



DATA AXIS MUNDI

Professeur Serge Miranda (UCA)

Seminar is going to start at 2pm (CET)









Professeur Serge Miranda

(miranda.serge@gmail.com)

Director of MBDS (and eMBDS) Master degrees at UCA <u>www.mbds-fr.org</u> & MS BIHAR (and eBIHAR) at ESTIA



Series of ESTIA webinars on **« AI and BIG DATA »**

for students from MBDS, BIHAR, eBIHAR (and its GRADEOs), Miage (ANR THEMES) and ...others

To register :

https://forms.office.com/Pages/ResponsePage.aspx?id=vCENNyq VPkmiyRPPoeY1IMbaYPunPfpDvd2_5dohilhUOEhMVIMzR0tXTk U0RzdIQTBZNIhIMVgxVS4u&qrcode=true





ESTIA·Webinars·on[¶] Artificial·intelligence·and··Big·Data[¶] ··MSc·BIHAR·MSc·(·2020-2021)[¶]

 Open-to-graduate-students-and-companies-II

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 Importance of the experiment of the experi

To·register·:·1











MBDS and BIHAR : Two CS masters on DATA Technologies with an INNOVATION laboratory on USAGE engineering (disruptive ICT technologies)





MBDS (Mobiquitous BIG-DATA Systems)





(Big data Intelligence for Human Augmented Reality)*







Changing the world of professional learning



* « BIHAR » means « TOMORROW » in Basque Language

ch.	Serge Miranda	Edit your profile
Sault -	© SergeM06 Professor of CS, New Technologies, University of Nice Sophia Antipolis, founder of MBDS master degree and DreamIT University foundation http://www.mbds.tr.org	2,607 TWEETS
460		906 FOLLOWING
1.		621 FOLLOWERS

The two first MOOC-based European master degrees in CS in Europe : eMBDS (UCA) in 2019 and eBIHAR (ESTIA) in 2020 with ORACLE as a professional partner and great feedback

The two first GRADEOs (micromasters) in Europe on FUN MOOC plaform on BIG DATA and AI on January the 4th < for continuous education>



« I'm writing to you to express my gratitude for the courses I took at University of Nice. It was great to be a part of E-mbds program. I was very pleased with the selection of courses as they covered the latest and greatest technologies on the market. I also was impressed with professors' knowledge level, and amount of work they put into their classes. I hope I will have an opportunity to take other classes at your University in the future. Please keep me informed on your future programs. » Irina Mok, Oracle Senior Manager Software Development (Oracle USA)



« It was awesome being a part of the eMBDS learning program! I never imagined MOOCs and online learning could be so effective and was apprehensive initially when i signed up but as I progressed through the courses, i felt more confident that this degree would definitely help enrich my skills and help me at my work place and further educational endeavors. Some of my personal favorites were the courses on Javascript, Native Mobile Programming and the ones on Data Mining and Machine Learning. In addition, the Oracle University courses were also very detailed with hands-on lab sessions. A big thank you to (Datum Academy) namely Mishket Hamida, Betty Schmitt for being available and patiently answering all my questions on the administrative part and to all the professors for the wonderful MOOCs, live sessions and support on the courses."

-Amrita Panda, Principal QA Analyst (Oracle USA)



"I'm very pleased that I was one of the first students who graduated Master of Computer Science degree program based on MOOCs. The eMBDS program offered by the University of Nice with a partnership with Datum academy and Oracle University will boost your technical knowledge and allows you to master all hands-on expertise in emerging technology. At the same time, you will have a chance to adopt Oracle technology and gain professional certificates from Oracle University. It is big deal. Thank you very much to all of our professors, faculty staff, facilitators, and their support and collaboration. I can recommend this unique opportunity to anyone who wants to advance their career and deepen their IT credentials."

Zolbayar Zorigoo, Orale Senior Sales Consultant (Oracle Romania)



"Course content is very apt and adheres to current IT trends, I really liked the graduate course content. It includes Big Data, Mobile Technologies, Javascript, Database, Agile, NFC, Blockchain etc. All the courses included in eMBDS are must for any IT Professional. Really liked the content of each of the courses : it covers all the basic and intermediate levels of content. Later individuals can scale themselves to Expert Level. As a conclusion, eMBDS is a very good on-line master degree for any person who wants to improve their skills and keep themselves updated; it includes all the latest technologies. I would highly recommend taking it up mainly because of the course content and the great support from Datum Academy. This online course would be difficult or impossible without great support from Datum Academy". Dharmendra Singh, Oracle Principal Software Engineer (Oracle India) B

DATA AXIS MUNDI!

« AXIS MUNDI ? »









Q1 : Quantity of DATA produced since the beginning of humanity (5000 years ago)? Produced evey second on Internet ?

Quantité de données produite depuis le début de l'écriture il y a 5000 ans (Google)? et aujourd 'hui par seconde (UC Berkeley) ?

>Q2 : Quantity of data to get a digital twin ?

Quantité de données utile pour construire un double numérique « complet » (Jim Gray et Digital Immortality) ?

```
1 TERA BYTES : 10**12
1 PETA BYTES : 10**15
1 EXA BYTES : 10**18
1 ZETA BYTES : 10**21
1 YOTTA BYTES : 10**24
```



March 2020 and COVID Confinement → paradigm switch in a new data-centrics digital era of ANTHROPOCENE





- Digital transformation: e-services, e-commerce, NFC payment, e-life
 - eHEALTH : Doctolib with 100 000 queries a day (April 2020)
 - Remote working : Ex : Zoom : 300 million meeting connections a day (in April 2020) < 10 million in Dec 2019> ; 1st app on Appstore (August 2020)
 - Blended Learning : from centripete university to centrifugal multiversity

zoom and Moocs!

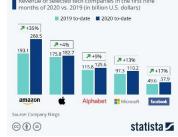




Wall Street jette le masque

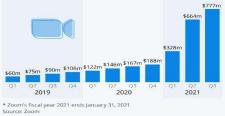
A U RYTHME où ca va, Acple vaudra bientôr plus cher que tout le CAC 40 réuni ! A lui seul, il dépasse les 1 500 miliards de dollars. Mi- crosoft itou. Et Amazon vient de passer les 1 000 miliards. Jamais Wall Street n'avait au- tant pété la forme. Il faut re- monter à 1998, remarquent «Les Echos » (1/7), pour trou- ver un trimestre « aussi flam- boyant ». On a failli s'inquiéter. Le Covid a entraîné une chute	« vertigineuse » des marci financiers. Mais le rebond « spectaculaire ». En un to nemain, les effets du krach- tét aux trois quarts effacés faut dire que les fameux Gafa les mastodontes américains Net et du high-tech, s'en s mis plein les poches. Le té travail, le téléconseignement, téléréunions, la télémédeci la téléconnerie, le téléconme ont connu un succès foudroy. On attend la deuxième va ovec imericante.
Covid a entraîné une chute	avec impatience

Tech Giants Shrug Off COVID-19 Crisis Revenue of selected tech companies in the first nine



Zoom's Revenue Skyrockets On Pandemic Boost

Quarterly revenue of Zoom Video Communications*



 \odot () (=)

statista 🗹

Some news in the last six days and WEBINAR CONTENTS

December the 2nd :

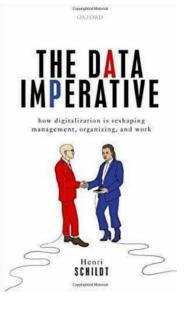
blended learning « ADIEU aux AMPHIS (Farewell amphiteatres) » LE MONDE Diplomatique, December the 2nd : « May 1968 dream it and virus made it »

ARTIFICIAL INTELLIGENCE and medecine <u>https://siecledigital.fr/2020/12/02/sante-intelligence-artificielle-deepmind-proteines</u>

December the 4th : Tweet on a <u>QR Code</u> built with 130 000 trees in China !

December the 5th : New book :
 « The DATA imperative » on BIG DATA applications

December the 7th : SAS Research report : « Innovation : from DATA to BUSINESS »





Le Monde diplomatique (carnets) mercredi 2 décembre 2020 1367 mots

L'adieu aux amphis

Alain Garrigou

Data hai anaka 1960, "Ingulandi ma dhafhi dulada data hai tu ba paga d'Angu rista angu paga di angu rista data angu paga di angu rista data angu paga di angu rista data angu paga di ang

Course in homogeners, the surplication of homo is too contributions and a deptice control and the gives lateration of paths (a studie due to subprise) in the surplication of the studies of the studies of the studies of the paths (a studie due to subprise). The studies are studies of the studies of the studies of the studies (a studie due to subprise) and (a studies) and (a stu



GLOBAL RESEARCH STUDY Innovation: From Data to Business.

Peer insights to help you navigate the journey to analytically driven innovation

Santé : une intelligence artificielle résout u problème vieux de 50 ans Cette découverte pourrait aider à quérir le paludisme et certaines formes de cancers.

PAUNDer MARK And Krist Standers 2020 Stands





Pauline Escande-Gauquié et Bertrand Naivin COMPRENDRE LA CULTURE NUMÉRIQUE Abécédaire **Un auteur par mot** DUNOD

COMPRENDRE LA CULTURE NUMÉRIQUE

D



PLAN

Disruptive technologies in the DATA economy

- DATA (IOT, Smart objects) & BIG DATA
- AI and DATA learning (ML & DL)
- NFC, LIFI, Blockchain,...etc

DATA PARADIGMS : SQL & NO SQL

Three types of DATA : structured, semi-structured and *unstructured*

Three dimensions in the DATA economy

- BOTTUM UP paradigm
- little Big Data
- smart places (DATA Spaces)

Conclusion : "Spiralist" innovation in the DATA economy

Part of introduction of the Mooc on "Distributed big data management" (GRADEO in January 2020); eBIHAR MSc on FUN platform

Partie aussi du Chapitre du Livre pluridisciplinaire DUNOD de Sept 2019 & (Keynote, Assises CNAEMO, TOULOUSE, 30 septembre 2020)

RAW RESOURCE of this millennium like love and happiness ?



English – "Happiness is a marvellous thing : the more you give, the more you are left with" (Pascal)

French – « Le bonheur est une chose merveilleuse : plus tu en donnes plus il t'en reste » (PASCAL)

كل تيقب املك اهتيطعا املك ليمج ءيش قداعسلا : Arabic

Creole (Haïti) - Ala yon bèl bagay se kontantman, plis ou bay ladan'l plis ourete ladan'l! Russian : Счастье – волшебная вещь: чем больше ты его даришь, тем больше тебеостаётся» Spanish - la felicidad es un artículo maravilloso: cuanto más seda, más le queda a uno Occitan - la felicitat una chausa meravelhosa:mai ne'n donas, mai te'n rèsta Swedish- lycka är något underbart:ju mer du har att ge, desto mer har du kvar av den. Italian - la felicità è qualcosa di meraviglioso: più ne dai e più te ne rimane German- Glück ist eine wunderbareSache: je mehr du schenkst, destomehr hast du Roman - 'a felicità è quarcosa de meravijoso: più 'a dai e più te ce rimane Hungarian- a boldogság csodálatosdolog: minél többet adsz belõle, annáltöbb marad neked Brazilian Portuguese - a felicidade é uma coisa maravilhosa: quantomais você dá, mais você recebe



DATA / INFORMATION



> **Properties** \odot ?

1-1 = 2!

>1+1 = 4 (METCALFE 's law)

*« PAUVERTY is DATA-access denial »*F. Verella (Haïti)

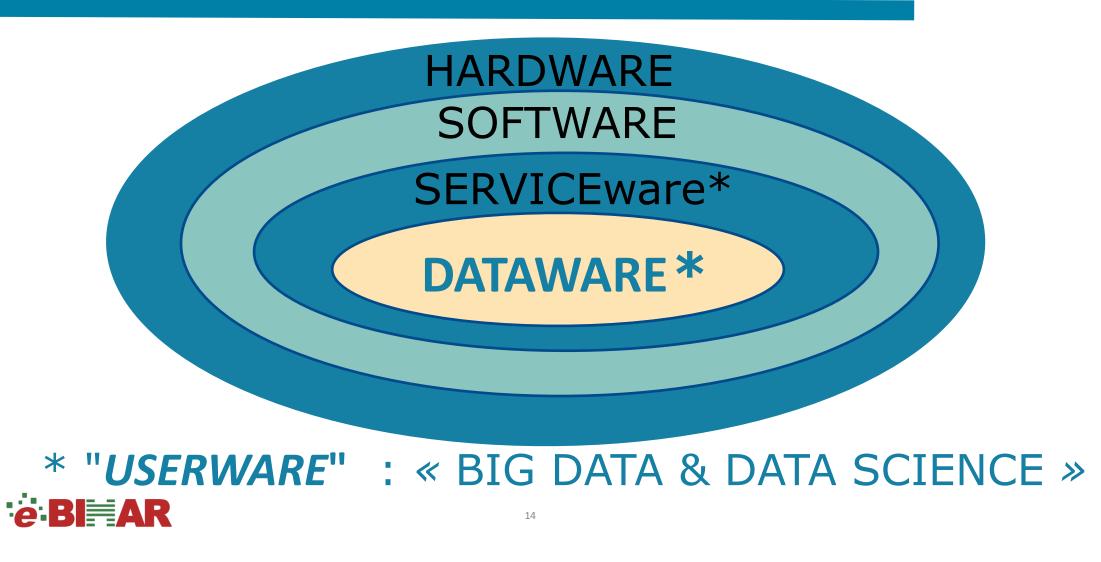


World Bank (Washington)



28 years of innovation at MBDS with 4 Copernician digital revolutions !





Some visions of the future of big-data management



>CLOUD COMPUTING

- > INFRASTRUCTURE as a SERVICE (IaaS)
- > PLATFORM as a SERVICE (Paas)
- DATA as a Service (DaaS)

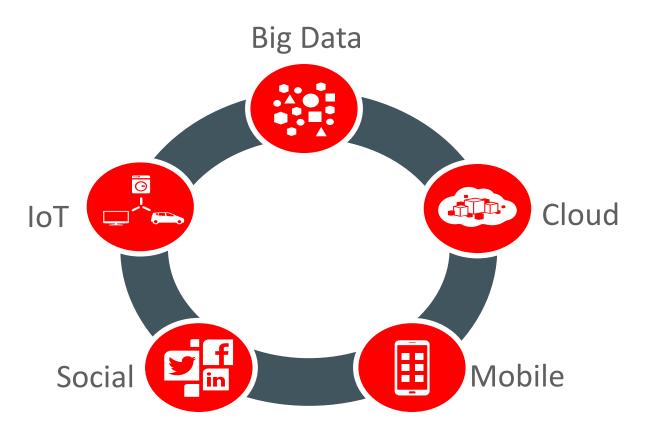
from Oracle ; ANALYTICS as a SERVICE (AaaS) from Google, IBM, etc. >« **CAMS** » (IBM 2014)

- CLOUD for servers
- ▶DaaS/AaaS :
 - « (DATA) ANALYTICS as a service »
- >Mobility (smartphones applications)
- >Social Networks (for data integration)



ORACLE vision : CI-MBDS[©]







A strategic vision of the digital DATA revolution







(in RAKU by Marina Latta for MBDS 20th anniversary)



To be AUDACIOUS : « Be OUT of the box » !





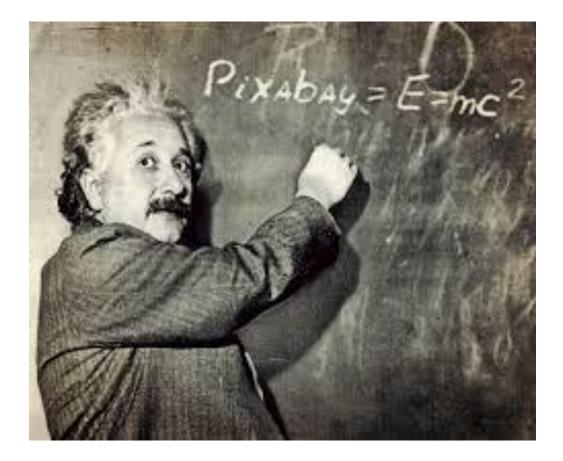
Your Highness ...determined to send me, to the country of India...and furthermore directed that I should not proceed by land to the East as is customary, but by a Westerly route, in which direction we have hitherto no certain evidence that anyone has gone »

Christopher COLUMBUS



Michel Serres on 5 key contributors to humanity and ...





Moses : « Everything is LAW »
Jesus : « Everything is LOVE »
Marx : « Everything is MONEY »
Freud : « Everything is SEX »
Einstein : « Everything is RELATIVE »
&...

≻Jim GRAY:

« Everything is DATA »



« DATA » as prefix or suffix !



DATA as prefix:

DATA base (19/8/1968 : Ted Codd and relational data model), DBMS DATA Schema DATA bank, DATA STORE DATA warehouse DATA mart DATA mining (OLAP, Correlations, ..), DATA Analytics, DATA Pumping (ETL), Little Big Data DATA Systems

DATA Systems DATA mash up DATA SCIENCE DATA LAKE DATA WEB



Relational DATA Linked DATA, Labelled DATA Meta DATA Open DATA Web data Smart DATA BIG DATA and

DATA as suffix:

new DATA-centrics jobs Big Data architect CDO « Chief DATA Officer », « DATA SCIENTIST », « DATA BROKER » « DATA ENGINEER »



Data-centrics Economy & DATA « deluge »



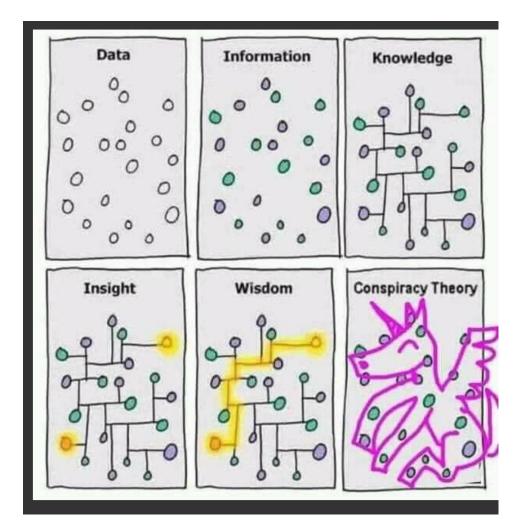














DATA & two major human defaults !

- **1.** Man forgets
- 2. Man can be wrong « Errare humanum es »



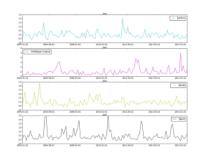


DATA ?



> Recording of ANYTHING (fact, measure, video,..) on ANY SUPPORT with a given code









Spirals on La Piedra Escrita Jayuya Puerto Rico







DATA ?



« Value of man consists in GIVING » Einstein « It is DATA i.e. STUPID » Jim Gray

ATUM » → « DATA » from DARE (to GIVE in Latin language) « what is given »

symmetric word : « CAPTUM » INFORMATION !

→ « CAPTA » (Kitchin 2014) from Captio (to TAKE in Latin)





« DATA »→ « INFORMATION » (CAPTA) → KNOWLEDGE (Insight)





KNOWLEDGE ?

3 Types of Knowledge for ARISTOTELES :

1. EPISTEME SCIENCE <Knowing>

2. TECHNE TECHNOLOGY **<Knowing to do>**

3. PHRONESIS

ETHICS

<Knowing to be ; wisdom>



« SMART OBJECT » = DATA + COMMUNICATION



(SMART City, car, home, bus stop, museum...)

>SMART OBJECT :

DATA

(Production/Processing/ retrieval) + **COMMUNICATION**

>LIFE IN BIOLOGY ? LIFE = INFORMATION + COMMUNICATION



Smart objects and IOT (Internet of Things)



50 billions of smart objects by 2020 (Gartner)
 from IOT to IOE (Internet of EVERY THING) :
 every object will become smart !

>IoT is a catalyst for Big Data



BIG DATA ?







11 BIG DATA facts SHAPING the future ! (www.graziti.com)



- >#1 :90% of DATA in the world were created in the last 2 years
- >By 2020 : 1.27 MB of data created EVERY SECOND for every human being
- >#2 : By 2020 : Global IP traffic will reach 44 ZETA BYTES
- >#3: By 2020: **30% of web browsing will be done WITHOUT A SCREEN**
- >#4: By 2020 100 million customers will shop thru augmented reality (and chatbots)
- >#5: in 2018, 3 million workers supervised by a ROBO-BOSS
- >#6: By 2020 algorithms will alter the job of 1 billion workers
- #7 : By 2020, 40% of employees will cut their healthcare costs by weering health trackers (smart watches)
- >#8 : By 2022, IOT will get consumers and business 1 trillion dollars a year
- >#9 : By 2019, 20% of brands will abandon their mobile applications
- >#10 : By 2020, 40 million cars will use ANDROID
- >#11: By 2020, 85% of Internet transactions will be processed by machines
 (GARTNER)»
 - Forecast of 75% grow on AI/CHATBOT from 2016 to 2021 (OVUM)



\prec The 3 V \gg of BIG DATA $\,$?



DATA deluge, DATA Tsunami, DATAnome, Dataware, DATAISM,...

The 3 « V » (M.Stonebraker)
Volume,
Variety
Velocity





« VOLUME » (« BIG » data) : → Exa-bytes per second !



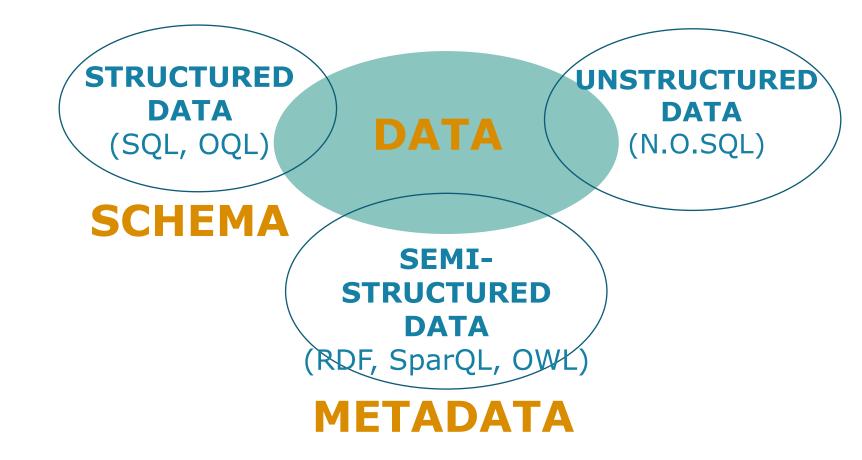
- 5 exa*bytes of data have been produced since the beginning of humanity until 2010
 - *Constant areases of the system of the system*

* NOTE : PETA : 10**15; EXA : 10**18; ZETA : 10**21 C:BI AR



« VARIETY » (BIG DATA) : 3 types of DATA in CS









« VELOCITY » (Big Data) : DATA flowing

>DATA from IOT (Captors, sensors)

Every second on INTERNET : <u>https://www.internetlivestats.com/one-second/</u> (2020) http://onesecond.designly.com/, <u>http://www.internetlivestats.com/</u>

- > 9200 tweets (400 M a day)
- > 1000 pictures loeaded on Instagram
- > 100 terabytes of Internet traffic
- >90 000 videos seen on youtube (> 1 hour of video posted on YOUTUBE every second)
- 90 000 queries on Google <Google reported earning more than \$50 billion in ad revenue in 2013, netting them around \$1,602 in profit per second</p>
- ➤ 3 M de mails
- ➤ 5000 skype calls
- > 10 000 meetings on ZOOM (300 M meeting a day on Zoom during the COVID; 10 Millions 3 months before)
- 3000 visits to Facebook (>3 billion friends end of 2020) < Every day, Facebook users like an average of 4.5 billion posts, share more than 4.7 billion status updates with their friends or followers, and watch over 1 billion videos.>

> 20 applications loaded every second

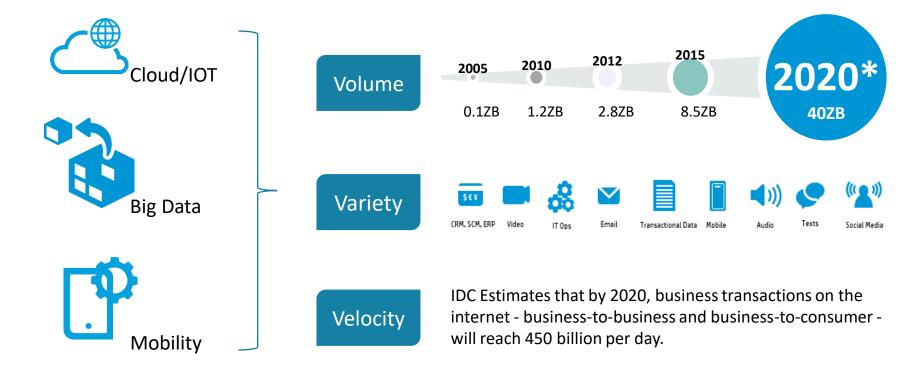
> 2 resumes posted on Linkedin (200 million resumes) and ...



Big Data is the evolution of computing boundaries



one Zeta Bytes (ZB) = 10**21; 1000 EXA



*Source : IDC Digital Universe in 2020



« DATAFICATION » & CORRELATIONS



>CORRELATIONS (HOW) >> CAUSES (WHY)





The « 8V » of BIG DATA (2020)



the « 3 V » +

- + VALUE
- ╋
- >Veracity
- >Viscosity
- Visualisation
- ➢Virality
- >+++



Extra « V » for VALUE : « Little » BIG DATA



LIBERATION, 2014

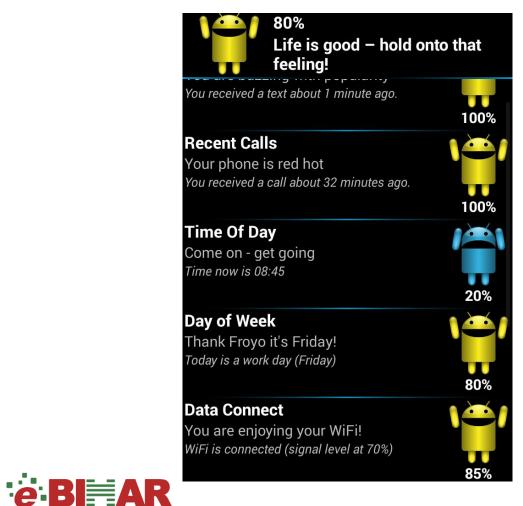






VALUE : Ex Moodmeter





🎔 🔟 🖬 🖬 24° 🛨 🖙 💭 🕏 i 😒 🖗 🖸	17:33
< 🐂 World Mood Meter	
83% Your mood vs. The world	
The World	\sim
Your mood is better than the world's average - well done Mood range 56% - 88%. Calculated about 16 minutes ago.	72%
Royaume-Uni	\sim
Why is this country so sad? Mood range 57% - 88%. Calculated about 16 minutes ago.	73%
Allemagne	~~~
What is wrong with them? Mood range 64% - 82%. Calculated about 16 minutes ago.	74%
Australie	
Why are they so miserable? Mood range 62% - 64%. Calculated about 16 minutes ago.	63%
Bangladesh	
When will they cheer up?	
amazon GRATUIT ★★★★★ (10 954)	.↓

The DATA WAR on **CONTENTS** for our... *« digital clone/digital assistant »*



>BOOKS

≻TV

>SPORTS (New comers : Amazon, Facebook, SFR,..)

MOOCs (courses)

DIGITAL RULE § **• If you do not pay for the product, YOU ARE THE PRODUCT** ! •



CLOUD COMPUTING



« everything as a service (EaaS) : « SERVICE SCIENCE » (IBM, 2011) !

« INFRASTRUCTURE as a SERVICE » (IaaS)
« PLATFORM as a SERVICE » (Paas)
« Software as a Service » (SaaS)

DATA ? « DATA SCIENCE »
 « DATA as a Service » Oracle (DaaS)
 » « ANALYTICS as a SERVICE » (AaaS) Google, IBM, Bigquery (Google 2012)



Parallelism and Big data



> Terabytes (10**12) per second ?

Typical hard disk : 100 Megabytes/sec
1 Terabytes (10**12)
10 000++ hard disks in parallel

```
    Solutions :
    Data compression
    SCALE UP : (SMP, MPP)
    SCALE OUT
```



Three major modes of DATA processing (Jim Gray)



DATA management (and storage/CLOUD)

>DATA RETRIEVAL

➢ READ focus : CODD's theorem

➤ → SQL esperanto

►DATA UPDATE

> DATA TRANSACTION (production support)

> WRITE focus : GRAY's theorem

DATA Analysis (decision support)

Data Learning (Machine learning & Deep Learning)

>DATA Communication



Gray's dream for... BIG DATA and his 4th paradigm of science (Turing Award 1998)



"to have a world in which all of the science literature is online, all of the science data is online, and they interoperate with each other."

- > Open source platforms for
 - ▷DATA Management →
 (Hadoop, Map Reduce, MongoDB,..)
 ▷DATA AnaLysis /Data Science →
 (R language, Tensorflow, ..)

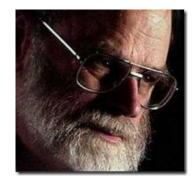
DATA Communication (Internet)



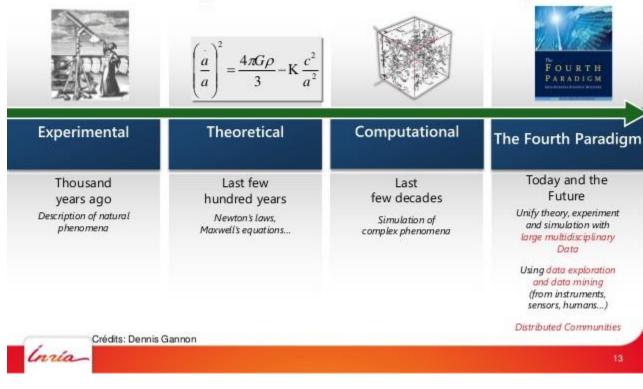


The 4th paradigm of science : the DATA paradigm !





The Data Science: The 4th Paradigm for Scientific Discovery





BIG DATA : a couple in Sciences !



« BIG DATA is an ART crossing different sciences »

(CS, Maths)





BIG DATA in science ? Computer Science & Mathematics



1. DATA MANAGEMENT (data-lake creation; data engineering) :

SQL3, OQL, BigquerySQL, NOSQL, CQL, HQL, HiveQL, N1QL, SPARQL, SPARKSQL, UnQL, coSQL, NEWSQL,..

REF Open Source : HADOOP/MAP REDUCE, MongoDB, Cassandra...

1. **DATA ANALYSIS** (DATA Science; data mining)

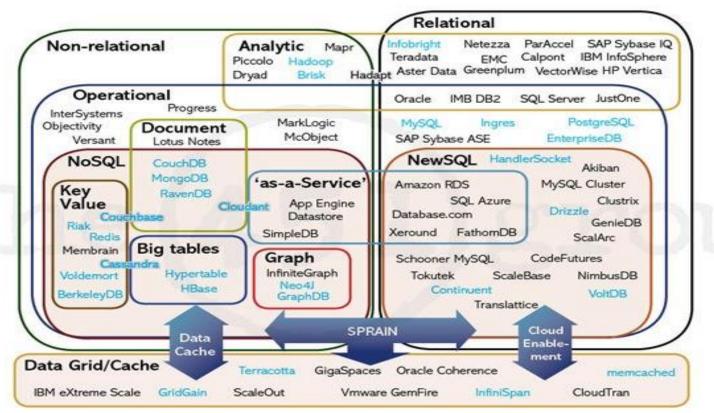
Ref OPEN SOURCE : R language (> 4000 packages), PYTHON, TENSORFLOW, CAFFE,...



Plethora of BIG-DATA management Systems (Aslett, 2015)



<u>https://blogs.the451group.com/information_management/2011/04/</u>





BIG DATA management systems



TOP DOWN approach for structured and semi-structured DATA
 SQL2, SQL3, ODMG
 Semantic Web (SPARQL, OWL)

BOTTOM UP Approach for UNSTRUCTURED DATA
 N.O. SQL (NOT ONLY SQL)
 NEWSQL



DATA BASE market & standards?



2020

20% of cont.

Growing

2x (1)!

 $1/100 \times (1)$

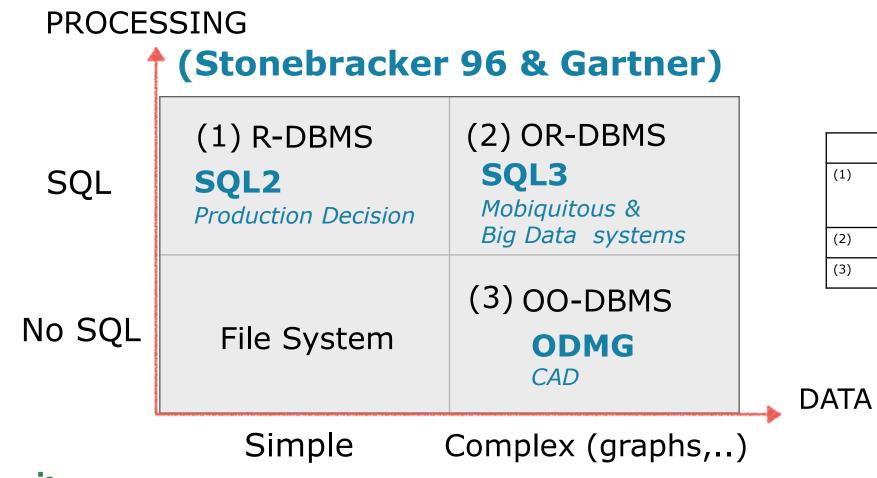
rate

2010

2x (3)

10 G dollars

 $1/100 \times (1)$





TOP DOWN approach for structured and semi-structured DATA BASES



>TOP DOWN approach with predefined SCHEMA and metadata

STRUCTURED DATA standards

- SQL2 and VALUE paradigm
- SQL3 and POINTER-VALUE paradigm
- ODMG and OBJECT-VALUE paradigm

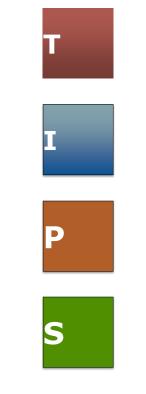
SEMI-STRUCTURED DATA standards

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SPARQL and PREDICATE-VALUE (RDF) paradigm
```



DB contibution to Computer Science : TIPS properties





Transactions (with *ACID properties*)

No-procedural Interface (SQL)

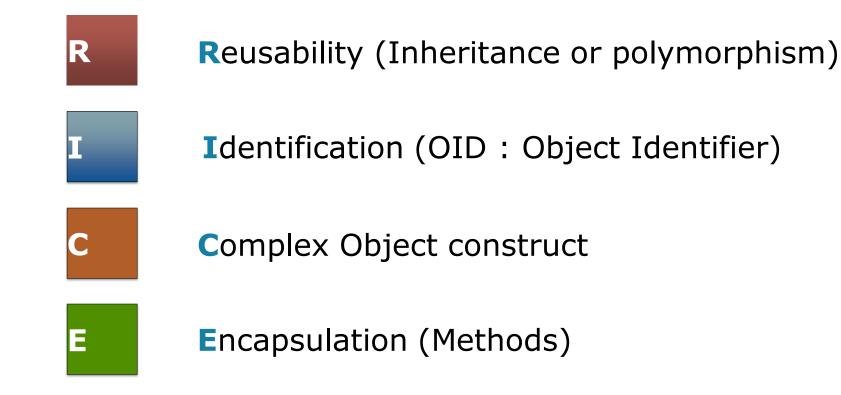
Persistency (virtual paged memory)

Structuration (Schema)



Object contributions to the DB World : RICE properties an object = (OID, Value)

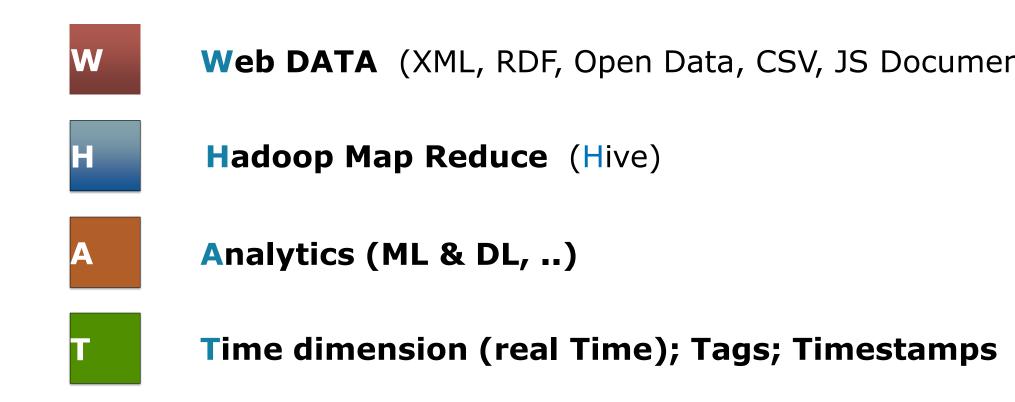






Semi-structured and unstructured DATA

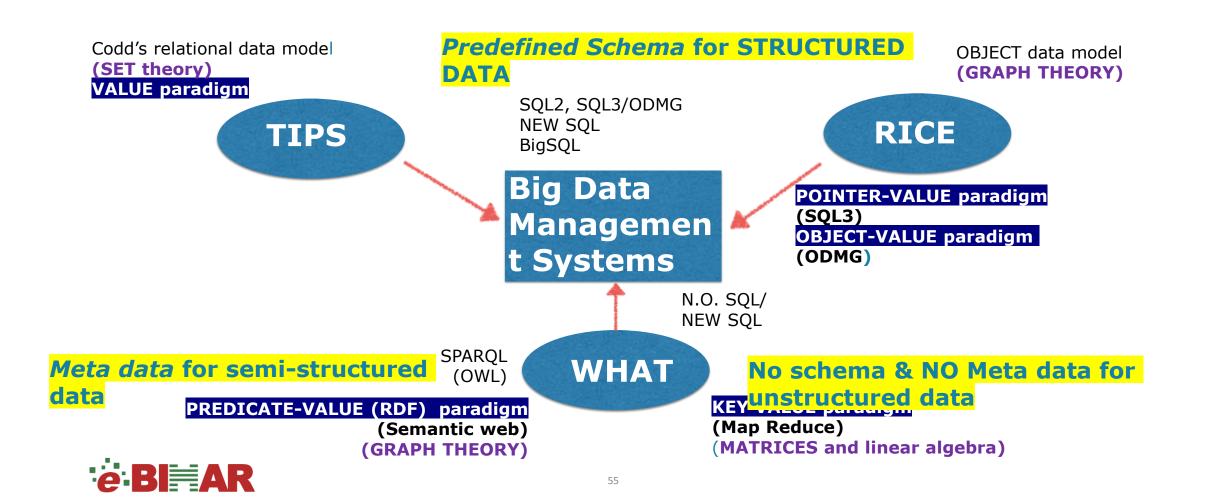






DATA PARADIGMS





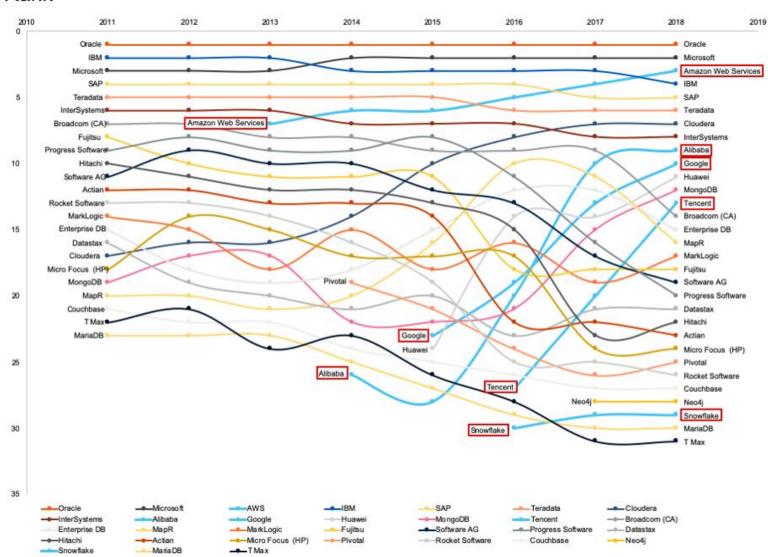
Gartner 's quadrants on DBMS (2019)





Gartner Market Share Ranking, 2011-2018

Rank



Source: Gartner (June 2019)

Note: The following historical vendor revenues were combined to reflect the state of the market in 2019: Cloudera, reflecting the merger with Hortonworks; Micro Focus, reflecting the acquisition of HPE Vertica; Broadcom, reflecting the acquisition of CA. ID: 347472

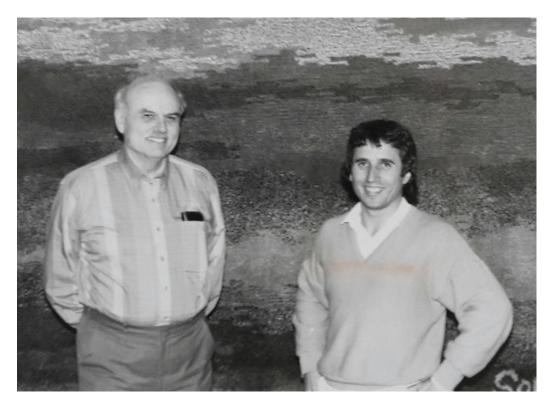
« The future of DBMS market is the CLOUD » (GARTNER)

- DBMS cloud services are already \$10.4 billion of the \$46.1 billion DBMS market in 2018.
- the overall DBMS Market grew at 18.4% from 2017 to 2018 – its best growth in over a decade. Cloud DBMS accounted for 68% of that growth.
- Only two vendors (<u>Amazon Web</u> <u>Services</u> and <u>Microsoft</u>) account for 75% of the growth from 2017 to 2018. AWS is 100% cloud and Microsoft DBMS was almost 100% cloud (See previous Figure).

• DBMS innovation is cloud-first or cloud-only for development

BIG DATA MANAGEMENT A.C. (After Codd)





With Ted Codd in Sophia Antipolis (1986)

> Ted CODD 1968 (Relational ALGEBRA & SQL2) : « <u>Everything is VALUE »</u>

Chris DATE & Mike Stonebraker 1995 (SQL3) :

 Everything is POINTER-VALUE >>

 TIM BERNERS LEE 1998 (SparQL, RDF) :

 Everything is PREDICATE-VALUE >> (WEB DATA)

 Chang 2006 (N.O.SQL) : «*Everything is KEY-VALUE* »
 STONEBRAKER 2013 (NEW SQL) : « *Everything is SQL* »

ElMore 2015 « *Everything is POLYSTORE* » Deep Learning : « *Everything is an IMAGE* »

> and Evariste Gallois 1832 !! :
 « Everything..is a GROUP (CATEGORY) »

Jim Gray : « Everything is DATA (4th paradigm of science) » ...and « Everything is a TRANSACTION »



Bottom up approach for unstructured data (no schema, no metadata)



- « N.O. SQL » (Not Only SQL)
 - > « KEY /VALUE Paradigm »
 - GRAPH paradigm

➤ « NEW SQL »

SQL paradigm »



« BASE » properties



≻BASE :

- Basically
- Available
- Scalable (OUT)
- Eventually consistent (final consistency)
 - > Replica consistency ; Cross Node Consistency

SOL

CAP Theorem

(Eric Brewer, Prof Berkeley, 2000 & 2012 ; Revised by Altend MIT,

2002)

Consistency,

> Availability,

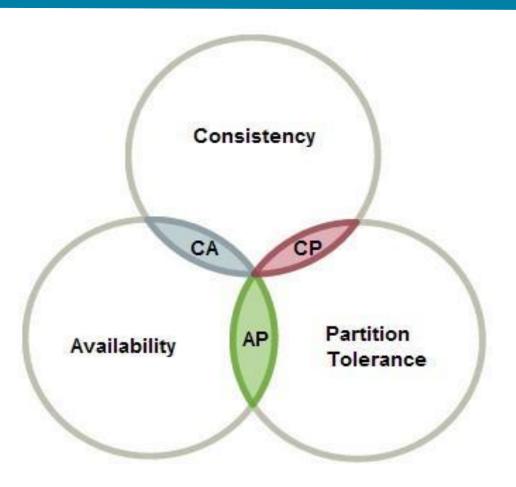
Partitioning

NO SQL



CAP Theorem : « Pick 2 ! » (Brewer 2000 ; 2012)





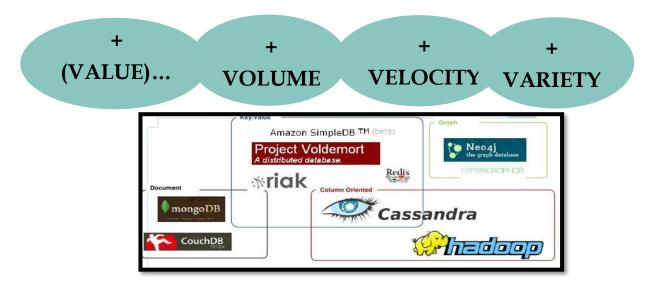






4 « no » :

- 1. no SCHEMA (schema-less ; Variability) & NO METADATA
- 2. no RELATIONAL/ NO JOIN (extract data without joins)
- 3. no DATA FORMAT(graph, document, row, column)
- 4. no (ACID)Transactions (CAP theorem ; BASE)





2 Complementary approachs for big data management



	SQL	N.O.SQL
VOLUME & VARIETY	STRUCTURED (SCHEMA) TERA/PETA bytes	Unstructured (no schema) EXA/ZETA++ bytes
VELOCITY	NO	YES
TRANSACTIONS	YES (ACID and Gray's theorem)	NO (BASE & CAP theorem)
SCALABILITY	UP (Scale up)	OUT (scale OUT)
USER INTERFACE	AD HOC Queries, JOIN & Transaction oriented	Predefined queries, NO JOIN & Decision oriented
STANDARDS	SQL3/ODMG	Not yet (BIG SQL)
Typical approach	TOP DOWN (predefined Schema)	Bottom UP (no schema)
Administrator	Yes	No
Vendor support	Yes	No (Open Source)



« N.O. SQL » DBMS



4 data paradigms: 3 KEY-VALUE oriented and one GRAPH oriented

- KEY-VALUE with BLOBS (Binary Large Objects)
 - ex : Hadoop, Cassandra, Ryak, Redis, DynamoDB, BerkeleyDB, etc.

→ HASHING arrays (no query engine)

KEY-VALUE with JSON/XML documents

ex : MongoDB, CouchDB, etc.

- > JSON simpler than XML with Java Script interface
- <KEY, VALUE> model with VALUE in JSON (BSON, XML) for documents ;

➢ KEY−VALUE with COLUMNS

- ex : **HBASE**, **Cassandra**, BigTable/Google,...
 - <KEY, (SETofcolumns, VALUE, TIMESTAMP)>

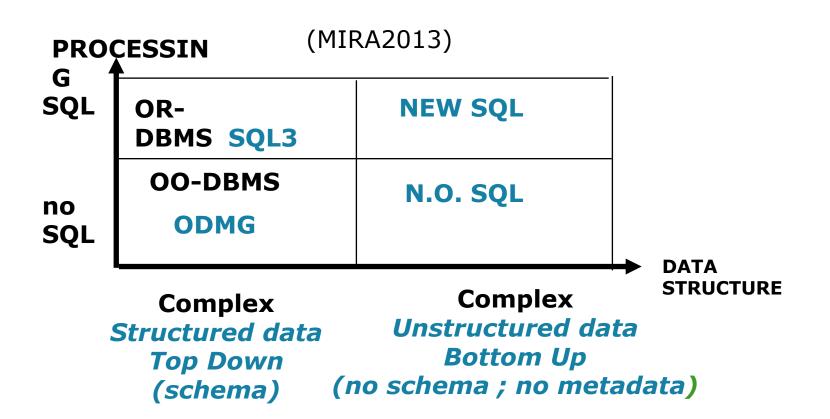
➢ GRAPH oriented

ex: **Neo4j**, OrientDB... : towards GQL (Graph Query Language)



« COMPLEX » data : SQL3, N.O. SQL et NEWSQL?

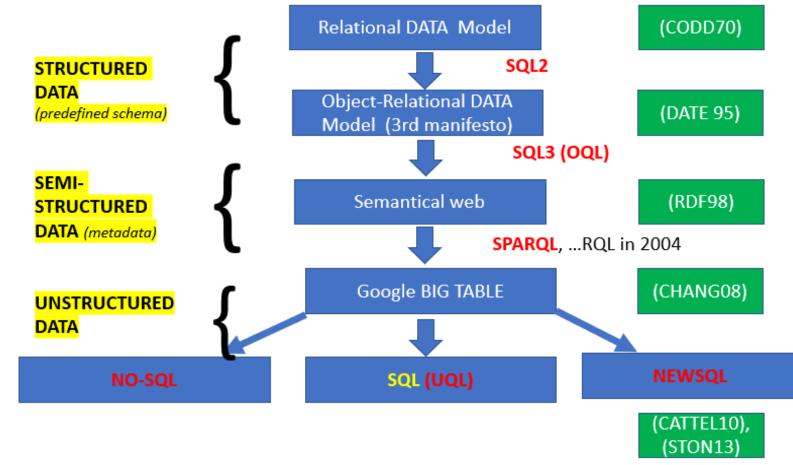








SQL evolution (a.c.)





A relational-schema example with three predicates



PILOT (<u>PIL#</u>, PILNAME, ADDR)

PIL#: Pilot ID then NAME and ADDRESS (City)

PLANE (P#, PNAME, CAP, LOC)

CAP : Capacity, LOC : localization city

FLIGHT (FL#, PIL#, P#, DC,AC, DT, AT)

DC : Departure City, AC : arrival city, DT : Departure Time, AT : Arrival Time

Note : *Primary keys* are underlined





Example : SQL2 (Relational)



Who are the pilots (PIL#, PILNAME) from Nice driving a plane from Nice ?

In SQL2:

SELECT PIL#, PILNAME

FROM PILOT, FLIGHT

WHERE PILOT.PIL# = FLIGHT.PIL# and PILOT.ADDR = 'Nice' and FLIGHT.DC = 'Nice';

In Codd's relational algebra :

V1 = Join PILOT (PIL #= PIL #) FLIGHTV2 = Select V1 (ADDR= 'Nice' and DC='Nice') RESULT = Project V2 (PIL#, PILNAME) **BI**■AR

Example : SQL3 (object relational)



Who are the pilots from Nice driving a plane from Nice ?

In SQL3 : SELECT REFPIL → PIL#,PILNAME FROM FLIGHT WHERE DC= `Nice' and REFPIL → ADDR =`Nice';

Note : with

REFPIL : REF type attribute containing ROWID (OID) from PILOT and
 > < > : Dereferencing operator



Example : OQL (ODMG)



Who are the pilots from Nice driving a plane from Nice ?

In OQL

SELECT p.PIL#, p.PILNAME FROM

p in PILOT v in p.performFLIGHT WHERE

```
p.ADDR= 'Nice ' and v.DC='Nice';
```

Note : with « performFLIGHT », bidirectional persistent REF pointer from PILOT class towards FLIGHT class



SPARQL (Example)



Who are the pilots from Nice driving a plane from Nice ?

Prefix rdf :<http:// www....>

SELECT ? PILOT WHERE { GRAPH ?g { ?PILOT rdf :ADDR rdf: Nice ?FLIGHT rdf:DC rdf: Nice }}



Some SQL examples on KEY-VALUE NO SQL DBMS with N1QL (Couchbase), CQL (Cassandra), ...



Typical Example :

N1QL:

SELECT PIL#, PILName

From Pilot

Where ANY F in Flight SATISFIES F.DC= 'Nice' and ADDR = 'Nice';

CQL3 SELECT PIL#, PILNAME From PILOT JOIN EACH FLIGHT ON Pilot.pl#=FLIGHT.PL# and DC ='Nice' and ADDR = 'Nice';



Example : GQL (Graph Query Language)



Query : Name of the pilots who perform a flight from Nice with a Boeing 747 ?

```
SELECT
pl.name AS pilot.name
FROM GRAPH pilotflightsplanes
MATCH
// graph pattern
(pl:Pilot)->{:PERFORMS}->(f:flight)<-{:IS-USED}<- (p:plane)
WHERE
p.name = 'B747' and f.DC = "Nice";</pre>
```

The pattern means that all data in the graph that matches the sequence of nodes and edges (each of which has a particular « label » or element type) will be identified.

> This operation lifts a «sub-graph » or a « projected graph » of flights for a particular pilot into the application.

> Properties on all instances of : PILOTnodes or : FLIGHTedges that match can now be read by the application.



Example : JSON integration (new data type in SQL)



Postgres (2013), Oracle (2013), SQL Server (2016)

New data TYPE containing Json documents : Jsonb

- > Examples :
- Create Pilot (PIL# : integer primary key, , Pilname : varchar (12), **flightreport : Jsonb)** Select Jsonb_each (flightreport) from pilot;

JSON view creation for SQL data (and conversely)

>Example : CREATE JSON_VIEW AS

SELECT JSON {"pilot" : {"pil#" : pl.pil_id, "Pilname" : pl.name, {"flight" : {"f#" :f.flight_id, "DC" : f.city, "AC" : f.city}} } FROM pilot pl, flight f WHERE pl.pil_id = f.pil_id ;

>With **functors** (categories) <see later>



Towards « BIG SQL » standard



SELECT FROM {T/Tables}, {V/Views} < SQL2; Create Table..Create View,..) { SQL query} < SQL3> JOIN {Pointer Chasing} < OQL> {**EXTERNAL TABLES**} < N.O.SQL DB> < Oracle, IBM, Microsoft, Informix, Sybase/SAP, MySQL,..> $\{GRAPH\} < GQL>$ WHFRF <POINTER DEREFERENCING operator on REF types> <SQL3> <Multiset operators> like **NEST/UNNEST** <Multivalued attributes> <GRAPHS operators>, <MATRICES operators>, UDF/UDT, MAP/REDUCE **PARTITION BY** < Splitting/Sharding>like **LIMIT/OFFSET**, **PIVOT/UNPIVOT** MATCH <GQL> GROUP BY /HAVING GROUPING SETS with CUBE, ML & DL operators



Looking for a unifying theory for BIG DATA management



« An effective mathematical model that encompasses the concepts of SQL, NEW SQL, NO SQL, (ML and DL) which would enable their interoperability » J. KEPNER (MIT, 2016)

4 types of DATA VARIETY with 3 theoretical frameworks and one core theory

- **STRUCTURED** (SQL) and **SET theory** (of VALUES/DATA) < core theory>
- **SEMI STRUCTURED** (SparQL, OWL) : **GRAPH THEORY** (inferences)
- >UNSTRUCTURED (NOSQL) : GRAPH THEORY
- NEW SQL and MATRICES (linear algebra)
 NOTE : DATA SCIENCE (ML and DL) and MATRICES management
- Specific extensions of set theory and SQL to tackle : >Hierarchical data: JSON, XML
 - >Graph data : RDF, OBJECTS, Social networks (and GQL)
 - >Tabular data : Tables, CSV, OLAP, tensors, pixel array (Deep Learning)



Tribute to an *assassinated* revolutionary mathematician and its contribution tothe future of DATA modeling for BIG DATA



Evariste GALOIS : (1811- « *killed in a duel* » in 1832 when he was 21 years old) :

Letter to Auguste Chevalier, 29th of May 1832 (eve of his death)



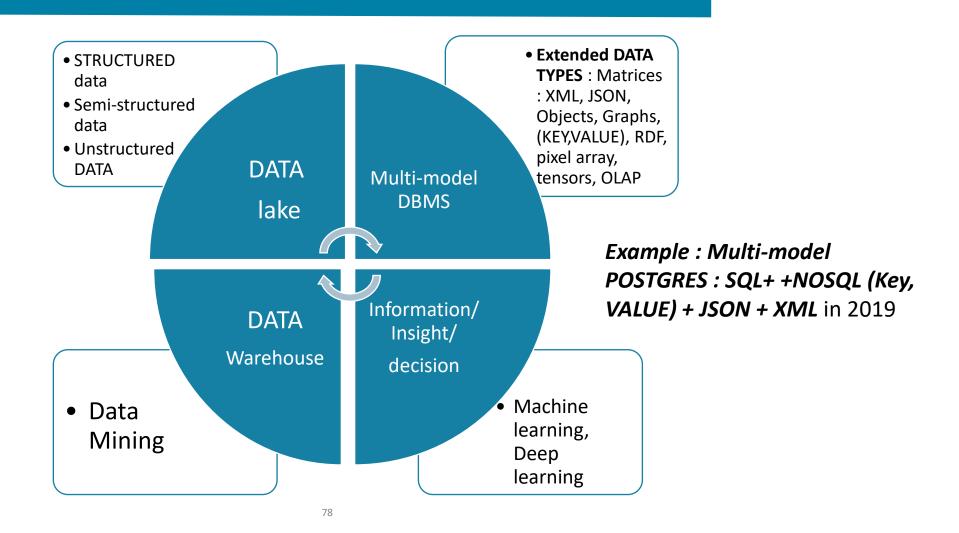
« GROUP theory »

→ « Category theory » and « Associative arrays » !



DATA refinery

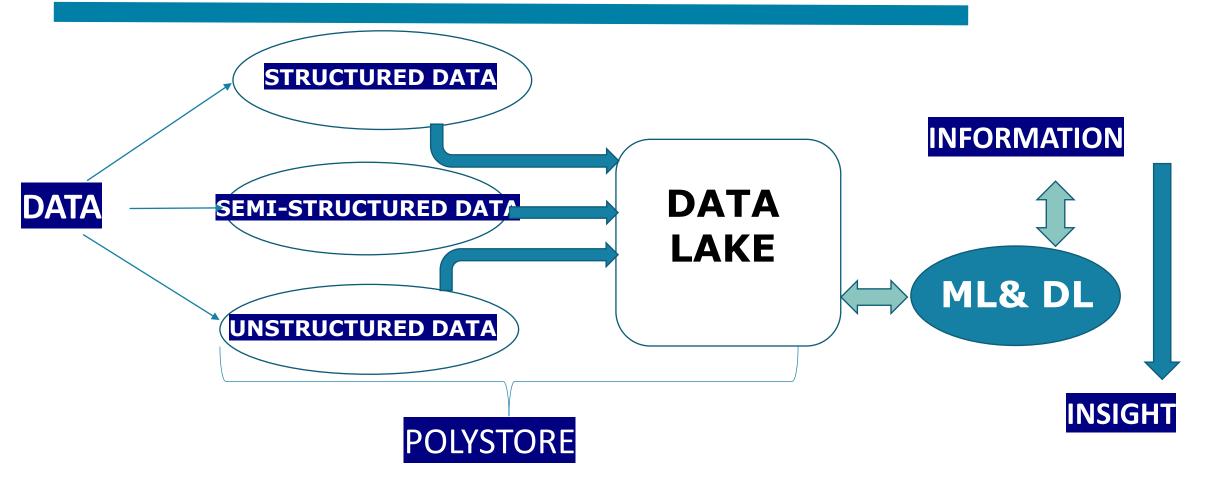






DATA LAKE and polystore







Dual approach for data lakes : polystores* vs Multi-model data store



« All leading operating DBMS will offer multiple data models, relational and NO SQL in a single DBMS platform » GARTNER 2016

« One size cannot fit all » (M.Stonebraker)..but can « fit a bunch » (Asterix DB)

- Goal : one application accessing multi-model DATA sources ! With 2 solutions : POLYSTORES vs MULTI-MODEL DBMS
- > POLYSTORES* : integration of multiple autonomous data stores
 - EX : Polybase (Microsoft); SparkSQL, BigDAWG (MIT)
 - > 3 types '** :
 - Loosely-coupled (common interface, mediator/wrapper around autonomous systems)
 - Tightly coupled
 - > hybrid

> MULTI-MODEL DBMS : one single integrated DBMS around a unified data model

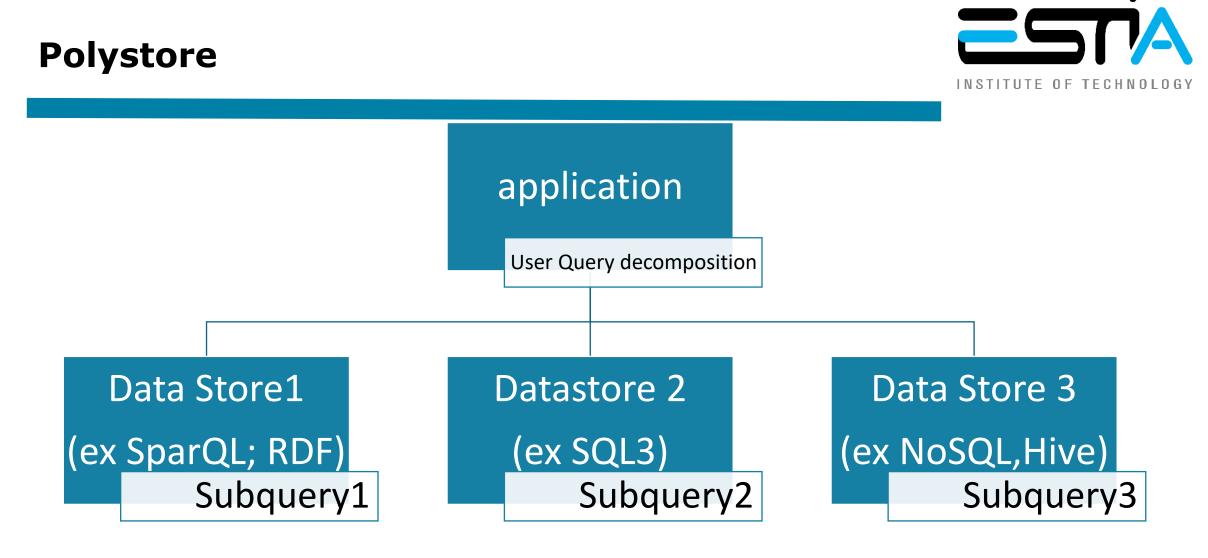
- EX Oracle, ORIENTDB, IBM, Cache, ARANGODB ...;
- > New types : sets, graph, key-value, object, Json, XML, RDF, text, multimedia, spatial, time-series, matrices, etc.

> > Need for a unified model theory for multi-model DB

*Mike Stonebraker « The case for POLYSTORES » 2015, <u>http://wp.sigmod.org/?p=1629</u>

** Bondiombouy, Carlyna, and Patrick Valduriez. "Query processing in multistore systems: an overview." International Journal of Cloud Computing 5.4 (2016): 309-346





Examples with Oracle : Oracle MySQL, Oracle DB (Relational, Json, XML) and Oracle NO SQL (relational and (KEY, VALUE))



Bridge between SQL, NoSQL and NewSQL ?



Bridge between

- >SET \rightarrow structured /SQL
- >GRAPH → semi-structured & unstructured (NoSQL)
- ►MATRIX → NewSQL & Data Analysis/R & Python

Uniform Mathematical model for SETS, GRAPHS and MATRICES + JSON, XML, OLAP, OBJECTS ?



Two formal unifying BIG DATA management



CATEGORY THEORY : Microsoft research <2011> and Oracle (+ Univ Helsinki) <2018>

A co-Relational Model of Data for Large Shared Data Banks », Erik Meijer and Gavin Bierman Microsoft Research, CACM 2011 M. Fokkinga, « SQL versus coSQL — a compendium to Erik Meijer's paper » 2012

UDBMS: Road to Unification for Multi-model Data Management Jiaheng Lu 1, Zhen Hua Liu 2, Pengfei Xu 1, Chao Zhang (1-University of Helsinki, Finland and 2-Oracle, Redwood Shore, CA, USA), Dec 2016
 "Multi model databases and highly integrated polystores" J.Lu et al, Tutorial CIKM 2018

> ASSOCIATIVE ARRAYS : MIT < 2015>

- Jeremy Kepner and al : « Associative array model of SQL, NoSQL and NewSQL Data bases » <MIT CS and AI laboratory, 2016>
- Kepner, J. Chaidez, V. Gadepally, and H. Jansen, « Associative arrays : Unified mathematics for spreadsheets, databases, matrices, and graphs » arXiv preprint arXiv:1501.05709, 2015.



DATA SCIENCE ? BIG CAPTA !



« DATA SCIENTIST » :

« Sexiest Job of this millenium » Harvard Business review

Skills shortage: The Data Scientist Opportunity !

Top 10 Jobs that didn't exist 10 years ago (Linkedin 2014)

Data scientist is #5 !

 Without data you're just a person with an opinion. » W. Edwards
 Deming





« Computer Science » evolution ?



>« SERVICE SCIENCE » (IBM, 2011) & CLOUD COMPUTING

>« DATA SCIENCE »

Machine learning
 Deep Learning

≻NOTE :

KAGGLE web site for data scientists, « *place to discover and seamlessly analyze publicly available data* »



Artificial intelligence ? Intelligence ?



AI and Deep Neural Net-DNN- is back with GPU computing power and BIG DATA

DNN Application domains : computer vision, image analysis,assisted car driving, natural language translation (Ex : DEEPL*),LIPNET (Oxford then Google), voice cloning (LYREBIRD), robots (ExMANTIS), Deep Fakes, BIG DREAM (Google) for enriched pictures..

**DeepL* translated an MIT book (800 pages) on... Deep Learning in 12 hours (from English to French) in October 2018

<u>« Will Machines Eliminate Us?</u> » Will Knight, MIT Technology Review, 29 January 2016

Yann Le Cun

Quand la machine apprend

La révolution des neurones artificiels et de l'apprentissage profond





« AI paradox » and the data economy



- "AI will contribute 13 TERA DOLLARS (1 TERA : \$1 trillion: 10**12) to the global economy over the next 10 years (Harvard Business Review, Dec 2019, P.40).
 - \rightarrow AI is not an off-the-shelf technology
 - > Moving from an experience-based TOP DOWN decision process to a DATA-based BOTTOM UP decision process

"« AI is colonizing every economic sector of our society : health, transport, industry and education ...The prodigious expansion of AI is linked to deep learning, which allows to train a machine to perform a task without explicitly programming it ... Deep Learning is the most promising form of AI because it is powered by the BIG DATA and GPU"

Yann Le Can, Turing award 2019

"We don't have better algorithms, we just have more DATA." Peter Norvig, current Google Head of AI (2019)

AI paradox "Yan Le Can no "common sense" or consciousness

Highly specialized intelligence and not generalist (recognize tumor ok but unable to make coffee)

Artificial intelligence is VERTICAL (highly specialized), human intelligence is HORIZONTAL (culture).



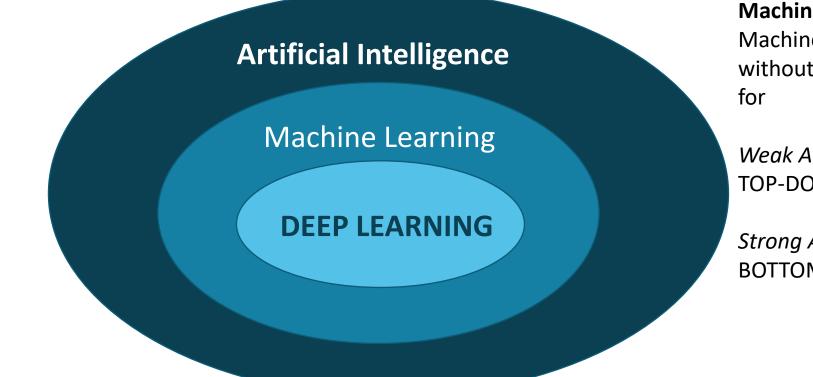


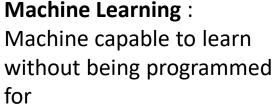
Some examples of recent gaming AI milestones

- May 1997 : DEEP BLUE (Ibm) beats Garry Kasparov, Chess World Champion
- >2015 : AlphaGO (GOOGLE) beats the GO World champion
- 2017 : LIBRATUS (Carnegie Mellon) won a poker marathon (1 766 250 dollars) against four poker world champions in Las Vegas (« Heads Up (1 vs. 1) No-Limit Texas Hold'em' »).

DATA SCIENCE : AI, Machine Learning, Deep Learning







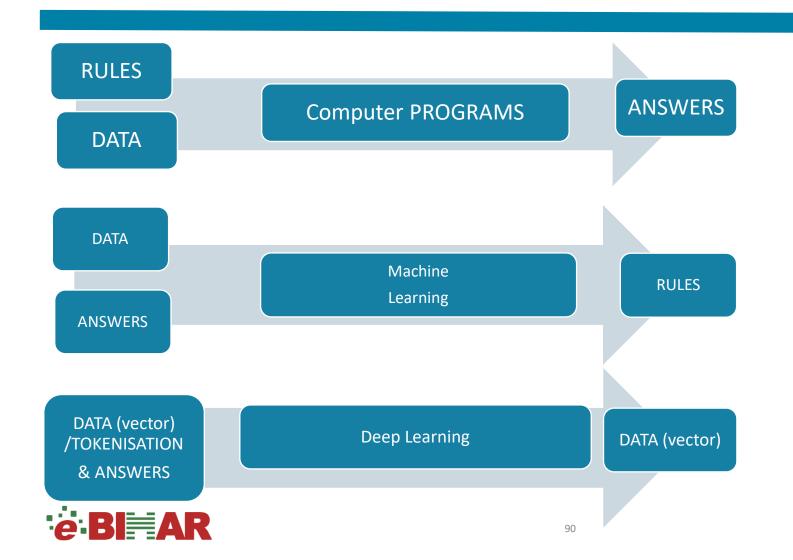
Weak AI : IMITATION and TOP-DOWN

Strong AI : CREATION and BOTTOM UP



Symbolic AI , ML & DL





ML is trained with labelled DATA without explicit programming

ML is strongly associated with applied statistics but on BIG DATA

DL is a simplistic modeling of brain neurons

« Machine learning (ML) » (DATA driven):

applied statistics meeting BIG DATA!



- « No free lunch theorem » (algorithm agnostic)
- « Every model is false but some could be useful » George BOX
- ML Description with 2 types of variables and 2 functions :
 - > Y = F(xi) , F real prediction function
 - > Xi : predictive variables (observation)
 - y : target variable (for prediction)
 - f « predictive function » (close to F)

>Machine LEARNING ?

> SUPERVISED

- (data labelling with Y being either a VALUE or a CATEGORY) :
- REGRESSION
- CLASSIFICATION
- > UNSUPERVISED
 - (clustering); No Y ! :
 - CLUSTERING
 - ASSOCIATION
- > Reinforcement :

Learning paradigm by trial-and-error, from rewards or punishments

≻Adversarial,...



Artificial Intelligence ? = DIGITAL ALGORITHMS ?





►Born in 1957 after ...

<u>https://youtu.be/ZtwgqpUibfU</u>

Dartmouth conference in August 1956 organized by Marvin Minsky and John McCarthy (MIT Professors ...followed by « *Moon project* » John Kennedy andtwo long darkness winters ...until 2012....

until BIG DATA and GPU !

2019 : TURING AWARD for *Y.Bengio, G. Hinton* and *Y. Le Cun* < DEEP LEARNING>

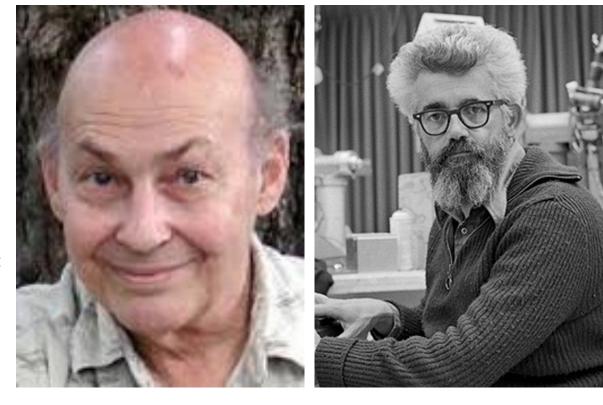
Artificial Intelligence ? not a (single) TECHNOLOGY !

a platform for DIGITAL ALGORITHMS based upon different technologies : predicate logic, linear algebra, graph theory, ...

with 2 generic formal approaches :

UNIVERSAL THEORY (brain model) vs EMPIRISM (Neural Nets,..)

SYMBOLIC AI vs CONNECTIONIST AI





In 2010 NEURAL NETS rebirth with BIG DATA and SILICON for AI (GPU)



> SILICON for AI : CPU, ASIC and GPU

CPU : highly programmable but no performance

ASIC (Application Specific Integrated Circuit) and ASSP (application specific standard product) in Deep Learning

- >Special purpose integrated circuit (since the 80's)
 - > Example : Matrix product
- Training of neural networks for AI
 - > Example : CLOUT (Google, 2017) Tensor Flow Processing Unit (TPU)

GPU (Graphical processing units): Asic used for processing graphics!
 introduced to accelerate 3D graphics, gaming and video
 GPU was then designed to perform MATRIX operation as fast as possible
 High-level programming languages are compiled to the GPU (Java, Python, Matlab, Haskell, ..)



« SMART CHIPS » for DNN from CPU to GPU : « Moore's law is obsolete » ! JH Huang (Nvidia)

1965 : Intel founder « Moore's law »

2017 : Jen-Hsun Huang (Nvidia founder): « *Moore's law is obsolete* »

- > NVIDIA created in 1993
 - 7 G dollars of revenue in 2016-2017 with 53% only in video games (18% for data centers, 6% for car indusytry (Tesla, Toyota, Audi, <u>Baidu, ..) and 2 G Dollars of net profit</u>
 - From Graphical Processing units (GPU) to DNN with parallel processing (vs CPU)
 - ➢ In 2007 CUDA platform for processing any variety of DATA→ IA, CLOUD, IOT
 - > Pascal Architecture (P100) then VOLTA GPU

> OTHER GPU providers :

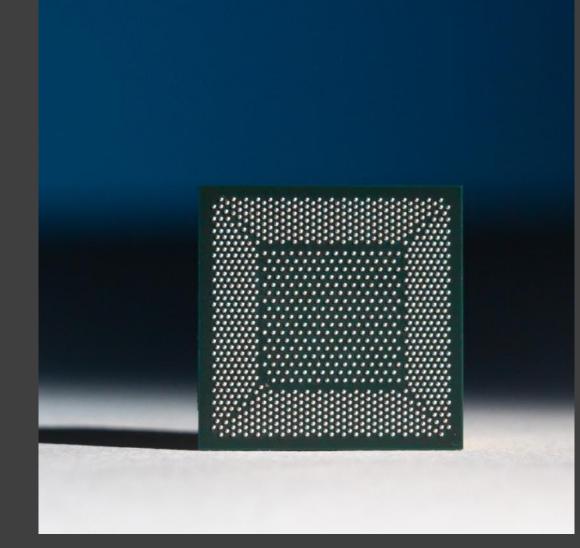
- INTEL and NERVANA , GOOGLE : Deep Mind; TensorFlow (Open Source since 2015), AMD and its processors: ZEN; VEGA GPU
- Cerebras, Knupath, Grapgcore,...

NEUROMORPHIC COMPUTING * (INTEL) with

LOIHI research chip :

- emulating the neural structure and operation of the human brain,
- 3rd generation of AI
- "SPIKING NN": Each "neuron" in the SNN can fire independently of the others

https://www.intel.de/content/www/de/de/research/ neuromorphic-computing.html



The Loihi research chip includes 130,000 neurons optimized for spiking neural networks (SNN) <on 14 nm>; 1 nm = 1.0E-9 m

AI + BIG DATA → CHATBOT (CHAT + roBOT) application replacement ?



> Alan Turing (1950) and ELIZA !

➤Gartner :

« 85% of Internet transactions will be performed without human beings before 2021 *»*

> OVUM : « 75% of growing rate for Chatbot market between 2016 and 2021 »

>2016 : FACEBOOK opened its interface for Chatbots (then Youtube/Microsoft,..)

 \rightarrow > 10 000 Chatbots in 2 years *

>tweets generated by robots (1/3 in the USA!)

➢Price alert , Customized press reveiew, ...

> OPEN SOURCE Chatbot generator, **Chatfuel :**

http://www.leptidigital.fr/reseaux-sociaux/creer-chatbot-messenger-8755/

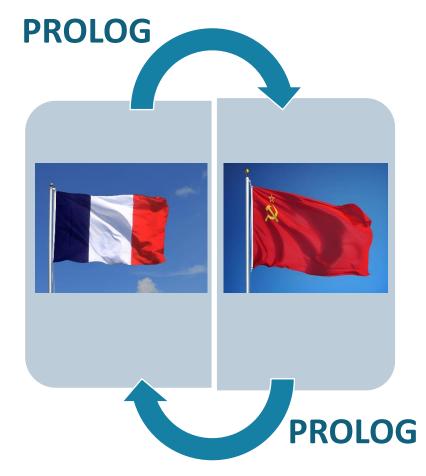


2 TYPES of AI . An example with PROLOG and natural language processing with Pr Alain Colmerauer in 1980



INPUT : « L'esprit est fort mais la chair est faible » (The spirit is willing but the flesh is weak)

Double OUTPUT : « La vodka est forte mais la viande est molle » (Vodka is strong but the meat is soft)



SYMBOLIC AI (GOFAI)

VS

CONNECTIONIST AI (Deep Learning)



2 types of AI & 2 major forms of intelligence: RATIONALE (reasoning) and INTUITION



1) Symbolic AI < rule languages and RATIONALE>

IF THEN ELSE rules Logic (Ex Prolog)

>Handwritten programs

Ex: Expert systems such as Mycin for infectious diseases (600 rules) or Airbus for the accuracy of its airliner control software.

Hierarchical inference engine with backward chaining Modeling expert knowledge

GOFAI (Good old-fashioned AI) !

Instead of trying to produce a programme to simulate the adult mind why not try to produce one which simulates the child's. If this were then subjected to an appropriate course of education (training) one would obtain the adult brain »

> Alan Turing, (Computing machinery and intelligence » MIND, Vol 59, N° 236, Oct 1950



Connectionist AI

"DEEP LEARNING is part of the future of AI" Yan Le Cun (Dec 2019)



2) CONNECTIONIST AI < Neural Networks / DEEP LEARNING/ML and INTUITION >

"Reasoning is only a part of human intelligence Perception, intuition and experience are all learned abilities and trained."

CONNECTIONIST AI < Neural Networks /DEEP LEARNING/ML and INTUITION (antisphexity!) >

- Having a Machine CAPABLE TO LEARN
 - DATA driven (supervision, non-supervision, reinforcement)
 - Engineering by DATA
 - > DATA LEARNING

> No programming but training a machine to perform a task (learn a task from examples)

>Intuition? "Antisphexity"!

IA tomorrow is a hybrid system with ML/DL, GOFAI and classical computing A DL system is not capable of logical reasoning. Logic today is incompatible with learning

>"The challenge for the coming years is to make them compatible" Yan Le Cun





Biological NEURONS, brains and computers

Biological NEURONS with DENDRITES (inputs) and AXONS (outputs)

- <100 billions* NEURONS in our brain (20 in our Cortex)
- Interconnexion among them thru SYNAPSES
 10 000 synapses/neuron < 1 peta synapses>
 In one brain cm**3 : 10 000 billions* SYNAPSES

 - > Each synapse can perform a computation several hundred times per sec.

(theoretical synaptic computing capacity of 100 PETA op. per second) > Average power consumption of 25 WATTS

- Information speed among synapses : 120 m/sec (430 km/h) and **1 PETA bytes** of stored data! > Learning: creating synapses, removing synapses or changing their effectiveness (Same logic in deep NR)

> On an intelligence cursor from 1 (mouse) to 100 (human), the AI D today would be 1.1

 \rightarrow possible simulation with a computer of **1 billion* op/sec** in 2020 (NOTE : 1 billion* more powerful computers by 2050)

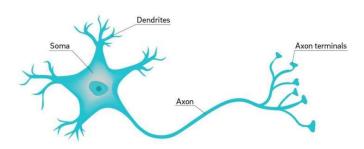
Supercomputers are approaching this computing power but with more energy! GPU card: > 10 teraflops/SEC (100 000 cards for brain computing power!) Note: a GPU card consumes 250 WATTS (10 times more than the brain)

In 1977: The 160 Mflops Cray 1 was worth 8 million dollars (5 tons and 115 Kwatts). GPU card 60 000 times more powerful for 300 Euros! (soon in smartphone)



*Billion : 10**9

Neuron



Digital neuron, perceptron and neural nets



« Simplified view of a natural neuron which could be useful » Alice Guyon

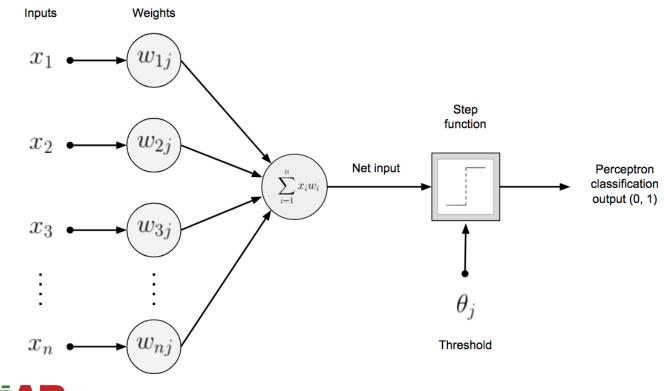


FIGURE : Typical *PERCEPTRON* (1957) view of one digital Neuron

From single neuron to NN

...

→ multi-layered perceptron (MLP) or NEURAL NETS (with activation function)

Linear algebra is the bedrock of Deep Learning :

Ax = b in basic machine learning with the matrix A , the parameter vector x , to get output column vector b

X VECTOR : {w1j, w2j, ..wnj}



Deep-Learning Neural Network (DNN)



 x_2

DEEP LEARNING is a rebranding of NEURAL NETWORKS (with more than 2 layers)

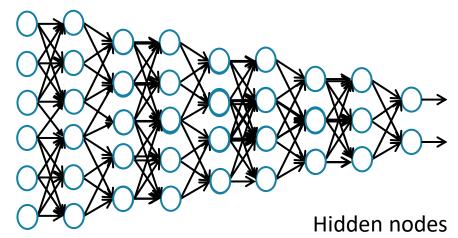
- DNN is a multi- layer Neural Net which can be processed efficiently with GPUs (Graphical Processing Units) and trained with Big Data (data-centrics learning)
- Millions of Neurons in HIDDEN LAYERS with
 - no intra communication among neurons within each layer

➢Neurons

Computational units

Connections

Weight inputs from previous layers before feeding into next layer

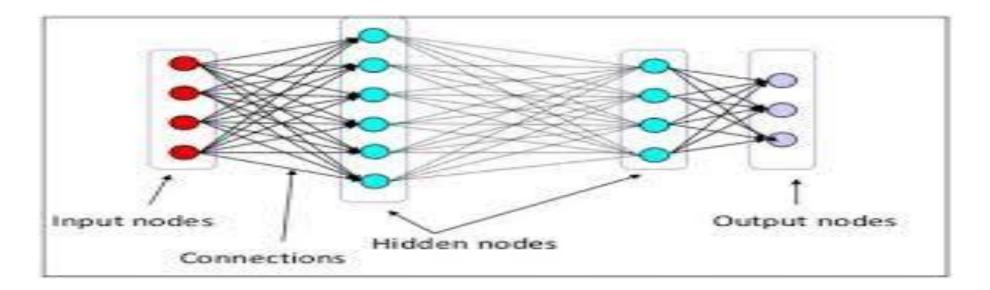


 W_1



Deep learning



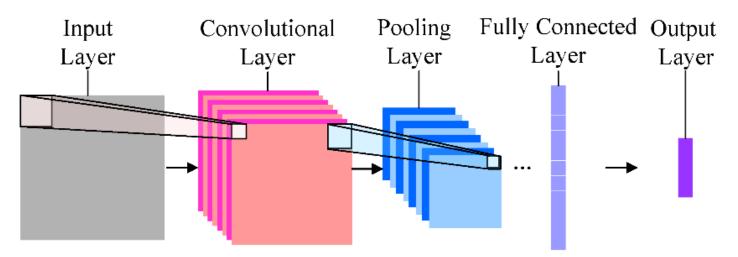






Convolutional neural nets (CNN or CONVnets)



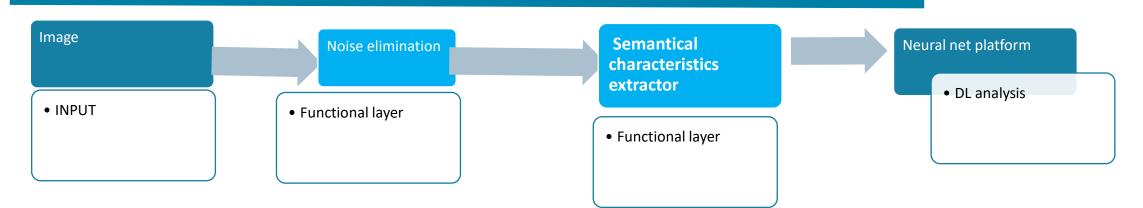


- Convolutional layer (CONV) The convolution layer (CONV) uses filters that perform convolution operations. Its hyperparameters include the filter size F and stride (step) S. The output is called *feature map* or *activation map*.
- Pooling (POOL) The pooling layer (POOL) is a down-sampling operation to reduce size of an image without loss of important information.



Pipe Line architecture & DEEP LEARNING





Data preparation and noise elimination (Ockham's razor)

> « Everything shoud be made as simple as possible but not simpler » Einstein

Last functional layer before DL platform : « characteristics extractor »

➢In manual mode :

Ex : SVM (Support Vector Machine) method from Isabelle Guyon (Orsay) well formalized but ... « far from reality »(Yann Le Cun) !

In (data) learning mode : « DL challenge » (Yan Le Cun)



AI "is a diligent assistant who works fast without fear of repetitive tasks".



"INTUITION for me has always preceded mathematical FORMALIZATION ...avoiding the evil of the French search for mathematical beauty per se (Ex SVM of the Univ d Orsay or DATA LOG)" Yan Le Can

>Example : Multilayer Neuron Networks cf CAT vision (2 Nobel awards in Biology)

1981 : two neurobiologists (D.Hubel and T.Wiezel) are awarded the Nobel Prize for their work on the cat's VISUAL system composed of several layers of neurons :

retina to the primary visual cortex (simple cells) then to the inferior temporal cortex (complex cells)

- → NEOCOGNITRON machine of Fukushima (Japan)
- → CNN (Convolutional NN)

Artificial neuron with neuron = Simple mathematical function with input/output vector and intermediate matrix



Some other disruptive technologies in the data economy



NFC (Near Field Communication) LIFI (Light Fidelity) Blockchain





NFC and... MOBIQUITOUS systems ?







Tweet on Mobiquity*





Serge Miranda @SergeM06

MOBIQUITY ? = MOBIlity of the cell phone who became a computer (a "smartphone") and ubiQUITY of Internet who became social and broadband

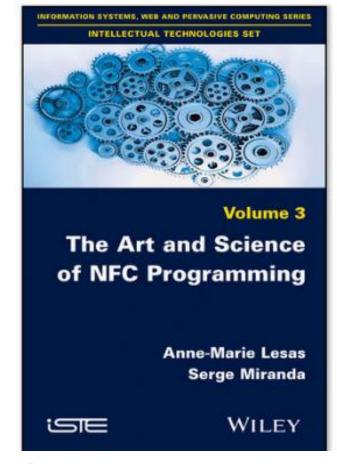
🛧 Reply 🛍 Delete 🔺 Favorite

* Part of a « TWEETED SEMINAR » on NFC Technology and Mobiquitous information systems at University of Tampa, Florida (2012) < Tweet Presentation on Slide Share>



MBDS books on NFC Programming and mobiquitous systems (2011 & 2017 & 2019)





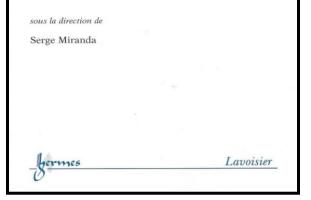


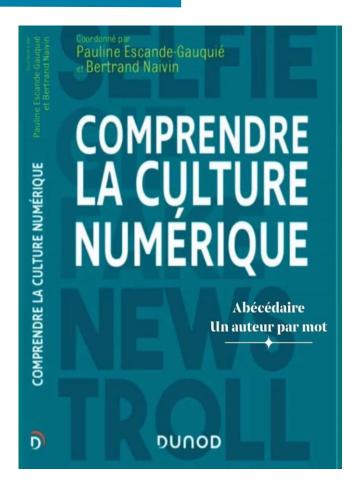


Ingénierie des systèmes d'information

RSTI série ISI · Volume 16 - nº 4/2011

Systèmes d'information mobiquitaires





« Homo Mobiquitus & commonactors »

50% of the planet owns a smartphone in 2015 (50% being NFC)







Bouthan

Sister Flora (Haiti)

e BI AR

NFC (world) STANDARD



NFC (Near Field Communication) : « TOUCH'n PLAY » for universal connector...





#NFC world standard since 2004 to enable a cell phone to PAY, OPEN DOOR, CONNECT, GET/PRODUCE information just by touching a tag

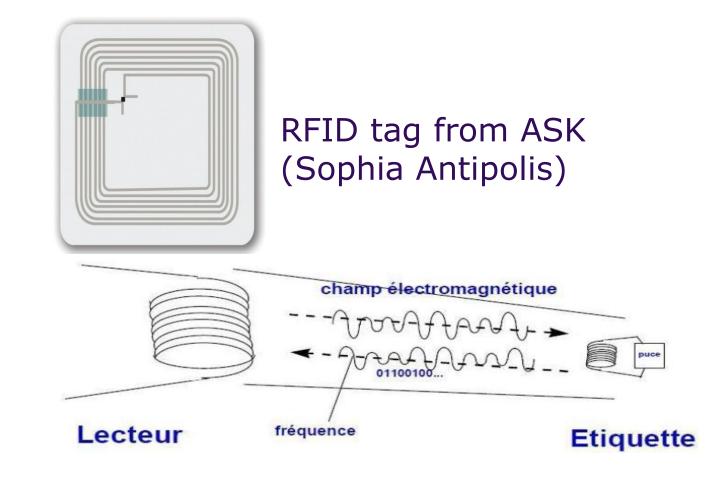
🛧 Reply 🛍 Delete 🄺 Favorite

(TWEET Seminar at University of TAMPA in 2012)



NFC/ RFID (Radio Frequence IDentification) tag ?







The three modes of NFC standard



- 1. « **READ/WRITE** » (active/passive)
- 2. « CARD EMULATION » (passive/active)

« SECURE ELEMENT » (SIM or ?) or HCE (Cloud)

TSM (Trusted Service Manager)/SE

3. « PEER TO PEER » P2P / (Active/active)



The five « W » of NFC applications



2) WHERE & 3) WHEN ? (Ici et maintenant!)

4) WHERABOUT ? (GOAL)



5) WHAT ?

1) WHO ? (USER Profile)



« Mobiquitous effect »?

(combination of Moore's, Morris', Metcalfe's, Gilder's laws)

Gilder's law on bandwidth

>Bandwidth doubles every year and half

Metcalfe's law on Network value

Network value depends on squaring the number of its nodes

>Morris law on storage.

Number of gigabits per square inch doubles every year

> OC law on smart/tagged objects (IOT) :

>Number of smart objects doubles every year

►(BIG) DATA law

>The quantity of data doubles every year

>Moore's law on

computer power :

The CPU processing power (number of transistors per chip) doubles every 18 months (100 times per decade) until 2030 then obsolete and... new

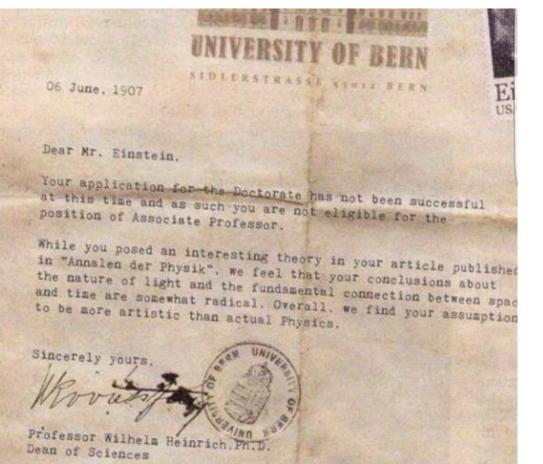
NVIDIA- founder's law on GPU !





1st DATA equation for the future: E=MC2







≻E = MC2 !

Energy Multimedia Computer & Communication

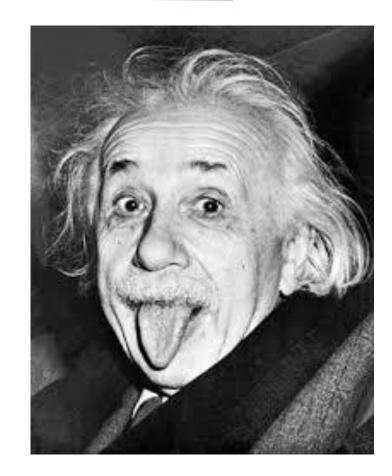


2nd DATA equation for the future : E = MC3 !



« E= MC3 »

Energetic resource M obiquitous systems Computer + Communication + Consumer Electronics





LIFI (LIGHT FIDELITY)



Harald HAAS

>LIFI in 60 seconds <in French>

https://youtu.be/RtMmKBQJz6k





LIFI (Light Fidelity) ?



>HIFI (High Fidelity) then :

WIFI (RADIO portion of the electromagnetic spectrum)

>LIFI (LIGHT sprectrum from LEDS)

>communication technology based on the LIGHT spectrum and the use of the VISIBLE BLUE

(450 nm) and THE VISIBLE RED (760 nm) of lights generated by LEDs

>LED includes a semiconductor :

Fast switching of light (LEDs are semiconductors : 10**9 per second !)

Long life + LOW POWER + HIGH DATA RATE (10 times WIFI)

+ **SAFE** → HD Streaming

>Standardized : IEEE 802.15.7 since 2011



LIFI applications (with location-based services)



OUTDOOR applications in smart cities : **Smart Public Lighting**

>INDOOR applications

- Smart Homes
- > Smart Offices
- > Smart Campus
- Smart Airports
- > Smart Hospitals

Smart MUSEUM

LIFI demo video (in French) of Mbds JMAGINE* project in the International Museum of Parfume in Grasse (France) :

https://www.youtube.com/watch?v=tHKG9CkQm7U

*Open Source platform for teachers to create invisible paths in smart territories (and smart museum)

Le LiFi, WiFi du futur, décrypté au MIP

Et s'il existait un outil de assurait Serge Miranda communication encore plus «Notre fantasme, c'est de moderne que le WiFi? Une conférence au MIP. mardi soir, permettait de faire toute la lumière sur le Lassus, précurseur il y a LiFi: une technologie de communication sans fil utilisant l'oscillation de lumières LED. Un cocorico bienvenu.

Le principe est simple : il suffit de passer son smartphone équipé d'un tait encore Serge Miranda, Dongle ou la caméra du avant de citer l'exemple de smartphone - s'il est com- la Suède qui a banni le WiFi patible - sous un faisceau de tous ses hôpitaux au prolumineux pour accéder à du fit du LiFi, ou encore les micontenu. litaires qui ont fait le même choix.

75 % de LED en 2020 «La créativité sur les usages Au Musée International de la est infinie», insistait Serge Parfumerie, trois prototy-Miranda. Le fondateur et directeur du master Mobipes avaient été mis en place. En passant son téléphone quité, Big Data et intégrasous la première lampe LED, tion de systèmes (MBDS) on découvrait - en multilinreçoit régulièrement des stague - le contenu de la malgiaires qui viennent se forlette de Marie-Antoinette exmer à la manipulation du posée dans les salles du LiFi. En ce moment, deux musée. Le second prototype étudiantes marocaines répermettait d'accéder à une fléchissent à un projet vidéo réalisée par les colléd'éclairage public qui pergiens de Saint-Hilaire (lire mettrait aussi de recharger par ailleurs) et le troisième son téléphone grâce à la LiFi ... un projet qu'elles esprototype était un diffuseur de parfum très amélioré! pèrent développer à Casa-«Quand la lumière déclenblanca, la ville qui acche une odeur, c'est le début cueillera la COP22. d'une créativité sans limite »,

faire en sorte que la région devienne la capitale mondiale de la LiFi, aioutait Marc quelques années, dans le domaine de la carte à puce. La France est en avance !» «D'ici 2020, 75 % des ampoules seront des LED », no-

Grâce au LED, on pouvait découvrir le contenu de la mallette de Marie-Antoinette... Dans toutes les langues! (Photo L. S.)

Le collége Saint-Hilaire et la LiFi

Sous l'impulsion de Mélanie Fillon-Robin, professeur d'arts plastiques, les élèves de 4°4 au collège Saint-Hilaire ont réalisé un courtmétrage de trois minutes. En utilisant la technologie LiFi, la vidéo « s'infiltre » dans le téléphone du

visiteur et le captive.







C'est-à-dire? On ne consulte les informations que si on est intéressé en placant le mobile sous le faisceau. Si on ne veut pas être embêté, on garde son téléphone dans sa poche.





Questions à

Les avantages de la LiFi? Il n'y a pas d'ondes électromagnétiques. La vitesse de transmission des informations est 10 à 100 fois supérieure au WiFi

Et les inconvénients?

Il faut être sous le faisceau lumineux. Mais le LiFi peut fonctionner même quand on ne voit pas la lumière, avec des infrarouges par exemple C'est ciblé. C'est aussi un avantage: la géolocalisation est non intrusive.

Blockchain (*distributed data base*) and digital record-keeping (transaction tracking, ...) & everlasting application !



>In proof we trust

The GOD protocol »
 Nick SZABO cf Lederman's « The GOD particle »

> « the GOD DATA » !

>End of serendipity ?

You are YOUR projects >> (Tom Peters)

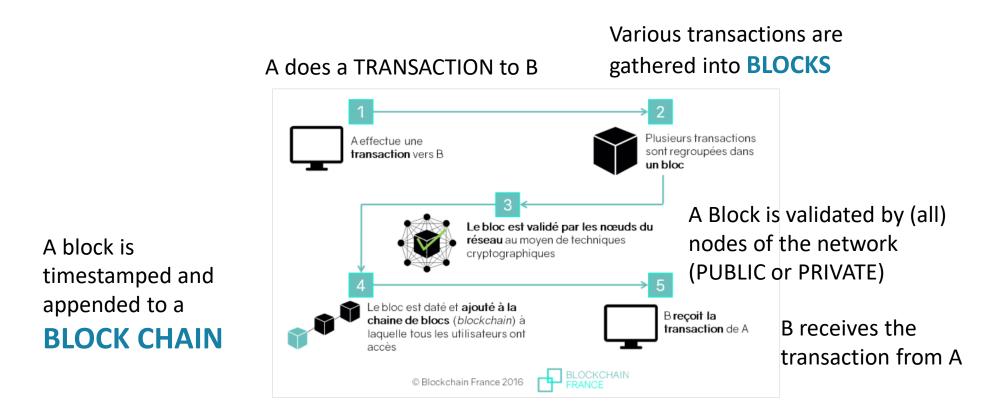
→ « You are YOUR DATA » !

Blockchain technology will revolutionise far more than money : it will change your life !



Blockchain and fully-duplicated ledger





https://www.cigionline.org/multimedia/what-blockchain



DATA future (*Let us decode it !*)?







Three dimensions of the future in the DATA ECONOMY

Three dimensions of our DATA future

- Internet of Everything SMART PLACES & Little BIG DATA
- BOTTOM UP paradigm (innovation, energy, computing,..)
- Homo Mobiquitus and « commonactors »

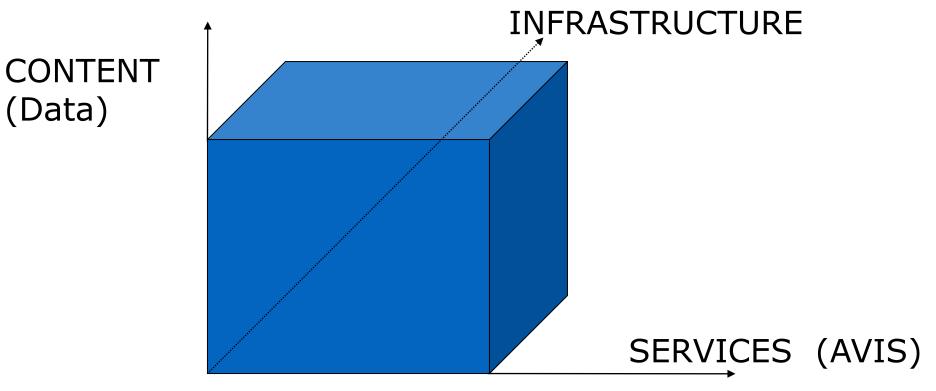


Caricature PAVO (Conf Cnameo Toulouse, 30/9/2020)

ICT CUBE



« A cube is a metaphor for a strong relation » J.Olsson





From TOOLS to SERVICES (AVIS) and SMART PLACES



If we can predict the future of the infrastructure we cannot predict the future of services... services cannot be controlled TOP DOWN... Digital divide on services not in technology... from services to SMART PLACES... »

Pr. Leonard Kleinrock (UCLA), June 2008, Brussels

>AVIS >> HERTZ

>AVIS :

Added-value information services >HERTZ :

Heoric Executive Retreat to Zero

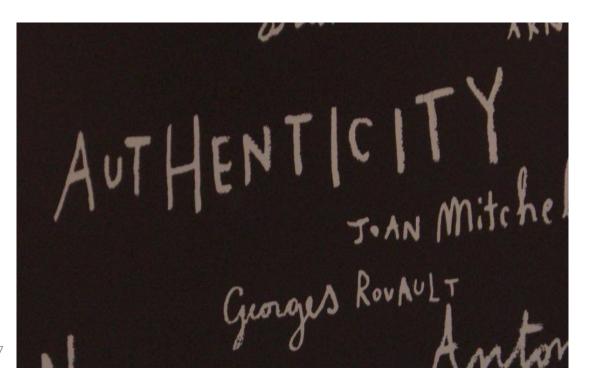


From Services to SMART PLACES



►TOOLS → « Quantity »,
►SERVICES → « Quality »,
►SMART PLACES
→ « Authenticity* »

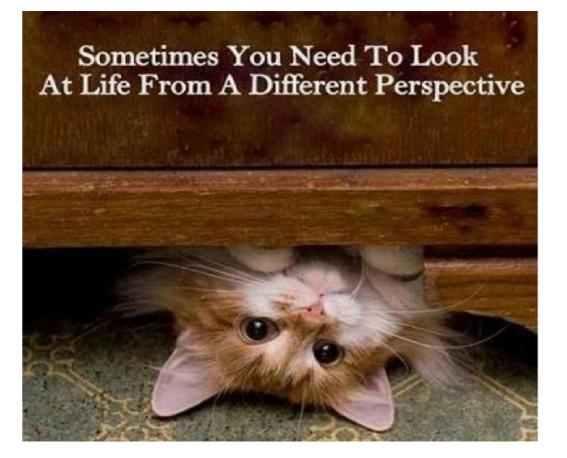
* *Authenticity » J.H.Gilmore, B.J.Pine, Harvard Business Review, 2007





From TOP DOWN (infrastructure) to BOTTOM UP approach (services)





From hierarchical Top down (1:N) of the past to the « Bottom Up » (N:1) of the future

BOTTOM UP :

- Computer science (PC ! Internet, Smartphone !)
- 2. Renewable energy
- 3. Society (Holocraty)
- 4. Innovation,
- 5. Deep Learning, ...





Homo Mobiquitus ?

Homo Habilis
 Homo Sapiens
 Homo Mobiquitus (and COMMONactors*)

> The Smartphone won the battle of the pocket !



*Serge Miranda, « New data territories/Nouveaux Territoires numériques », Book, Ecole des Mines, Nov 14 [MIRA2014]



Society evolution



CONSUMPTION (production) society

COMMUNICATION society

COMMONACTION society





Society evolution ?



Society life in which reigns the <u>PRODUCTION</u> <u>Mode</u> will come out with a large accumulation of GOODS » Karl Marx – The Capital (1867)

Industrial revolution

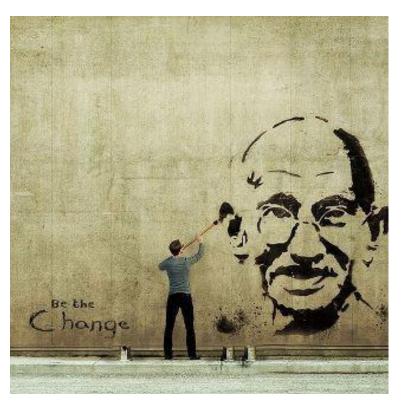
 « ...(<u>COMMUNICATION mode</u>)... a large accumulation of SHOWS » Guy Debord (1967)

Internet revolution

 « ...RECOMMENDATION/COMMONACTION mode ...a large accumulation of DATA » (2017)

→ DATA revolution
 BI AR

« Be the change you want to see in the world» GANDHI



Towards a student head ...



 Well « FULL» with Writing
 well « MADE » (Montaigne) with Printing
 well « CONNECTED » (Michel Serres) with Internet

towards well « AUGMENTED » with mobiquity/Smartphones, AI and Little Big Data !





DANGER : « ANYWHERE » vs « SOMEWHERE » *



Digital divide on

Social CULTURAL aspects

(identity, Ecology, Immigration, flexibility) vs

Social ECONOMICS

(Consensus on regulated free trade with social and education framework)

> ANYWHERE :

flexible urban persons of the Knowledge data society with GLOBAL trade and international living vs SOMEWHERE (deeply rooted with LOCAL living) DANGER (domination) : ANYWHERE>> SOMEWHER

* David Goodhart, « The road to somewhere », 2017





Danger : « Panopticon* 2.0 » (*CONFINEMENT* 2.0**)**

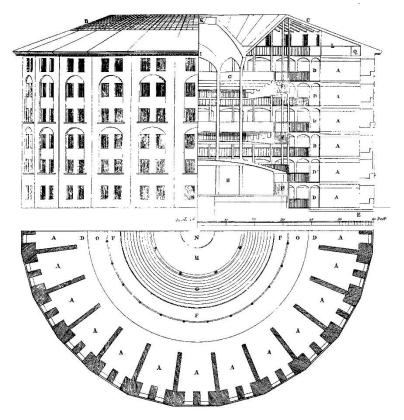


Less freedom for more security !?
 Everybody can KNOW anything on anybody

Jail architecture with a factory model imagined by Jeremy BENTHAM to enable a centralized guard to view and control every prisoner*

* <u>(Panopticon by Bentham, philosopher and architect, 1780)</u>





Conclusion : Spiralist Innovation



In the data economy :

« EVERYTHING is SPIRAL »





*Creator of SPIRALISM concept in litterature





DATA-centrics spiralist Innovation ?



>Innovation ?

>INVENTION meeting an USAGE !

Bottom up and multidisciplinary

>(traditional academic research is top down and mono disciplinary)

➢Quadrants of digital innovation by Pr. Gary PISANO* (Harvard)

- ROUTINE Innovation
- ➤TWO DISRUPTIVE INNOVATIONS :
 - > Disruptive TECHNICAL Innovation
 - Disruptive ECONOMICS (Busines-model) Innovation
- >ARCHITECTURE Innovation
- * Gary Pisano « You need an innovation strategy » Harvard Busines Review, June 2015 (in French Gary Pisano, Harvard Business Review, Summer 2016, pp 16-25)



Innovation quadrants by Pr. Gary Pisano



	Old technologies	New Technologies
NEW BUSINESS MODEL	Disruptive economics (BM) Innovation Sharing Economy (Uber, AirB&B,)	Disruptive ARCHITECTURAL INNOVATION APP STORE CLOUD
OLD Business model	ROUTINE INNOVATION <i>New car, new smartphone</i>	Disruptive TECHNOLOGICAL INNOVATION <i>BIG DATA, NFC, LIFI, Blockchain, Deep Learning</i>



SPIRALIST INNOVATION (some kinetics)



	OLD TECHNOLOGIES	NEW TECHNOLOGIES
NEW BUSINESS MODEL	Disruptive economics INNOVATION	Disruptive architectural INNOVATION
OLD BUSINESS MODEL	Routine INNOVATION	(2) (1) Disruptive technological INNOVATION



SPIRALIST INNOVATION in the DATA ECONOMY



	OLD TECHNOLOGY KNOW-HOW	NEW TECHNOLOGY KNOW-HOW
New Business Model (BM)	disruptive BM innovation	ARCHITECTURE INNOVATION
Old Business model	Big Data (DL) Blockchain NFC, LIFI ROUTINE INNOVATION TECHNICAL DISRUPTIVE INNOVATION	

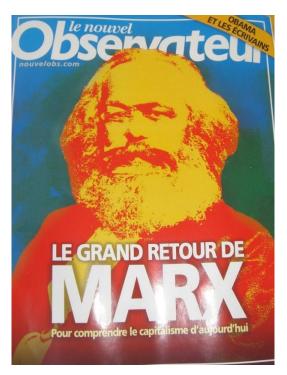


CONCLUSION 1 Sister FLORA (Haïti) & Karl Marx !



«If you cannont change the world try to change YOUR world »

Marx (last sentence)



« **An ant can bear an elephant** » Sister Flora (Haiti, June 2013)





CONCLUSION2 : Be « *innovation warriors* » !







« Tribe of IMAGINATION warriors »

« J'ai la certitude que nous sommes .. de la même race, de la même tribu des VIEUX GUERRIERS DE L'IMAGINAIRE »

FRANKETIENNE (1/9/2011)



Questions ?

< DATA humanum es © > <The world as a neural net (V.Vanchurin 2020> < Category theory as a uniform formal data model for polystores>



« If you are crazy, it is possible. Remain open to creativity and innovation » John Gage, 28 Oct 99 MBDS Sophia

« *Stay hungry, stay foolish* » **Steve Jobs**, Stanford, 2007

Charles Babbage en 1812 :

« Propose to any english man any principle or any new instrument however admirable and you 'll observe he will spend his energy to demonstrate it could 'nt work.
Propose it to an american, he will congratulate you and spend his energy to find new applications »



The two first European GRADEOs in January the 4th with three complementary concomitances



(i) **eBihar* MSc launching** on FUN platform on January the 4th (one video-tutoring session from January to May with a genuine Oracle Learning Subscription) for initial education

https://www.datumacademy.com/masters

- (ii) **BIHAR/ESTIA GRADEO (microcredential) on « BIG DATA and AI » starting** on January the 4th (the 2 first GRADEOSin Europe) for continuous education; registration on FUN MOOC platform:
- GRADEO 1 :<u>https://gradeo.fun-mooc.fr/sql-programming</u>
- GRADEO 2 : <u>https://gradeo.fun-mooc.fr/big-data</u>

(iii) New Oracle University Learning Subscription starting in January with key data (cloud) expertise to provide professional complementary courses within BIHAR Gradeos

OTHERS ...7 free webinars on AI and BIG DATA in December 2020, January 2021 and February 2021

NOTE : * **BIHAR** (**B**igdata **I**ntelligence for **H**uman **A**ugmented **R**eality) also means « **TOMORROW** » in Basque language



GRADEOs LAUNCH WEBINAR

Catherine Mongenet (FUN) Patxi Elissalde (ESTIA) Valérie Hayotte (Oracle University) Pr. Serge Miranda (UCA & ESTIA) - eMBDS and eBIHAR Master degrees in CS Pr. Marco Gori (UNISI, University of Siena Italy) Mishket Ben Hamida (Datum Academy)





FRANCE UNIVERSITÉ NUMÉÉRIQUE INTUTÉ D' TECRABOLORY

Succesful launching of GRADEOS with FUN, ORACLE, University of Siena, ESTIA and Datum Academy on December the 2nd 2020 (300 on-line attending people))

Yet to come in 2021 around Bihar MSc



➢ 6 webinars on AI and Big Data, 7 GRADEOs in English (January) and in French (October)

>OCT 2021 : Popularization MOOC on **AI by Example** (**AI360**)

In French (ANR THEME)
 Aquitaine region support with 4 start ups ?

OCT 2021 : French version of eBIHAR MS degree (with CAMPUS France) for Africa : ESATIC (Ivory Coast), ITU (Madagascar) along with their French Gradeos
 Local « Digital connected campus » as third learning place

- OCT 2021 : M1 and M2 for BIHAR (2 years) at ESTIA (and on-line with eMiage with projects in Africa (Senegal) and Oceania (Tahiti)
- > European PROPOSALS around ESTIA BIHAR:
 - DATA TOKI Erasmus proposal in 2020 with an annual event : The FORUM of the DATA ECONOMY in Biarritz
 ERASMUS MUNDUS Master project in 2021 based upon blended learning (and moocs) with University of
 - ERASMUS MUNDUS Master project in 2021 based upon blended learning (and moocs) with University of Siena (Italy) and Bilbao (Spain)
 - DEEP BRIDGE research project on Scanner image analysis for brainstroke detection (with Hospital of Nice, ECRIN, Inria, Eurecom, Siena Univ,...)
 - > LIMAD project in Senegal (UVS) with AI blended curriculum from BAC to BAC+8 with Univ of Bordeaux





EXTRA SLIDES ⁽²⁾











« DATA HUMANUM ES »!



JOB OPPORTUNITIES and bottom-up approach for Gradeos: 130,000 engineers needed by 2025

	Occupation	Total Job Postings	Job Postings Requesting Skill(s)(#)	Job Postings Requesting Skill(s)(%)	Projected Growth Within Occupation (%)	Associated Education Level
	Software Developer / Engineer	1,088,223	33,395	3.1%	30.7%	Bachelor's degree
	Data Scientist	<mark>42,050</mark>	<mark>28,611</mark>	68.0%	<u>19.0%</u>	Bachelor's degree
	Network Engineer / Architect	177,097	7,830	4.4%	6.5%	Bachelor's degree
	Data Engineer	<mark>38,571</mark>	6,928	18.0%	11.5%	Bachelor's degree
	Data / Data Mining Analyst	89,573	6,257	<mark>7.0%</mark>	<mark>9.3%</mark>	Bachelor's degree
	Computer Systems Engineer / Architect	187,204	4,937	2.6%	9.3%	Bachelor's degree
	Researcher / Research Associate	82,175	4,511	5.5%	27.5%	Bachelor's degree
	Product Manager	101,358	3,940	3.9%	10.1%	Bachelor's degree
	Database Architect	<mark>50,583</mark>	<u>3,011</u>	<mark>6.0%</mark>	9.3%	Bachelor's degree
	Business / Management Analyst	306,954	2,448	<mark>0.8%</mark>	14.3%	Bachelor's degree

Source: Burning Glass (JOBS that require ML/DL)

The use of artificial intelligence (A.I.) and machine learning (ML), technologies that help people and organizations handle customer personalization and communication, data analytics and processing, and a ions continues to grow. An IDC report found three-quarters of commercial enterprise applications could lean on A.I. by next year alone, while an Analytics Insight report projects more n<mark>ter applications</mark> continues to grow. An IDC report jou niflion available jobs in <u>artificial intelligence</u> by 2023.

Due to A.I. and ML's transformational reach, specialists with the right skills could find themselves with job opportunities across a wide range of industries.





« LES » Sciences (Science des DATA)

CONCEPTSMETHODESOUTILS



SIM / MIS ? (Mobiquitous Information system)



>« MIS supports eniantrodomic** holomophic infostructures for commonactors SURFING our ROR* future in smart places among smart objects with smartphones in a bottom-up serendipity (4th) paradigm of science based upon DATA »

Système d'Information Mobiquitaires/Massives »

(SIM) : « Les SIM correspondent à des infostructures holomorphes eniantrodiomiques^{**} permettant aux communacteurs de surfer en mode ROR^{*} les écounomènes intelligents dans un 4ième paradigme oblatif de sérendipité de la science des DATA »

* ROR : return on relationship (>> ROI) **Eniantrodomia (Greek) : interdependy of opposites »



Deep Learning holomorphism

Holomorphic set : « **ALL is DEEP LEARNING** » cf Vitaly Vanchurin (August 2020)

Cf MONADS (Leibnitz)

The world as a neural network

Vitaly Vanchurin

Department of Physics, University of Minnesota, Duluth, Minnesota, 55812 Duluth Institute for Advanced Study, Duluth, Minnesota, 55804

E-mail: vvanchur@d.umn.edu

Abstract.

We discuss a possibility that the entire universe on its most fundamental level is a neural network. We identify two different types of dynamical degrees of freedom: "trainable" variables (e.g. bias vector or weight matrix) and "hidden" variables (e.g. state vector of neurons). We first consider stochastic evolution of the trainable variables to argue that near equilibrium their dynamics is well approximated by Madelung equations (with free energy representing the phase) and further away from the equilibrium by Hamilton-Jacobi equations (with free energy representing the Hamilton's principal function). This shows that the trainable variables can indeed exhibit classical and quantum behaviors with the state vector of neurons representing the hidden variables. We then study stochastic evolution of the hidden variables by considering D non-interacting subsystems with average state vectors, $\bar{\mathbf{x}}^1, ..., \bar{\mathbf{x}}^D$ and an overall average state vector $\bar{\mathbf{x}}^0$. In the limit when the weight matrix is a permutation matrix, the dynamics of $\bar{\mathbf{x}}^{\mu}$ can be described in terms of relativistic strings in an emergent D + 1 dimensional Minkowski space-time. If the subsystems are minimally interacting, with interactions described by a metric tensor, then the emergent space-time becomes curved. We argue that the entropy production in such a system is a local function of the metric tensor which should be determined by the symmetries of the Onsager tensor. It turns out that a very simple and highly symmetric Onsager tensor leads to the entropy production described by the Einstein-Hilbert term. This shows that the learning dynamics of a neural network can indeed exhibit approximate behaviors described by both quantum mechanics and general relativity. We also discuss a possibility that the two descriptions are holographic duals of each other.



« BIG FIVE » in the data wild world ?



GAFAM...





« BIG FIVE » in the data wild world ?









Google and (Androïd-based) SCREENS







Android and Smart TV



ANdroïd and Smart Home (NEST)





Android and Smart Car, Smart Glasses, Smart Watch...

Google and geo_loc advertising







Google and health







Google Strategy



- 1. « KNOWING YOU »
- 2. « multi-screen addiction »
 - Google Home/assistant, Google car, Google Health..)





TOP DOWN approach for semi-structured DATA stores



≻OPEN DATA

>WEB DATA (Semantic web)

>RDF (Resource Description Framework) paradigm



OPEN DATA formats



PDF for documents

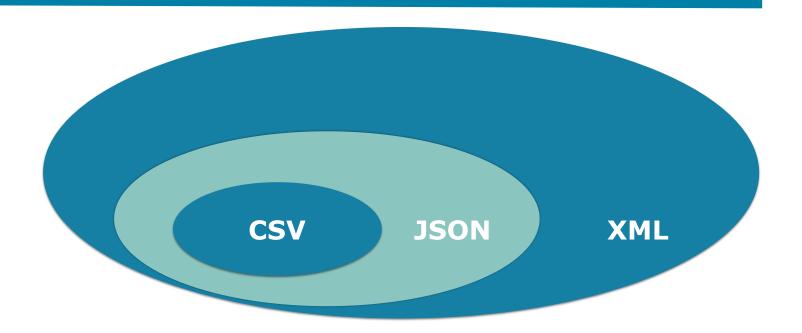
For DATA :

- >CSV (Excel)
- >Web standards for publication and sharing
 - ➢HTML (HTML5), XML, RDF
- >Web standards for syndication
 - ►RSS, Atom, JSON



OPEN DATA : CSV, JSON, XML





CSV (Comma Separated Value) for flat files (1) **JSON (Java Script Object Notation)** for hierarchical documents (2) **XML (eXtensible Markup Language**) for (1), (2), namespaces,...



CSV, JSON and XML (Examples)



#CSV example

First, Name, Course title, date « Serge », « Miranda », « From data bases to Big Data », « 2020 »

// JSON example

{« First »: « Serge », « Name »: « Miranda », « course »: {« title »: « From data bases to BIG DATA », « date » : « 2020 »}}

<!- XML example -->

<xml> <professor>serge Miranda</professor> <list> <course>From data bases to BIG DATA</course> <date>2020</date> </list> </xml>





« I have a dream for the Web [in which computers] become capable of analyzing all the data on the Web — (the content, links, and transactions between people and computers). .. A « Semantic Web », which should make this possible, has yet to emerge, but when it does, the day-to-day mechanisms of trade, bureaucracy and our daily lives will be handled by machines talking to machines. The « intelligent agents » people have touted for ages will finally materialize » TIM Berners Lee (2001, Weaving the web)

> WEB evolution : ➢Network of PAGES → >Network of structured documents (XML) \rightarrow ▷DATA WEB/Network of DATA (RDF)→ Semantic web (Linked RDF) < W3C> 161

RDF (*Resource Description Framework*)



>Defined by W3C (January 15th, 2008)

Derived from XML

- **URI** for resource identification
 - >Web page (identified by URL)
 - >Web Service
 - >XML document fragment
 - >Any object (even physical) having collected DATA



DATA in RDF



RDF triples to describe WEB resources

- (:serge: insureFLIGHT:AF100)
- (:Peter:insureFLIGHT:AF110)
- (:AIRBUSA320:isusedinFLIGHT: AF100)
- (:Paul:ispassengerinFLIGHT:AF100) ...

Note :

A RDF triple<S.P.O>

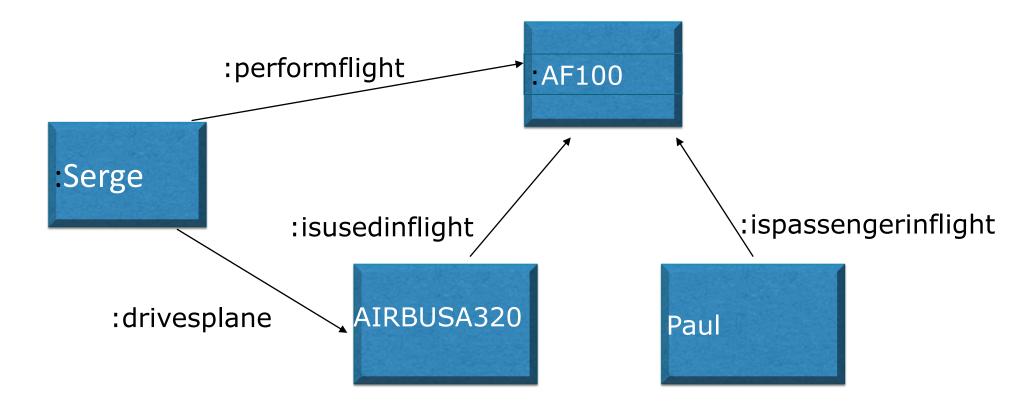
- is a fact in 1st order predicate logic
- P(S,O) with *P* Predicate, *S* Subject and O object

Example : INSUREFLIGHT (Serge, AF100)



RDF graph (Example)







R language : esperanto in DATA SCIENCE (top 10 language in 2015 by IEEE; top 5 in 2016....)



R is OPEN SOURCE (GNU GPL) for STATISTICA ANALYSIS on Linux, Windows, MacOS,.. with 2 major assets :

- Social network
- CARTOGRAPHY

 Created in 1993 by Ross Ihaka and Robert Gentleman from BELL (derived from S and SCHEME)
 Writtent in C++, Java , Fortran and C

Thousand of open libraries « PACKAGES » beyond basic statistics : from social network analysis to Deep Learning DATA FRAMES (matrices)

➤R Interface with every major DBMS → Enterprise adoption Oracle, Microsoft, IBM, Teradata, Postgres, MySQL,.. With RMySQL, ROracle, RPostgreSQL ,...



R cartography example*

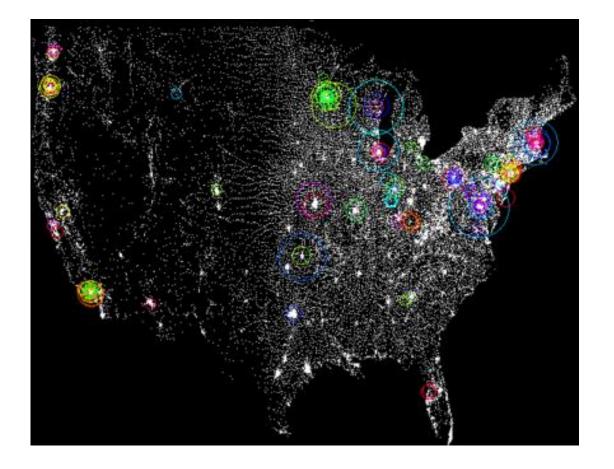


Credit card fraud scheme featuring time, location, and loss per event, using R :

Each circle is a fraudulent transaction in one particular fraud case, over several months. Circle radius represents dollar amount. Color represents recency, from blue (old) to red (new). The fraud spread from the East to the West coast, as you can tell by the colors.

*GRANVILLE 2008

http://www.analyticbridge.com/photo/20 04291:Photo:1417?context=featured



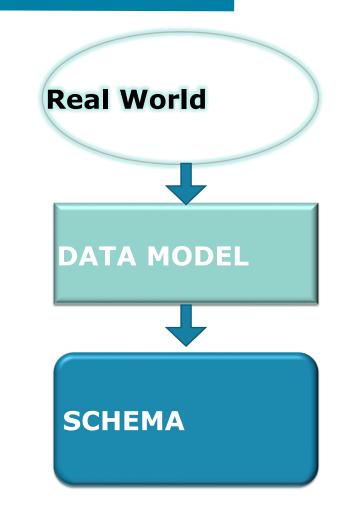


Top Down approach with SQL/ODMG



TOP DOWN approach for DATA **STRUCTURATION**

→ pre-definition of a fixed schema





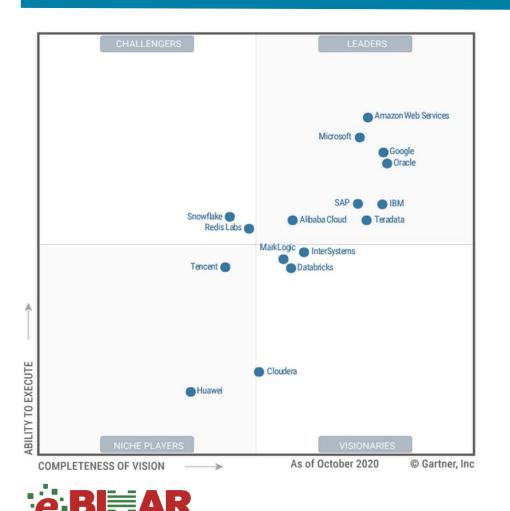
Gartner 's quadrants on DBMS (2019)





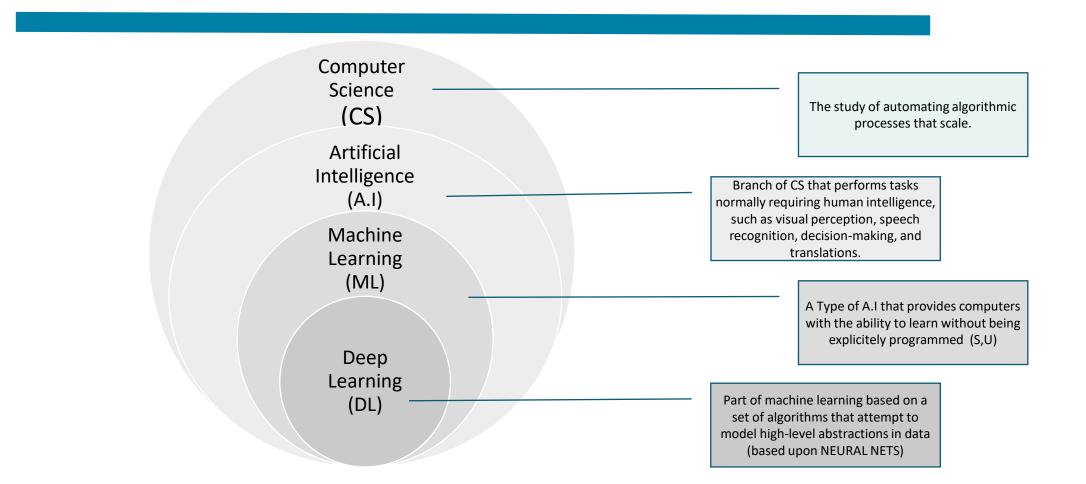
Gartner magic quadrants on DBMS in the cloud (Nov 2020)





Gartner has positioned Google as a Magic Quadrant Leader with AWS, Microsoft and Oracle

The case of Deep Learning (« neural nets »)





AI birth in Darmouth (August -5 1956) INSTITUTE OF TECHNOLOGY

1943 : **CONNECTIONISM** with Warren McCulloch, Walter Pitts, neurologists : 1st Neurone modelling

1950 (oct) **COGNITIVISM** with Alan Turing : « **Computing machinery and intelligence** » : Can machines think?

1951 : **Snarc** (Stochastic Neural Analog Reinforcement Calculator) by Marvin Minsky (MIT) based upon Donald Hebb principles written in 1949 with learning capability from digital neurons

August 1956 : AI birth in Darmouth College with Marvin Minsky from MIT (1st digital neural net)s) and John McCarthy (LISP creator and words « ARTIFICIAL INTELLIGENCE »*)

* AI by John McCarthy : « computing programs doing human tasks »



956 Dartmouth Conference: The Founding Fathers of AI









tryin Manky

Claude Shanson

Hay Solamonett

Adap St



thur Samuel



Oliver Selfridge.



Nathaniel Boohester



Treachaite



AI history < cont'>



- 1957 : Neural nets with Franck ROSENBLATT (Psy, Univ Cornell) who built PERCEPTRON (1 layer of neurons) inspired by Donald Hebb theory
- Multi-layer perceptron (MLP) for group classification which are non-linear
- >Artificial Neuron = mathematics f**unctio**n

1959 : **reinforcement machine learning** by Arthur Samuel

Then 2 long AI winters...until 2012 (Imagenet)

2019 : Turing Award for 3 researchers on digital neural nets & Deep Learning (Y.Bengio, G. Hinton and Y. Le Cun)



Yann Le Cun

Prix Turing

Quand la machine apprend

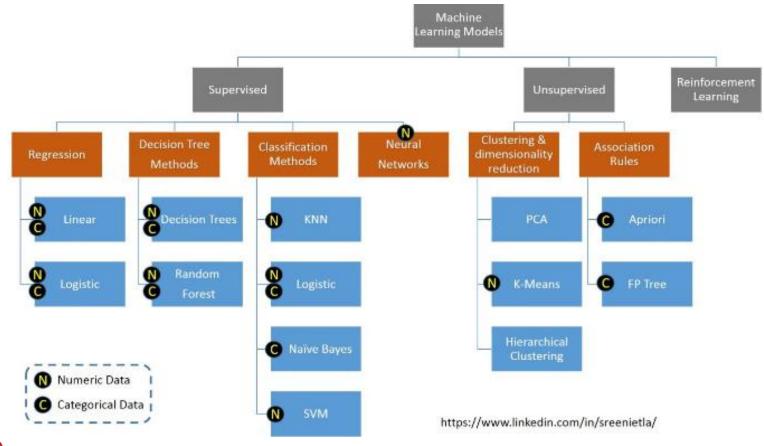
La révolution des neurones artificiels et de l'apprentissage profond



Decoding Machine Learning



https://www.linkedin.com/pulse/decoding-machine-learning-sreenivasa-etla/





Digital Algorithms ?



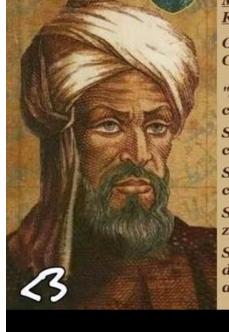
➤ A recipe/method ☺

> AL KHOVARISMI (Persia, 9th century) & algebra !

- « human algorithm »
 - LIVING is algorithmic!

« digital algorithms »

- Recommandation algorithms (ITTT paradigm)
- Evolutionary algorithms (ML and Deep Learning)
 - > Autonomous



<u>Merveilleuse Équation de l'homme d'après Al-Khawarizmi (le père de l'algèbre)</u> :

On interrogea le père de l'algèbre sur l'homme. Ce dernier a répondu humblement:

"Si l'homme est éthique et plein de morale, c'est = 1 ;

S'il est en plus charmant, on lui ajoute un zéro, c'est = 10 ;

S'il est riche, on lui ajoute un autre zéro, c'est = 100 ;

S'il est d'origine noble, on lui ajoute un autre zéro et c'est = 1000 ;

Si la valeur morale (nombre 1) de cette personne disparait, il ne lui reste que les zéros qui n'ont aucune valeur."



Treshold and activation/step function



► ACTIVATION (STEP) function

- >Applied to the weighted sum of INPUTS to get an OUPUT
- New parameter to be added to the sum before the activation function : BIAS of the neurons
- Learning methods for WEIGHTS (supervised, non-supervised, reinforced):optimization methods

>Types of activation function (for neurons differences)

- LINEAR function
- Treshold function
- Radial function
- Stochastic function





- **Parameters :** We learned that parameters relate to the x parameter vector in the equation Ax = b in basic machine learning. Parameters in neural networks relate directly to the weights on the connections in the network.
- > Layers
- > Activation functions
- Loops (output > input) or NOT
- Loss functions
- Optimization methods (such as gradient descent to find good values for the weights)
- Hyperparameters (layer size, number of neurons per layer,..)



Cost function and back-propagation of the gradient in CNN



Function selection?

- >2 parameters : polynomial of degree 1 (straight line)
 - > Linear function y = f(x,a) = ax + b (a : slope)
- >3 parameters : polynomial of degree 2 (parable)

GRADIENT : Direction of the greatest slope = gradient of the cost function

- First derivative of f(x,a) = a
 - > Partial derivative : N-variable function derivative for one variable only
 - > The vector built with partial derviatives is the gradient

Cost function : square of the difference between the generated output and

the expected output Y

> If one output : Cost = $(Y-f(x,a))^{**2}$

>If n outputs : VECTOR with n cost values

>Learning mechanism : minimization of the cost function by gradient descent



Major DNN architectures



>Unsupervised Pretrained Networks (UPN) :

- > Autoencoders, Deep Belief Networks (DBNs), Generative Adversarial Networks (GANs)
- Recurrent Neural Networks (texts,..)
- Recursive Neural Networks
- Multi-layered perceptron (MLP)
- Convolutional* Neural Networks (CNNs)

>Well suited to object recognition (image, sound, etc.)

* **Convolution** is a mathematical function performed on two functions (used in digital signal processing); images could be treated as 2-dimensional functions



Machine learning and *Convolutional** Neural Nets



AX = B in basic machine learning with the matrix A , the parameter vector x , to get output column vector b with X VECTOR for weights : {w1j, w2j, ...wnj}

- Machine learning, statistical learning (neuron learning : weights?) with data-centrics approach :
 - Supervised (labelled data) :
 - correct human guidance and B exists to find F (the prediction function)
 - >Unsupervised :
 - >no $B \rightarrow$ classification (*clustering*)
 - ≻Hybrid
 - Réinforced : millions of probes to learn
 - Adversarial* : uncertainty prediction

Review, Dec 2018 < TURING AWARD in 2019>

SEMI-STRUCTURED DATA in RDF



TRIPLES (OBJECT-PREDICATE-VALUE)

To describe WEB resources

(:serge: performflight:AF100)

(:Peter:performflight:AF110)

(:AIRBUSA320:isusedinflight: AF100)

(:Paul:ispasengeroflight:AF100) ...

≻Note :

One triple RDF <S.P.O> is a fact in 1st-order predicate logic : P(S,O) with

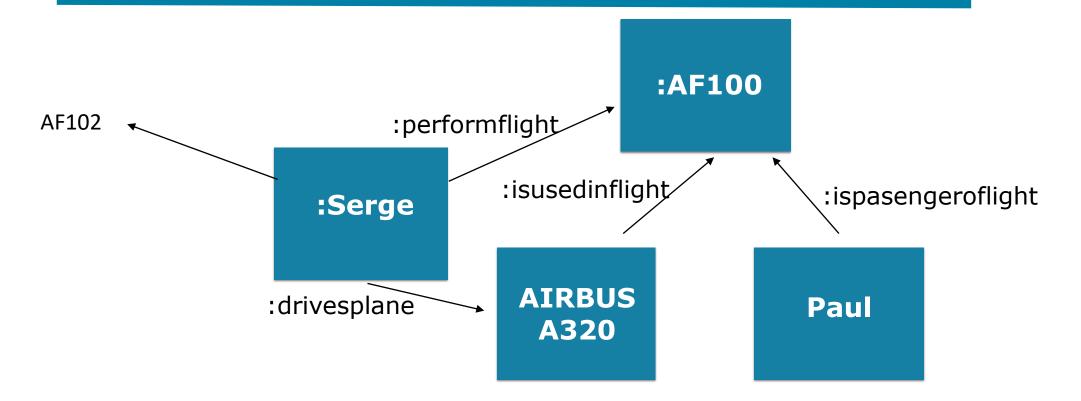
P: Predicate, S Subject et O object

Example : Performflight (Serge, AF100)





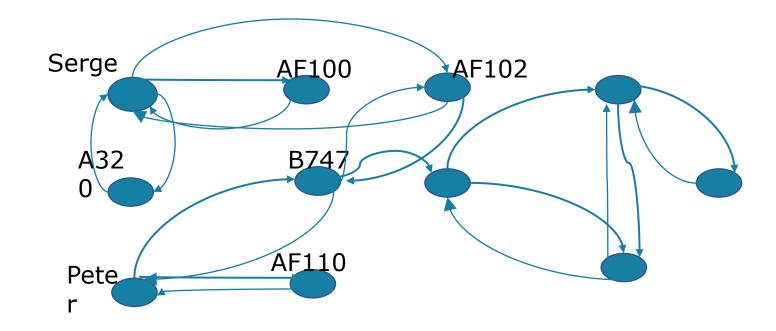
RDFS graph (Example)





NoSQL graph for unstructured data

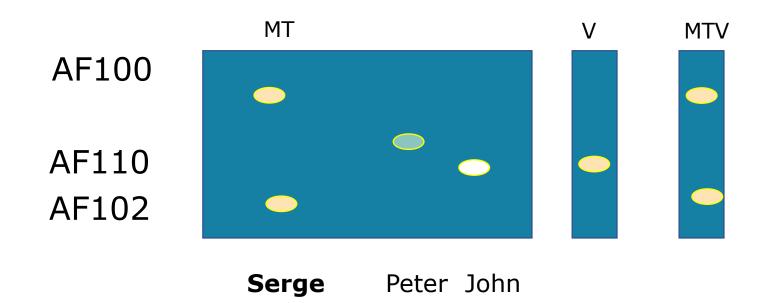






NewSQL matrix





Sparse matrices and linear algebra!





Fact table (STAR or SNOWFLAKE) / Dimensions

>Generating Cube operator (with ALL value)

- Aggregation operations
 - ➢Slicing
 - ➢Dicing
 - ≻Roll-up
 - ➢Drill-down/up



SQL and No SQL/new SQL



SQL focus on SET THEORY for **TRANSACTIONS**

NoSQL and NewSQL focus on Graph theory and Matrix mathematics (linear algebra) for high-performance DATA ANALYSIS and decision support with mathematical properties such as : Associativity, commutativity, distributivity, identity, annihilator and inverses



Graph algebra*



Some basic binary and unary operations

➤3 binary : UNION, INTERSECTION, SYMMETRIC DIFFERENCE

- ▶4 Unary :
 - Vertex Removal
 - Edge Removal
 - Vertex Identifying
 - Edge Contraction
- Search or Graph Traversal algorithm :
 - > Such as breadth-first search (BFS), depth-first search (DFS), ...
- YII Haxhimusa. The Structurally Optimal Dual Pyramid and its Application in Image Partitioning. Vienna University of technology, Faculty of Informatics, Institute of Computer Aided Automation, Pattern Recognition and Image Processing Group. PhD Thesis, Chapter 2, 2006
- + GQL (Graph Query Language) proposed to standardization by Neo4J, Oracle... with MATCH operator in 2018





- Matrices are common representation for computation
- common data representation for Machine Learning (ML) and Deep Learning (DL)
 - ML algorithms (such as Linear regression, Logistic regression and K-Means (Clustering) can be expressed succinctly using LA operators such as matrix multiplication and inversion*
- *L. Chen, A. Kumar, J. Naughton, et J. M. Patel, « Towards linear algebra over normalized data », Proceedings of the VLDB Endowment, vol. 10, no 11, p. 1214 1225, August 2017



Linear Algebra for ML / DL



Operation	Arithmetic
Matrix Addition	C = A + B
Matrix Subtraction	C = A - B
Matrix Multiplication (Hadamard Product)	C = A o B
Matrix Division	C = A / B
Matrix-Matrix Multiplication (Dot Product)	C = A * B C(m,k) = A(m, n) * B(n ,k)
Matrix-Vector Multiplication	c = A . v
Matrix-Scalar Multiplication	C = A . b
Transpose	$C = A^T$
Inversion	B = A^-1
Trace	tr(A)
Determinant	det(A)
Matrix Rank	rank(A)

sources :

http://wiki.fast.ai/index.php/L inear Algebra for Deep Learn ing

https://towardsdatascience.co m/linear-algebra-cheat-sheetfor-deep-learningcd67aba4526c

https://machinelearningmaste ry.com/matrix-operations-formachine-learning/



Unifying underlying theory for **BIG DATA**



	Paradigm	Data structures	Math theory	Data model
SQL	VALUE	Relation/ Table	SET theory	Relational model (Codd's)
Semi- structured	PREDICATE/ VALUE	Class and RDF	Graph theory	RDF data model
NoSQL	Key-value & graph	Class Document (JSON)	Graph theory	Key/BLOB Key/document (JSON) Key/(column/ value)
NewSQL	Value & graph	Table	Sparse matrices / Linear algebra	Extended Relational model
R, Python interface	VALUE	Arrays	Linear algebra	Matrix



Some books of reference on Data bases



In English :

- Chris Date « An Introduction to data base systems » (8th Edition), Addison Wesley <the reference book on data bases>
- E.F Codd (1990). « The Relational Model for Database Management » (Version 2). Addison Wesley Publishing Company. ISBN 0-201-14192-2. <Codd's book>
- M.Stonebraker et al « Readings in data base systems » < The « red book » > 5th Edition 1998, Morgan Koffmann
- S.Abitboul et al « Foundation of data bases » Addison Wesley <data base theory >

In French :

- JL Hainaut « Bases de données (Concepts, applications et développement) », DUNOD, 4ième Edition, 2018
- G. Gardarin « Bases de Données » Eyrolles, Version gratuite sur georges.gardarin.free.fr
- S. Miranda « L'Art des Bases de données » (3 Tomes), EYROLLES
- S. Miranda « Bases de données : Architectures, modèles relationnels et objets, SQL3 et ODMG », DUNOD, 2002



Some books of reference on Big Data



In English

Rajendra Akerkar (Ed) "Big Data Computing" CRC Press, 2014

- >Jules Berman "Principles of Big Data" Morgan Kaufman, 2013
- >Joe Celko ""A Complete guide to NO SQL > Elsevier 2014
- >W.CHU Editor « Data mining and knowledge Discovery for big data » Springer 2014
- >Dan Mc Creary, Ann Kelly « Making sense of NO SQL » Manning 2014
- F.Provost, T Fawcell « DATA SCIENCE for Business » O'Reilly 2013
- >Jordan Tigani, Siddartha Naidi « Google Bigquery Analytics » WILEY, 2014 (510 pages)
- Mike Stonebraker, "New SQL: An Alternative to NoSQL and Old SQL for New OLTP Apps » ACM, June 2011

In French

R.Bruchez « Les bases de données NO SQL et le Big Data », Eyrolles 2015

- >I.lemberger et al « « Big data et machine learning", Dunod 2016
- C.Azencott "Introduction au Machine learning » Dunod 2018
- ➢G.Grolemund « R pour les data science », Eyrolles 2017

