HDFS API's
 - Map Reduce Framework

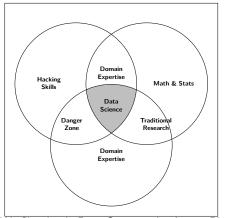


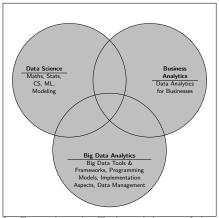
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 - Map Reduce Framework
- Spark

Big Data in Context of Data Science





W. Cleveland, Data Science: An Action Plan for Expanding the Technical Areas of the Field of Statistics, in International Statistical Review, 69(1), 2001

Overview

Understanding the Scale

- New York Stock Exchange: 1 TB / Day
- Large Hadron Collider: 15 PB / Year
- Internet Archive: 2 PB stored, Growing @ 20 TB / month
- Surveillance Drones (Multiple cameras, several TB / minute)
- Facebook, Google, Twitter, Instagram, Youtube, ...
- . . .
- Amount of Data Overwhelms Analysts & Decision Makers

Characteristics

Collections of datasets whose **Volume**, **Velocity**, and **Variety** is so large that it is difficult to **Store**, **Manage**, **Process**, and **Analyze** the data using traditional databases or processing tools.

Job Prospects

P@sha IT Salary Survey 2017

| Job Title | Salary (Entry) | Salary (Medium) | Salary (Senior) |
|---|----------------|-----------------|-----------------|
| (Big) Data Engineer, Business Analyst, Data Analyst | 74,110 | 118,115 | 144,770 |
| Data Scientist | 64,674 | 119,478 | 233,470 |

Sample Entry Requirements

- Technology expertise of solutioning in Hadoop, Hive, Spark / PySpark, SQL, Oozie along Data Modelling in Hive
- Expertise in programming Languages- Java / Python / Scala
- Ability to demonstrate micro / macro designing and familiar with Unix Commands and basic work experience in Unix Shell Scripting
- .

Job Prospects (cont.)

Companies

- IBM
- Afiniti
- Telecom (Mobilink, Telenor, Zong)
- Banks (Allied)

- Logistics (Careem, Bykea, Keep Trucking)
- 10Pearls, i2c
- ...

Job Prospects (cont.)

Number of Jobs

| Job Role | Pakistan | Middle East | Europe | USA |
|-----------------------------|----------|-------------|--------|-------|
| Data Scientist | 7 | 197 | 6011 | 6561 |
| Data Analyst | 15 | 160 | 4845 | 8564 |
| Data Manager | 0 | 11 | 1283 | 1255 |
| Data Architect | 4 | 27 | 1220 | 2184 |
| Business Analyst | 9 | 212 | 9595 | 15244 |
| Financial Analyst | 2 | 69 | 1194 | 6395 |
| Big Data Engineer | 3 | 24 | 603 | 674 |
| Data Engineer | 6 | 135 | 5894 | 6838 |
| Machine Learning Specialist | 1 | 3 | 46 | 14 |

Table 1: DS Jobs Worldwide (Source: LinkedIn, fetched October 13, 2020)

Job Prospects (cont.)



Figure 1: On a Lighter Note

Course Overview

Learning Outcomes

| CLO1 | Perform analytics on large scale datasets |
|------|--|
| CLO2 | Deploy massive threading solutions on Parallel systems |

- Deploy massive threading solutions on Parallel systems
- CLO3 Deploy massive threading solutions on Distributed systems
- CLO4 Be able to visualize Large Scale Multi-Dimensional Datasets
- Be familiar with algorithms and tools for mining massive datasets CLO₅

Marks Breakdown

- Sessional I: 15%
- Sessional II: 15%
- Final Examination: 50%
- Assignments: 20% (including Takehome Lab Activities)
- HPC Setup with support for various parallel and distributed computing frameworks will be made available to all students for duration of semester (and beyond upon request)

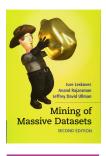
Course Overview (cont.)

Generating Public Key for Assignments

- On Windows, Use https://winscp.net/eng/docs/ui_puttygen
- On Linux, use ssh-keygen command
- Share generated key with me by email.

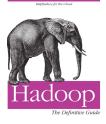
Probability Distribution of Previous Grades 0.3 0.2 0.1 0.1 0.4 0.2 0.2 0.1 0.4 0.2 0.4 0.2 0.4 0.4 0.2 0.4 0.4 0.4 0.4 0.5 0.7 0.8 Figure 2: Spring 2019 Figure 3: Spring 2020 Figure 4: Spring 2021

Books









Tom White



- Overview
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- Sparl

Data

Raw Data Sources

- Logs: Web applications/servers/daemons
- Transactions:E-Commerce/Banking/Financial
- Social Media: JSon
- Databases: RDBMS
- Sensor Data: IoTs/WSNs
- Clickstream Data: Patterns of user activities

- Surveillance: Sensors/Images/Video Data
- Healthcare: Sensors/Hospital Records
- Network: Info generated by Network Devices
- ...

Data Storage

- Issues: Disk Density, Access Times, Storage Formats
- Parallel Disk Access & Distributed Storage Solutions



Data (cont.)

Data Processing

- Combining Data (Parallel Access, Distributed Storage)
- HPC and Super-Computing Systems
- MPI, GPU Computing, ...

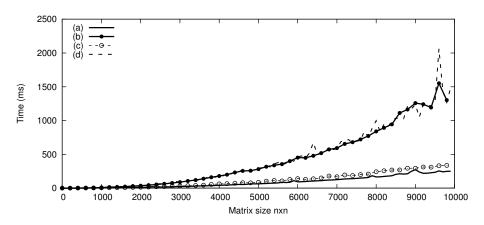


Effect of Algorithm Styles

Which code is going to be the fastest?

```
(a) for (i = 0; i < n; i++) (b) for (j = 0; j < n; j++) for (j = 0; j < n; j++) for (i = 0; i < n; i++) sum += a[i][j]; sum += a[i][j]
```

Effect of Algorithm Styles (cont.)





Clock Cycles

- What is a single clock cycle worth?
 - xchg: Exchange values in two registers
 - push: Push operation using registers
 - pop: Pop operation using registers
 - add,sub: 3 additions/subtractions

involving registers

- cmp: 3 comparisons involving registers
- mul: half a fp multiplication involving registers

Where are We Today?

- \bullet Clock rates 40 MHz (MIPS R3000 1988) \to 4.0 GHz (Intel Core-i7-4790K 2015), 4.4 GHz (Intel Xeon X5698 2015)
- Higher processor speed

 More heat dissipated
- Transistor has reached size of 32 nm (Generation 3 Core-i7). Size limit: How much more smaller can it get?
- Support for executing multiple instructions per clock cycle, fast cache technologies, superscalar architectures . . .

Ranking of Super Computers

| Rank | Site | System | Cores | TFLOPs | Power (kWh) |
|------|-------------------------------|-------------------------------------|------------|-----------|----------------|
| 1 | Wuxi, China | TaihuLight: Sunway 1.45Ghz | 10,649,600 | 125,435.9 | 15,371 |
| 2 | Guangzhou, China | Tianhe-2: Intel Xeon | 3,120,000 | 54,902 | 17,808 |
| 3 | Oak Ridge Lab, USA | Titan: Cray Opteron, NVIDIA K20 | 560,640 | 27,112 | 8,209 |
| 4 | DoE, USA | Sequoaia:, IBM BlueGene/Q | 1,572,864 | 20,132 | 7,890 |
| 5 | RIKEN Ins., Japan | K-Computer: Fujitsu SPARC64 | 705,024 | 11,280 | 12,660 |
| 6 | DoE, USA | Mira: IBM BlueGene/Q | 786,432 | 8,586.6 | 3,945 |
| 7 | DoE, USA | Trinity: Cray XC40 | 301,056 | 11,078 | =. |
| 8 | Swiss S.Comp., Switzerland | Cray, Intel Xeon, NVIDIA K20 | 115,984 | 7,788 | 2,325 |
| 9 | HLRS, Stuttgart, Germany | Hazel Hen: Cray XC40, Intel Xeon | 185,088 | 7,403.5 | - |
| 10 | KAUST, S. Arabia | Shaheen: Cray XC40, Intel Xeon | 196,608 | 7,235.2 | 2,834 |
| - | Your Home | Intel Core-i7 | 4 | .026 | 0.3 |
| - | Your Home | NVIDIA K40 | 2,880 | 4.29 | 0.3 |
| - | Your Home | NVIDIA K80 | 4,992 | 8.73 | 0.3 |

Table 2: Top 10 Supercomputers: June 2016, top500.org

Ranking of Super Computers (cont.)

| Rank | Site | System | Cores | TFLOPs | Power (kWh) |
|------|--------------------|---|------------|---------|----------------|
| 1 | RIKEN, Japan | Fugaku: Fujitsu 2.2 GHz | 7,630,848 | 442,010 | 29,899 |
| 2 | Oak Ridge Lab, USA | Summit: IBM 3GHz, NVIDIA Volta GV100 | 2,414,592 | 148,600 | 10,096 |
| 3 | DoE, USA | Sierra: IBM 3.1 GHz NVIDIA Volta GV100 | 1,572,480 | 94,640 | 7,438 |
| 4 | Wuxi, China, | TaihuLight: Sunway 1.45GHz | 10,649,600 | 125,435 | 15,371 |
| 5 | DoE, USA | PerlMutter: Cray 2.4GHz, NVIDIA A100 | 761,856 | 70,870 | 2,589 |

Table 3: Top 10 Supercomputers: Nov 2021, top500.org

Ranking of Super Computers (cont.)

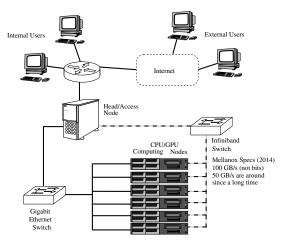


Figure 5: Setup of a typical HPC facility

Preparedness

Moore's Law, 1965

Cramming more components onto integrated circuits

With unit cost falling as the number of components per circuit rises, by 1975 economics may dictate squeezing as many as 65,000 components on a single silicon chip A prediction that would define the pace of digital revolution. Many interpretations:

- Computing would increase in power exponentially
- Computing would decrease in relative cost exponentially
- Transistory density will double every year (revised to double every 18 months)

By Gordon E. Moore

Director, Research and Development Laboratories, Fairchild division of Fairchild Camera and Instrument Corp.

The future of integrated electronics is the future of electronics itself. The advantages of integration will bring about a proliferation of electronics, pushing this science into many new areas.

Integrated circuits will lead to such wonders as home computers—or at least terminals connected to a central computer—automatic controls for automobiles, and personal portable communications equipment. The electronic wristwatch needs only a display to be feasible today.

But the biggest potential lies in the production of large systems. In telephone communications, integrated circuits in digital filters will separate channels on multiplex equipment. Integrated circuits will also switch telephone circuits

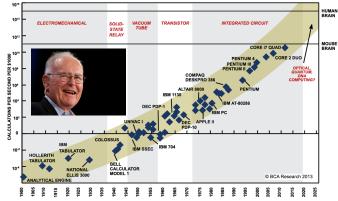
and perform data processing.

Computers will be more powerful, and will be organized in completely different ways. For example, memories built of integrated electronics may be distributed throughout the

The author



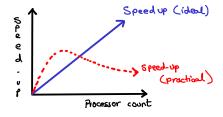
Dr. Gordon E. Moore is one of the new breed of electronic engineers, schooled in the physical sciences rather than in electronics. He earned a B.S. degree in chemistry from the University of California and a Ph.D. degree in physical chemistry from the California Institute of Technology. He was one of the founders of Fairchild Semiconductor of the research and development laboratories since of the California institute of Technology. He was one of the founders of Fairchild Semiconductor and has been director of the research and development laboratories since



SOURCE: RAY KURZWEIL, 'THE SINGULARITY IS NEAR: WHEN HUMANS TRANSCEND BIOLOGY", P.67, THE VIKING PRESS, 2006, DATAPOINTS BETWEEN 2000 AND 2012 REPRESENT BCA ESTIMATES.

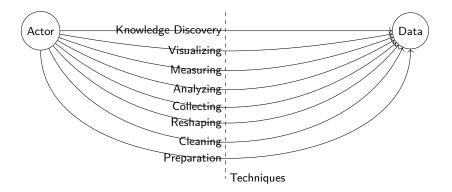
Electronics, Volume 38, Number 8, April 19, 1965

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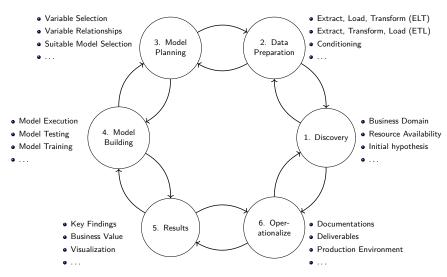
- Why ideal speedup is not possible: data transfer (through message exchanges), I/O bottlenecks, race conditions, dependencies, contention (critical section), load balancing, deadlocks, synchronization, node failures, . . .
- Programmers lacking skills in parallel & distributed regime . . .

Overview



- Data scale may render techniques useless
- New techniques (from other discplines) employed to guarantee functioning of operations on data

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Analysis Techniques

- Batch Analysis
- Real-Time Analysis

Descriptive Analytics

(What happened?)

- Reports - Alerts

Diagnostic Analytics

(Why did it happen?)

- Queries - Data Mining

Predictive Analytics

(What is likely to happen?)

- Forecasts - Simulations

Prescriptive Analytics

(What can we do to make it happen?)

> - Planning - Optimization

Basic Statistics

- Mean
- Median - Variance
- Counts
- Top-N - Distinct

Generalized N-Body Problem

- Distances
- Kernels
- Similarity between pairs of points
- Nearest
- Neighbor
- Clustering
- Kernel SVM

Linear Algebraic Computations

- Linear Algebra
- Linear Regression - PCA

- Graph Search
- Betweenness - Centrality

Graph-theoretic

Computations

- Commute distance
- Shortest Path
- Minimum Spanning Tree

Optimization

- Minimization - Maximization
- Linear Programming
- Ouadratic Programming
- Gradient Descent

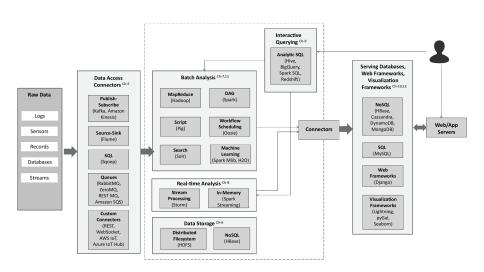
Integration

- Bavesian Inference
- Expectations
- Markov Chain Monte Carlo

Alignment Problems

- Matching hetween data sets (text, images, sequences)
- Hidden Markov Model

Big Data Stack



Hadoop

- Open Source Framework by Apache for Distributed Batch Processing
- Uses Map-Reduce Programming Model
- Data Stored on Hadoop Distributed File System (HDFS)
- Data processed in Hadoop Clusters
- Contains other tools for job scheduling, and machine learning
- Available directly from Apache, or Cloudera, or HortonWorks

Spark

- Open Source Framework by Apache for Distributed Parallel Processing
- Uses Map-Reduce Programming Model
- Data Stored in Memory (RAM)
- Visualizes operations by constructing Directed Acyclic Graphs
- 100s of times faster than Hadoop for sorting, machine learning operations

R Overview

- Software Framework for Statistical Analysis and Graphics
- GNU General Public License
- R, Rscript, Rstudio

```
Sample Code
#Command to Run: Rscript file.R
data <- read.csv("diabetes.csv")
                                           # Read CSV File
head(data)
                                           # CSV Header
summary(data)
                                           # Descriptive Analytics
plot(data$Age, data$Glucose)
                                           # Plot 1 Col against Other
results <- lm(data$Age, data$Glucose)
                                           # Apply Linear Regression (e.g.)
summary(results)
                                           # Descriptive Analytics again
hist(results$residuals)
                                           # Plot Histogram
```

Quick Commands

| Get Help | help(command) |
|-----------------------------------|--|
| Set working directory | setwd("/path") |
| Write data | <pre>write.table(data, "/path/data.txt",</pre> |
| Install Packages | install.packages("RODBC") |
| Load Package | library(RODBC) |
| Save Image | (1) jpeg(file="/path/test.jpg") |
| | (2) hist(results\$residuals) |
| | (3) dev.off() |
| Get Class and Typeof variables | class(var) and typeof(var) |
| Type forcing | j <- as.integer(var) |
| Count of elements | length(var) |

| Function | Headers | Separator | Decimal Point |
|---------------|---------|-----------|---------------|
| read.table() | False | | |
| read.csv() | True | , | |
| read.csv2() | True | ; | 1 |
| read.delim() | True | \t | |
| read.delim2() | True | \t | , |

Table 4: Different ways of Opening CSV/Text Files

Connect Through ODBC Driver

```
conn <- odbcConnect("dbName", "user", "password")
data <- sqlQuery(conn, "select * from table")</pre>
```

Vector Datatype

```
u <- c("red", "yellow", "blue")</pre>
                                     # create a vector "red" "yellow" "blue"
                                     # returns "red" "yellow" "blue"
                                     # returns "red" (1st element in u)
u[1]
v <- 1:5
                                     # create a vector 1 2 3 4 5
sum(v)
                                     # returns 15
w <- v * 2
                                     # create a vector 2 4 6 8 10
z <- v + w
                                     # sums two vectors element by element
z > 8
                                     # returns FALSE FALSE TRUE TRUE TRUE
z[z > 8]
                                     # returns 9 12 15
z[z > 8 \mid z < 5]
                                     # returns 3 9 12 15
```

Array and Matrix Types

```
data <- array(0, dim=c(3,4,2))
data[1,1,1] <- 22

data <- matrix(0, nrow=3, ncol=4)
data[1,1] <- 22

data <- matrix(c(1,2,3,4,5,6,7,8,9), nrow=3, ncol=3)
data_transpose <- t(data)
data_inverse <- matrix.inverse(data)
data_matrix_mul <- data %*% data_inverse

data[,1]  # Show 1st column
data[1,1]  # Show 1st row
data[1,2,  # Show 1st two rows
data[1,3] # Show 1st two rows
data[.2,1,3] # Show 1st tand 3rd col</pre>
```

DataFrame and List Types

• Multiple Type/Object Support

```
data[c("Glucose")]
list1 <- list("basketball", "cricket")
list2 <- list("cricket", 1, 2, 3)</pre>
```

```
data <- as.data.frame(cbind(list1, list2)) # Numerical binding
```

Applying a Function to Multiple Values

```
apply(data[,c(1:2)], MARGIN=2, FUN=sd)
```

Functions

```
doubleUpOne <- function(v)
{
   return( 2 * v[1:length(v)]) }
}
doubleUpTwo <- function(v)
{
   test <- 1:length(v)
   for(x in 1:length(v)) {
     test[x] = 2 * v[x]
   }
   return(test)
}
doubleupOne(v <- 1:5)
doubleupTwo(v <- 1:5)</pre>
```

Data Analytics

Analytics

- Processes, Technologies, Frameworks, and Algorithms that extract meaningful insights from (raw) data
- Insights organized and structured to infer knowledge

Case 1: Descriptive Analytics

- Present Data in summarized form (what has happened so far)
- Descriptive Statistics: Counts, Mins, Maxs, Means, Top-N, Percentages, ...
- Finding Correlation between News Items and Stock Prices
- Which pages are popularly visited on a website
- What is the average rainfall per year in Peshawar
- Top 10 coldest days in a year



Data Analytics (cont.)

Case 2: Diagnostic Analytics

- Analysis of Past Data to Diagnose why certain events Happen (why did something happen)
- Example: Causes of fault occurence in light of data from sensors
- Why did patient X die in hospital when patient Y survived?
- Which candidate is suitable to hire given certain parameters?

Case 3: Predictive Analytics

- Predict occurrence of an event likely to happen (What is likely to happen)
- Example, when a fault will occur, tumor is benign or malignant, predicting pollution levels, weather, natural disasters
- Is a transaction fraudulent?
- Is a tumor malignant or benign?
- Is it going to rain on a particular day?



Data Analytics (cont.)

Case 4: Prescriptive Analytics

- Uses multiple prediction models to predict various outcomes and the best course of action for each outcome (What can we do to make it happen)
- Finding similar news items (similar patients, or similar products)
- Finding similar images in an image search
- Best medicine for treatment of patients (based on outcomes of medicines for similar patients)
- Best mobile data plan given customers usage

Descriptive Analytics

Data Summarization

Definition 1 (Mean)

$$\bar{y} = \frac{1}{N} \sum_{i=1}^{n} y_i \tag{1}$$

 Easily influenced by outliers (may be remedied as trimmed mean and/or winsorized mean)

$$\bar{y}_k = \frac{1}{N - 2k} \sum_{i=1}^{n-k} y_i \tag{2}$$

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Data Summarization

Definition 2 (Median)

- 50% less, 50% more
- Data must be sorted before obtaining m
- Not influenced by outliers
- If n is odd:

$$m = y_{\frac{n+1}{2}} \tag{3}$$

If n is even:

$$m = \frac{1}{2} \left(y_{\lfloor \frac{n+1}{2} \rfloor} + y_{\lceil \frac{n+1}{2} \rceil} \right) \tag{4}$$

• the Q2



Data Summarization

Definition 3 (Q1)

If n is odd:

$$Q1 = y_{\frac{n+1}{\epsilon}} \tag{5}$$

If n is even:

$$Q1 = \frac{1}{2} \left(y_{\lfloor \frac{n+1}{4} \rfloor} + y_{\lceil \frac{n+1}{4} \rceil} \right) \tag{6}$$

Definition 4 (Q3)

If n is odd:

$$Q3 = y_3 \frac{n+1}{4} \tag{7}$$

If n is even:

$$Q3 = \frac{1}{2} \left(y_{\lfloor 3\frac{n+1}{4} \rfloor} + y_{\lceil 3\frac{n+1}{4} \rceil} \right) \tag{8}$$

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Data Summarization

Definition 5 (min, max)

$$y_{\min} = y_0 \tag{9}$$

$$y_{\max} = y_{n-1}$$

Definition 6 (Mode)

- Most frequently occurring data in dataset
- Can be multiple modes if same frequency applies to terms
- Can be zero mode if frequency of all terms is not more than 1

(10)

Descriptive Analytics

Data Spread Measurements

Definition 7 (Range)

$$R = y_n - y_1 \tag{11}$$

- Distance between two numbers (i.e., resembles deviation)
- Sign Affected by quadrant of operations

| y = | { | 7.5 | 8.0 | 8.0 | 8.5 | 9.0 | 11.0 | 19.5 | 19.5 | 28.5 | 31.0 | 36.0 | } | , $\bar{y} = 17$ |
|-----------------|---|------|------|------|------|------|------|------|------|------|------|------|---|------------------|
| $y - \bar{y} =$ | { | -9.5 | -9.0 | -9.0 | -8.5 | -8.0 | -6.0 | 2.5 | 2.5 | 11.5 | 14.0 | 19.0 | } | |

Average Deviation:

$$\frac{1}{N} \sum_{i=0}^{N-1} (y_i - \bar{y}) = 0 \tag{12}$$

Data Spread Measurements

Average Absolute Deviation

$$\frac{1}{N} \sum_{i=0}^{N-1} |y_i - \bar{y}| = 9 \tag{13}$$

Definition 8 (Variance)

$$var(y) = \sigma^2 = \frac{1}{N-1} \sum_{i=1}^{n} (y_i - \bar{y})^2$$
(14)

- Averaged square deviation from mean \bar{y}
- Square takes care of sign change problem, but it gives more weightage to data far from mean whereas closer data contribution is negligeable

7.5 8.0 8.0 8.5 9.0 11.0 19.5 19.5 28.5 31.0 36.0 $\sigma_u^2 = 113$

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Data Spread Measurements

Definition 9 (Standard Deviation)

$$std(y) = \sigma = \sqrt{\frac{1}{N-1} \sum_{i=1}^{n} (y_i - \bar{y})^2}$$
 (15)

$$y=$$
 { 7.5 8.0 8.0 8.5 9.0 11.0 19.5 19.5 28.5 31.0 36.0 } , $\sigma_y=11$

Descriptive Analytics

Similarity Measures

Euclidean Distance

$$d(X,Y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$
 (16)

Manhattan (Taxicab) Distance

$$d(X,Y) = \sum_{i=1}^{n} |x_i - y_i|$$
(17)

Chebyshev Distance

$$d(X,Y) = \max\{|x_i - y_i|\}$$
 (18)

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DS5008, CS6011

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Similarity Measures

Minkowski Distance

$$d(X,Y) = \sqrt[p]{\sum_{i=1}^{n} (x_i - y_i)^p}$$
 (19)

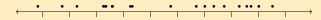
Other similarity measures: Cosine Similarity, Pearson Correlation Coefficient, Mahalanobis Measure, Jaccard Similarity, Levenshtein Distance, Hamming Distance, Chi-Square

Descriptive Analytics

Visualization

Dot / Scatter Plot

Place dots at appropriate location on a number line



- Dot Chart in R: dotchart(data\$colx)
- Extended as a 2D dot plot where point cloud / scatter plot can be constructed
- Scatter Plot in R: plot(data\$colx, data\$coly)

| pch | pointer change | 1, 2, 3, |
|------|----------------|-------------------|
| col | colour | blue, red, green, |
| main | Title | string |
| xlab | X title | string |
| ylab | Y title | string |

Table 5: Additional Arguements to plot() in R

Visualization

Trend Line

- $\bullet y = mx + b$
- abline(lm(data\$coly ~ data\$colx), col="red")
- Slope

$$m = r \frac{\sigma_y}{\sigma_x} \tag{20}$$

Intercept

$$b = \bar{y} - m\bar{x} \tag{21}$$

Pearson's Correlation Coefficient

$$r = \frac{\sum_{i} (x_{i} - \bar{x}) (y_{i} - \bar{y})}{\sqrt{\sum_{i} (x_{i} - \bar{x})^{2} \sum_{i} (y_{i} - \bar{y})^{2}}}$$
(22)

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Visualization

Standard Deviation

$$\sigma_x = \sqrt{\frac{1}{N-1} \sum_{i=0}^{N-1} (x_i - \bar{x})^2}$$
 (23)

Curve Fit

- $y = m_0 x^p + m_1 x^{p-1} + \ldots + m_{p-1} x^0 + \epsilon$
- Use Polynomial Regression Fitting
 fit <- predict(loess(data\$colx ~ data\$coly))
 points(data\$colx, fit, col="blue")

Bar Plot

• barplot(sales_delim\$Glucose)

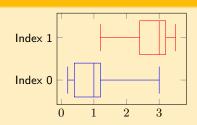


Visualization

Box Plot

- Sort Data
- Get min and max
- Get Q1, Q2, and Q3

• in R: boxplot(data\$col1)



Visualization

| Stem | / Leaf | Diagram |
|---------|--------|----------|
| O CCITI | / LCui | Diagrain |

| Decide units for Stem (column 1) and Leaves (column 2) | stem | leave |
|--|------|-----------------|
| Prepare linearly increasing sequence of stems (with no gaps) | 1.2 | 3 |
| | 1.3 | 1, 4 2, 7, 8 |
| • For each variable, assign its units of leaves to respective bin | 1.4 | 2, 7, 8 |
| of stem (bins must be of equal size) | 1.5 | 4, 1 |
| | 1.6 | 4 |

| | _ | | |
|---|------|-------|-------|
| • | Freq | uency | Lable |

| | • | Identify | bins | (not | necessarily | of | equal | size) |) |
|--|---|----------|------|------|-------------|----|-------|-------|---|
|--|---|----------|------|------|-------------|----|-------|-------|---|

| | | | | | , |
|---|------------|-----------|------------|---------|-----------|
| • | Place each | item in | respective | bin and | increment |
| | counter on | its inclu | ısion | | |

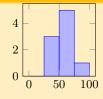
| Bin | Count |
|------------------|-------|
| $0 < x \le 25$ | 0 |
| $25 < x \le 50$ | 3 |
| $50 < x \le 75$ | 5 |
| $75 < x \le 100$ | 1 |

イロト (部) (を) (を) 200

Visualization

Histogram from Frequency Table

- Horizontal axis representing bins
- Rectangular bars corresponding to count (frequency)
- No gaps if bins are continuous
- Represents Density

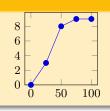


- In R: hist(data\$colx, breaks=50) for histogram
- In R: plot(density(data\$colx)) for kernel density with kernel options of gaussian, triangular, cosine, rectangular, etc.

Visualization

Cummulative Frequency from Frequency Table

- Horizontal axis representing bins
- Cummulative Frequency on Vertical axis
- Plot and join all the points



Example

- Sorted results for the Density of Earth (unknown units) by Cavendish (1798):
- 4 88 5 07 5 10 5 26 5 27 5 29 5 29 5 30 5.34 5.34 5.36 5.39 5.42 5.44 5.46 5.47 5 50 5 53 5 55 5 57 5 58 5 61 5 62 5 63 5.65 5.68 5.75 5.79 5.85

Normal Datasets

- ullet Highest at Middle Interval \bar{y}
- Histogram is symmetric
- 68% of observations are within $\bar{y} \pm \sigma$
- 95% of observations are within $\bar{y} \pm 2\sigma$
- 99.7% of observations are within $\bar{y} \pm 3\sigma$

Skewness

$$g_1 = \frac{\frac{1}{N} \left(Y_i - \bar{Y} \right)^3}{\sigma^3} \tag{24}$$

• Approximately Symmetric: $-0.5 < g_1 < 0.5$, Highly Skewed: $g_1 < -1$, $g_1 > +1$

Statistical Approaches to Outlier Detection (1D)

2 2 3 3 4 4

y =

Classical Approach (|Z-Score|)

$$\frac{\left|X - \bar{X}\right|}{\sigma} \ge \{1.5, 2, 2.5, 3\} \tag{25}$$

1000

$$\frac{|1000 - 145.43|}{376.83} \ge 2 \implies 2.26 \ge 2$$

$$y = \{ 2 \ 2 \ 3 \ 3 \ 4 \ 4 \ 1000 \ 1000 \ \}$$
(26)

$$\frac{|1000 - 252.25|}{461.52} \ge 2 \implies 1.62 \ge 2 \tag{27}$$

Boxplot Approach

$$X < Q_1 - 1.5(Q_3 - Q_1)$$

(28)

$$X > Q_3 + 1.5(Q_3 - Q_1)$$

(29)

4□ > 4個 > 4 를 > 4 를 > 3 = 4

Statistical Approaches to Outlier Detection (1D) (cont.)

$$y = \{ 2 2 3 3 4 4 1000 \}$$

$$1000 > 4 + 1.5 (4 - 2) \implies 1000 > 7$$

$$y = \{ 2 2 3 3 4 4 1000 1000 \}$$

$$1000 > 502 + 1.5 (502 - 2.5) \implies 1000 > 1251.2$$
(31)

Definition 10 (Covariance)

$$cov(X,Y) = \frac{1}{N} \sum_{i=1}^{n} (x_i - \bar{x}) (y_i - \bar{y})$$
(32)

Joint variability of two variables

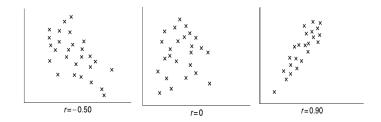
Definition 11 (Correlation)

$$\operatorname{corr}(X,Y) = \frac{\operatorname{cov}(X,Y)}{\sqrt{\operatorname{var}(X)\operatorname{var}(Y)}}$$
(33)

$$\operatorname{corr}(X,Y) = \frac{\operatorname{cov}(X,Y)}{\sqrt{\frac{1}{N^2} \sum_{i=1}^{n} (x_i - \bar{x})^2 (y_i - \bar{y})^2}} = \frac{\operatorname{cov}(X,Y)}{\operatorname{std}(X)\operatorname{std}(Y)}$$
(34)

4 D > 4 D > 4 E > 4 E > E 990

Measuring Associations (cont.)



- If corr(X, Y) = +1 represents points on straight line with positive slope, strong correlation
- If corr(X,Y) = -1 represents points on straight line with negative slope, weak correlation
- If corr(X, Y) < +1 represents scattered points

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- Spark

Overview



Hadoop common

For Storage

Hadoop File System

For Processing

Map Reduce

Implementations

- Cloudera
- Amazon
- Ali Baba
- or Direct Installation

Overview (cont.)

Topics Covered

- Software Stack
- Distributed File System (HDFS)
- Physical Organization of Compute Nodes (Compute Nodes, Redundant Nodes, etc.)
- Map Reduce Framework
 - Key Value Pairs
 - Concept of Grouping Keys
 - Mappers & Reducers
- Sample Algorithms (See sample questions given)

Hadoop File System

Design Consideration

- Break files into blocks $B = \{b_1, b_2, \dots, b_n\}$ of certain size s
- ullet Distribute blocks across multiple (data) nodes $N=\{n_1,n_2,\ldots,n_m\}$ within a cluster
- Challenges:
 - ullet For large m, node failures are quite probable. So introduce redundancy.
 - For large n, high throughput is required. So introduce concepts such as write once read many, and move computation closer to data.

Hadoop File System (cont.)

Performance Impact

- File Size, Block Length, Block Quantity, all affect performance
- Block quantity ↔ Number of Threads
 - Queues
 - Thread Creation/Deletion Time
 - I/O
 - Messages exchanges between threads
- Strategies: Merge Files, Load Files in Sequence

Hadoop Common Architecture

Name Node (Master Server)

- Manages File System Namespace
- Regulates/Control access to files
 - Read/write requests from client
 - Create/Delete/Replicate blocks on data nodes

Data Nodes

- Manages Physical Storage of Blocks
- Serve Read/Write requests of Clients
- Serve Create/Delete/Replicate block requests of Name Node

Node Failures

Data Node Failure

- Server Crash / Disk Crash / Data Corruption / Network Failure
- Name node sends periodic heart-beats
- If true, mark dead, re-replicate block copy

Network Failure

- Denial of Service
- Physical Network failure

Namenode Failure

- Server Crash / Disk Crash / Data Corruption
- Send data/metadata to secondary nameserver (if configured)



HDFS Tuning Parameters

(Name, Value) properties in /etc/hadoop/hdfs-site.xml

- dfs.replication : 3 for Replication Factor
- dfs.namenode.name.dir: /var/lib/hadoop/hdfs/name for Name Node
- dfs.datanode.data.dir: /var/lib/hadoop/hdfs/data for Data Node
- dfs.namenode.secondary.http-address : hdfs://localhost:50090 For Secondary Name node
- dfs.permissions.superusergroup: hadoop for User Permissions (must belong to this group)
- dfs.block.size : 134217728 for changing block size (across all clusters)
- dfs.datanode.handler.count : 10 for changing threads per data node.
- dfs.namenode.fs-limits.max-blocks-per-file : 100 for fixing maximum allowable blocks per file
- Dozens of other parameters specified in hdfs-default.xml (search online)

Specific Adjustments

• hdfs dfs -D dfs.blocksize=134217728 -put test_128MB.csv /user

HDFS Commands

- hdfs dfs -ls /
- hdfs dfs -lsr / ls with recursive display
- hdfs dfs -du Disk usage
- hdfs dfs -dus Disk usage summary
- hdfs dfs -mv src dest
- hdfs dfs -rm xyz Remove file or empty directory
- hdfs dfs -rmr xyz Recursive remove file or directory
- hdfs dfs -put local remote
- hdfs dfs -get remote local
- hdfs dfs -cat file
- hdfs dfs -tail file
- hdfs dfs -head file
- hdfs dfs -chmod 777 file
- hdfs dfs -chown group file
- hdfs dfsadmin -report Shows utilization of HDFS

Using C

libhdfs

- Part of the Hadoop distribution (Located pre-compiled in \$HADOOP_HDFS_HOME/lib/native/libhdfs.so)
- Compatible with both Linux/Windows
- Java Native Interface (JNI) to Core Interface API in Java
- Thread Safe
- To compile (gcc)

```
gcc -I /opt/hadoop-3.2.1/include hdfsC.c
```

- -L /opt/hadoop-3.2.1/lib/native -lhdfs
- -L /opt/nadoop-3.2.1/11b/native -indis
- -L /opt/oracle-jdk-bin/jre/lib/amd64/server -ljvm|
- To run

```
CLASSPATH=$CLASSPATH:$(/opt/hadoop-3.2.1/bin/hadoop classpath --glob)
LD_LIBRARY_PATH=$LD_LIBRARY_PATH:/opt/oracle-jdk-bin/jre/lib/amd64/server: \
/opt/hadoop-3.2.1/lib/native
./a.out
```

./a.out

Using C (cont.)

HTTP Rest API

- Support for HTTP Get, Put (-X PUT), Post (-X POST), Delete (-X DELETE)
- Configuration for dfs.webhdfs.enabled required in hdfs-site.xml (default is true)
- General Usage:

- ullet Default port: 50090
 ightarrow 9870
- Responses in JSON

HTTP Rest API (cont.)

Sample Operations

- op=GETFILESTATUS Get Information about files
- op=MKDIRS for creating directory
- permission=755 for specifying Linux permissions
- op=CREATE for creating a (blank) file. For copying contents of an existing file, (use with -T <LOCAL_FILE>
- blocksize=<LONG> for Block Size
- replication=<SHORT> for replication factor
- op=APPEND for appending to a file
- op=OPEN for opening and reading a file
- op=RENAME&destination=<PATH> for renaming a file
- op=DELETE for deleting a file/directory, (Use with -X DELETE)
- ... and others (See hadoop.apache.org/docs/current/hadoop-project-dist/hadoop-hdfs/WebHDFS.html

Map Reduce Framework

Mapper Function

0

- Reducer Function
- Shuffle and Sort

Map Reduce Framework (cont.)

Example: Word Count

- <word, 1>
- Tokenize text and produce key-value pairs in a stream.
- Get new word from stream. If new word is same as previous word, increment a counter, else reset the counter.

```
import sys
                                 import sys
for line in sys.stdin:
                                 current word = None
  line = line.strip()
                                 current count = 0
  words = line.split()
                                 word = None
  for word in word:
   print ("%s\t1" % word)
                                 for line in sys.stdin:
                                     line = line.strip()
                                     word, count = line.split('\t', 1)
                                     count = int(count)
                                          if current word == word:
                                          current count += count
                                     else:
                                          print ('%s\t%s' % (current_word, current_count))
                                          current count = count
                                          current word = word
```

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Map Reduce Framework (cont.)

To run Job

```
hadoop jar $HADOOP_HOME/share/hadoop/tools/lib/hadoop-streaming-3.2.1.jar
-file /home/omar/work/codes/hadoop/mapper.py
-file /home/omar/work/codes/hadoop/reducer.py
-mapper mapper.py
-reducer reducer.py
-input /4300-folder/*
-output /4300-output
```

• Reducer Threads controlled using -D mapred.reduce.tasks=16

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Spark Overview

- ullet Cluster computing platform designed for speed (mostly in-memory operations rather than file I/O)
- Support for Stream Processors (GPU's)
- API's available in Python, Java, Scala, and SQL

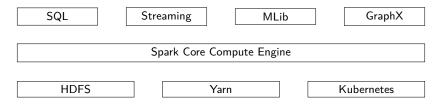


Figure 6: Spark System Architecture

Web based Monitoring Interface on http://localhost:4040

Spark Shells

- bin/pyspark for Python
- bin/spark-shell for Scala
- bin/sparkR for R



• Can also be interfaced with Python Notebooks (e.g. Jupyter or iPython)

Hello World (Word Count)

Resilient Distributed Dataset RDD

- Computations performed on distributed collections that are automatically parallelized across a cluster.
- Immutable Objects (always new RDD returned)
- These Collections are the RDD's (more in coming slides)
- Created using parallelize() or textfile() methods of spark context.

Hello World (Word Count) (cont.)

Standalone Application

- Same API, but have to create Spark Contxt yourself
- Run using bin/spark-submit

```
from pyspark import SparkConf, SparkContext
conf = SparkConf().setMaster("local").setAppName("My App")
     = SparkContext (conf = conf)
sc
# User program from here onward
lines = sc.textFile("/4300-folder/4300-0.txt")
count = lines.count()
def hasBook(line):
   return "Book" in line
bookLines = lines.filter(hasBook)
bookcount = bookLines.count()
```

Core Spark Concepts

Driver Program (e.g., pyspark shell)

- Launches various parallel operations on a cluster
- Contains your applications main function
- Contains your applications distributed datasets
- Accesses Spark through a Spark Context object. This context is automatically created as object sc.
 - <SparkContext master=local[*] appName=PySparkShell>
- RDD's created from Context

Executors

- Present on each Worker Node (computer)
- Managed by Driver



Core Spark Concepts (cont.)

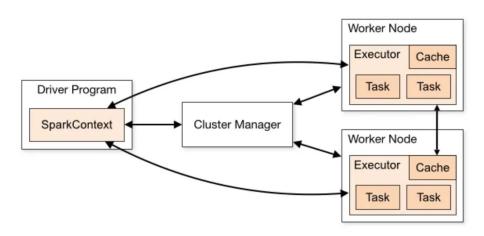


Figure 7: Components for Distributed Execution in Spark IMG: Apache Spark

Resilient Distributed Dataset (RDD)

Creation Approaches in Driver Program

- Loading an External Dataset from File rddObj = sc.textFile("myFilename")
- Collection of List objects rddObj = sc.parallelize(["FAST", "I Like FAST"])
 rddObj = sc.parallelize([1, 2, 3, 4])

Creation of DataFrame from RDD Object

```
dataCol = Seq("key", "value")
dataObj = Seq(("k1", v1), ("k2", v2))

rddObj = sc.parallelize(dataObj)
dfRddObj = rddObj.toDF(dataCol)

dfRddObj.printSchema()
dfRddObj.show()
dfRddObj.select("key").show()
dfRddObj.filter(dfRddObj("value") > 100).show()
```

Operations on RDD

- Actions (operations directly on RDD; Output displayed to Driver program, or to HDFS storage). For example: count(), first(), take(), collect()
- Transformations (new RDD from existing one). For example: Filtering(), Union(), Map(), FlatMap()

```
inputRDD = sc.textFile("log.txt")
inputRDD.count()
                                                           # Action
inputRDD.first()
                                                           # Action
           = inputRDD.filter(lambda x: "Error" in x)
errorRDD
                                                           # Transformation
warningRDD = inputRDD.filter(lambda x: "Warning" in x)
                                                           # Transformation
badLinesRDD = errorRDD.union(warningRDD)
                                                           # Transformation
print("Bad Lines: " + badLinesRDD.count())
                                                           # Action
for line in badLinesRDD.take(10):
                                                           # Action
```

4 D > 4 D > 4 D > 4 D >

```
print(line)
                                                          # or file write
for line in badlinesRDD.collect():
                                                           # Danger Action
     print(line)
inputRDD = sc.parallelize([1, 2, 3, 4])
squareRDD = inputRDD.map(lambda x: x * x).collect()
                                                           # Map Collect
for num in squareRDD:
     print("%d" % num)
inputRDD = sc.parallelize(["Coffee Panda", "Happy Panda"])
outputRDD = inputRDD.map(lambda line: line.split(" "))
outputRDD.take(2)
# Displays: [['Coffee', 'Panda'], ['Happy', 'Panda']
outputRDD = inputRDD.flatMap(lambda line: line.split(" "))
outputRDD.take(4)
# Displays: ['Coffee', 'Panda', 'Happy', 'Panda']
```

Lazy Loading Principle

- Compute/Retrive RDD only when required (determined through internal metadata)
- For transformation RDD's, maintain Lineage Graph
- Recompute again and again, any time you need it, with certain degree of caching (makes sense for large datasets). To override:

```
lines.persist() # Hold data in memory
lines.count()
lines.first()
```

Other Transformation Operations

- RDD1.distinct() returns unique members
- RDD1.union(RDD2) returns Union
- RDD1.intersection(RDD2) returns Intersection
- RDD1.subtract(RDD2) returns RDD1 RDD2
- RDD1.cartesian(RDD2) returns RDD1 × RDD2

Saving RDD's (to HDFS)

• lines.saveAsTextFile("Directory")



Spark with Key Value Pairs

```
from pyspark import SparkContext, SparkConf

conf = SparkConf().setMaster("local").setAppName("My App")
sc = SparkContext(conf=conf)

words = sc.textFile("/documenttxt").flatMap(lambda line: line.split(" "))
wc = words.map(lambda word: (word, 1)).reduceByKey(lambda a,b : a +b)
wc.saveAsTextFile("/sparktest")
```