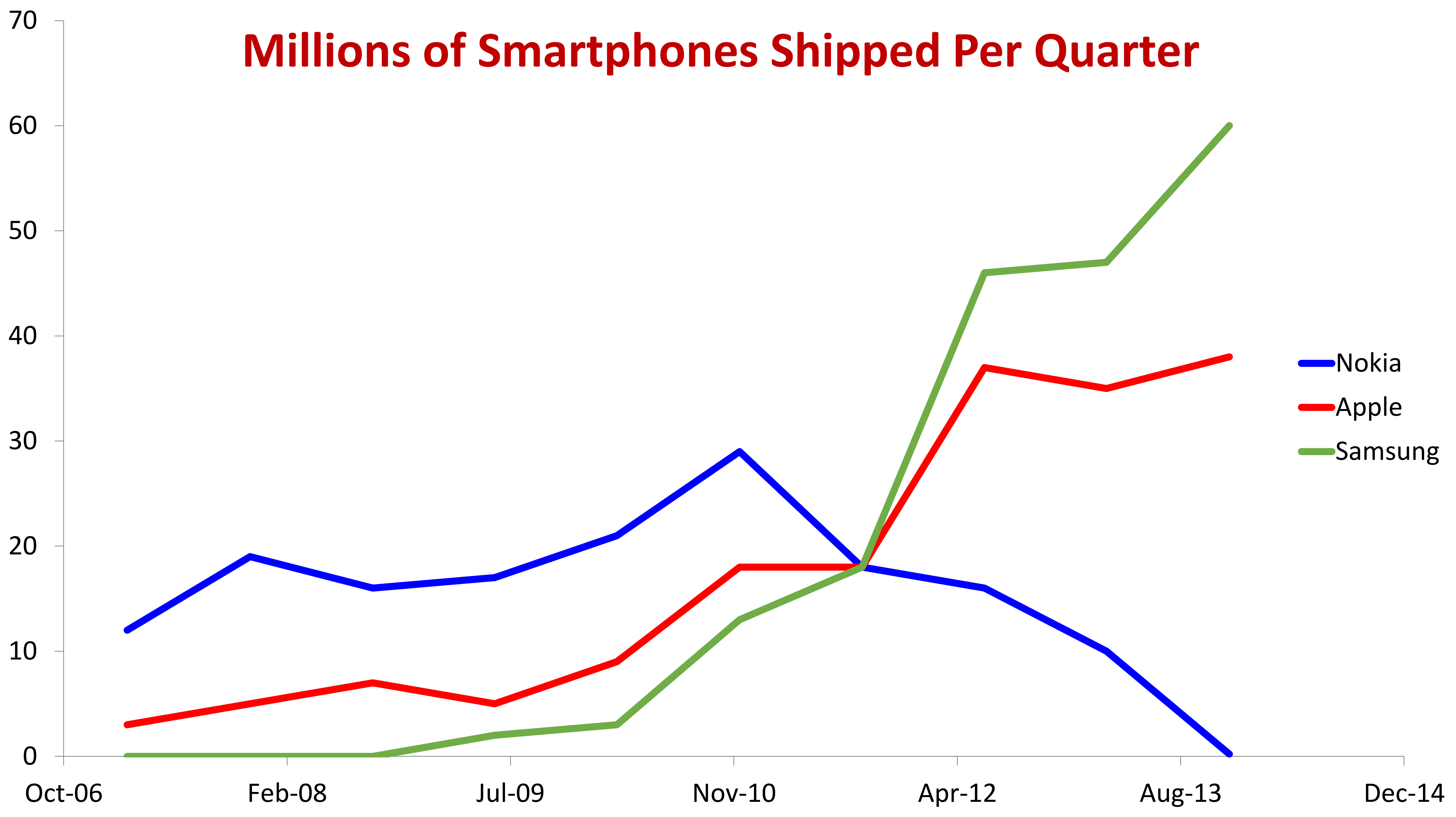
DSRAT

Data Science Research Arab Team RESEARCH BY DATA SCIENCE

OCT 8, 2013, 11:41 AM

Since 1865
The yearly profit amount is 13 billion $
European telecom giant
Advanced Research Center

DSRAT


Millions of Smartphones Shipped Per Quarter
70
60
50
40
30
20
10
0
Oct-06
Feb-08
Jul-09
Nov-10
Apr-12
Aug-13
Dec-14
Nokia
Apple
Samsung

The collapse of Nokia

0%

0%

NOKIA

Since 1865

DSRAT

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The Difference

NOKIA

2011

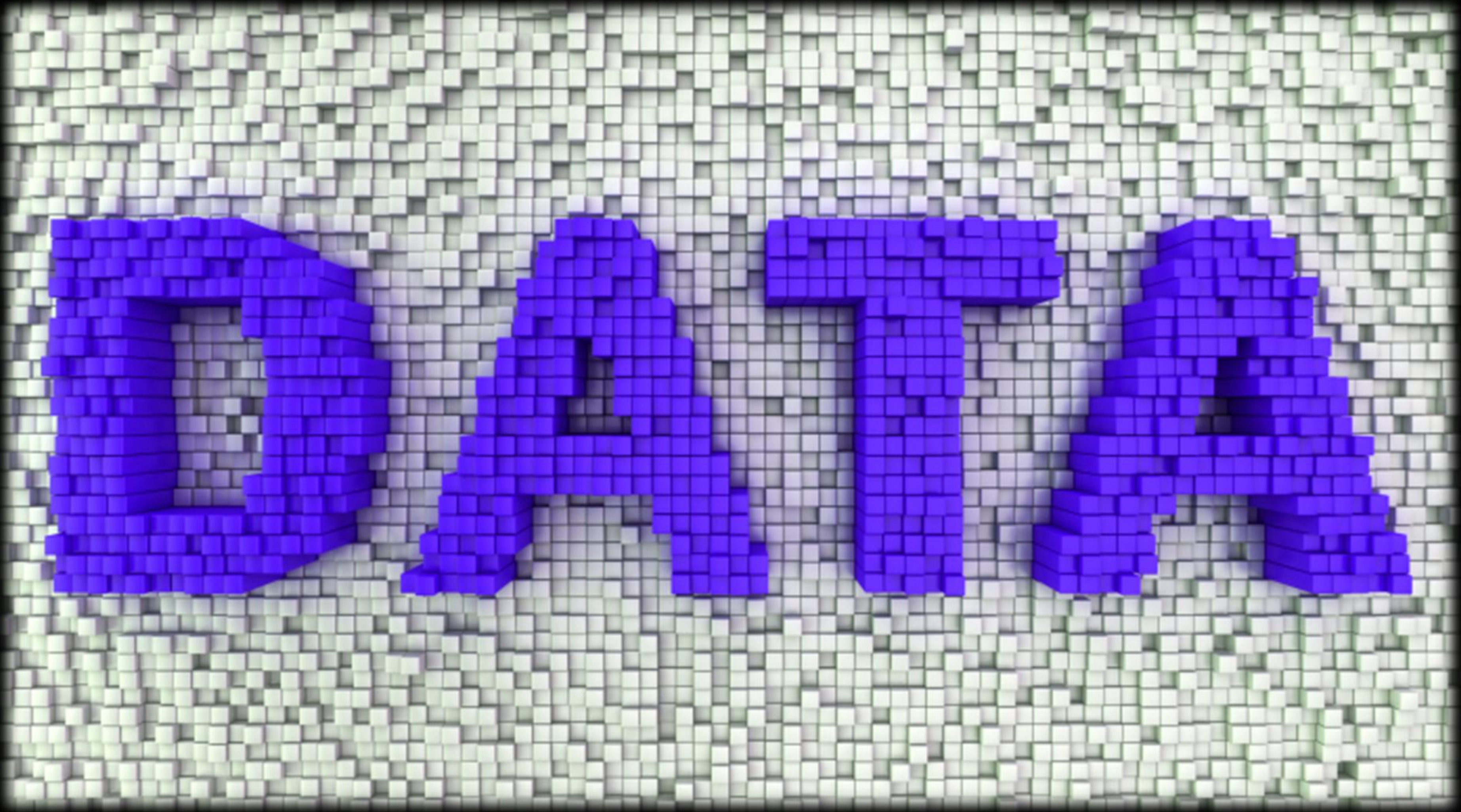
UNIVERSITYS

2018

UNIVERSITY

fourth industrial revolution

2012



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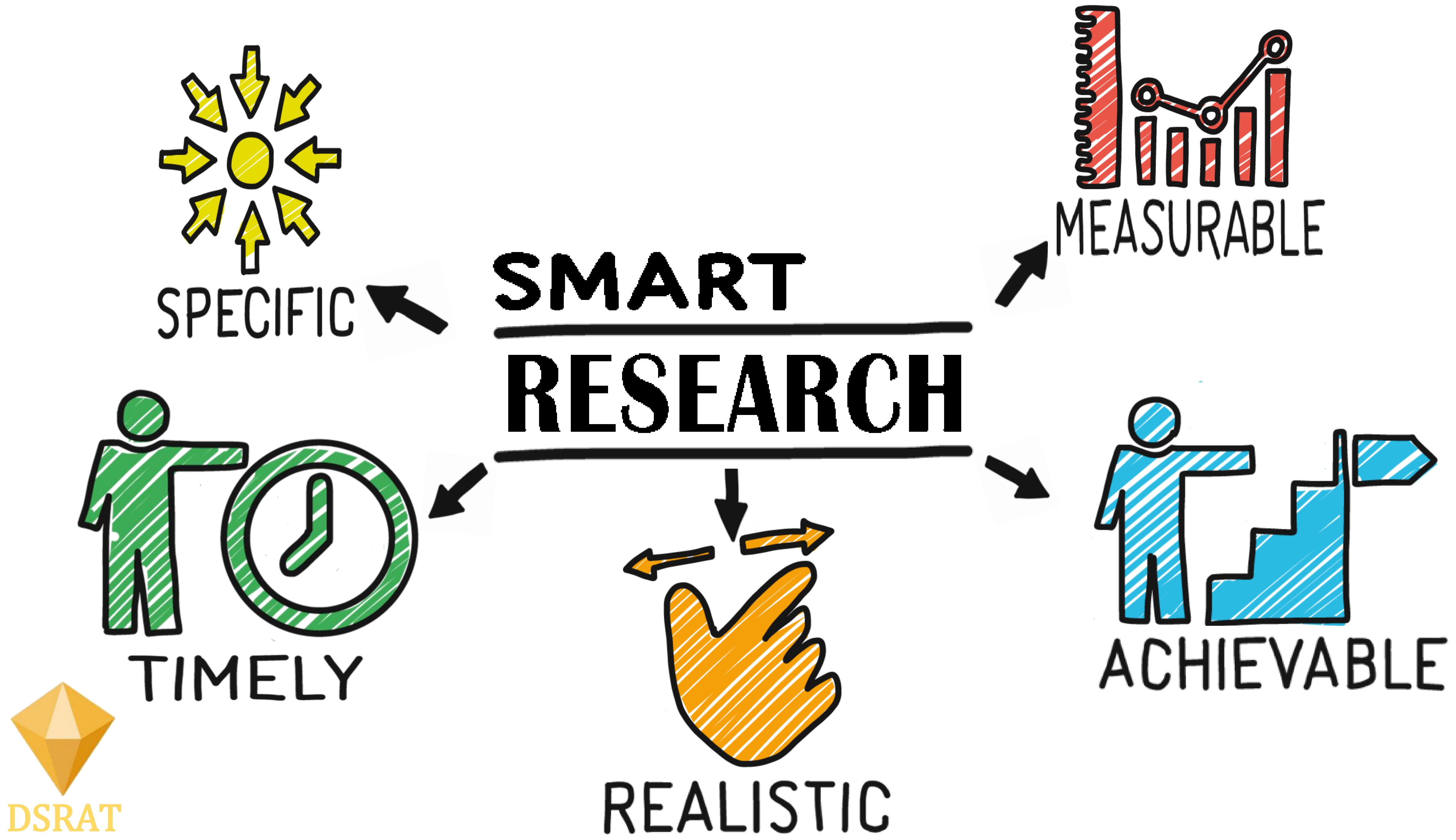
DATABASE DEVELOPMENT

Cyberspace Data

Before
2009

after
2009

DSRAT

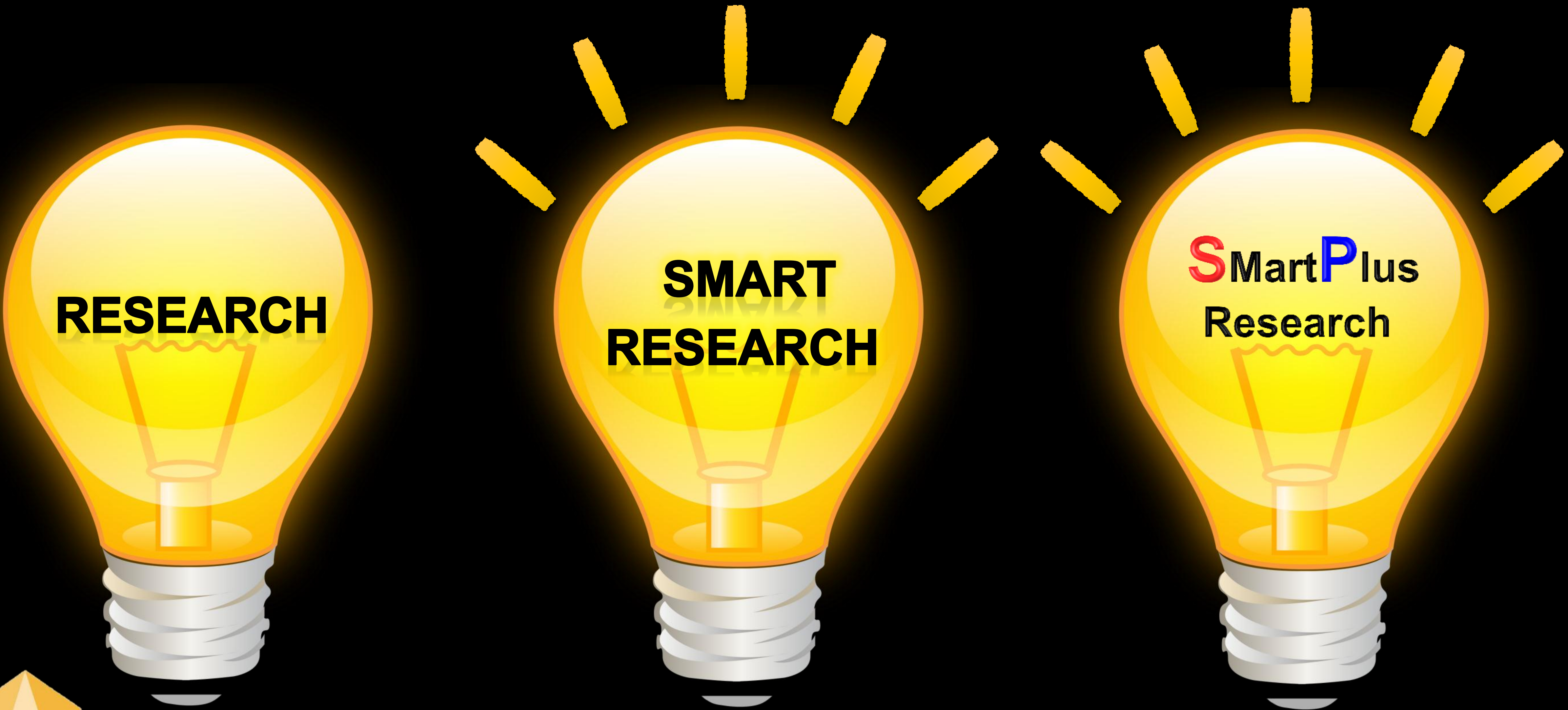

SMART
RESEARCH
SPECIFIC
MEASURABLE
ACHIEVABLE
REALISTIC
TIMELY
DSRAT

Low applied

sample

Simulation

Your idea



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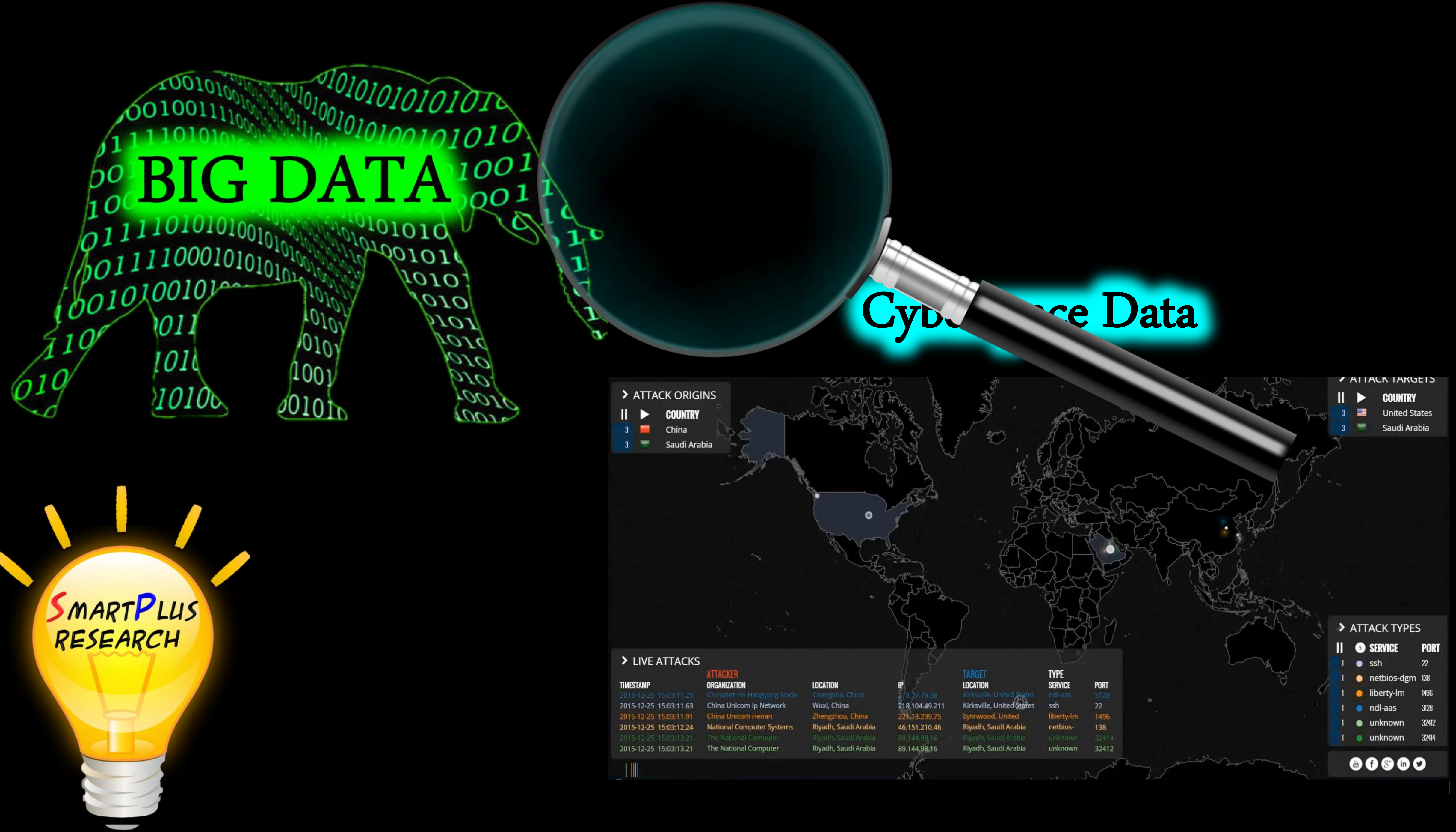
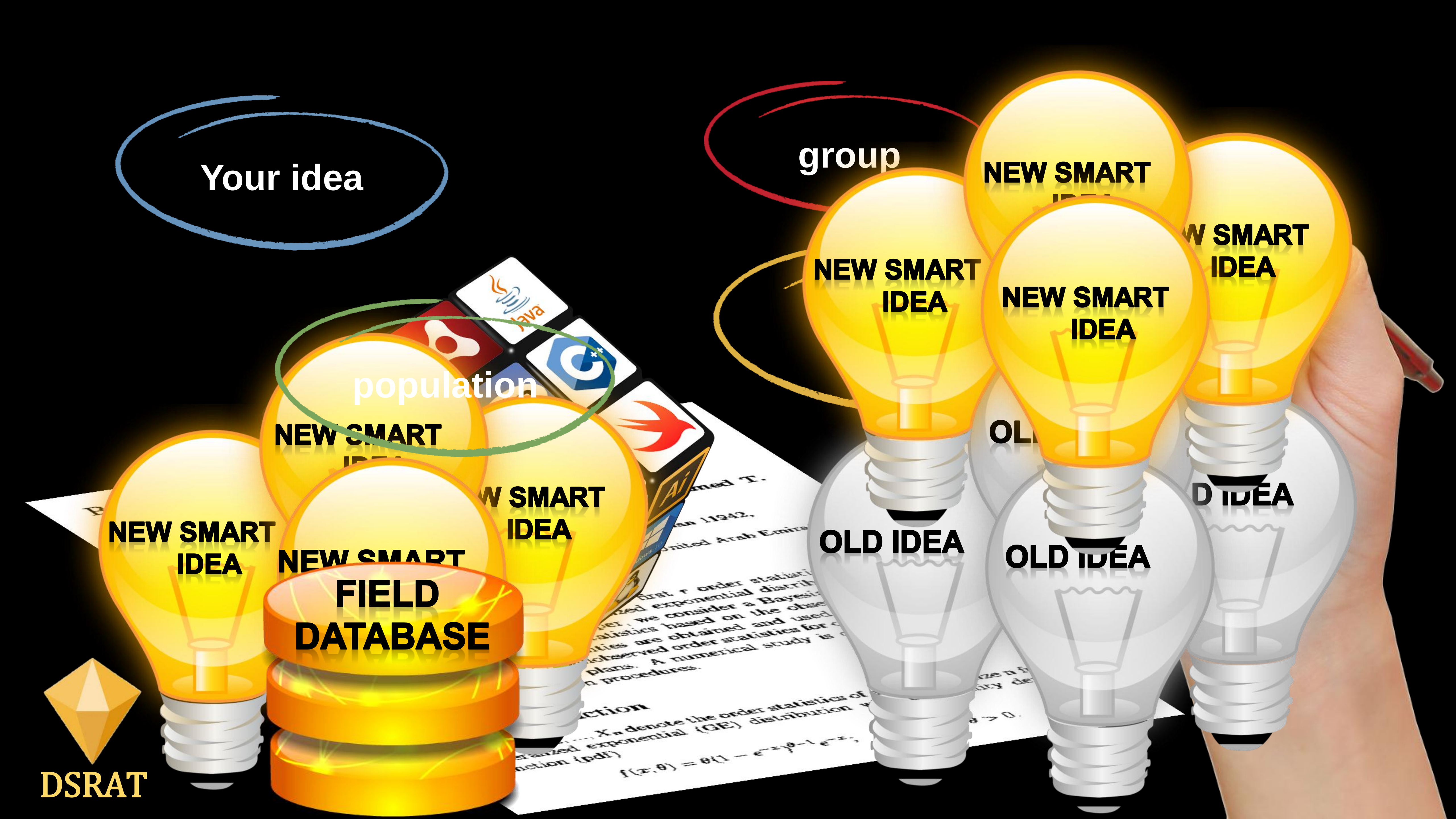

BIG DATA
Data
ATTACK ORIGINS
COUNTRY
3 China
3 Saudi Arabia
ATTACK TARGETS
COUNTRY
3 United States
3 Saudi Arabia
LIVE ATTACKS
ATTACKER
TARGET
TIMESTAMP | ORGANIZATION | LOCATION | IP | LOCATION | TYPE SERVICE | PORT
2015-12-25 15:03:11.25 | Chinanet-Hn Hengyang Node | Changsha, China | 218.77.79.38 | Kirksville, United States | ndl-aas | 3128
2015-12-25 15:03:11.63 | China Unicom Ip Network | Wuxi, China | 218.104.49.211 | Kirksville, United States | ssh | 22
2015-12-25 15:03:11.91 | China Unicom Henan | Zhengzhou, China | 221.13.239.75 | Lynnwood, United | liberty-lm | 1496
2015-12-25 15:03:12.24 | National Computer Systems | Riyadh, Saudi Arabia | 46.151.210.46 | Riyadh, Saudi Arabia | netbios- | 138
2015-12-25 15:03:13.21 | The National Computer | Riyadh, Saudi Arabia | 89.144.98.16 | Riyadh, Saudi Arabia | unknown | 32414
2015-12-25 15:03:13.21 | The National Computer | Riyadh, Saudi Arabia | 89.144.98.16 | Riyadh, Saudi Arabia | unknown | 32412
ATTACK TYPES
SERVICE PORT
1 ssh 22
1 netbios-dgm 138
1 liberty-lm 1496
1 ndl-aas 3128
1 unknown 32412
1 unknown 32414
SmartPlus
RESEARCH



Your idea
group
population
NEW SMART IDEA
NEW SMART IDEA
NEW SMART IDEA
NEW SMART IDEA
OLD IDEA
OLD IDEA
FIELD DATABASE
DSRAT

DATA ENCE

DSRAT

IT'S A TESTIMONY

THE WHITE HOUSE

WASHINGTON

www.WHITEHOSE.gov

The elementary definition of DATA SCTENCE

Is the updating the Statistics science and Computer information systems science.

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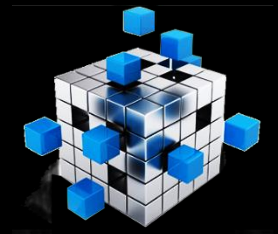
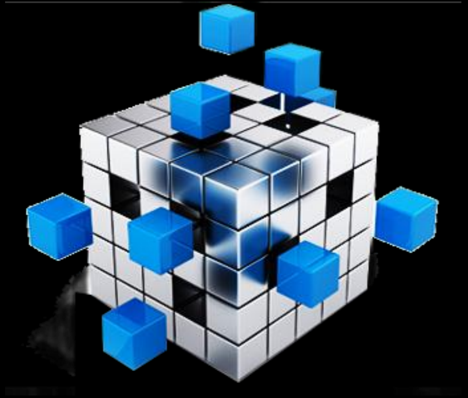
Data Science history

1996-2009

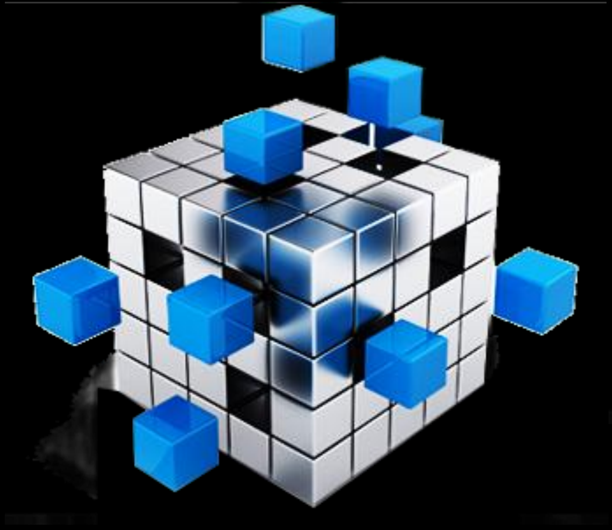
Kobe, Japan



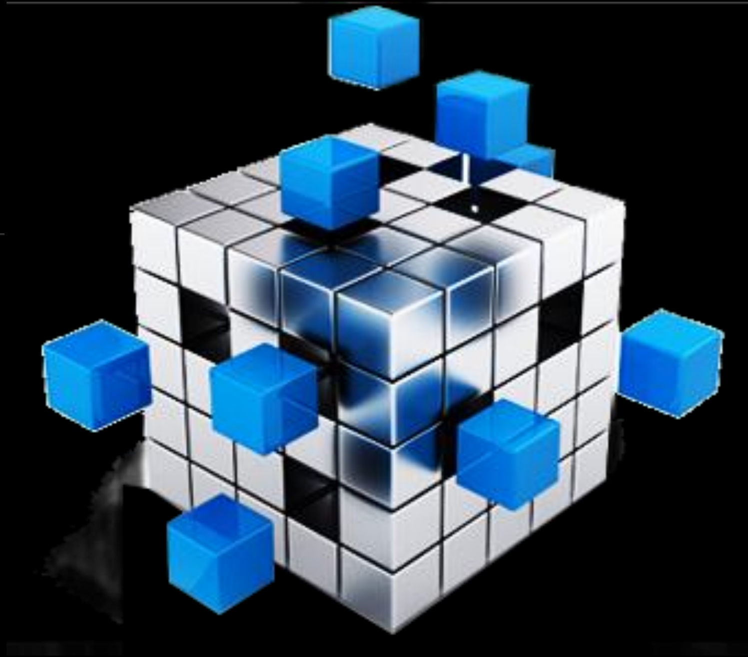
Providence, Island



Shanghai, China



Shanghai, China



1996

1997

2007

2009

The origin of data science:

- The emergence of new structures of data is one of the most important motive for the origin of data science.

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I. BIG DATA

- The McKinsey World Institute in 2011, defined the BIG DATA as "any datasets, whose size is beyond the ability of traditional data analysis tools to organize, store, manage, and analyze."

- The TechAmerica Foundation's Federal Big Data Commission in 2012, defined the BIG DATA " is a term that describes large volumes of high velocity, complex and variable data that require advanced techniques and technologies to enable the collect, storage, distribution, management, and analysis of the information."

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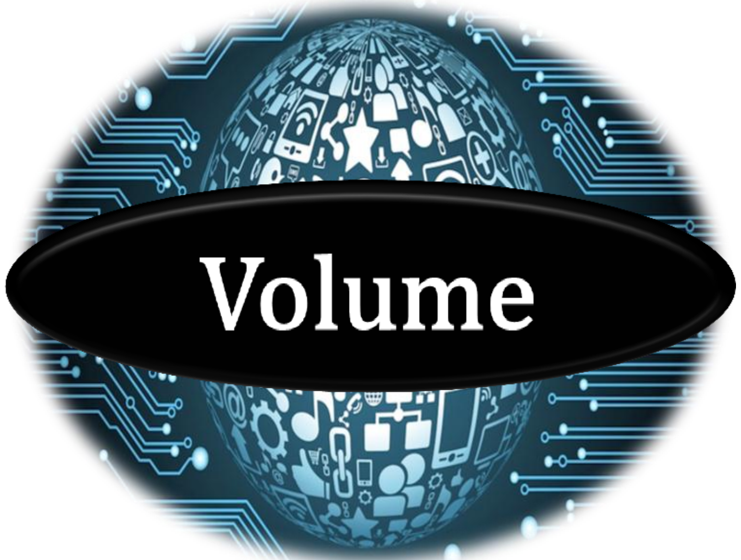
What happens in a ONE MINUTE?

250 million
E-mail sent

1,000,000
Payment card
transactions

17 TB
of data is processing by
Google

200,000
Photos are uploaded &
300,000
Statuses are updated



2,350 TB
Of data is created

UBER
1,000
Uber Rides

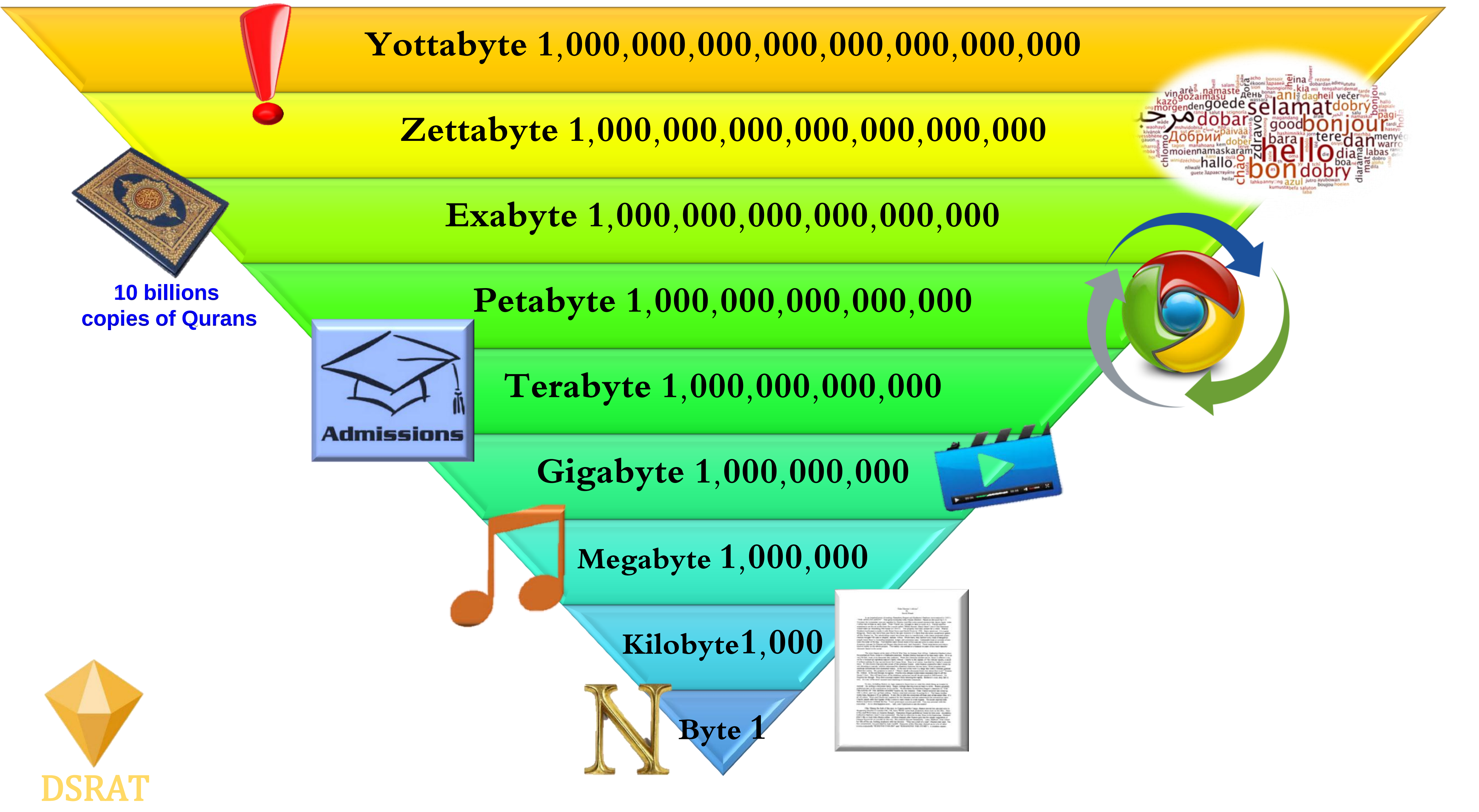
550,000
New Tweets &
350
New Twitter Accounts

55,000,000
Massages &
540,202
Photos
Are processing

McDonald's
30,000$
McDonald's Sales

10,0000 flights
& 1,800,000
passengers

DSRAT


Yottabyte 1,000,000,000,000,000,000,000,000
Zettabyte 1,000,000,000,000,000,000,000
Exabyte 1,000,000,000,000,000,000
Petabyte 1,000,000,000,000,000
Terabyte 1,000,000,000,000
Gigabyte 1,000,000,000
Megabyte 1,000,000
Kilobyte1,000
Byte 1
10 billions
copies of Qurans
Admissions
hello
bonjour
selamat
bon
dobry
DSRAT

What happens in a ONE MINUTE?

250 million
E-mail sent

1,000,000
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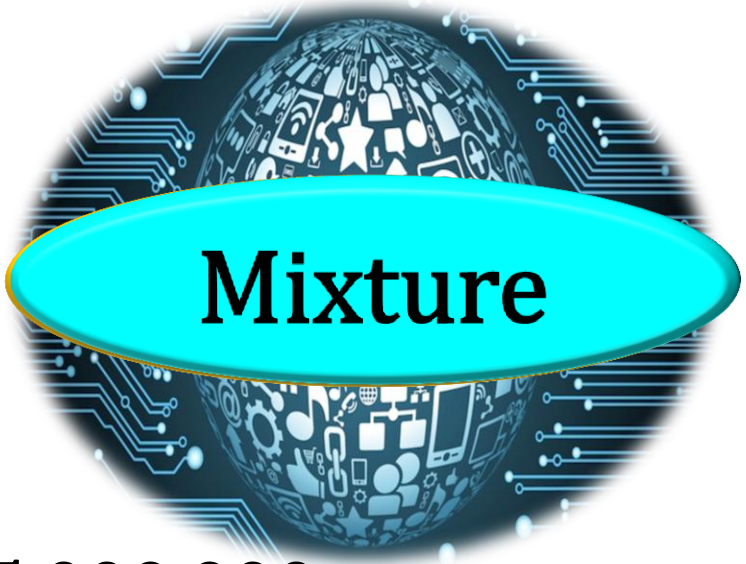


2,350 TB
Of data is created

1,000
Uber Rides

550,000
New Tweets &
350
New Twitter Accounts

55,000,000
Massages &
540,202
Photos
Are processing

30,000$
McDonald's Sales

10,0000 flights
& 6,950
passengers

DSRAT

McDonald's

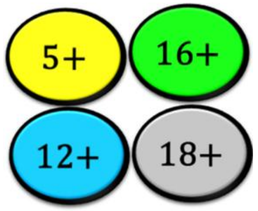
Big Data

Region

Gender

Demographics

Sales



Age

Seasons

Religions

Income

DSRAT

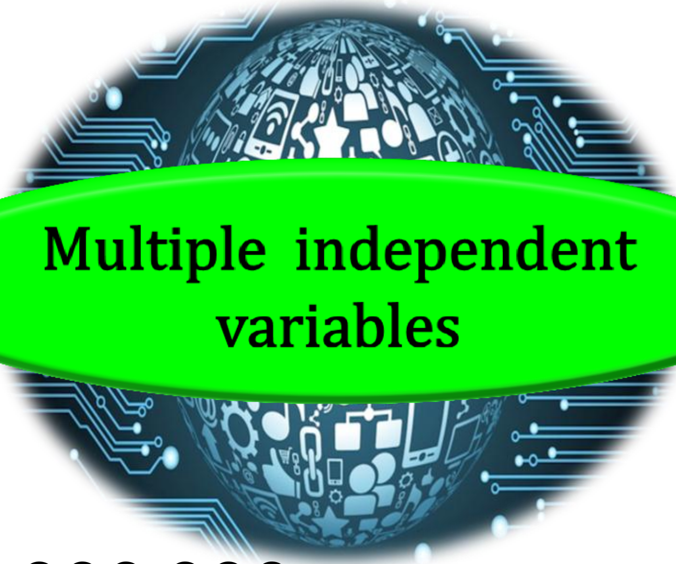
What happens in a ONE MINUTE?

250 million
E-mail sent

1,000,000
Payment card
transactions

17 TB
of data is processing by
Google

200,000
Photos are uploaded &
300,000
Statuses are updated



Multiple independent
variables

2,350 TB
Of data is created

1,000
Uber Rides

550,000
New Tweets &
350
New Twitter Accounts

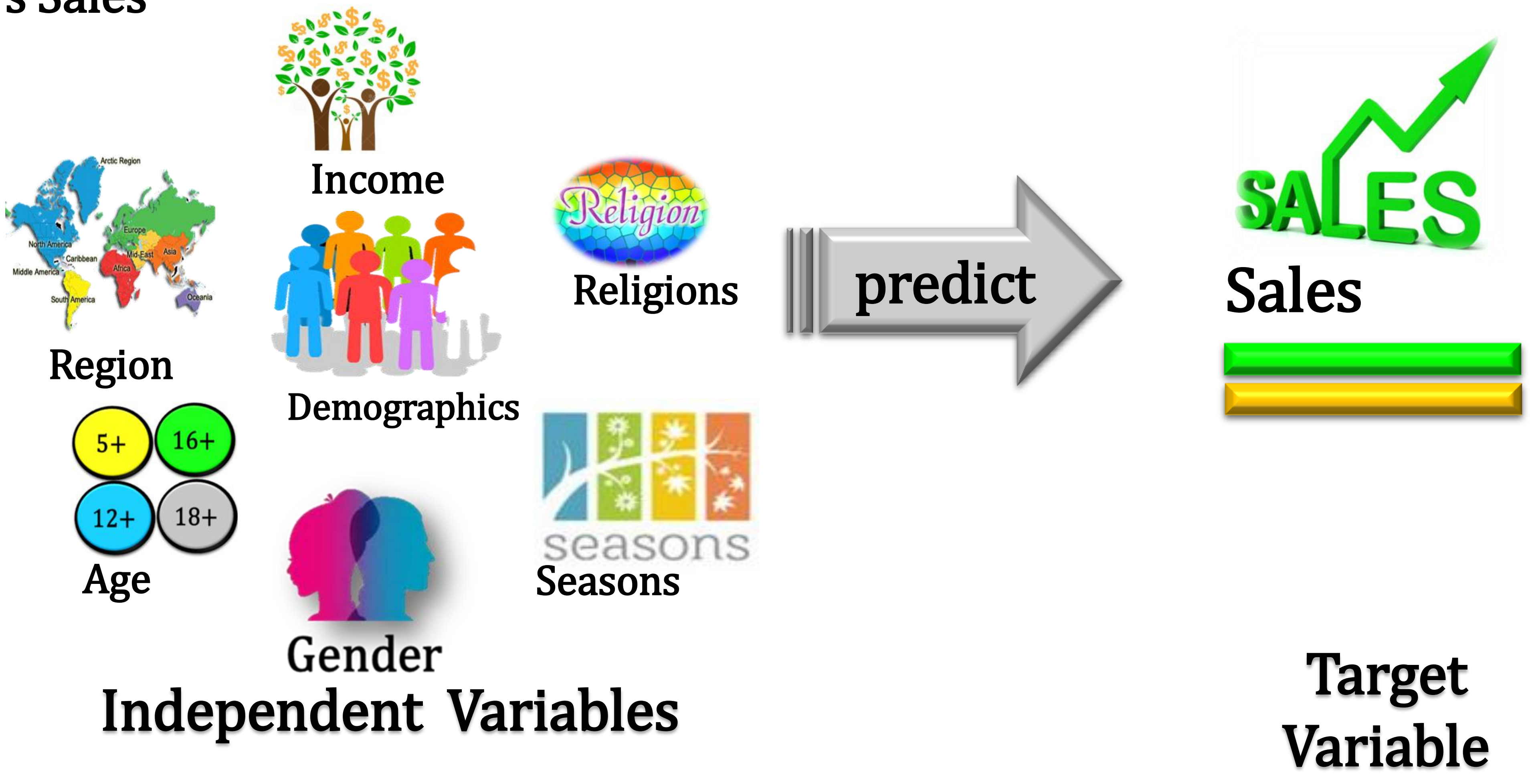
55,000,000
Massages &
540,202
Photos
Are processing

30,000$
McDonald's Sales

10,0000 flights
& 6,950
passengers

DSRAT

McDonald's Sales



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The DATA SCIENCE definition based on BIG DATA;

- Is the breakthrough of this century, and it is the science that specialized in extracting knowledge from organized or unorganized big data.

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The Big Data analytic before the Data Science

CIS

Data Mining

Statistics

Predictive Analytics

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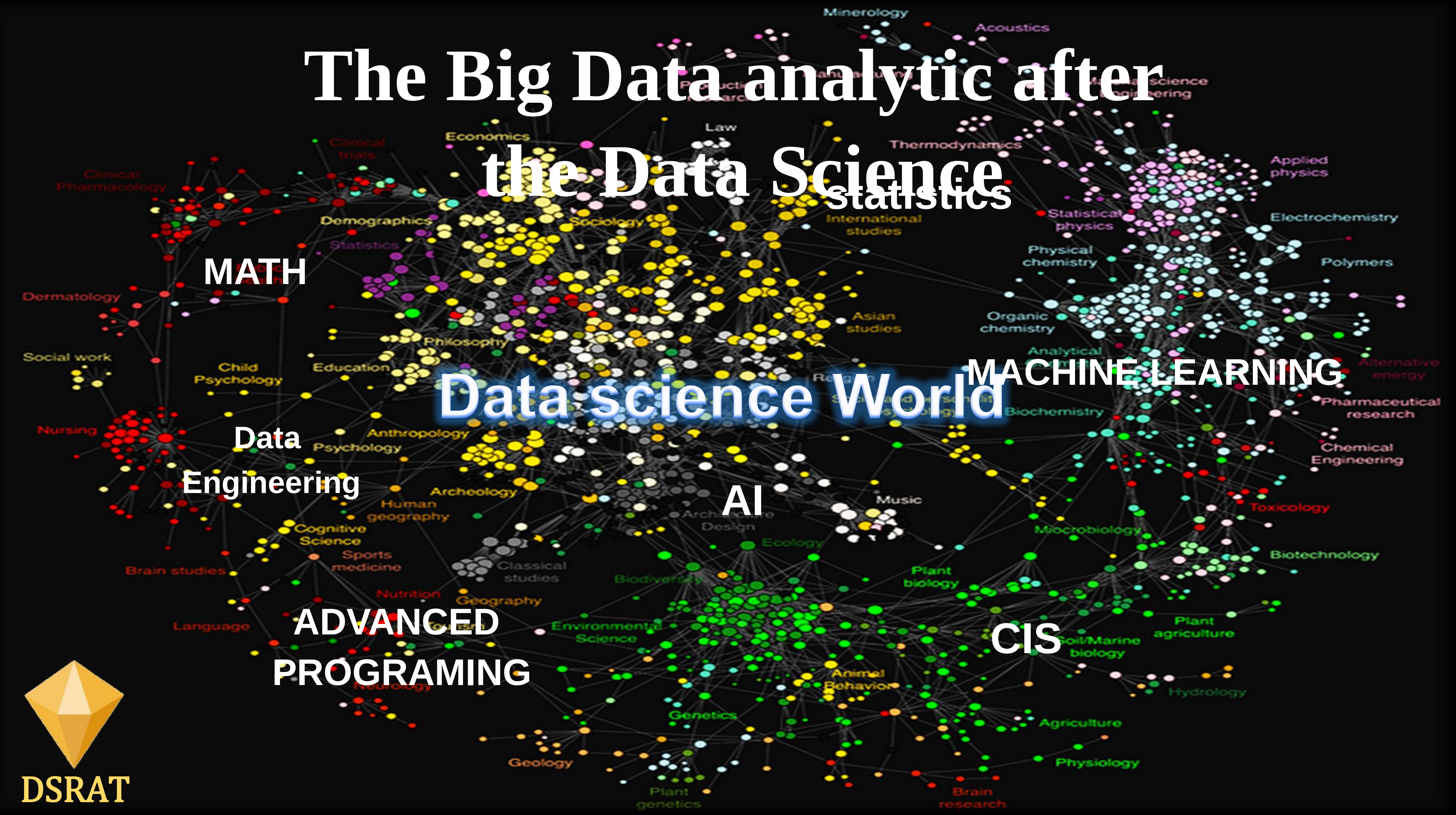
The Big Data analytic after the Data Science



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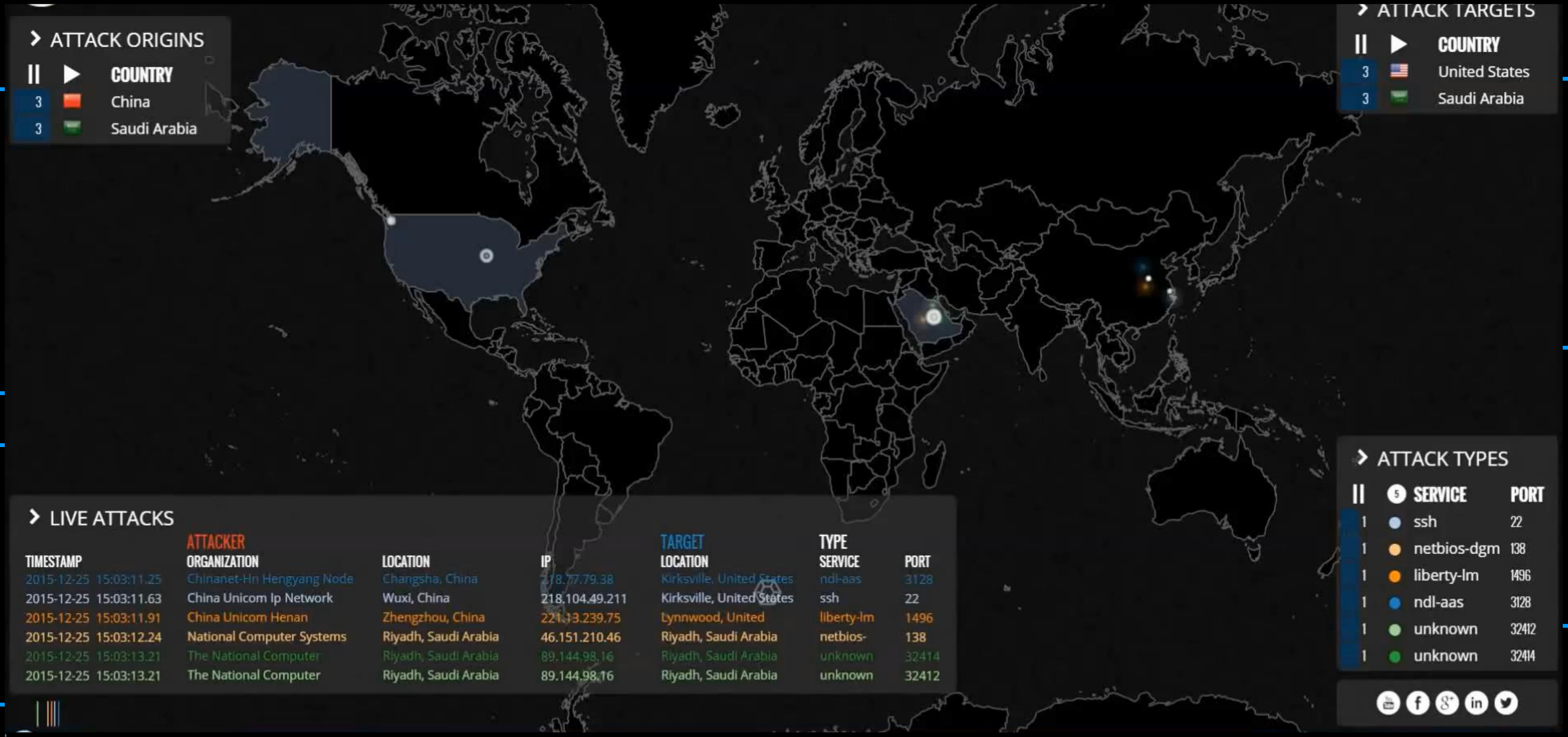
II. CYBERSPACE



II. CYBERSPACE

- CYBERSPACE is the Virtual Environment in which communication over computer networks occurs.

- ## CYBERSPACE DATA

Is the data that are generated in cyberspace.

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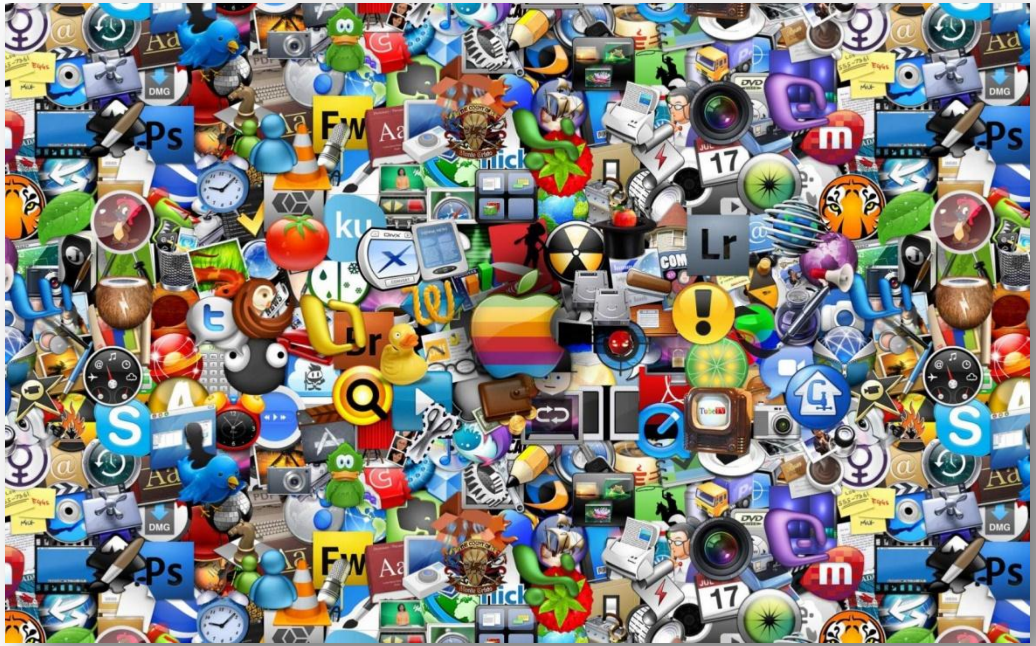
BIG DATA

The major properties of cyberspace data are;

Data has no behavior
in the natural or human sciences



Data can’t be organized

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The DATA SCIENCE definition based on CYBERSPACE;

- Is As a complex scientific field, aimed to processing raw data which is believed to be meaningless for making decisions and predict future events, like the "Behavior ".

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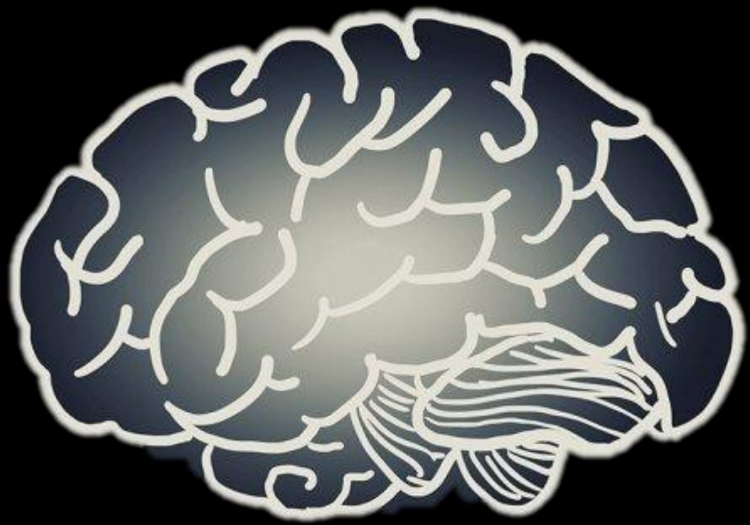
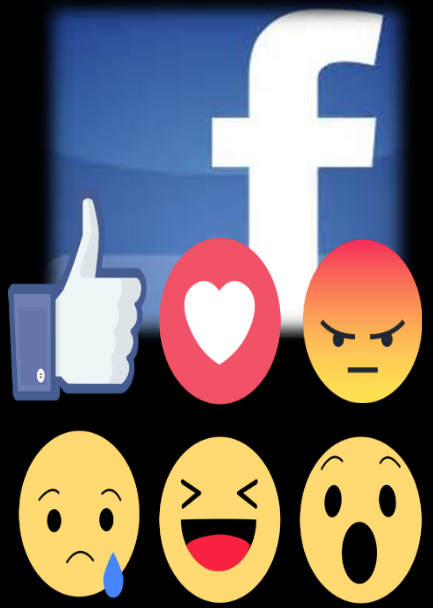
Big Five



Michal Kosinski

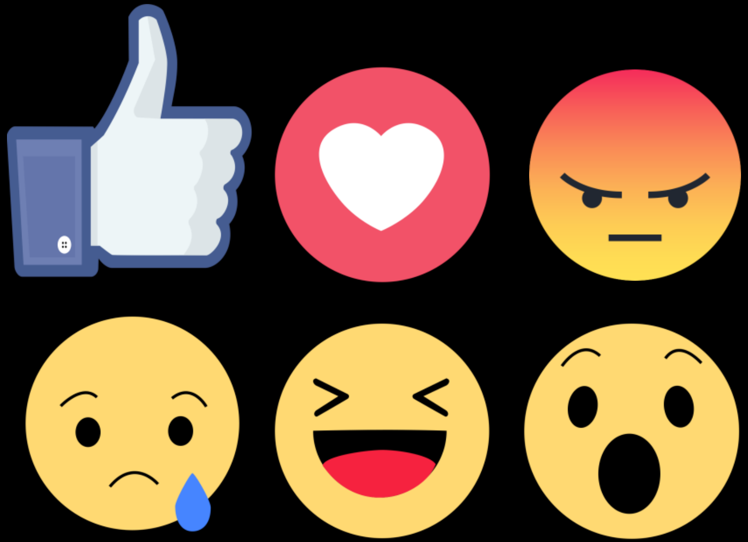


Cambridge Analytica

BIG FIVE

Open

Ideal

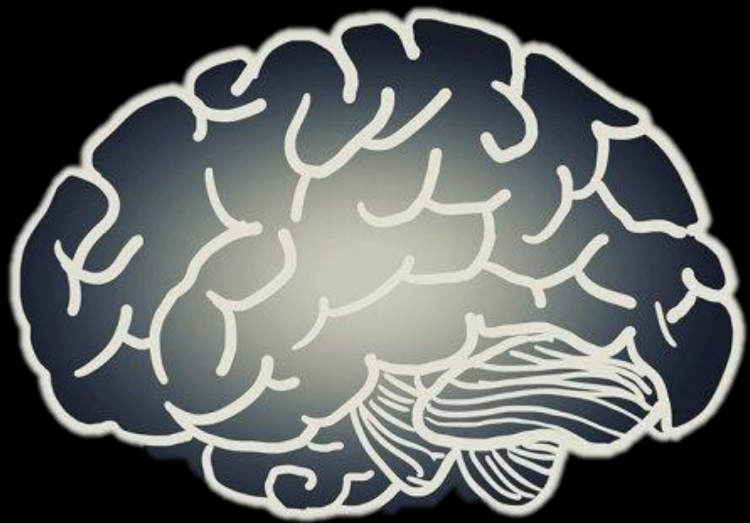


Emotional

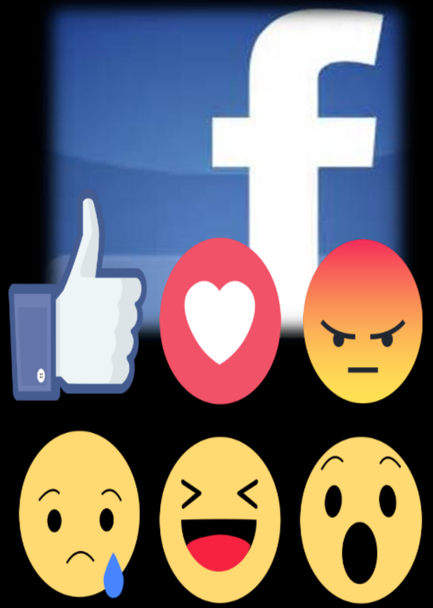
Sociable

Helpful

Big Five



Michael Kozinsky



Cambridge Analytica

PNAS

Private traits and attributes are predictable from digital records of human behavior

Michal Kosinski[a,1], David Stillwell[a], and Thore Graepel[b]

[a]Free School Lane, The Psychometrics Centre, University of Cambridge, Cambridge CB2 3RQ United Kingdom; and [b]Microsoft Research, Cambridge CB1 2FB, United Kingdom

Edited by Kenneth Wachter, University of California, Berkeley, CA, and approved February 12, 2013 (received for review October 29, 2012)

We show that easily accessible digital records of behavior, Facebook Likes, can be used to automatically and accurately predict a range of highly sensitive personal attributes including: sexual orientation, ethnicity, religious and political views, personality traits, intelligence, happiness, use of addictive substances, parental separation, age, and gender. The analysis presented is based on a dataset of over 58,000 volunteers who provided their Facebook Likes, detailed demographic profiles, and the results of several psychometric tests. The proposed model uses dimensionality reduction for preprocessing the Likes data, which are then entered into logistic/linear regression to predict individual psychodemographic profiles from Likes. The model correctly discriminates between homosexual and heterosexual men in 88% of cases, African Americans and Caucasian Americans in 95% of cases, and between Democrat and Republican in 85% of cases. For the personality trait "Openness," prediction accuracy is close to the test–retest accuracy of a standard personality test. We give examples of associations between attributes and Likes and discuss implications for online personalization and privacy.

social networks | computational social science | machine learning | big data | data mining | psychological assessment

A growing proportion of human activities, such as social interactions, entertainment, shopping, and gathering information, are now mediated by digital services and devices. Such digitally mediated behaviors can easily be recorded and analyzed, fueling the emergence of computational social science (1) and new services such as personalized search engines, recommender systems (2), and targeted online marketing (3). However, the widespread availability of extensive records of individual behavior, together with the desire to learn more about customers and citizens, presents serious challenges related to privacy and data ownership (4, 5).

We distinguish between data that are actually recorded and information that can be statistically predicted from such records. People may choose not to reveal certain pieces of information about their lives, such as their sexual orientation or age, and yet this information might be predicted in a statistical sense from other aspects of their lives that they do reveal. For example, a major US retail network used customer shopping records to predict pregnancies of its female customers and send them well-timed and well-targeted offers (6). In some contexts, an unexpected flood of vouchers for prenatal vitamins and maternity clothing may be welcome, but it could also lead to a tragic outcome, e.g., by revealing (or incorrectly suggesting) a pregnancy of an unmarried woman to her family in a culture where this is unacceptable (7). As this example shows, predicting personal information to improve products, services, and targeting can also lead to dangerous invasions of privacy.

Predicting individual traits and attributes based on various cues, such as samples of written text (8), answers to a psychometric test (9), or the appearance of spaces people inhabit (10), has a long history. Human migration to digital environment renders it possible to base such predictions on digital records of human behavior. It has been shown that age, gender, occupation, education level, and even personality can be predicted from people's Web site browsing logs (11–15). Similarly, it has been shown that personality can be predicted based on the contents of personal Web sites (16), music collections (17), properties of Facebook or Twitter profiles such as the number of friends or the density of friendship networks (18–21), or language used by their users (22). Furthermore, location within a friendship network at Facebook was shown to be predictive of sexual orientation (23).

This study demonstrates the degree to which relatively basic digital records of human behavior can be used to automatically and accurately estimate a wide range of personal attributes that people would typically assume to be private. The study is based on Facebook Likes, a mechanism used by Facebook users to express their positive association with (or "Like") online content, such as photos, friends' status updates, Facebook pages of products, sports, musicians, books, restaurants, or popular Web sites. Likes represent a very generic class of digital records, similar to Web search queries, Web browsing histories, and credit card purchases. For example, observing users' Likes related to music provides similar information to observing records of songs listened to online, songs and artists searched for using a Web search engine, or subscriptions to related Twitter channels. In contrast to these other sources of information, Facebook Likes are unusual in that they are currently publicly available by default. However, those other digital records are still available to numerous parties (e.g., governments, developers of Web browsers, search engines, or Facebook applications), and, hence, similar predictions are unlikely to be limited to the Facebook environment.

The design of the study is presented in Fig. 1. We selected traits and attributes that reveal how accurate and potentially intrusive such a predictive analysis can be, including "sexual orientation," "ethnic origin," "political views," "religion," "personality," "intelligence," "satisfaction with life" (SWL), substance use ("alcohol," "drugs," "cigarettes"), "whether an individual's parents stayed together until the individual was 21 y old," and basic demographic attributes such as "age," "gender," "relationship status," and "size and density of the friendship network." Five Factor Model (9) personality scores ($n = 54{,}373$) were established using the International Personality Item Pool (IPIP) questionnaire with 20 items (25). Intelligence ($n = 1{,}350$) was measured using Raven's Standard Progressive Matrices (SPM) (26), and SWL ($n = 2{,}340$) was measured using the SWL Scale (27). Age ($n = 52{,}700$; average, $\mu = 25.6$; SD = 10), gender ($n = 57{,}505$; 62% female), relationship status ("single"/"in relationship"; $n = 46{,}027$; 49% single), political views ("Liberal"/"Conservative"; $n = 9{,}752$;

Author contributions: M.K. and T.G. designed research; M.K. and D.S. performed research; M.K. and T.G. analyzed data; and M.K., D.S., and T.G. wrote the paper.

Conflict of interest statement: D.S. received revenue as owner of the myPersonality Facebook application.

This article is a PNAS Direct Submission.

Freely available online through the PNAS open access option.

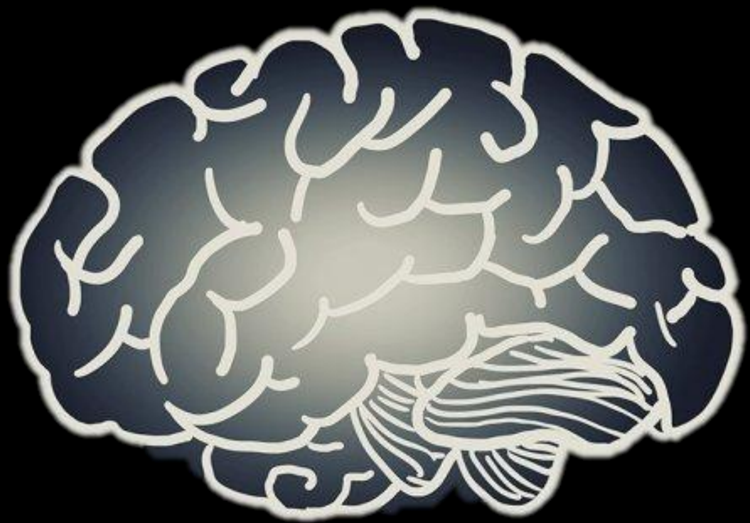
Data deposition: The data reported in this paper have been deposited in the myPersonality Project database (www.mypersonality.org/wiki).

[1]To whom correspondence should be addressed. E-mail: mk583@cam.ac.uk.

This article contains supporting information online at www.pnas.org/lookup/suppl/doi:10.1073/pnas.1218772110/-/DCSupplemental.

 www.pnas.org/cgi/doi/10.1073/pnas.1218772110

Big Five



Michael Kozinsky

Cambridge Analytica

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The main Features of data science

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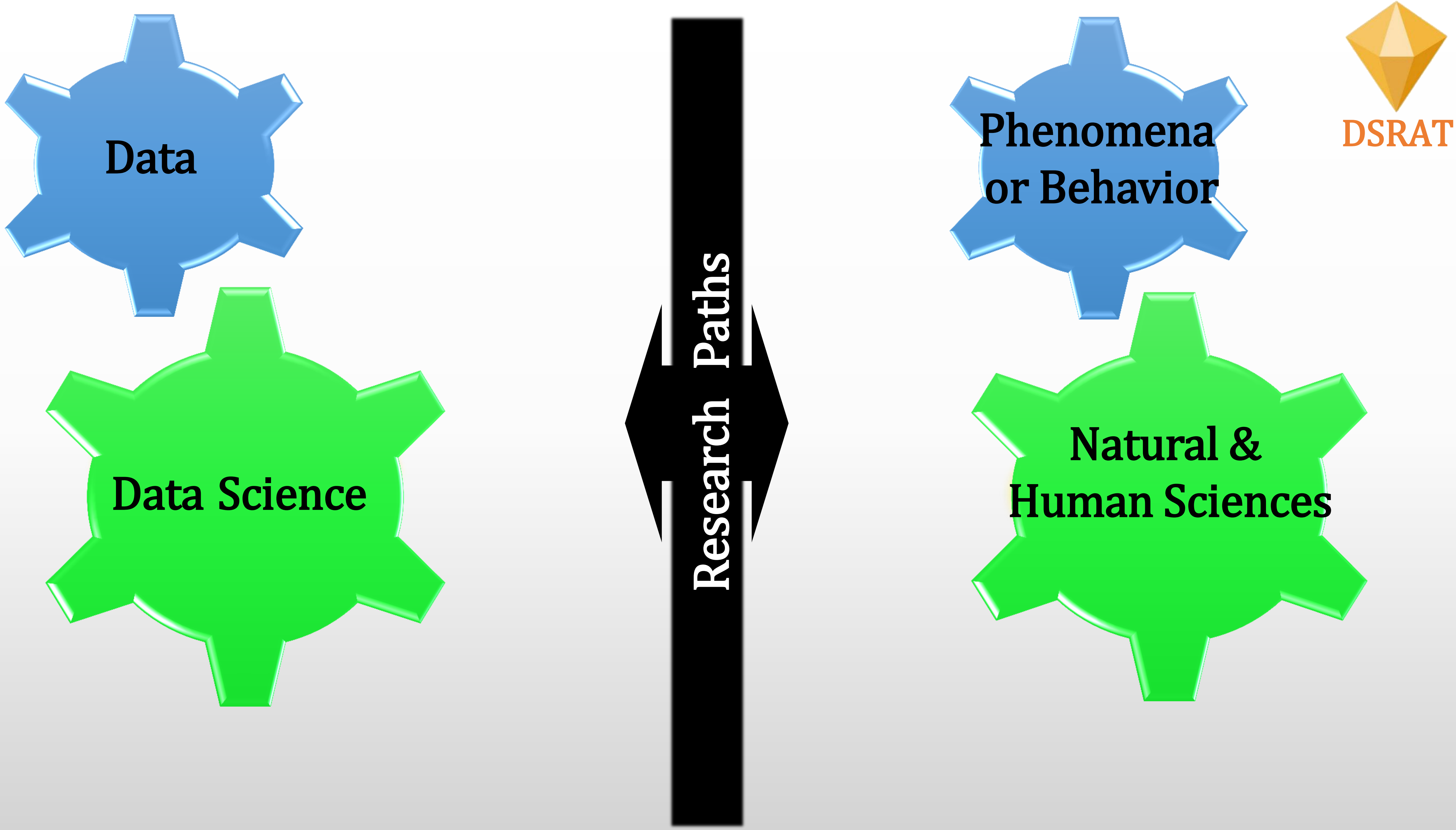
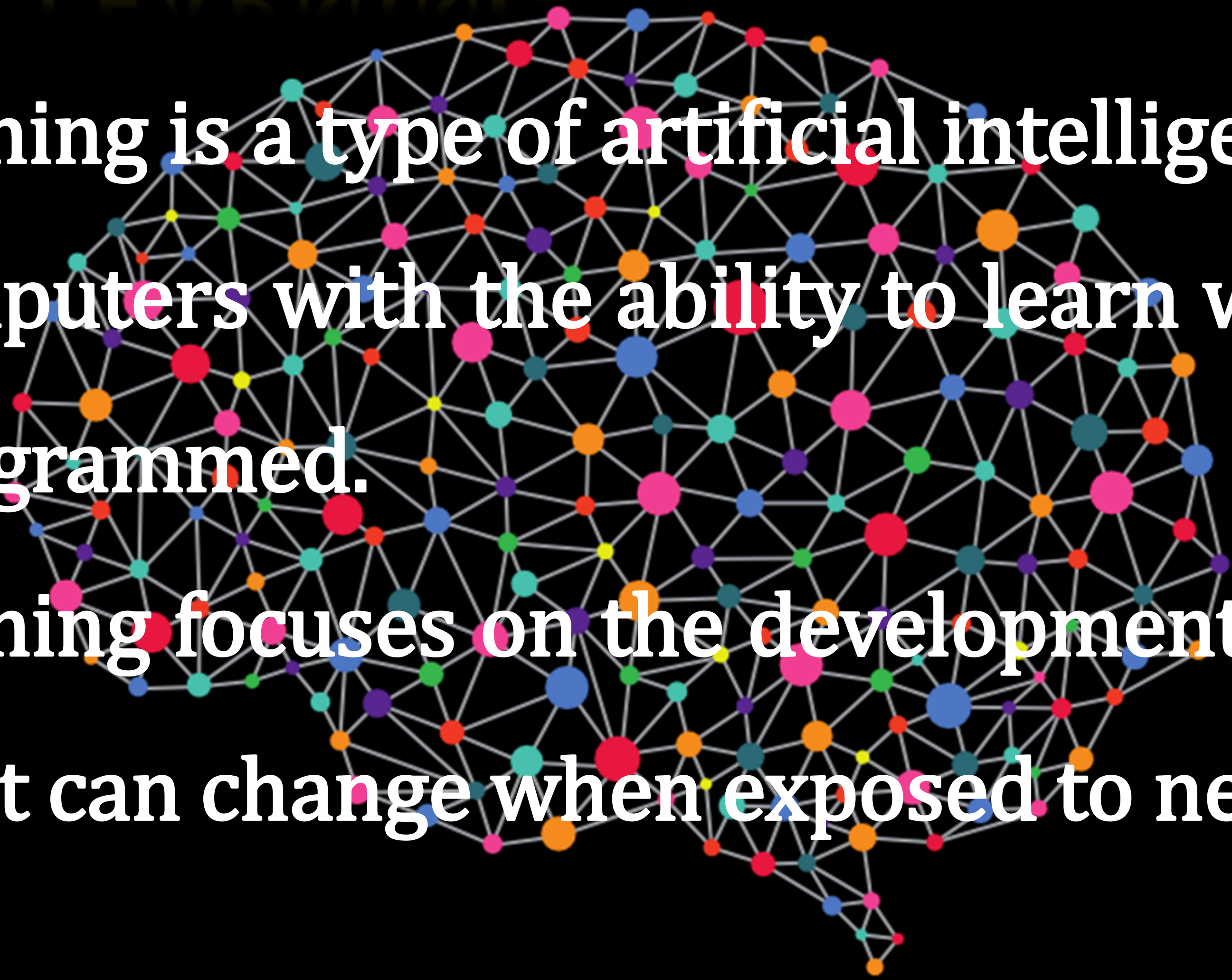

Data
Data Science
Research Paths
Phenomena
or Behavior
Natural &
Human Sciences
DSRAT

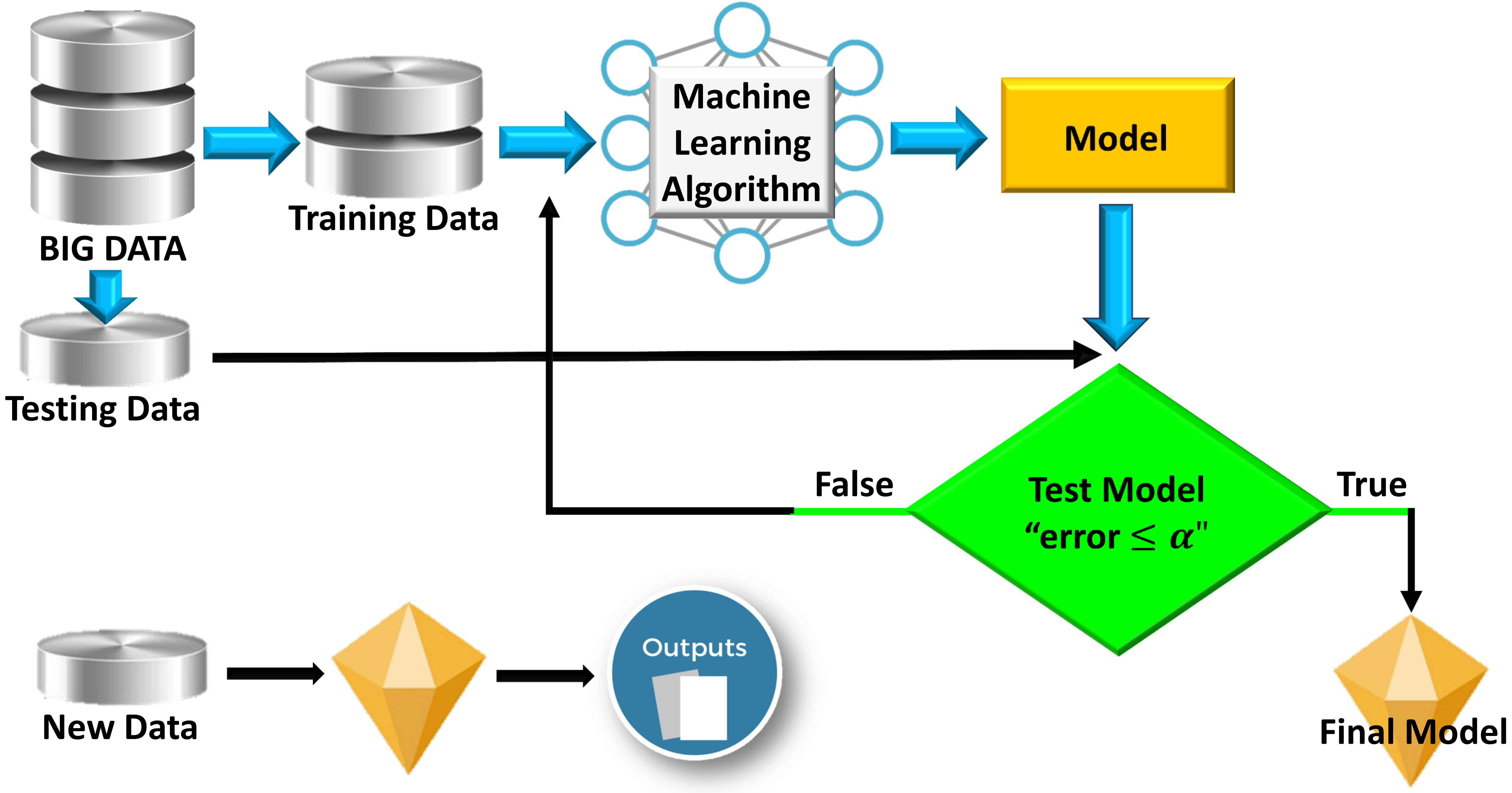
MACHINE LEARNING



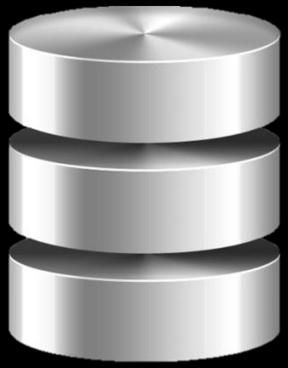
Machine learning is a type of artificial intelligence (AI) that provides computers with the ability to learn without being explicitly programmed.

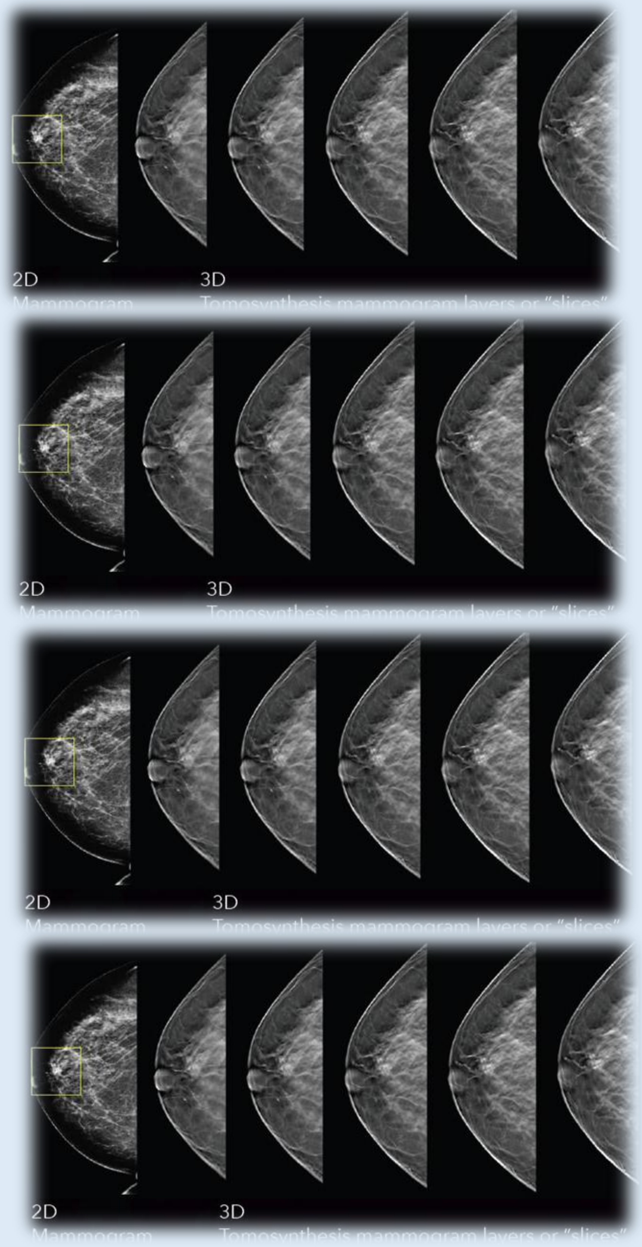
Machine learning focuses on the development of computer programs that can change when exposed to new data.

DSRAT

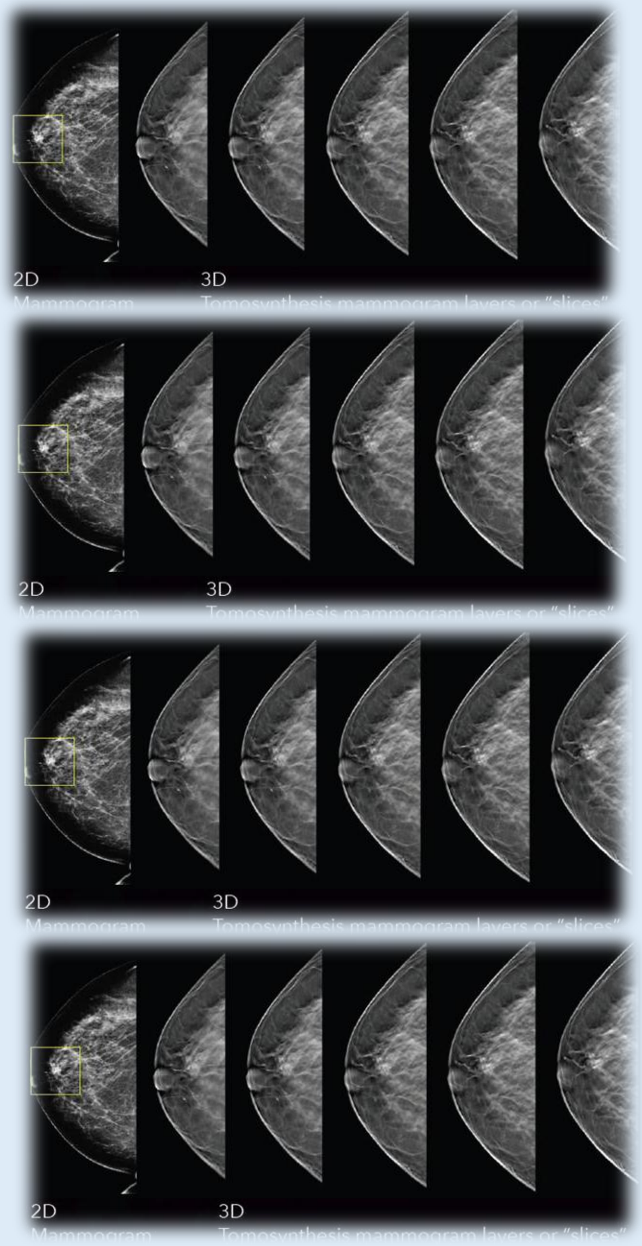

BIG DATA
Training Data
Machine Learning Algorithm
Model
Testing Data
False
Test Model
“error ≤ α"
True
Final Model
New Data
Outputs

BIG DATA

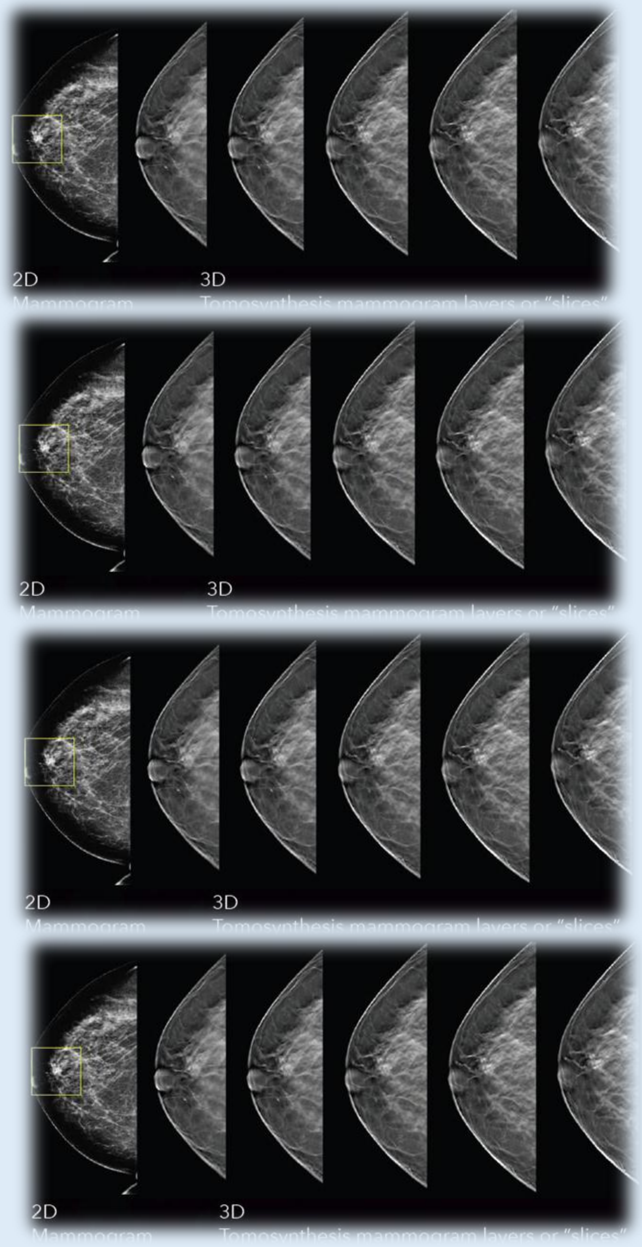




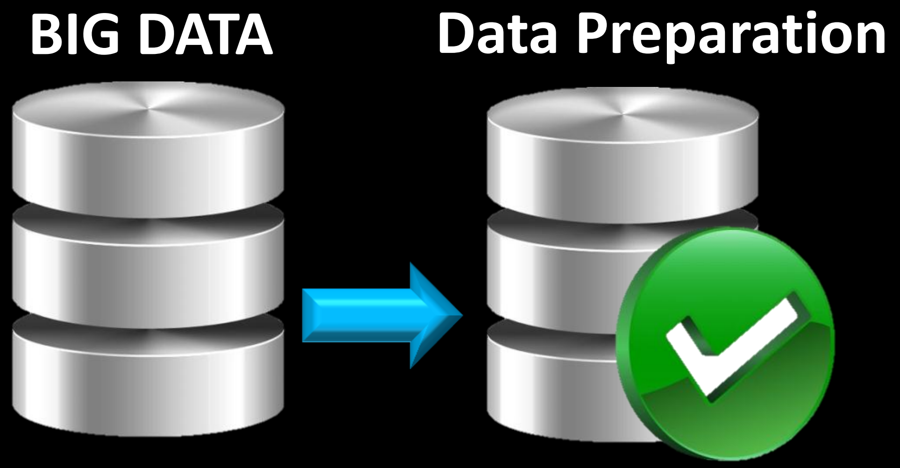
first patient



second patient



Third patient


BIG DATA
Data Preparation

255	255	255	255	255	255	255	255	255	255	255	255	25	25	255	180	99	29
255	255	255	255	255	255	255	255	255	255	109	100	25	25	23	22	22	22
255	255	255	255	255	255	255	255	100	22	22	77	25	25	25	25	25	77
255	255	255	255	255	255	120	22	22	22	22	25	25	25	25	25	25	25
255	255	255	255	117	25	25	25	25	25	25	22	25	21	25	21	25	22
255	255	255	25	25	25	25	25	25	25	21	19	20	21	20	21	20	19
255	240	120	25	25	75	62	60	19	19	19	19	19	21	19	21	19	19
255	100	119	25	25	75	30	22	17	17	15	10	17	21	17	21	17	10
249	120	122	25	25	30	14	14	13	11	11	16	17	21	17	21	17	16
245	80	100	25	25	22	15	14	14	11	11	18	17	21	17	21	17	18
255	84	110	25	25	30	25	22	19	11	11	19	17	21	17	21	17	19
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255	255	255	255	255	255	255	255	255	255	255	255	255	250	100	98	70	77
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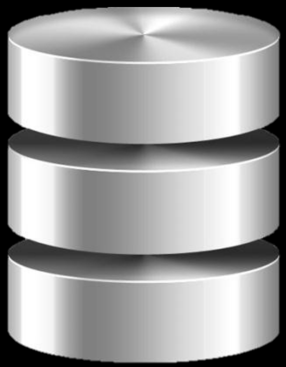
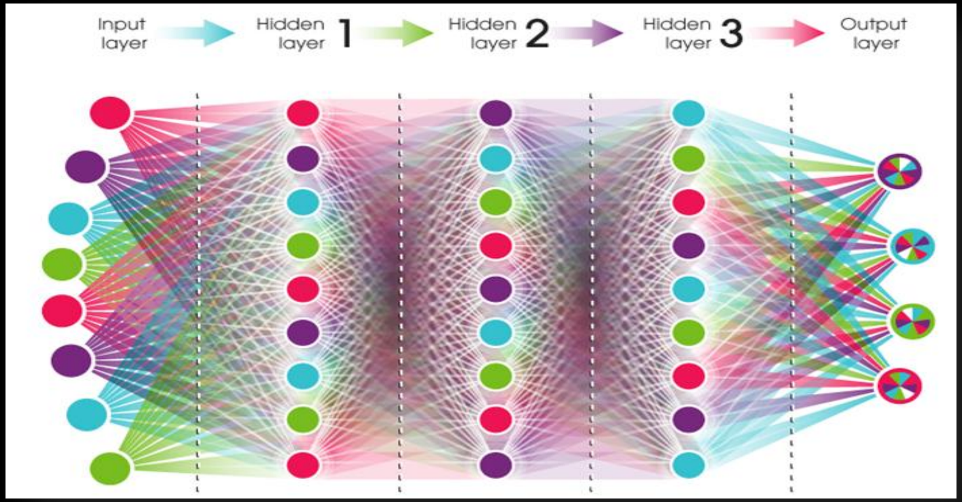
BIG DATA



Data Preparation

Neural Network Model

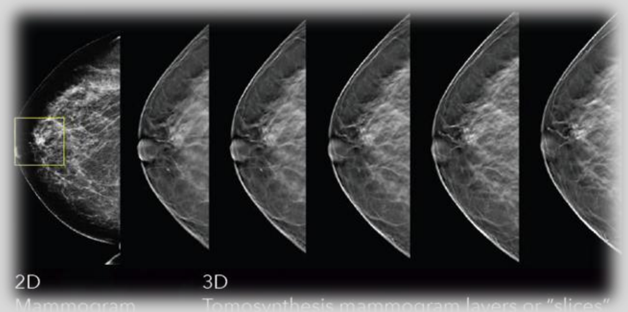


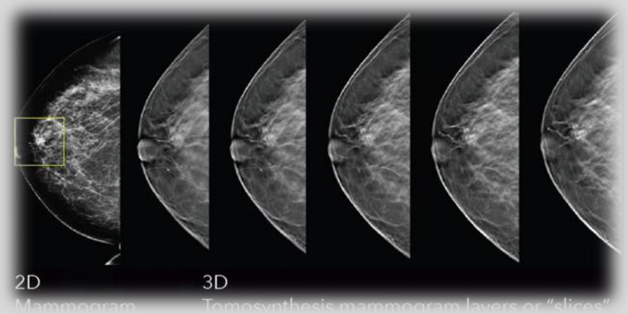
Final Model

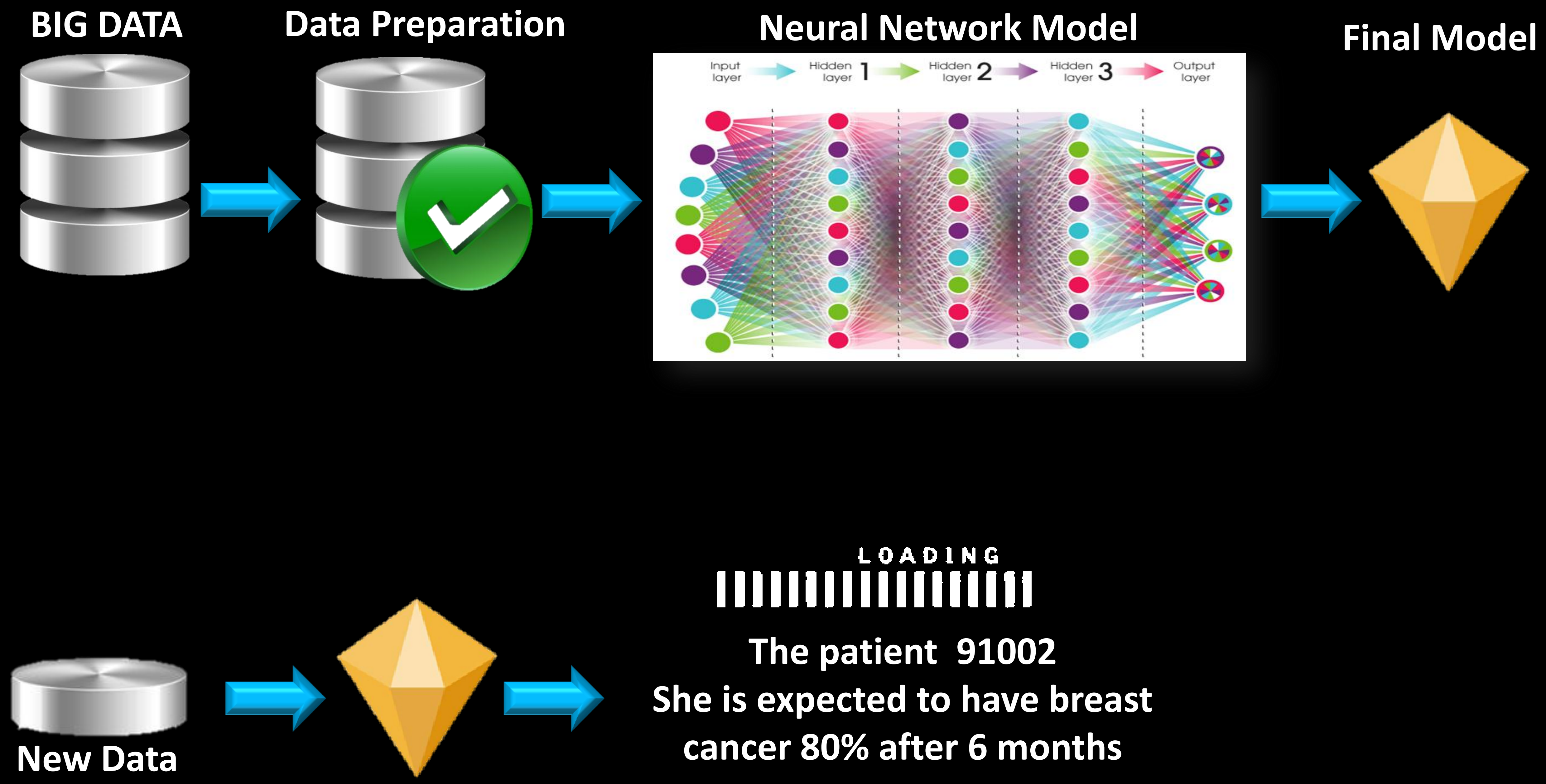
Testing Data

Patient No: 91002
Gender: F
Age: 46

(01)12345678901234(17)140102(11)100102(10)A1234(21)1234






BIG DATA
Data Preparation
Neural Network Model
Input layer
Hidden layer 1
Hidden layer 2
Hidden layer 3
Output layer
Final Model
New Data
LOADING
The patient 91002
She is expected to have breast cancer 80% after 6 months

Approval of Bank Loan

- Age
- Gender
- Profession & Status
- Financial Situation
- Sources of Income
- Property
- Bank Record
- Repayment

255

Scenario

51,

Detection of Fraud
by Smart System

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Fake signature

A Comparative Study on Handwriting Digit Recognition Using Neural Networks

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***Abstract*—The handwritten digit recognition problem becomes one of the most famous problems in machine learning and computer vision applications. Many machine learning techniques have been employed to solve the handwritten digit recognition problem. This paper focuses on Neural Network (NN) approaches. The most three famous NN approaches are deep neural network (DNN), deep belief network (DBN) and convolutional neural network (CNN). In this paper, the three NN approaches are compared and evaluated in terms of many factors such as accuracy and performance. Recognition accuracy rate and performance, however, is not the only criterion in the evaluation process, but there are interesting criteria such as execution time. Random and standard dataset of handwritten digit have been used for conducting the experiments. The results show that among the three NN approaches, DNN is the most accurate algorithm; it has 98.08% accuracy rate. However, the execution time of DNN is comparable with the other two algorithms. On the other hand, each algorithm has an error rate of 1–2% because of the similarity in digit shapes, specially, with the digits (1,7) , (3,5) , (3,8) , (8,5) and (6,9).**

Keywords* —*Handwriting Digit Recognition; Neural Network; CNN; DNN; DBN

I. Introduction

Nowadays, more and more people use images to represent and transmit information. It is also popular to extract important information from images. Image recognition is an important research area for its widely applications[1, 2]. In the relatively young field of computer pattern recognition, one of the challenging tasks is the accurate automated recognition of human handwriting. Indeed, this is precisely a challenging problem because there is a considerable variety in handwriting from person to person. Although, this variance does not cause any problems to humans, yet, however it is more difficult to teach computers to recognize general handwriting [3]. For the image recognition problem such as handwritten classification, it is very important to make out how data are represented in images[1]. The data here is not the row pixels, but should be the features of images which has high level representation[2, 4]. For the problem of handwritten digit recognition, the digit's structure features should be first extracted from the strokes. Then the extracted features can be used to recognize the handwritten digit. The high performance of large-scale data processing ability is the core technology in the era of big data. Most current classification and regression machine learning methods are shallow learning algorithms [4]. It is difficult to represent complex function effectively, and its generalization ability is limited for complex classification problems[5, 6]. Deep learning is a multilayer neural network learning algorithm which emerged in recent years. Applications of deep learning to various problems have been the subject of a number of recent studies ranging from image classification and speech recognition to audio classification [5, 7-9]. It has brought a new wave to machine learning, and making artificial intelligence and human-computer interaction advance with big strides. Deep Learning algorithms are highly efficient in image recognition tasks such as MNIST digit recognition[10].

In this paper, we apply deep learning algorithms to handwritten digit recognition, and explore the three mainstream algorithms of deep learning; the Convolutional Neural Network (CNN), the Deep Belief Network (DBN) and the Deep Neural Network (DNN)[4].

II. BACKGROUND

In this section, we give an overview of the three algorithms and the tools employed in our paper: -

A. Convolutional Neural Network (CNN):

A simple CNN model can be seen in Fig. 1. The first layer is the input layer; the size of the input image is 28 × 28. The second layer is the convolution layer C2, it can obtain four different feature maps by convolution with the input image. The third layer is the pooling layer P3. It computes the local average or maximum of the input feature maps [11].

The next convolution layer and pooling layer operate in the same way, except the number and size of convolution kernels. The output layer is full connection; the maximum value of output neurons is the result of the classifier in end [12].

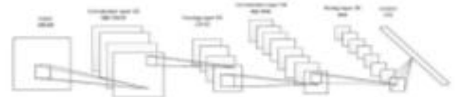

Fig. 1. A simple structure of CNN [13] .

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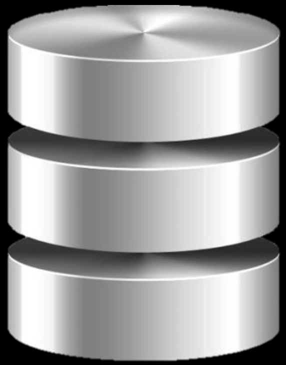
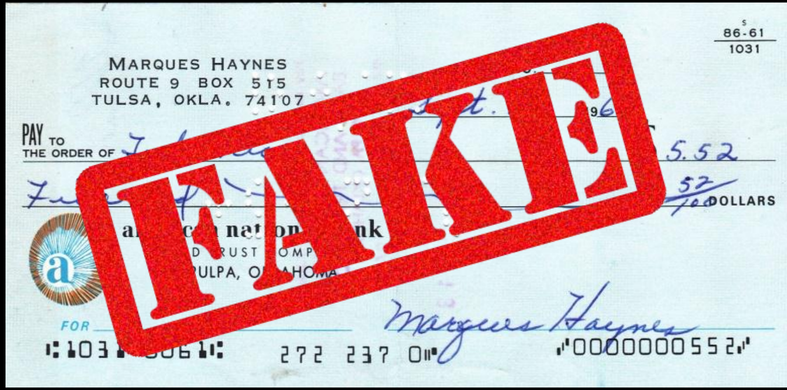
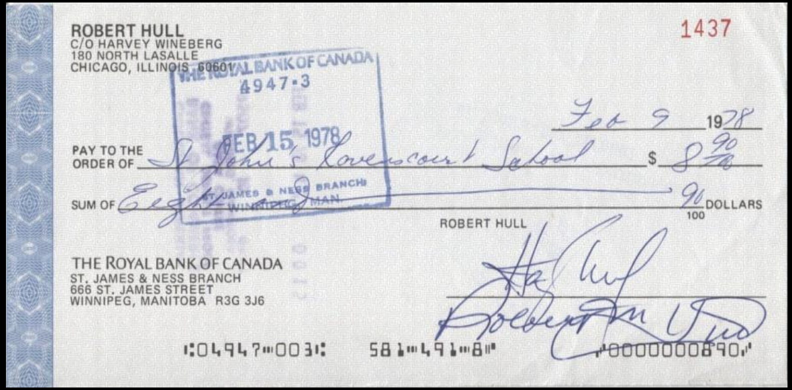
BIG DATA




MARQUES HAYNES
ROUTE 9 BOX 515
TULSA, OKLA. 74107
86-61
1031
PAY TO THE ORDER OF
DOLLARS
FAKE
FOR
Marques Haynes


ROBERT HULL
C/O HARVEY WINEBERG
180 NORTH LASALLE
CHICAGO, ILLINOIS 60601
1437
THE ROYAL BANK OF CANADA
4947-3
FEB 15 1978
Feb 9 1978
PAY TO THE ORDER OF
St. John's Ravenscourt School
$ 8 90/100
SUM OF
DOLLARS
ROBERT HULL
THE ROYAL BANK OF CANADA
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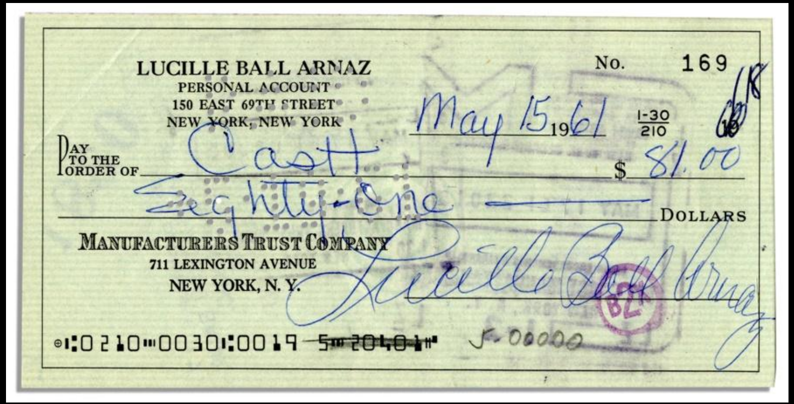
666 ST. JAMES STREET
WINNIPEG, MANITOBA R3G 3J6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PERSONAL ACCOUNT
150 EAST 69TH STREET
NEW YORK, NEW YORK
No. 169
May 15 1961
1-30
210
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Eighty-One
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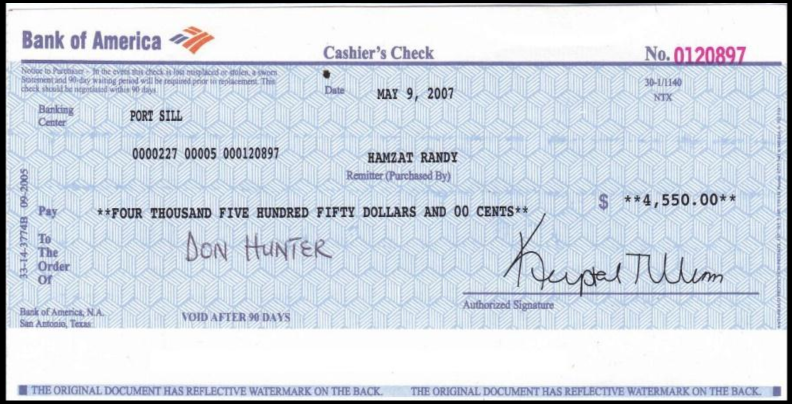
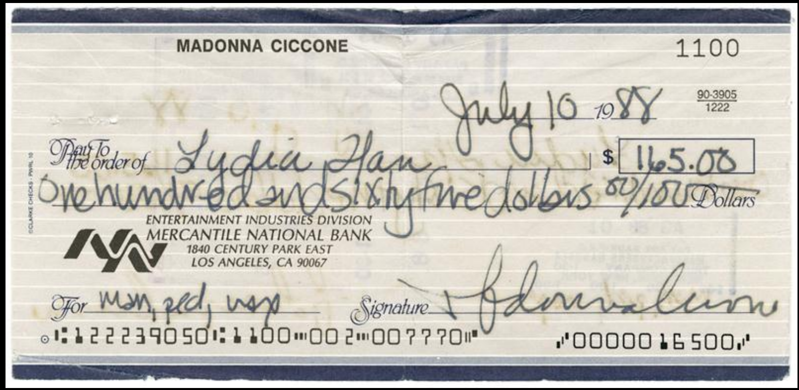
MANUFACTURERS TRUST COMPANY
711 LEXINGTON AVENUE
NEW YORK, N. Y.
Lucille Ball Arnaz


Bank of America
Cashier's Check
No. 0120897
Date MAY 9, 2007
Banking Center PORT SILL
0000227 00005 000120897
HAMZAT RANDY
Remitter (Purchased By)
$ **4,550.00**
Pay **FOUR THOUSAND FIVE HUNDRED FIFTY DOLLARS AND 00 CENTS**
To The Order Of DON HUNTER
Authorized Signature
Bank of America, N.A.
San Antonio, Texas
VOID AFTER 90 DAYS
THE ORIGINAL DOCUMENT HAS REFLECTIVE WATERMARK ON THE BACK.


WAITE C. HOYT
2303
13-1
420
DOLLARS
FAKE


OFFICIAL CHECK
citibank
SLSVC-829599055
CLOSE
Pay Exactly
PAY TO THE ORDER OF
DEREK J BALLING
557 BROADWAY APT. 37A
PORT EWEN NY 12466-5510
DEREK J BALLING


MADONNA CICCONE
1100
July 10 1988
90-3905
1222
Pay To the order of Lydia Han
$ 165.00
One hundred and sixty five dollars 00/100 Dollars
ENTERTAINMENT INDUSTRIES DIVISION
MERCANTILE NATIONAL BANK
1840 CENTURY PARK EAST
LOS ANGELES, CA 90067
For
Signature


2PACALYPSE ENTERTAINMENT
805-254-7995
23236 WEST LYONS AVE.
NEWHALL, CA
111
11-24/295
1210(8)
PAY TO THE ORDER OF
$
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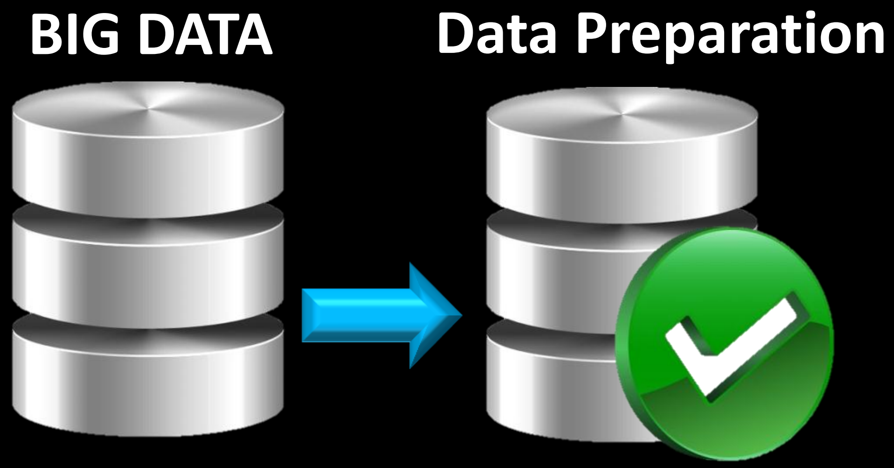
FAKE
MEMO


BIG DATA
Data Preparation

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255	174	94	51	52	78	200	94	255	255	255	255
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255	114	255	130	145	255	255	255	255	255	255	255
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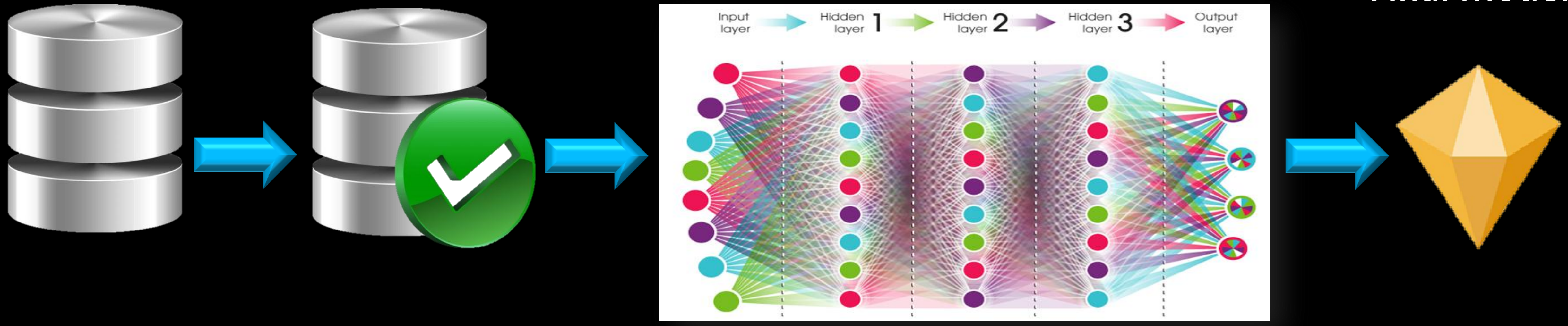
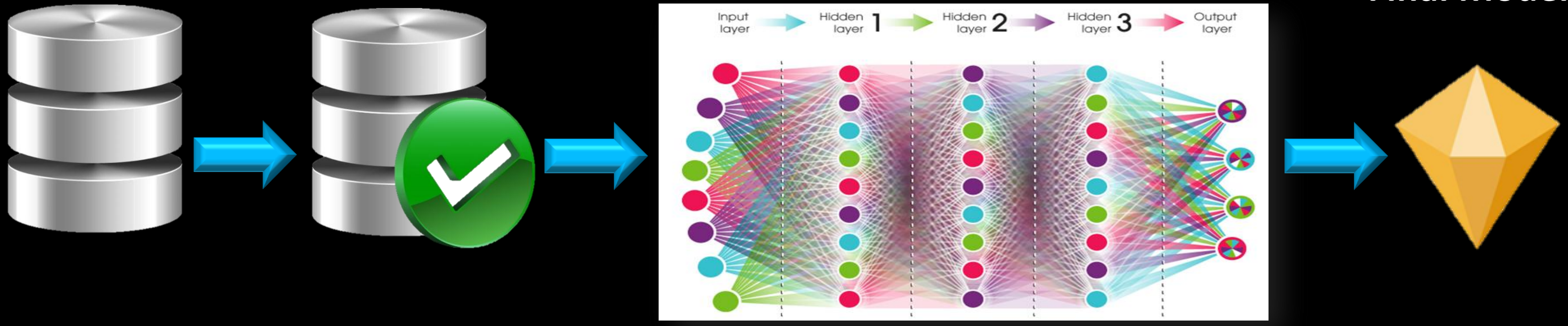
BIG DATA → Data Preparation → Neural Network Model → Final Model



BIG DATA Data Preparation Neural Network Model Final Model



New DATA

Client Barcode:

⑆1241023921⑆0707847101⑈ 0493⑈

ELSA M. IRWIN
OR CHARLES A. IRWIN
RT. 1 BOX 3590
DRIGGS, ID 83422

493

8 May 19 91

92-239/1241

Pay to the order of Pikes Peak Numismatic Assoc. $ 19.80

Nineteen and 80/100 Dollars

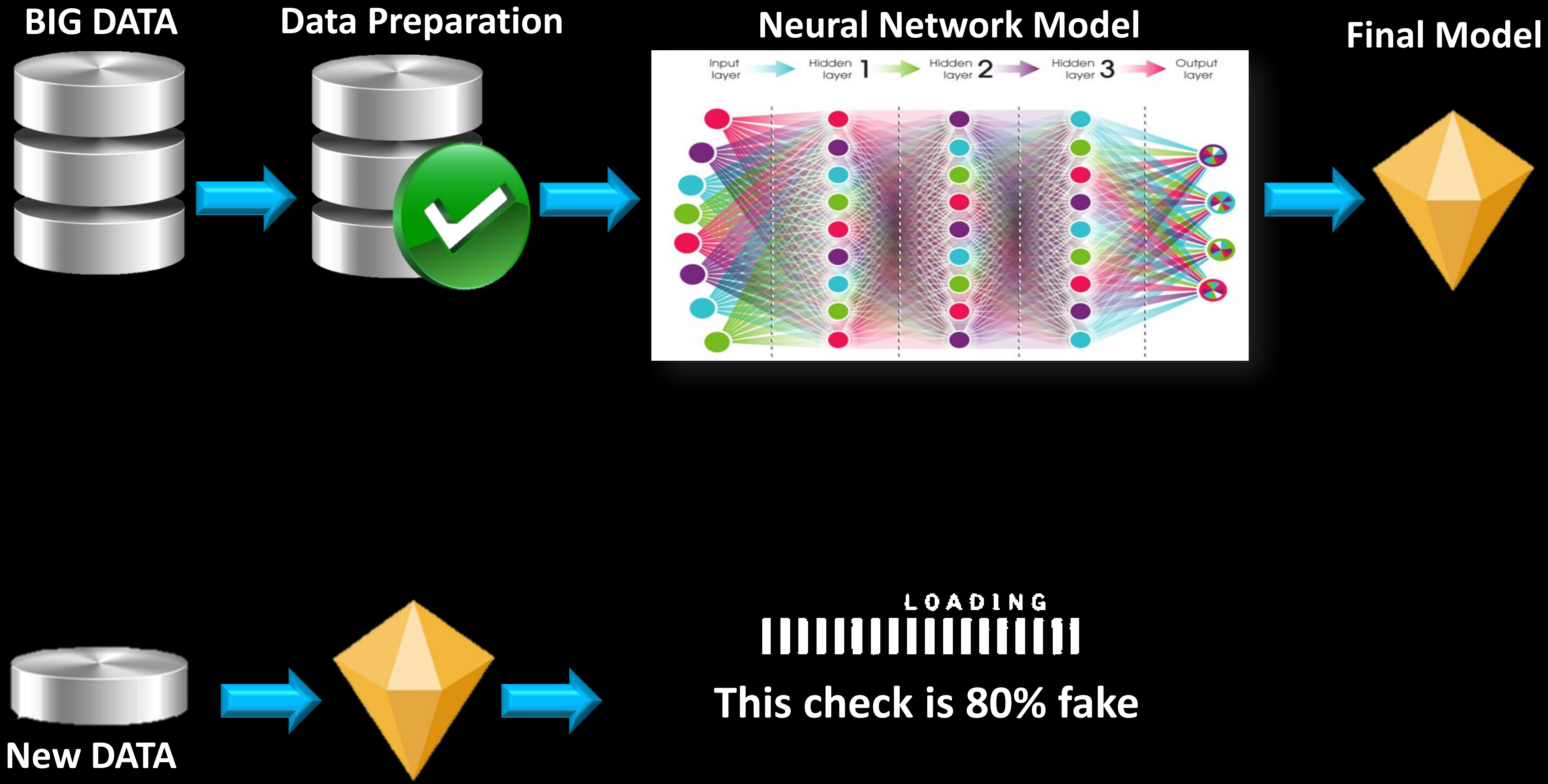
VALLEY BANK
Gold Account
P.O. BOX B DRIGGS, IDAHO 83422

For

James B. Irwin

⑆1241023921⑆0707847101⑈ 0493⑈ ⑈0000001980⑈

Rocky Mountain Bank Note B


BIG DATA
Data Preparation
Neural Network Model
Input layer
Hidden layer 1
Hidden layer 2
Hidden layer 3
Output layer
Final Model
New DATA
LOADING
This check is 80% fake

IBM TECHNOLOGY

The IBM technology is one of the most important software's used to apply Data Science on Big Data & Cyberspace Data.

The most important features of IBM technology

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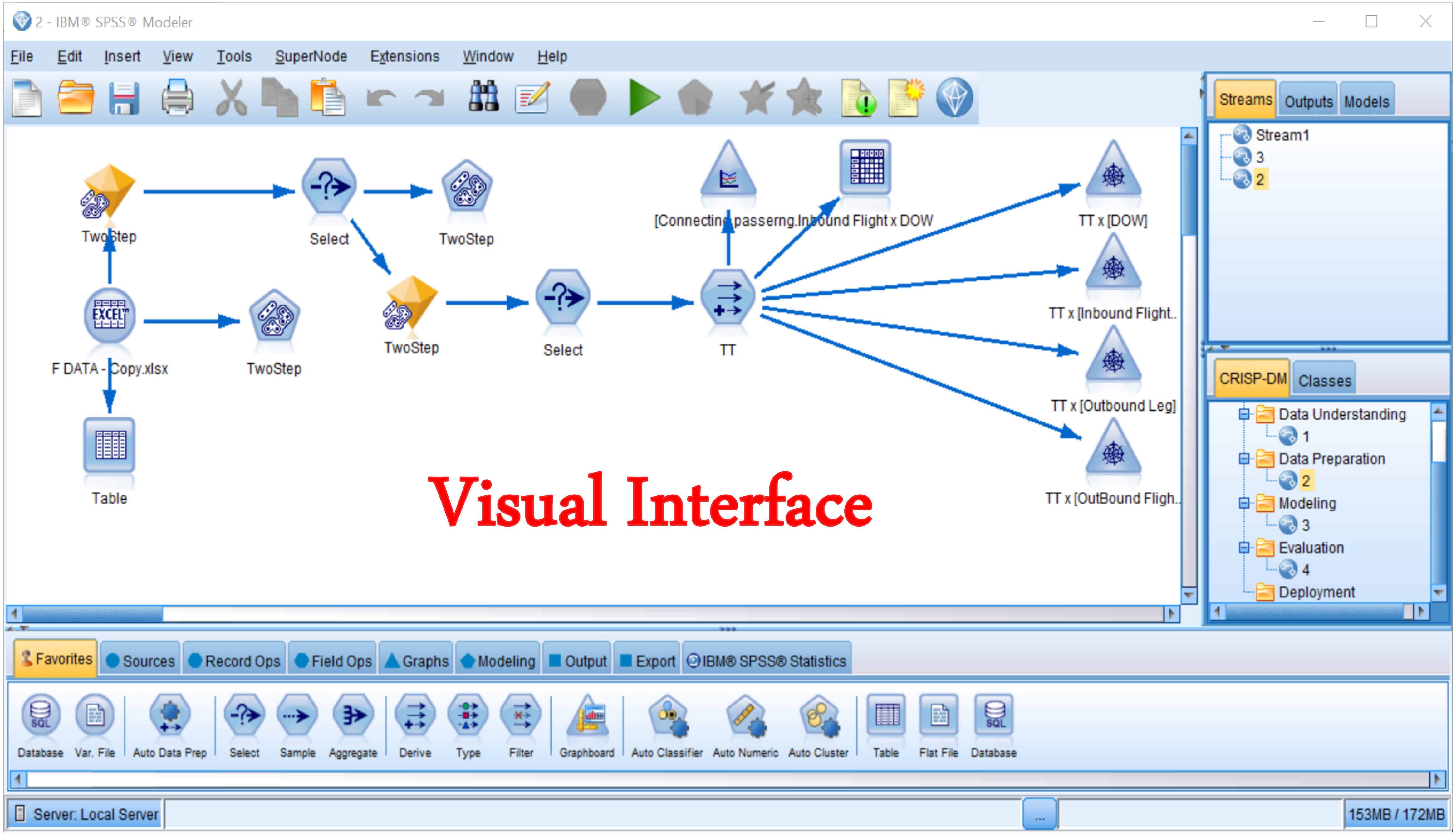
2 - IBM® SPSS® Modeler
File Edit Insert View Tools SuperNode Extensions Window Help
Streams Outputs Models
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TwoStep
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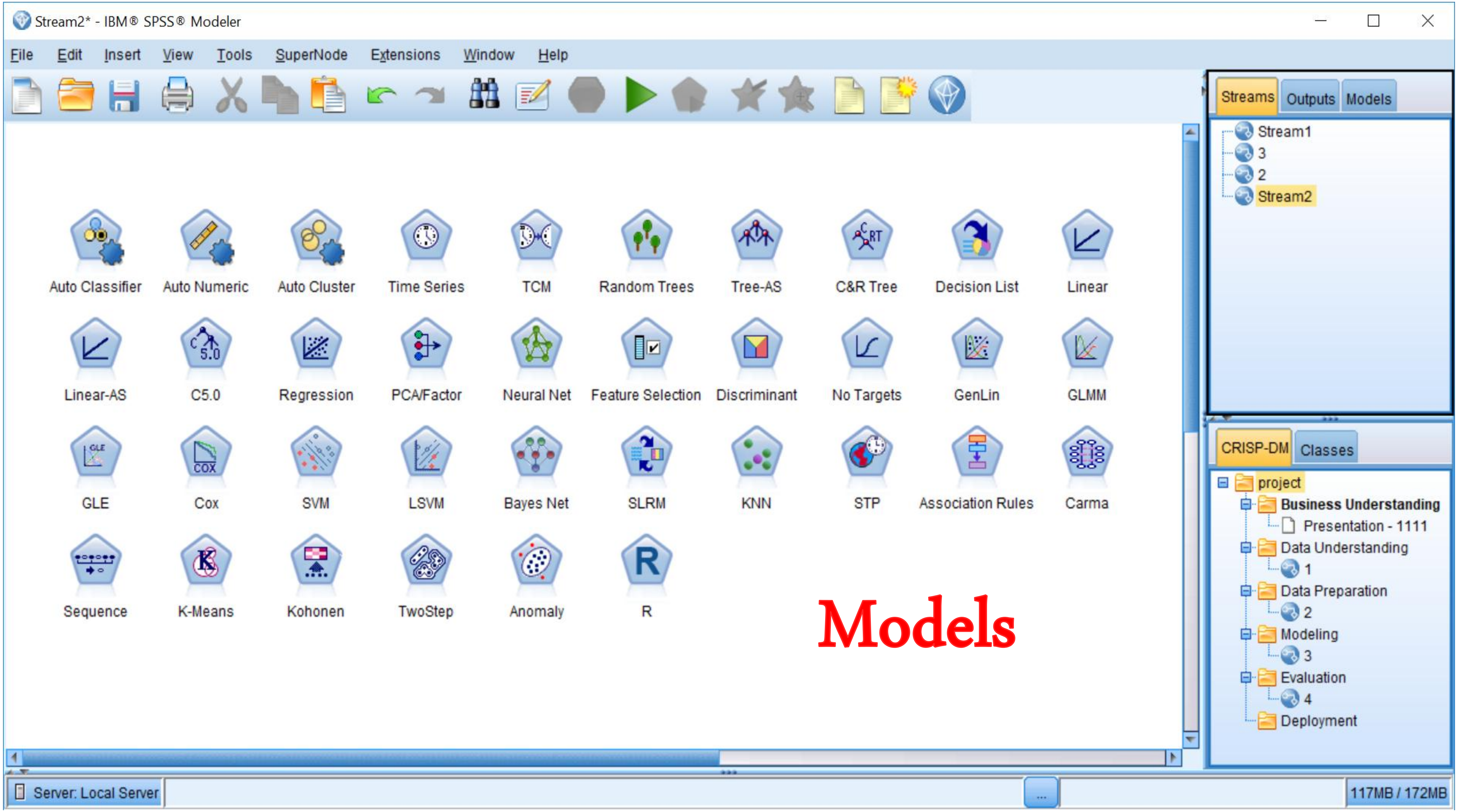
Table
Visual Interface
CRISP-DM Classes
Data Understanding
1
Data Preparation
2
Modeling
3
Evaluation
4
Deployment
Favorites Sources Record Ops Field Ops Graphs Modeling Output Export IBM® SPSS® Statistics
Database Var. File Auto Data Prep Select Sample Aggregate Derive Type Filter Graphboard Auto Classifier Auto Numeric Auto Cluster Table Flat File Database
Server: Local Server
153MB / 172MB

Data Engineering Tools


Stream2* - IBM® SPSS® Modeler
File
Edit
Insert
View
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SuperNode
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Window
Help
Streams
Outputs
Models
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3
2
Stream2
Auto Classifier
Auto Numeric
Auto Cluster
Time Series
TCM
Random Trees
Tree-AS
C&R Tree
Decision List
Linear
Linear-AS
C5.0
Regression
PCA/Factor
Neural Net
Feature Selection
Discriminant
No Targets
GenLin
GLMM
GLE
Cox
SVM
LSVM
Bayes Net
SLRM
KNN
STP
Association Rules
Carma
Sequence
K-Means
Kohonen
TwoStep
Anomaly
R
Models
CRISP-DM
Classes
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Business Understanding
Presentation - 1111
Data Understanding
1
Data Preparation
2
Modeling
3
Evaluation
4
Deployment
Server: Local Server
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Weather in
Amman
Jordan

IBM SPSS MODELER

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Future Education
2020 - 2030

by

DSRAT

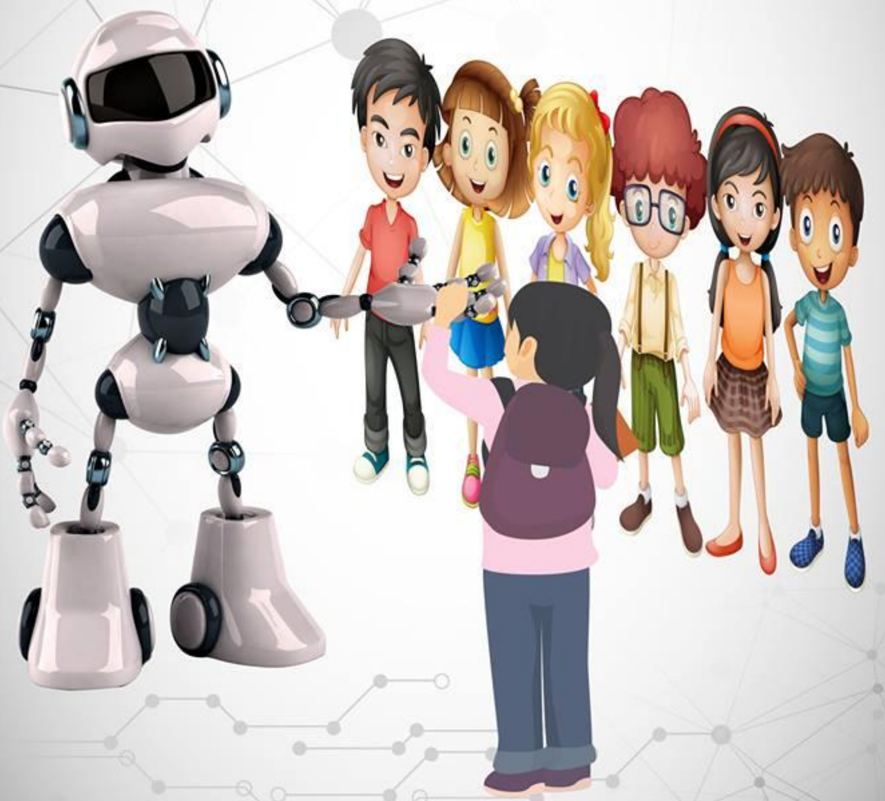
Data Science Research Arab Team

فريق أبحاث علم البيانات العربي

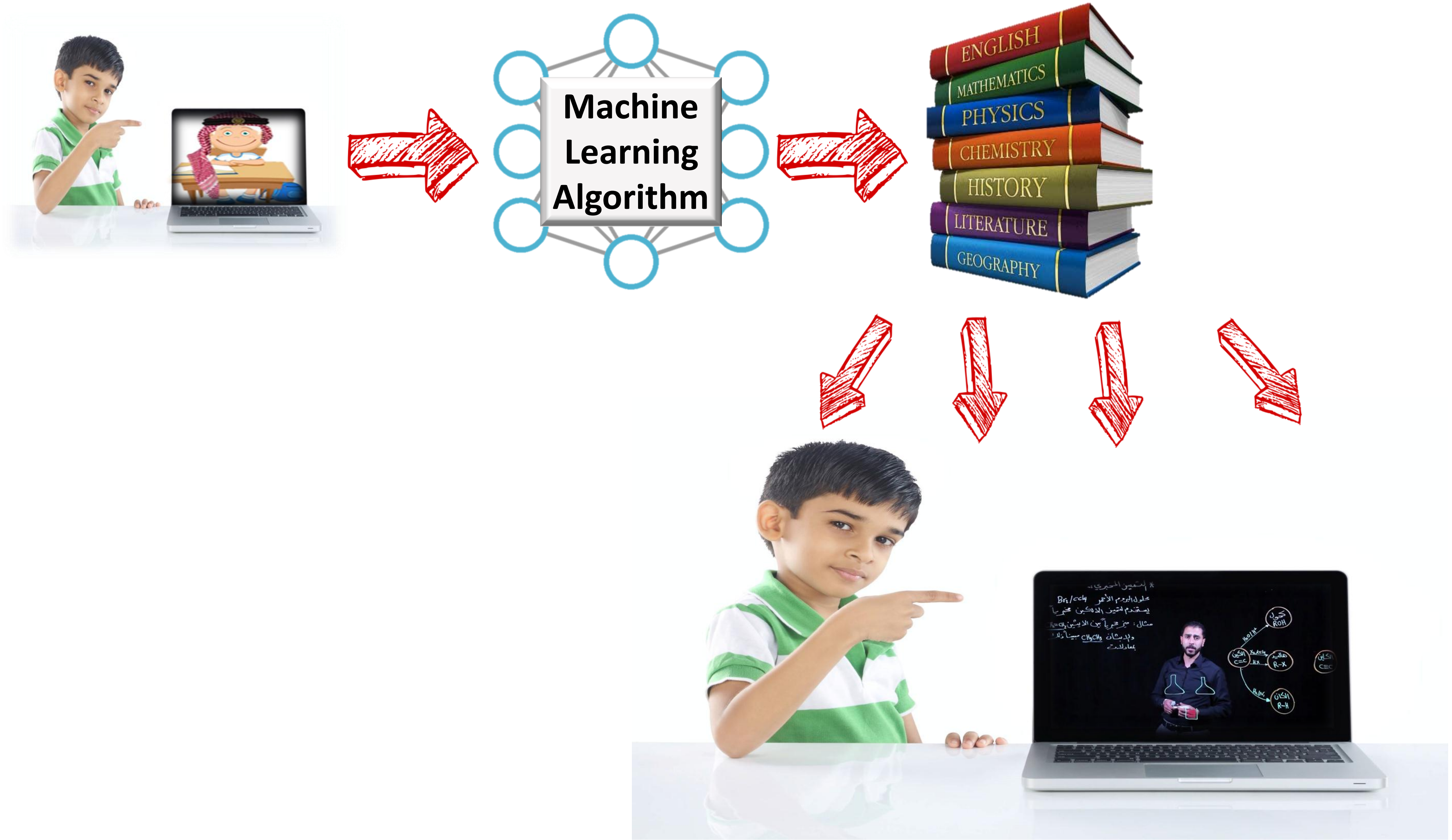
Be Different

Education Directed

2020 - 2030



Ahmad Alamm - Hussam Awwad - Saleh Hammouri


Machine Learning Algorithm
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PHYSICS
CHEMISTRY
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LITERATURE
GEOGRAPHY

Thanks

Data scientist

AHMAD ALAMM

2018

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