

Dr. Abbas Maaroof aimaaroof@gmail.com 29-03-2021

WORKSHOP OUTLINE

- 1. Big Data Analytics-Day #1
- 2. Machine Learning Tools: R Programming language and Graphical Interfaces Day#1
- 3. Data Mining Analytical Tools-Day#2
- 4. Data Visualization-Day#2
- 5. Digital Data Collection-Day#3
- 6. Drone Technology and Multispectral Sensor, Geospatial and Remote sensing Technology-Day#3

PART#1: BIG DATA ANALYTICS

Part#1: Presentation Outline

- ➤ Understanding Big Data: What is Big Data
- > How big is the big data
- ➤ Big Data Types and Sources
- > Application for Big Data Analytics
- ➤ Top Big Data Analytics Tools

Big Data Interesting Facts

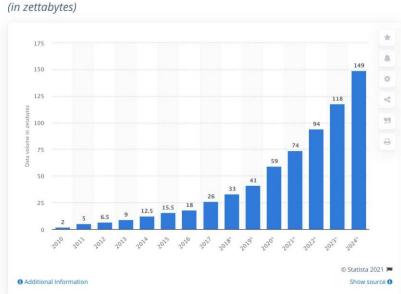
"From the dawn of civilization until 2003, humankind generated five Exabyte (10¹⁸ bytes) of data. Now we produce five Exabytes every two days....and the pace is accelerating"

Eric Schmidt Executive Chairman, Google

90% of the world's data was created in the last few years alone! With new devices, sensors, and technologies emerging, the data growth rate will likely accelerate even more...

Big Data Interesting Facts

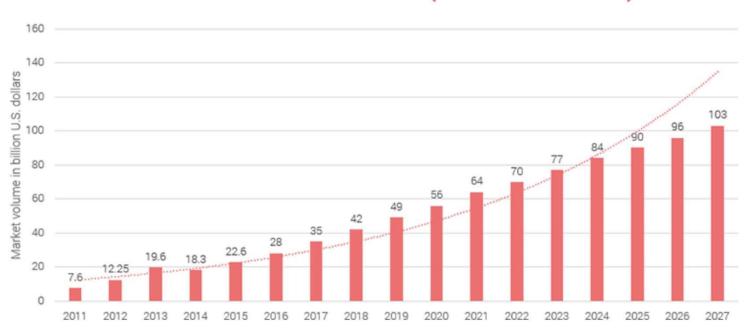
- Every minute we send 204 million emails, generate 1,8 million
 Facebook likes, send 278 thousand Tweets, and up-load 200 thousand photos to Facebook, etc.
- Google alone processes on average over 40 thousand search queries per second, making it over 3.5 billion in a single day
- Around 100 hours of video are uploaded to YouTube every minute and it would take you around 15 years to watch every video uploaded by users in one day
- Facebook processes 10 TB of data every day / Twitter 7 TB
- The total amount of data created, captured, copied, and consumed in the world is forecast to increase rapidly, reaching 149 zettabytes in 2024. The rapid development of digitalization contributes to the ever-growing global data sphere.



Big Data Interesting Facts

- Bad data or poor data quality costs US businesses \$600 billion annually
- Today's data centres occupy an area of land equal in size to almost 6,000 football fields.

Forecast of Big Data market size based on revenue (2015-2027)



Source: Statista

Understanding Big Data: What is Big Data?

Big data is a buzzword; used to describe a massive volume of both structured and unstructured data that is so large it is difficult to process using traditional database and software techniques.

Relevance of big data occurs when large amounts of relevant data is analyzed, turned into information and then into knowledge.



It requires specific skill sets and attention towards processes and context.

Understanding Big Data: What is Big Data?

MapReduce: Simplified Data Processing on Large Clusters

Jeffrey Dean and Sanjay Ghemawat

jeff@google.com, sanjay@google.com

Google, Inc.

Abstract

MapReduce is a programming model and an associated implementation for processing and generating large data sets. Users specify a map function that processes a key/value pair to generate a set of intermediate key/value pairs, and a reduce function that merges all intermediate values associated with the same intermediate key. Many real world tasks are expressible in this model, as shown in the paper.

Programs written in this functional style are automatically parallelized and executed on a large cluster of commodity machines. The run-time system takes care of the details of partitioning the input data, scheduling the program's execution across a set of machines, handling machine failures, and managing the required inter-machine communication. This allows programmers without any experience with parallel and distributed systems to easily utilize the resources of a large distributed system.

Our implementation of MapReduce runs on a large cluster of commodity machines and is highly scalable: a typical MapReduce computation processes many terabytes of data on thousands of machines. Programmers find the system easy to use: hundreds of MapReduce programs have been implemented and upwards of one thousand MapReduce jobs are executed on Google's clusters every day.

given day, etc. Most such computations are conceptually straightforward. However, the input data is usually

large and hundreds a reasona allelize th failures co tation wit these issu

tions we v and load spired by and many eration to

As a re abstractio tails of pa most of o compute : applying the same propriatel source organization, began using MapReduce specified

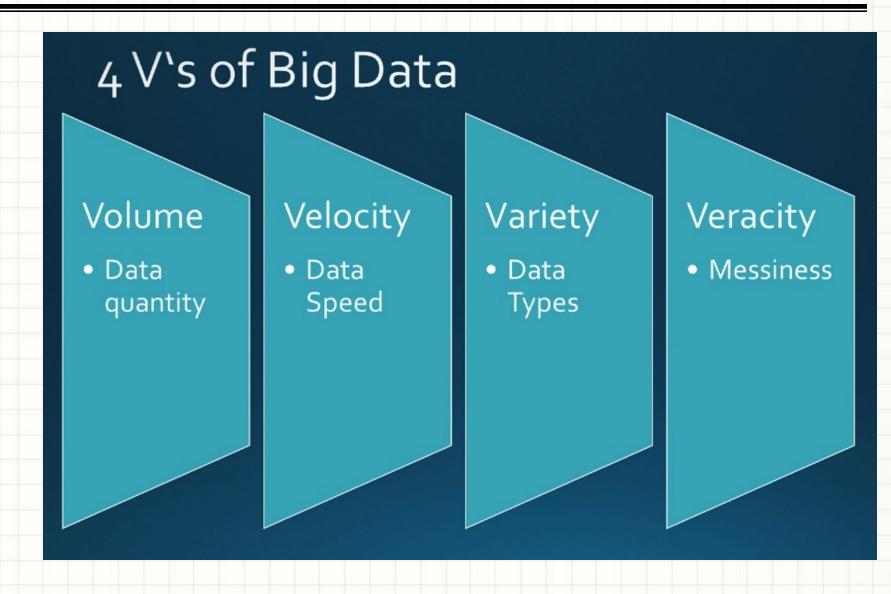
programming model in 2004 by Jeffery Dean and Sanjay Ghemawat of Google (Dean & Ghemawat, 2004). In their paper, "MAPREDUCE: SIMPLIFIED DATA PROCESSING ON LARGE CLUSTERS," they discussed Google's approach to collecting and analyzing website data for search optimizations. Google's proprietary MapReduce system ran on the Google File System (GFS). Apache, the open

MapReduce was first popularized as a

as the primary mechanism for fault tolerance.

The major contributions of this work are a simple and powerful interface that enables automatic parallelization and distribution of large-scale computations, combined

Big Data is characterized by the four "V's



Big Data is characterized by the four 'V's **IDC** Estimate **40 ZETABYTES** 2.5 QUINTILLION Of Data by 2020 200 BILLIONS PHOTOS BYTES of Data are Created each Day **50 EXABYTES** 2.4 EXABYTES per year ebook has PETTA Collider generates BYTES PETA BYTES Of Storage Hadoop compression data a are create per year VOLUME VARIETY Scale of Data Different Forms of Data You Estimated TERA BYTES a per US Company 100 MILLION VIDEO 500 MILLION 600 Years of Video **TWEETS** 13 Hours of video uploaded Have a cell Phone per minute Per day **BIG DATA** Poor Data Quality cost businesses 1.8 BILLION **600 BILLION A YEAR** SMARTPHONES 1 IN 3 LEADERS Don't just the information the to make decision MAP 30% OF DATA COLLECTE VELOCITY VERACITY By marketers are not usable for real-time decision making Analysis of Uncertainty of Data Data **20 BILLION NETWORK** CONNECTIONS REDUCE By 2016 Poor data across business and the government costs the US economy Stock Exchange generates 3.1 TRILLION DOLLARS **1 TERRA BYTES**

RESULT

Of Trade Data per day

a year

Typical Hadoop Cluster



Who uses MapReduce and for What ☐ At Google:

- 1. Index construction for Google Search
- 2. Article clustering for Google News
- 3. Statistical machine translation
- ☐ At Yahoo!:
- 1."Web map" powering Yahoo! Search
- 2. Spam detection for Yahoo! Mail
- At Facebook:
- 1. Data mining
- 2. Ad optimization
- 3. Spam detection
- At New York Times
- 1. Moving typeset into PDF

If you don't own a warehouses like this, go to the Cloud!

How Big is Big Data

Byte (1): One grain of rice Kilobyte (10³): cup of rice





Hobbyist

Megabyte (10⁶): 8 bags of rice

Gigabyte (109): 3 Semi trucks of rice



Desktop

Terabyte (10¹²): 2 Container Ships of rice

Petabyte (10¹⁵): Blankets Manhattan of rice



Exabyte (10¹⁸): Blankets west coast states of rice Zettabyte (10²¹): Fills the Pacific Ocean with of rice







Big Data

Yottabyte (10²⁴): A Earth Size Rice Ball

The Future?

Challenges Facing Big Data

- Data access and connectivity can be an obstacle
- The Big Data Talent Gap
- Getting Data into the Big Data Platform
- Synchronization across the Data Sources
- Getting Useful Information out of the Big Data Platform
- The technology landscape in the data world is evolving extremely fast

1. Structured Data

(i) Computer- or Machine-Generated Structured Data:

Sensor data, Web log data, Point-of-sale data, Financial data (ii) Human-Generated Data: Input data, Click-stream data, and Gaming-related data

fx			
	Α	В	С
1	first_name	last_name	order_id
2	Caroline	Forsey	124527
3			

2. Semi-Structured Data

Semi-structured data are increasingly occurring since the advent of the Internet

Semi Structured Data Examples

- 1. Email
- CSV, Extensible Markup Language (XML) and JSON (JavaScript Object Notation) documents
- 3. NoSQL databases
- 4. HTML
- 5. Electronic data interchange (EDI)
- 6. Resource Description Framework (RDF) s a framework for describing resources on the web

```
first_name : "Caroline",
last_name : "Forsey",
order_id : "124527",

Notation)
Stample of JSON
(JavaScript Object
Notation)
```

3. Unstructured DATA

Unstructured information is typically **text-heavy**, but may contain data such as dates, numbers, and facts as well:

(i) Machine-Generated Unstructured Data Examples:

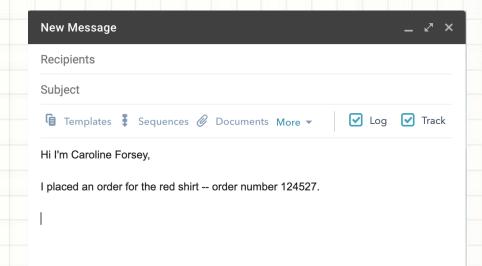
Satellite images, Scientific data, Photographs and video and Radar or sonar data:

(ii) Human-generated Unstructured Data Examples

Mobile and Voice data, Social media data, Image and Video Data,

Machine Data

An example of unstructured data includes email responses, like this one:



Top Big Data Applications

- Big Data in Retail
- Big Data in Healthcare
- Big Data in Education
- Big Data in E-commerce
- Big Data in Media and Entertainment
- Big Data in Finance
- Big Data in Travel Industry
- Big Data in Telecom
- Big Data in Automobile

Big Data Analytics Methods

- (1) <u>Data Visualization</u>: Big data visualization
- (2) <u>Data Mining: Social media</u>(Facebook, Twitter, Instagram, etc.), <u>text</u>, <u>email</u>, and <u>Internet</u> (Google)...etc. (It can be done at a fraction of the cost and in real time).
- (3) <u>Predictive analytics</u>: Machine learning, predictive and statistical modeling
- (4) <u>Crowdsourcing:</u> Data from various sources
 - text messages
 - social media
 - blogs, etc.
- (5) <u>Internet of things:</u> Real-time data collection to computing systems by sensors and actuators
- (6) <u>Mobile analytics</u>: massive amounts of data that mobile companies gather about their users in terms of:
 - calling volume and pattern
 - location
 - privacy & ethical use challenges

Applications of Big Data are Endless! It is just the beginning of a transformation into a big data economy.

Big Data Analytics Benefits

- Big data allows for better prediction of economic phenomena and improves causal inference
- Identify economic trends as they occur ("nowcasting") to testing agents' behaviour theories or creating a set of tools to manipulate and analyse these data
- Clustering and demand modelling
- Regularization to assist with variable selection in highdimensional <u>trade policy models</u>
- Predictive analytics of the development of specific complex processes, e.g. <u>climate</u>, <u>geological</u>, <u>natural</u>, <u>social</u>, <u>demographic</u>, <u>macroeconomic</u>, <u>etc</u>

Top Big Data Analytics Tools

Top Big Data Analytics Tools

- 1. **Apache Hadoop** and Map Reduce Apache Hadoop is an open source software framework employed for handling of big data. It processes datasets of big data by means of the MapReduce programming model.
- 2. Cloudera- Distribution for Hadoop (CDH)
- 3. **Spark** Apache Spark is an open source framework for data analytics
- 4. **Apache Cassandra** is free of cost and open-source distributed

Top Cloud Computing; such as Amazon Web Services (AWS), Google Al Platform, and Microsoft Azure

Big Data Analytics Case Studies

Case Study#1:

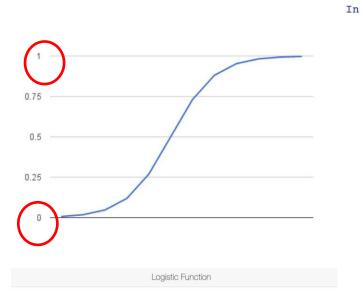
Predict hotel bookings via user Behaviour Machine learning, predictive and statistical modeling

Situation: A search session describes a user's journey to find his ideal hotel, by including all his interactions. Given user search sessions, we are interested in predicting the outcome of these sessions based on the users' interactions; as well determining which of these interactions have the highest importance for this estimation.

The task is to train a machine learning model to estimate if a booking occurred – the training and target sets have been provided for you.

Making Predictions with Logistic Regression:

To make predictions, we <u>must</u> train a final model. We can train models using train/test splits or k-fold cross validation of our data



Number of raw booking data= 20,170,405 can not be used by Excel

```
In [38]: # example of training a final classification model
         from sklearn.linear model import LogisticRegression
         from sklearn.datasets.samples generator import make blobs
         # generate 2d classification dataset
         X, y = make blobs(n samples=10, centers=2, n features=2, random state=1)
         # fit final model
         model = LogisticRegression()
         model.fit(X, y)
         # new instances where we do not know the answer
         Xnew, = make blobs(n samples=10, centers=2, n features=2, random state=1)
         # make a prediction
         ynew = model.predict(Xnew)
         # show the inputs and predicted outputs
         for i in range(len(Xnew)):
             print("X=%s, Predicted=%s" % (Xnew[i], ynew[i]))
         import pickle
         filename = 'finalized model.sav'
         pickle.dump(model, open(filename
         X=[-10.17014071 -4.83120697], Predicted=1
         X=[-11.09833168 -2.80862484], Predicted=1
         X=[-9.95549876 -3.37053333 , Predicted=1
         X=[-8.86394306 -5.05323981], Predicted=1
         X=[0.08525186 3.64528297], Predicted=0
         X=[-0.79415228 2.10495117], Predicted=0
         X=[-1.34052081 4.15711949], Predicted=0
         X=[-10.32012971 -4.337402], Predicted=1
         X=[-0.19745197 2.34634916] Predicted=0
```

Case Study#2:

Use Hadoop to Derive Descriptive Statistics about patent data, and look for interesting, non-obvious, patterns

Using Hadoop to Derive Descriptive Statistics about patent data, and look for interesting, non-obvious, patterns

Source of Data, National Bureau of Economic Research

- http://www.nber.org/data/
- http://data.nber.org/patents/
- Download acite75_99.zip (82MB) and apat63_99.zip (56Mb)

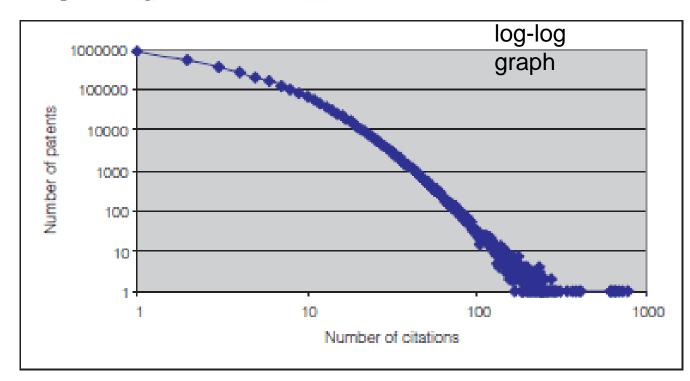
Description	Documentation	Data Pkzipped	
Description	Documentation	SAS .tpt	ASCII CSV
Overview	overview.bd		-
Pairwise citations data	Cite75_99.bd	Cite75_99.zip (68 Mb)	acite75_99.zip (82 Mb)
Patent data, including constructed variables	pat63_99.bd	pat63_99.zip (90Mb)	apat63_99.zip (56Mh)
Assignee names	coname.txt	coname.zip (2Mb)	aconame.zip (2Mb
Contains the match to CUSIP numbers	match.txt	match.zip (130Kb)	amatch.zip (98Kb)
Individual inventor records	inventor.bd	inventor.zip (98Mb)	ainventor.zip (82Mb)
Class codes with corresponding class names	classes.bd	200	
Country codes with corresponding country names	countries.txt		
Class, technological category, and technological	clace match by		

Source: USPTO, and Jaffe and Traitenberg computations. The Pat63 99 file includes all utility patents in the USPTO's TAF database granted during the period 1963 to December 1999. Classification information reflects the U.S. Patent Classification System as of December 31, 1999. No. of observations: 2,923,922

Patent Citation Data, cite75_99.txt File

- Source: US Patent office
- This file includes all US patent citations for utility patents granted in the period 1-Jan-75 to 31-Dec-99.
- No. of observations: 16,522,438
- Variable Name variable type Characters Contents
- CITING numeric 7 Citing Patent Number
- CITED numeric 7 Cited Patent Number
- The file is sorted by Citing Patent Number.

"CITING", "CITED"
6009552,5278871
6009552,5598422
6009553,4131849
6009553,4517669
6009553,4519068
6009553,4590473
6009553,4636791
6009553,5671255

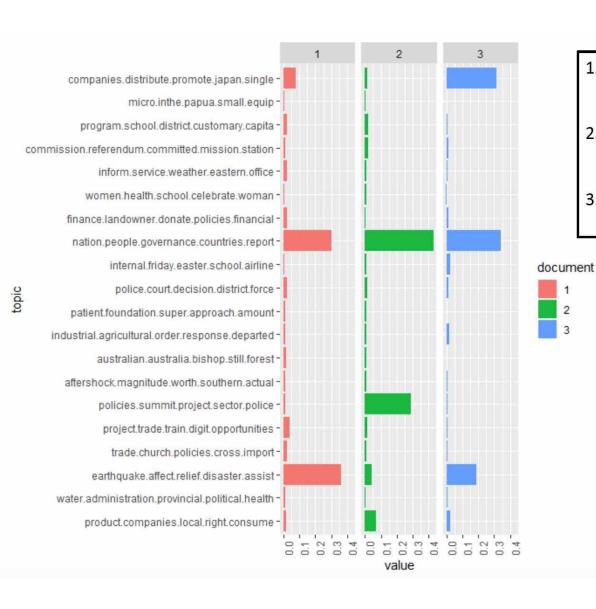


Case Study#3:

Data (Text) Mining of Papua New Guinea NBC National News Videos: Voice recognition algorithms technology

- ➤ Traditional statistics, household surveys and census data have been effective in tracking medium to long-term development trends, but are less effective in generating a real-time snapshot for policymakers, while Data Mining method can be done at a fraction of the cost and in real time.
- There is an ocean of data (Big Data)— generated by citizens in both developed and developing countries—that did not exist even a few years ago. Videos, Audios, Mobile phones, social media and Internet searches all leave digital traces that, when anonymized, aggregated and analyzed, can reveal significant insights that help governments make faster and more informed decisions.

Figure (1): Frequent words- Low frequency 100 times. watertoday -Inspect most frequently used words- Above 100 supportsupplied service reportreliefprovince papua provide prime highland police people assist papua character office affect nation water support provide million minister disaster million earthquake highland guinea today governance effortdevelop effort do ntinually earthquake continually disaster developcountries continually characterassistaffect-100 200 300 400 0 Abt Associates | pg 13 Count



- 1. The figure shows how topics within a document are distributed according to the model.
- 2. In the current model all three documents show at least a small percentage of each topic.
- However, two to three topics dominate each document.

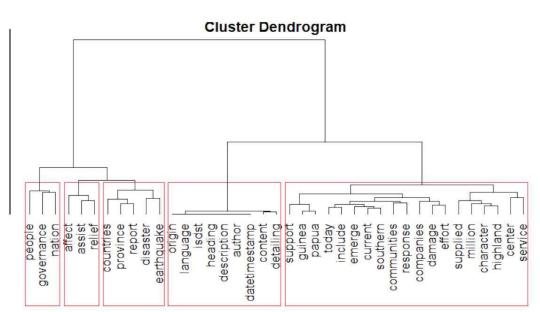
Let us first take a look at the contents of *three* sample documents:

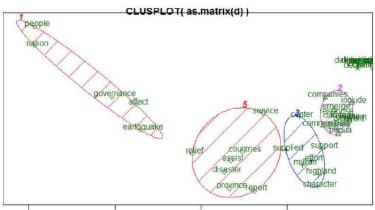
[1,10,20]

Topic distribution

Clustering by Term Similarity



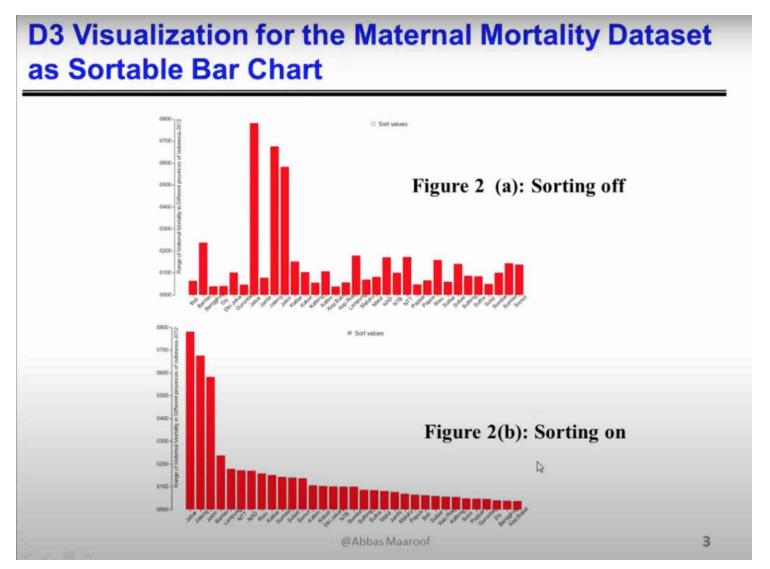




Case Study#4: Big Data Analytics in Public Health Maternal Mortality the case of Indonesia-D3.js code

Example of my previous research work in Asia:

Big Data Analytics in Public Health -Maternal Mortality the case of Indonesia-D3.js code https://www.youtube.com/watch?v=coanS5RgKxs&feature=em-upload_owner





D3 Visualization for the Maternal Mortality Dataset as a D3 Pie

Maternal Mortality in Indonesia

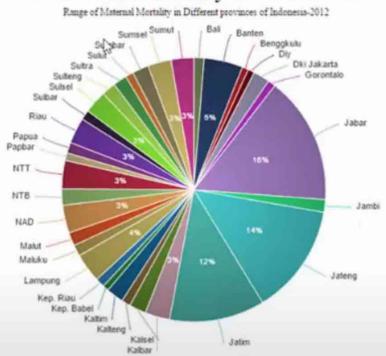


Figure 3(a): Full pie chart dynamic portion when is off

Maternal Mortality in Indonesia



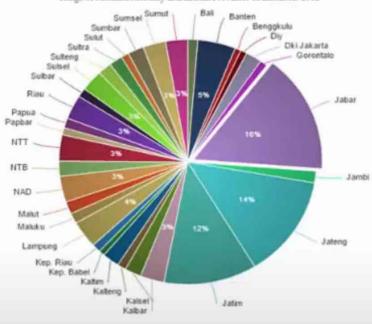


Figure 3(b): Full pie chart dynamic portion when is on

D3 Visualization of General Reasons for High Maternal Mortality in Indonesia as a D3 Donut Pie

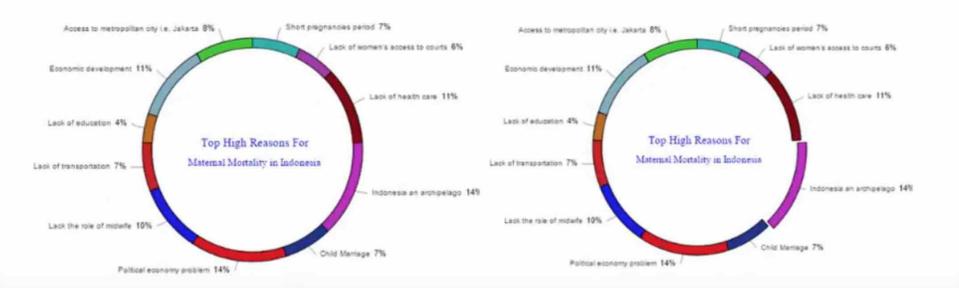


Figure 4(a): D3 donut chart dynamic portion when is off

Figure 4(b): D3 donut chart dynamic portion when is on

PART#2. MACHINE LEARNING TOOLS: R-PROGRAMMING LANGUAGE AND GRAPHICAL INTERFACES

Programming Tools and Types

Text Interfaces

These are generally programming languages that use written commands:

- One of the most fundamental tools in data mining is the statistical programming language R-Free-Open Source
- 2. Programming language Python 3-Free- Open Source

Graphical Interfaces

These include specialized applications that use menus, widgets, virtual connections, and it's really easy to see the process:

- 1. RapidMiner There is a free version and there is a paid version You can download the free version
- 2. KNIME- You can download it for free
- 3. **Orange**-You can download it for free
- 4. **BigML** on Server free for small task but they charge with big data analytics-Nice way to work with.

PART#2: MACHINE LEARNING TOOLS: R
PROGRAMMING LANGUAGE

Why Learn R programming language?

R Processing more than just statistics

R was developed by <u>statisticians</u> to make statistical processing easier. This heritage continues, making R a very powerful tool for performing virtually any statistical computation.

The result is that R is now eminently suitable for a wide variety of nonstatistical tasks, including Data processing, Graphic visualization, and analysis of all sorts

R is being used in

- The fields of finance,
- Natural language processing, Genetics,
- Biology,
- Market research, to name just a few

Which means that you can use R alone to program anything you want

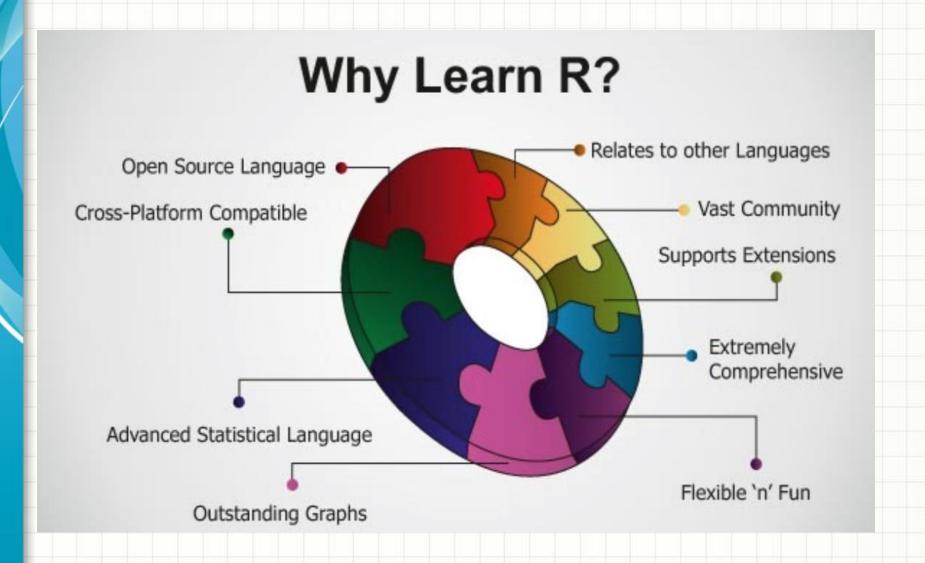
Running code without a compiler

R is an interpreted language, which means that — contrary to compiled languages like C and Java — you don't need a compiler to first create a program from your code before you can use it

Why Learn R programming language?

- 1. R-the programming language favoured by many statisticians because facilitate matrix arithmetic carrying out complex, often automated calculations on data which is held in a grid of rows and columns.
- 2. The style of coding is quite easy.
- 3. It's open source. No need to pay any subscription charges.
- 4. Availability of instant access to over 7800 packages customized for various computation tasks.
- 5. The community support is overwhelming. There are numerous forums to help you out.
- 6. Online, R code is everywhere although you won't see it, as it's always hidden behind pretty graphical interfaces. But when you use **Google, Facebook or Twitter** you are almost certainly executing R code running on the servers of those organizations.
- 7. It is also capable of executing code written in other languages such as C++ or Java, so resources coded in those languages can be made available. Because it can be compiled to run on any major operating system, R code can easily be ported between Unix, Windows or Mac environments.
- 8. With a reported more than **two million** users worldwide, and thousands of deployed applications created using it, **R** is undoubtedly one of the backbone technologies of the Big Data revolution.

Why Learn R programming language?



Things R does and What R does not do

R does	R does not
Data handling and storage: numeric, textual	Is not a database, but connects to DBMSs
Matrix algebraHas tables and regular	has no graphical user interfaces, however it connects to Java, TclTk
• Expressions	and it has R Studio
 high-level data analytic and statistical functions classes ("Object Oriented") Graphics 	language interpreters are not fast. However, R could be extended by compiled C/C++ code
 programming 	No spreadsheet view of data,
language: loops,	but connects to MS Excel.
branching, Subroutines	No professional / commercial Support

Comparing R with the classic Statistical Tools

Features	Stata	SPSS	SAS	R
Data extensions	*.dta	*.sav, *.por (portable file)	*.sas7bcat, *.sas#bcat, *.xpt (xport files)	*.Rdata
User interface	Programming/point-and-click	Mostly point-and-click	Programming	Programming
Data manipulation	Very strong	Moderate	Very strong	Very strong
Data analysis	Powerful	Powerful	Powerful/versatile	Powerful/versatile
Graphics	Very good	Very good	Good	Excellent
Cost	Affordable (perpetual licenses, renew only when upgrade)	Expensive (but not need to renew until upgrade, long term licenses)	Expensive (yearly renewal)	Open source
Program extensions	*.do (do-files)	*.sps (syntax files)	*.sas	*.txt (log files)
Output extension	*.log (text file, any word processor can read it), *.smcl (formated log, only Stata can read it).	*.spo (only SPSS can read it)	(various formats)	*.R, *.txt(log files, any word processor can read)

Useful R Packages

Out of ~7800 packages listed on CRAN, I've listed some of the most powerful and commonly used packages in predictive modeling in this article. Since, I've already explained the method of installing packages, you can go ahead and install them now. Sooner or later you'll need them.

Importing Data: R offers wide range of packages for importing data available in any format such as .txt, .csv, .json, .sql etc. To import large files of data quickly, it is advisable to install and use data.table, readr, RMySQL, sqldf, jsonlite.

Data Visualization: R has in built plotting commands as well. They are good to create simple graphs. But, becomes complex when it comes to creating advanced graphics. Hence, you should install ggplot2.

Data Manipulation: R has a fantastic collection of packages for data manipulation. These packages allows you to do basic & advanced computations quickly. These packages are *dplyr*, *plyr*, *tidyr*, *lubridate*, *stringr*. Check out this <u>complete tutorial</u> on data manipulation packages in R.

Modeling / Machine Learning: For modeling, *caret* package in R is powerful enough to cater to every need for creating machine learning model. However, you can install packages algorithms wise such as *randomForest*, *rpart*, *gbm* etc

Note: I've only mentioned the commonly used packages. You might check this interesting <u>Link</u> on complete list of useful R packages. And functionality https://rstudio.com/wp-content/uploads/2019/01/Cheatsheets 2019.pdf

R Programming Functionality: Insight/Analysis

1. Data Analysis

Exploratory data analysis is a term minted in data analysis using R. This is an approach for data analysis which includes a variety of techniques such as:

- 1. Extraction of important variables
- 2. Test underlying assumptions
- 3. Maximising insights into the dataset, etc.

2. Data wrangling

Data wrangling is the process of cleaning messy and complex data sets to enable convenient consumption and further analysis. The following packages can be used to do three main parts, import, tidy and transform:

- 1. **dplyr Package** –dplyr is best known for its data exploration and transformation capabilities and highly adaptive chaining syntax.
- **2.** data.table Package It allows for faster manipulation of data set with minimum coding. It simplifies data aggregation and drastically reduces the compute time.
- 3. readr Package 'readr' helps in reading various forms of data into R. By not converting characters into factors it performs the task at 10x faster speed

3. Machine learning

At some point in data science, a programmer may need to train the algorithm and bring in automation and learning capabilities to make predictions possible. R provides ample tools to developers to train and evaluate an algorithm and predict future events. Thus, R makes machine learning (a branch of data science) lot more easy and approachable. The list of R packages for machine learning is really extensive. R machine learning packages include MICE (to take care of missing values), rpart & PARTY (for creating data partitions), CARET (for classification and regression training), randomFOREST (for creating decision trees) and much more.

4. Data visualization

Data visualization is the visual representation of data in graphical form. This allows analyzing data from angles which are not clear in unorganized or tabulated data. R has many tools that can help in data visualization, analysis, and representation. The R packages ggplot2 and ggedit for have become the standard plotting packages. While the ggplot2 package is focused on visualizing data, ggedit helps users bridge the gap between making a plot and getting all of those pesky plot aesthetics precisely correct

5. Specificity

R is a language designed especially for statistical analysis and data reconfiguration. All the R libraries focus on making one thing certain — to make data analysis easier, more approachable and detailed. Any new statistical method is first enabled through R libraries. This makes R a perfect choice for data analysis and projection. Members of the R community are very active and supporting and they have a great knowledge of statistics as well as programming. This all gives R a special edge, making it a perfect choice for data science projects.

6. Big Data Analytics

- 1.RHIPE stands for R and Hadoop Integrated Programming Environment. It is a software package which allows the R user to create MapReduce jobs that work entirely within the R environment using R expressions. The package uses the Divide and Recombine technique to perform data analytics over Big Data. This integration with R is a transformative change to MapReduce as it allows an analyst to quickly specify Maps and Reduces using the full power, flexibility, and expressiveness of the R interpreted language. Hadoop is the go-to big data technology for storing large quantities of data at economical costs, and R programming language is the go-to data science tool for statistical data analysis and visualization. R and Hadoop combined prove to be an excellent data crunching tool for some seriously big data analytics for business.
- 2. ORCH stands for Oracle R Connector for Hadoop is a collection of R packages which provides predictive analytic techniques, written in R or Java as Hadoop MapReduce jobs, that can be applied to data in HDFS files. It also provides interfaces to work with Hive tables, the Apache Hadoop compute infrastructure, the local R environment, and Oracle database tables. There are several analytic algorithms in ORCH such as linear regression, neural networks for prediction, clustering, matrix completion using low-rank matrix factorization, and non-negative matrix factorization.

Statistical Models in R - Some Examples



HOME

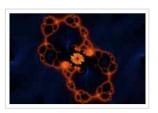
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SITE MAP

Elementary Statistics with R



Ever wonder how to finish your statistics homework real fast? Or you just want a quick way to verify your tedious calculations in your statistics class assignment. We provide an answer here by solving statistics exercises with R.

Here, you will find statistics problems similar to those found in popular college textbooks. The R solutions are short, self-contained and requires minimal R skill. Most of

them are just a few lines in length. With simple modifications, the code samples can be turned into homework answers. In additional to helping with your homework, the tutorials will give you a taste of working with statistics software in general, and it will prove invaluable in the success of your career.

We have included separate introductory tutorials for basic R concepts. The topics are by no means comprehensive. Nevertheless, even if you are not familiar with R, you can go through just the first *R Introduction* page. Then go straight to the statistics tutorials, and only come back for reference as needed.

Please find the topics you are interested in via the Site Map. If you still cannot find what you are looking for, please contact us and let us know.

- Qualitative Data
- Quantitative Data
- Numerical Measures
- Probability Distributions
- Interval Estimation
- Hypothesis Testing
- Type II Error
- Inference About Two Populations
- Goodness of Fit
- Analysis of Variance
- Non-parametric Methods
- Simple Linear Regression
- Multiple Linear Regression
- Logistic Regression

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R Tutorials

- R Introduction
- ☐ Elementary Statistics with R
 - Qualitative Data
 - Quantitative Data
 - Numerical Measures
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 - Hypothesis Testing

 - Inference About Two
 - Populations
 - Goodness of Fit

Qualitative Data >

- Analysis of Variance
- Non-parametric Methods
- Simple Linear Regression

http://www.rtutor.com/element ary-statistics

Case Study#1

Study the contribution of Fiscal Decentralization on the Local Economic Growth in PNG:

Aim.

Examine the relationship between fiscal decentralization policy, which has been implemented in all Provinces, and local economic performance. Is Fiscal decentralization contributes to economic growth?

Empirical model

$$GRDP_i = \alpha_0 + \alpha_1 FD_i + X_i \beta + \varepsilon_i, i = 1,....34,$$

Where *i* refers to Province or state

GRDP represents growth rate, which is represented by Per capita Gross Domestic Product

FDi represents indicators of fiscal decentralization in PNG

Xi is control variables for economic growth.

The parameters $\alpha 0$ and $\alpha 1$ are scalars, **b** represents a parameter vector to be estimated and

Ei is an error term, which is assumed to be normally distributed, homoscedastic, and independent across observations.

Moreover, this work will consider, population, employment and human capital as controlling variables. For human capital, it is used average years of schooling as a proxy. Therefore, the growth regression can be modified as:

$$GRDP_{(i,t)} = \beta_{0} + \beta_{1}FD_{(i,t)} + \beta_{2}(1 - .GDRP_{(i,t)}) + \beta_{3}GINI + \beta_{4}Pop_{(i,t)} + \beta_{5}Emplo_{(i,t)} + \beta_{6}Educ_{(i,t)} + \beta_{6}Location_{(i,t)} + \epsilon_{i},$$

Where:

- GRDP Per capita Gross Domestic Product
- ➤ FD Fiscal Decentralization indicator which involves three Fiscal Decentralization indicators (FD 1, FD 2, FD3) or more
- > Initial GRDP Initial level of per capita GRDP each region during period t-1
- > GINI Gini coefficient
- ➤ Pop The number of population

Case Study#2

Plotting the binomial distribution for p = 0.3, p = 0.5 and p = 0.8 and the total number of trials n = 60 as a function of k the number of successful trials. For each value of p, determine 1st Quartile, median, mean, and standard deviation.

We begin by calculating the value of k

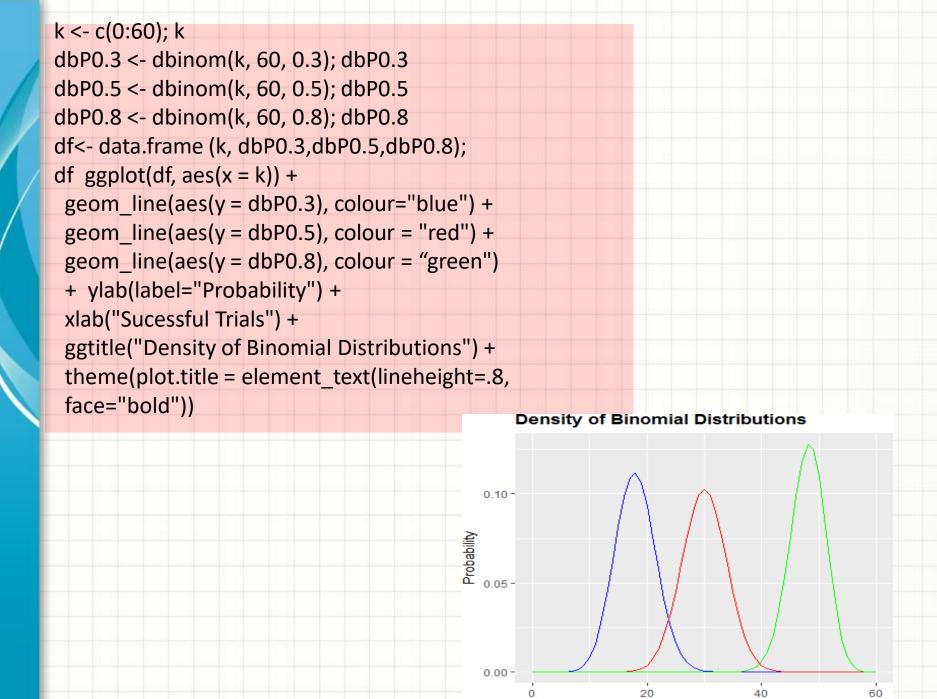
```
> k < -c(0:60); k
```

[1] 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60

Then, we calculate the distribution for each values of p by using

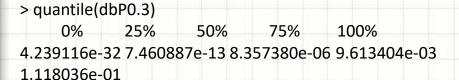
```
dbP0.3 <- dbinom(k, 60, 0.3); dbP0.3
dbP0.5 <- dbinom(k, 60, 0.5); dbP0.5
dbP0.8 <- dbinom(k, 60, 0.8); dbP0.8
```

After calculating the value of binomial distributions for each p, we can create the plots.



Sucessful Trials

For each value of p, determine 1st Quartile, median, mean, standard deviation and the 3rd Quartile.



The 1st Quartile is 7.460887e-13

> quantile(dbP0.5)

0% 25% 50% 75% 100%

8.673617e-19 3.349811e-10 4.613852e-05 1.227688e-02

1.025782e-01

The 1st Quartile is 3.349811e-10

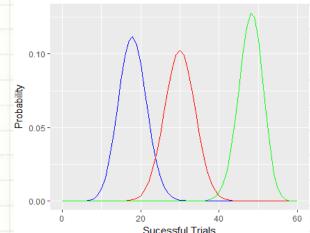
> quantile(dbP0.8)

0% 25% 50% 75% 100%

1.152922e-42 6.585109e-20 1.572006e-07 5.842579e-03

1.278228e-01 Density of Binomial Distributions

The 1st Quartile is 6.585109e-20



median

>median(dbP0.3)

>[1] 8.35738e-06

>median(dbP0.5)

>[1] 4.613852e-05

>median(dbP0.8)

>[1] 1.572006e-07

mean

>mean(dbP0.3)

> [1] 0.01639344

>mean(dbP0.5)

> [1] 0.01639344

> mean(dbP0.8) [1] 0.01639344

standard deviation

>sd(dbP0.3) [1] 0.03239755 >sd(dbP0.5) [1] 0.03062992 >sd(dbP0.8) [1] 0.03527981

Case Study#3

Using R Programming for Sustainable Development Goals Examples

Data Methodology Mapping Results of All SDGs Indicators Relevant for Iraq

IAEG- Category	National Methodology	Data	Number	Percentage
Tier (1)-Ready- Feasible with more effort	Methodology exists	1.Data only available at national level, not at subnational level (e.g. district, city or village level) 2. Indicators require data that need to be improved, adjusted or modified based on existing national data.	94	38%
Tier (2)-Not Ready-Feasible with strong effort	Methodology does not exist	Data is not available The indicators require data collected using a new methodology or approach	153	62%
			247	100%

Goal 9: Industry, Innovation and Infrastructure	Indicator 9.5.1. Research and development expenditure as a proportion of GDP	
Global Methodology	Research and development expenditure as a proportion of GDP (R&D _{Intensity}) is calculated as:	
	$R\&D_{intensity} = \frac{The\ total\ intramural\ expenditure\ on\ R\&D\ (GERD)}{GDP} \times 100$	
Global Indicator Variables	Computation of the indicator Research and development (R&D) expenditure as a proportion of Gross Domestic Product (GDP) is self-explanatory, using readily available G data as denominator.	
Global Methodology Data Disaggregation	R&D expenditure can be disaggregated by sector of performance, source of funds, field of R&D, type of research and type of cost. The Frascati Manual provides more details related to these breakdowns (what these breakdowns/classifications are, the purposes, including user needs, the main criteria that are applied, etc).	
lationally Adapted Methodology	NIL	
Nationally Adapted Variables	NIL	
evel and frequency of collection	NIL	
/alues per year	NIL	
Alissing Variables (Data gaps) against Global Methodology	Total intramural expenditure on R&D GDP	
ear data was last collected, frequency of collection	NIL	
Proposed Data Source	Central Statistical Organization (CSO) Ministry of Higher Education and Scientific Research	
otential specialized agencies	UNESCO-UIS	
Partner agencies	NIL	
Proposed Data Collection methods and Advanced Analytical Tools	 Advanced Mobile Based Data Collection tools support capturing data as text, numbers, dates, GPS, photos, video and audio such as Open Data Kit and Kobo Toolbox. They allow for offline data collection with mobile devices in remote areas with advanced data curatio and visualization on the device. R and Python are programming languages and free modern software environment for data Science, statistical computing and data visualization. The R and python languages have become very popular among statisticians and data miners (Big Data analytics) and is widely used for advanced data analysis in statistical methodology, survey creation, data 	
	cleaning and data analysis. 3. Data Visualization tools to visualize large amounts of complex structure and unstructured data and to identify areas that need attention or improvement such as Tableau, Highcharts, Power BI, etc.	
	4. Graphical User Interface softwares; these include specialized applications that use menus, widgets, virtual connections, no programming skills required Applying a hybrid of powerful analytical capabilities Text analysis, combined with predictive modelling and data visualization such as RapidMiner, KNIME, and Orange 5. Big Data Analytics and Data Mining tools for large volumes of data using Machine	
t-l-	Learning modelling.	
inks	Official SDG Metadata URL https://unstats.un.org/sdgs/metadata/files/Metadata-09-05-01.pdf	

PART#2. GRAPHICAL INTERFACES- RAPIDMINER SOFTWARE

RapidMiner Studio is a comprehensive data science platform with visual workflow design and full automation. Data science software provides an integrated environment for data preparation, machine learning, deep learning, text mining, and predictive analytics

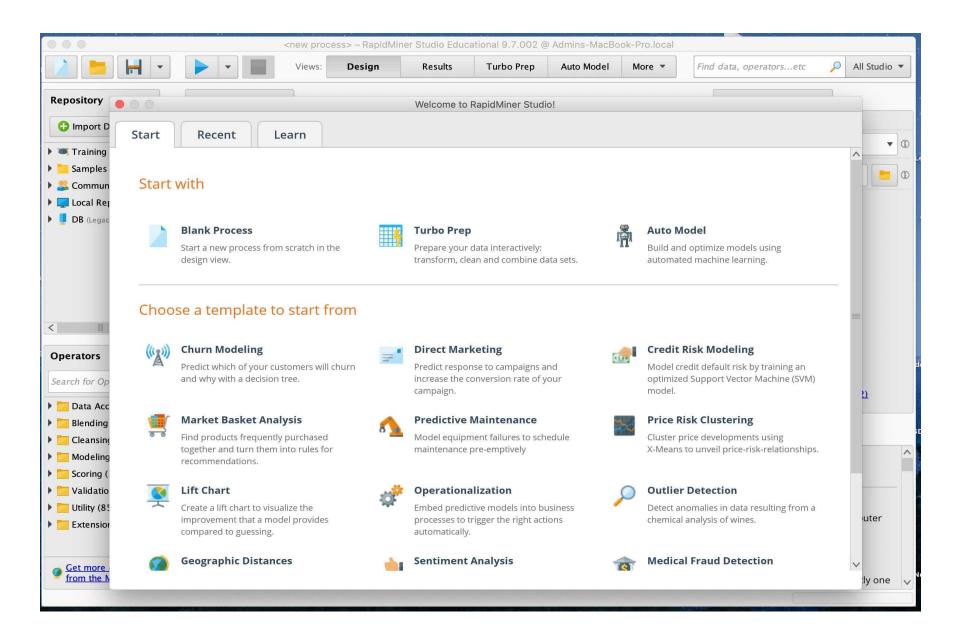
Drag and drop application in RapidMiner. RapidMiner's a very popular program, and there are several, very expensive commercial versions, but there's also a free community version

The community version can only handle 10,000 rows of data

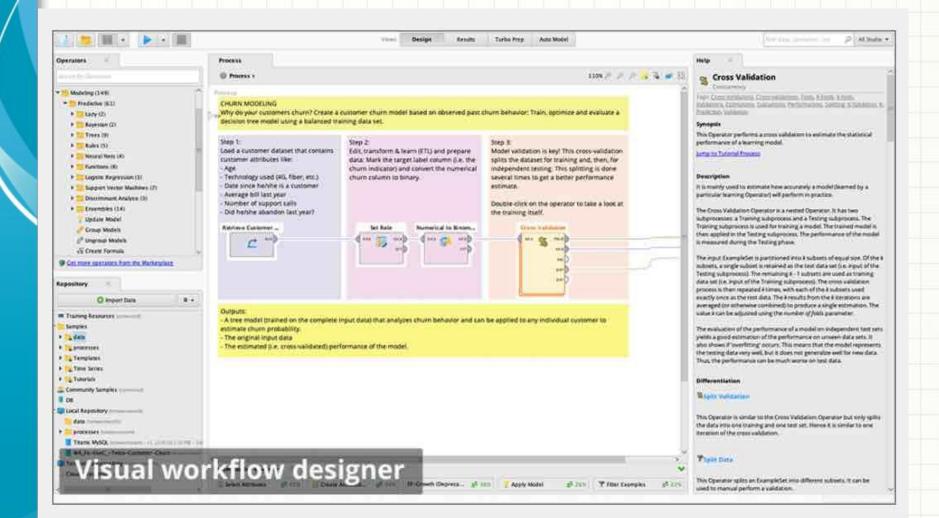


Loading Advanced File Connectors Extension
Educational Edition registered to Abbas Maaroof
Copyright (C) 2001–2020 RapidMiner GmbH

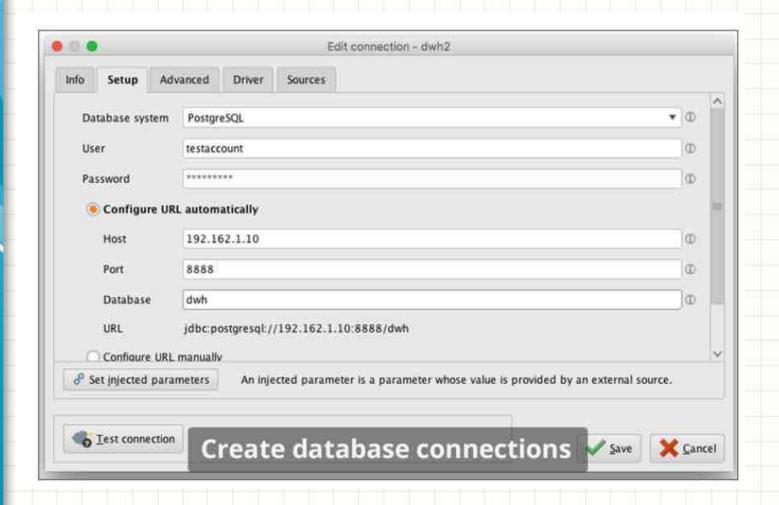




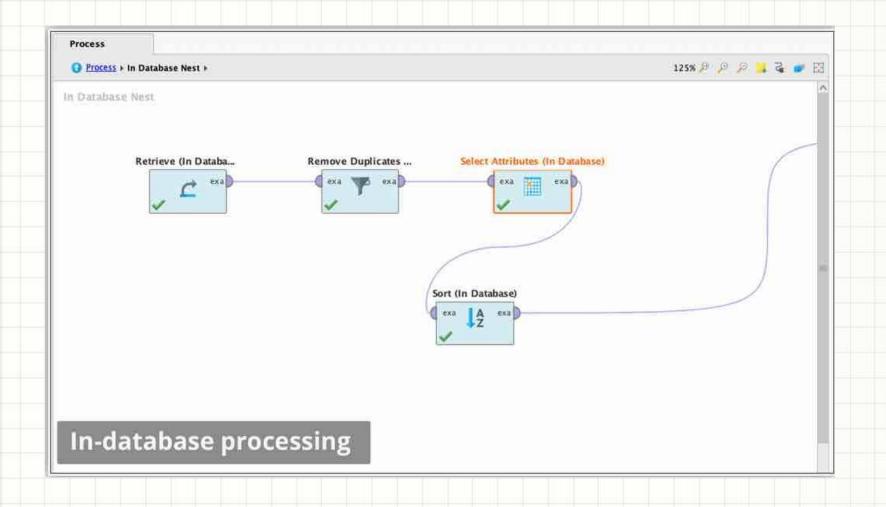
1. Visual Workflow Designer



2. Connect to Any Data Source:



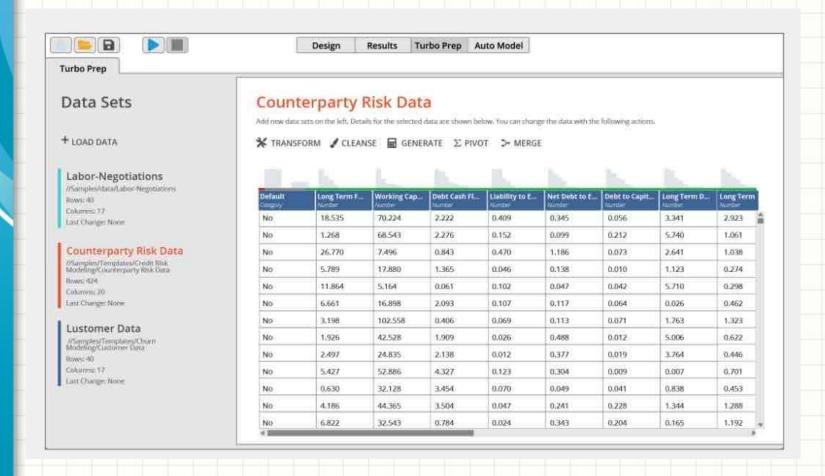
3. Automated In-Database Processing



4. Data Visualization & Exploration



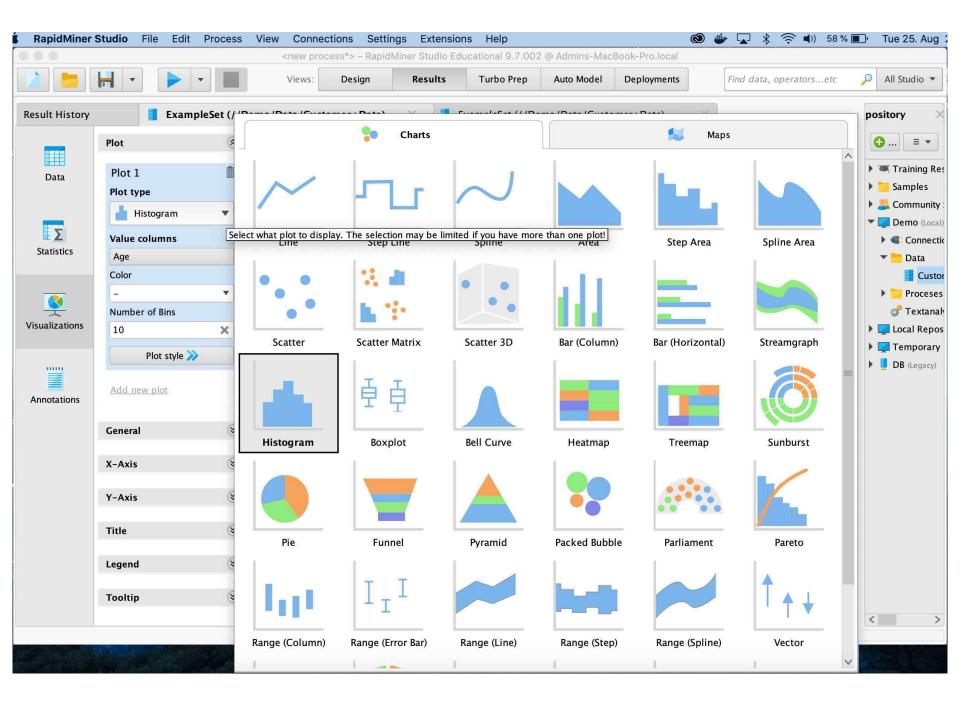
5.Data Prep & Blending



Why RapidMiner Studio?

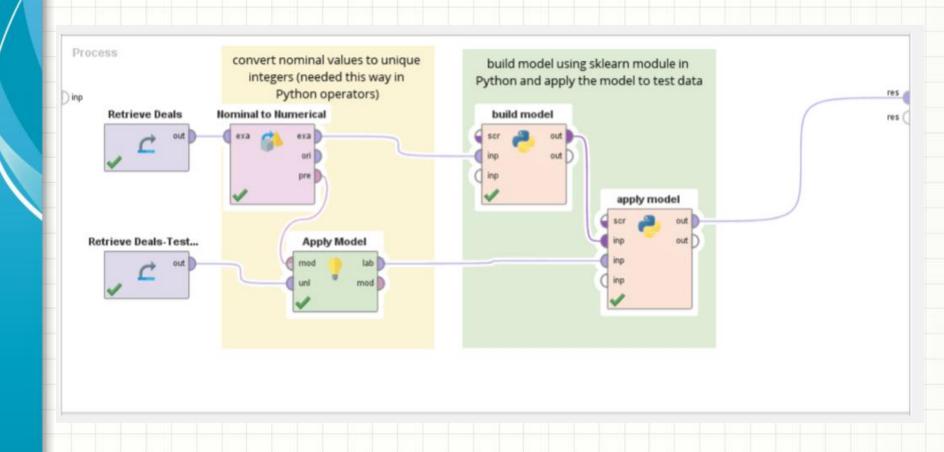
6. Visual & Automated Machine Learning





Why RapidMiner Studio?

7. Get More From R & Python Code



Case Study#1 customer churn rate

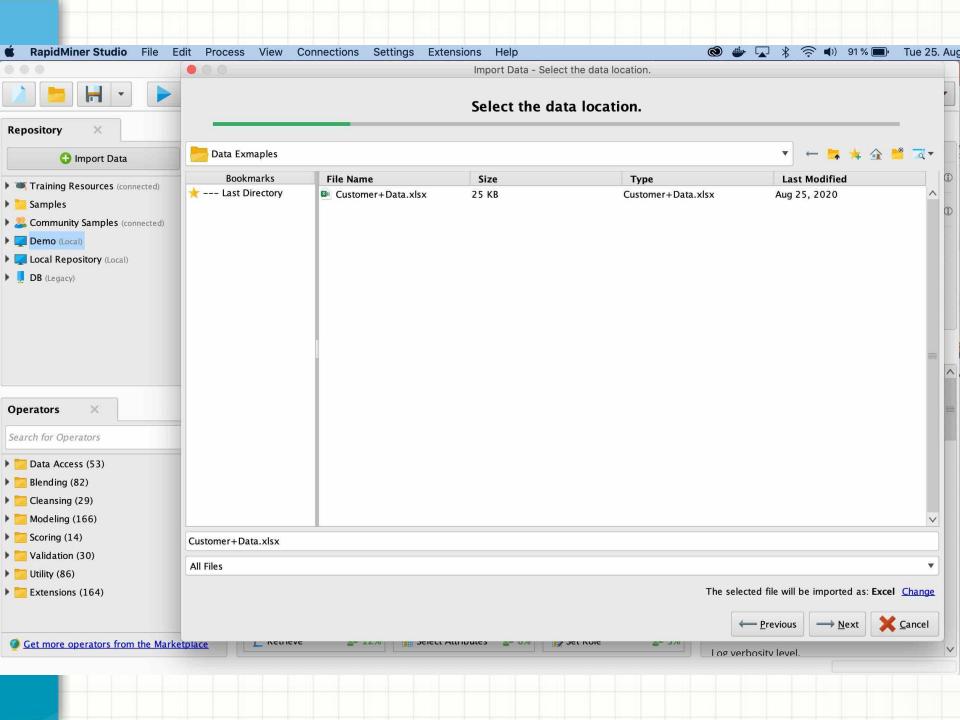
Customer churn rate is one of the most important metrics for businesses to track.

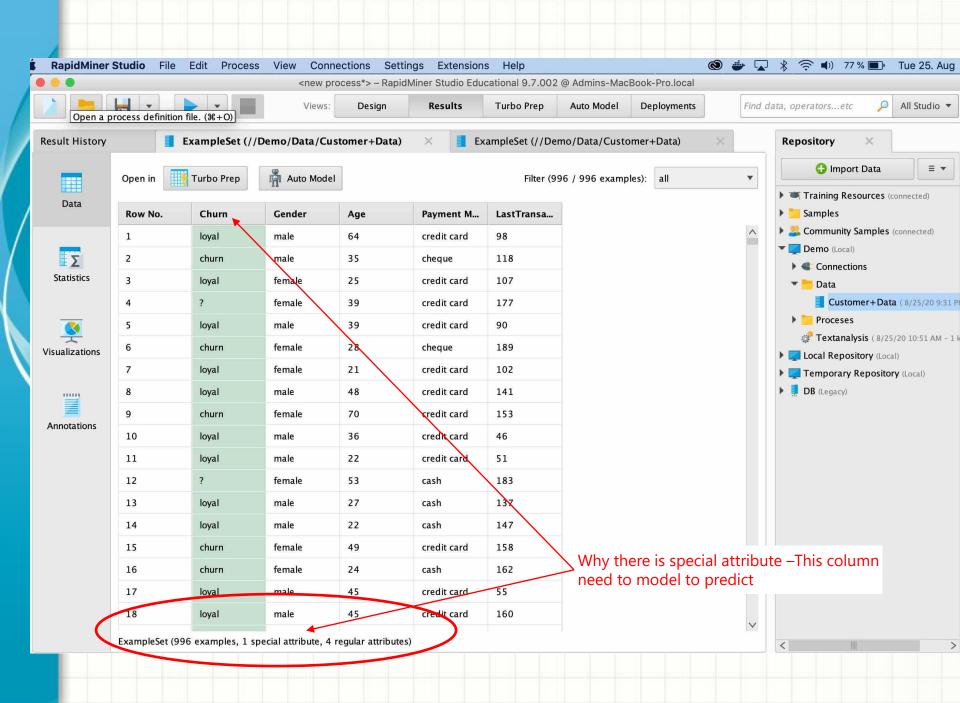
To identify your company's churn rate, choose a period of time you want to measure and identify the following values:

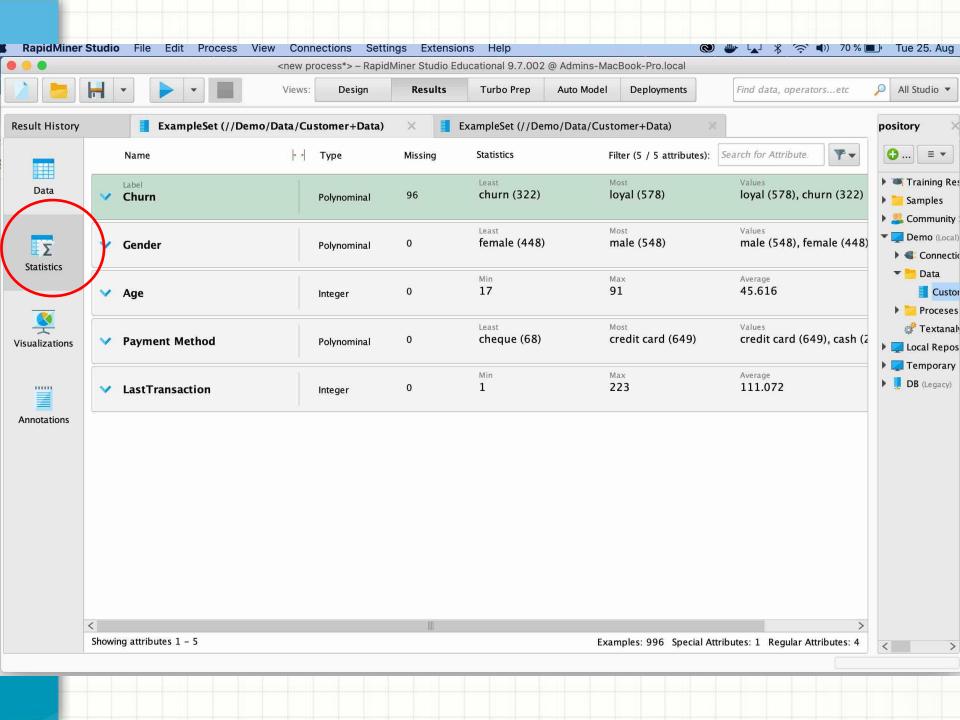
- •Number of customers at the start of the period (X)
- Number of customers lost during that period (Y)

Then, use the following formula to determine your customer churn rate (Z) as a percentage

Customer churn rate formula (Y/X) *100 = Z



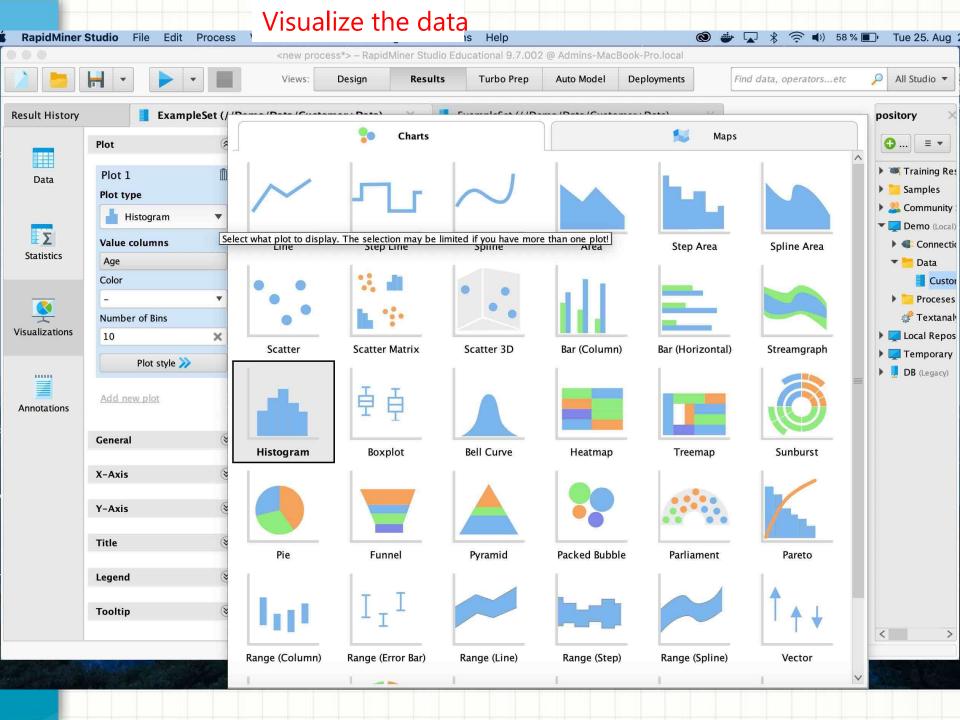


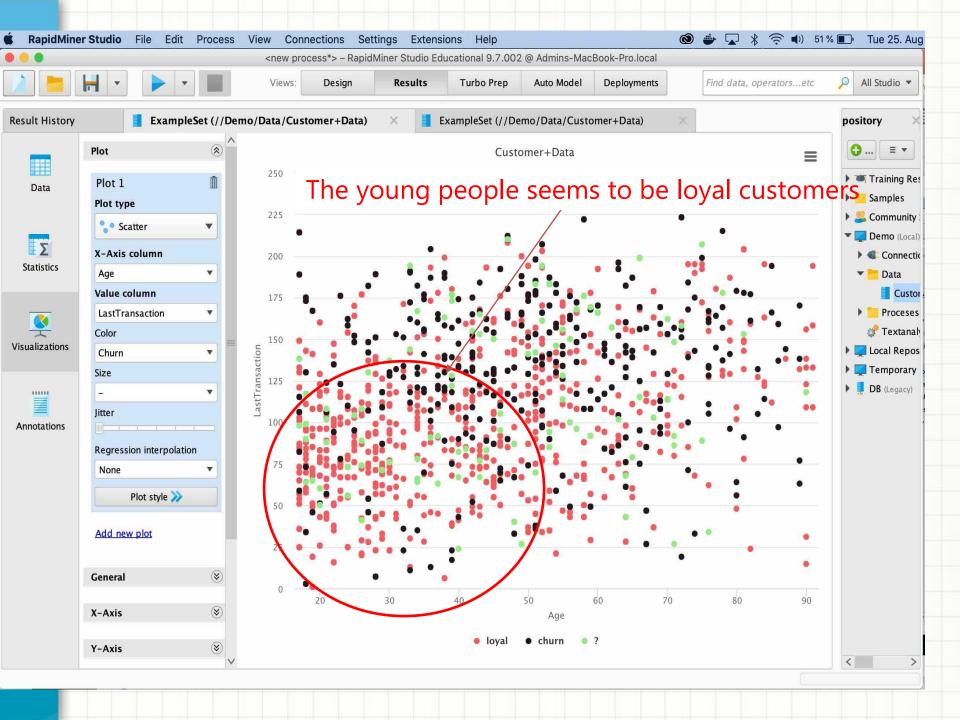


Hyper Link → ★ 🤝 •) 66 % • Tue 25. Aug RapidMiner Studio File Edit Process View Connections Settings Extensions <new proces**> - RapidMiner Studio Educational 9.7.002 @ Admins-MacBook-Pro.local Design All Studio ▼ Views: Results Turbo Prep Auto Model Deployments Find data, operators...etc Result History ExampleSet (//Demo/Data/Customer+Data) ExampleSet (//Demo/Data/Customer+Data) pository Search for Attribute: **...** = ▼ Statistics Name Type Missing Filter (5 / 5 attributes): Training Res 500 Data 400 Samples Most Least 300 churn (322) loyal (578) Community 96 200 Churn Polynominal 100 Demo (Local) loyal Connectic Open visualizations ▼ 📒 Data 500 400 Custor 300 Least Most Proceses female (448) male (548) 200 0 Gender Polynominal 100 # Textanal female Visualizations Local Repos Open visualizations Temporary 125 DB (Legacy) mm, 100 Min Max Average 75 17 91 45.61 0 Age Integer 50 Annotations 0 40 50 60 70 Open visualizations 500 400 300 cheque (68) credit card (64 **Payment Method** Polynominal 200 100 cred... cash Open visualizations 175 150 125 100 Min Max Average 75 1 223 111.0 LastTransaction Integer 50 Showing attributes 1 - 5 Examples: 996 Special Attributes: 1 Regular Attributes: 4

Visualize the data RapidMiner Studio File Edit Process View Connections Settings Extensions Help <new process*> - RapidMiner Studio Educational 9.7.002 @ Admins-MacBook-Pro.local Views: Design Results Turbo Prep Auto Model Deployments Find data, operators...etc All Studio ▼ **Result History** ExampleSet (//Demo/Data/Customer+Data) ExampleSet (//Demo/Data/Customer+Data) pository (\$) **⊕** ... ≡ ▼ Plot Customer+Data \equiv 160 Training Res Plot 1 Data Samples Plot type Community Histogram 140 Demo (Local) Value columns Connectic Statistics Age Data 120 Color Custor * Proceses 100 **Number of Bins** # Textanal Visualizations Local Repos 10 × Frequency ▶ ■ Temporary Plot style >> DB (Legacy) 1111111 Add new plot Annotations 60 (*) General 40 (8) X-Axis (\$) Y-Axis 20 (*) Title 0 20 30 40 50 60 70 80 (*) 90 Legend Age (*) **Tooltip** Age

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Case Study#2

Twitter Data Analysis Using RapidMiner

https://twitter.com/RapidMiner

