Introdução a ECI

Análise de Dados em Larga Escala (Big Data)

Marta Mattoso – marta@cos.ufr.br

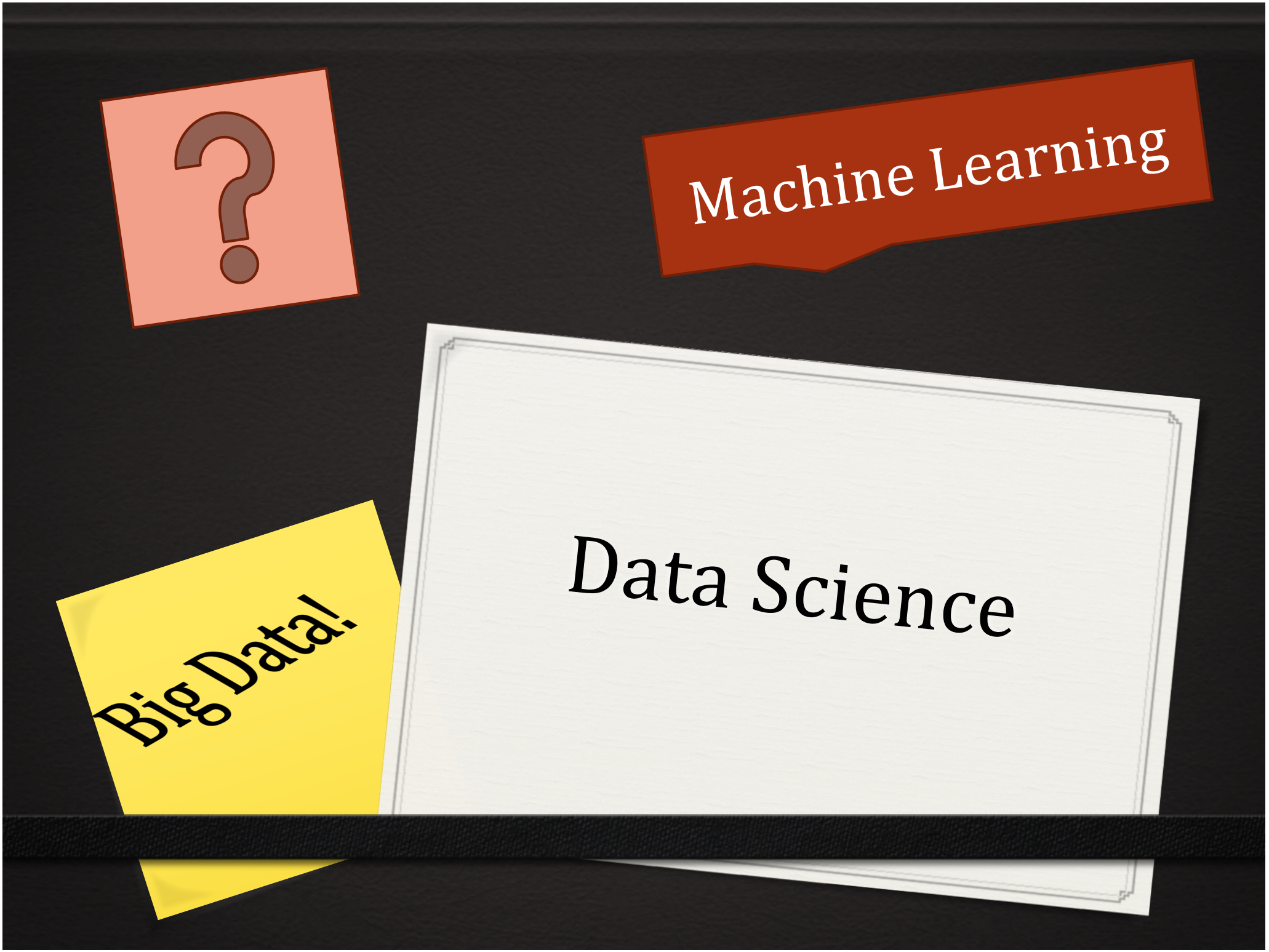
COPPE- Federal University of Rio de Janeiro

Brazil

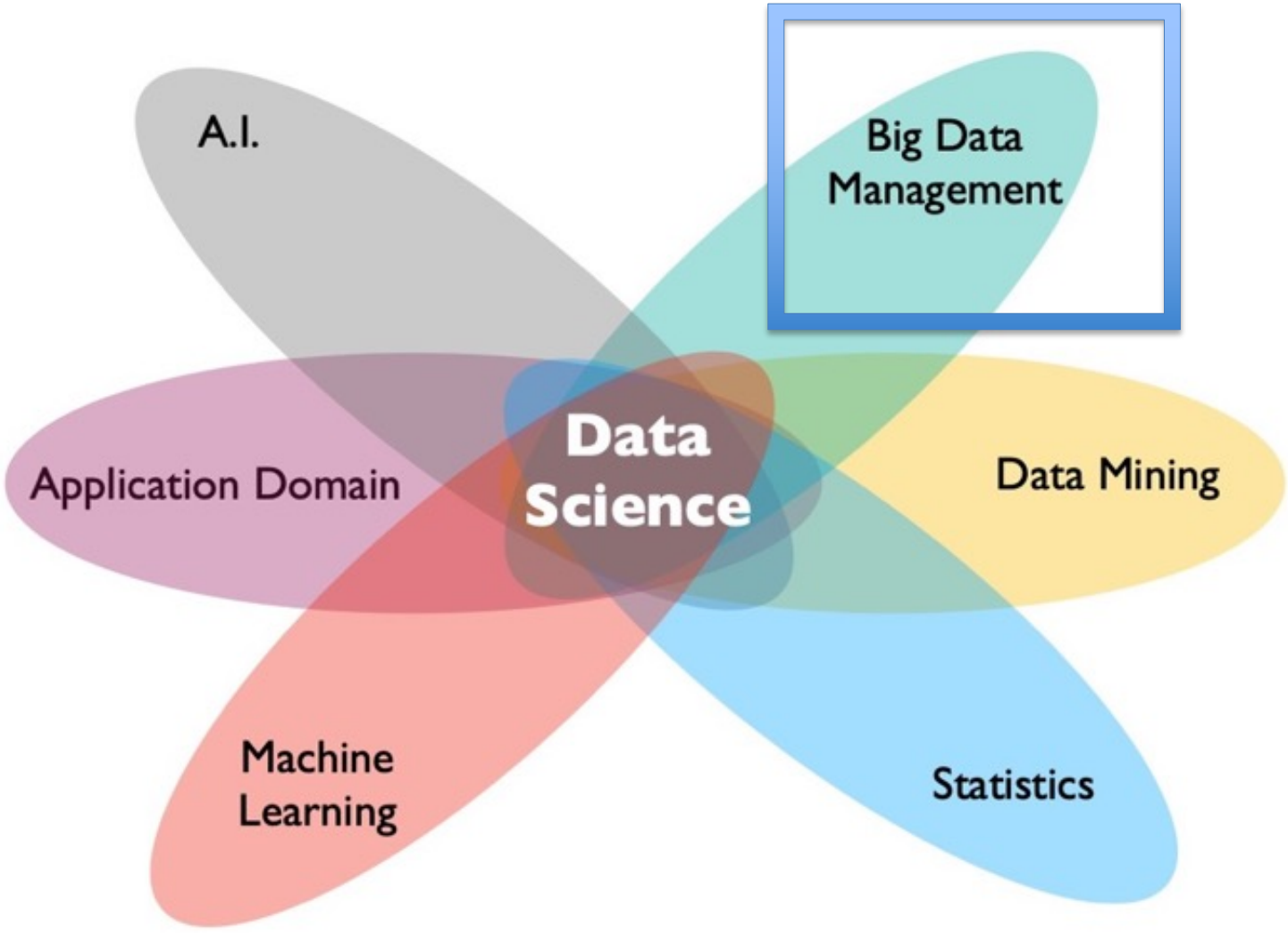
PESC
Programa de Engenharia de Sistemas e Computação

COPPE UFRJ

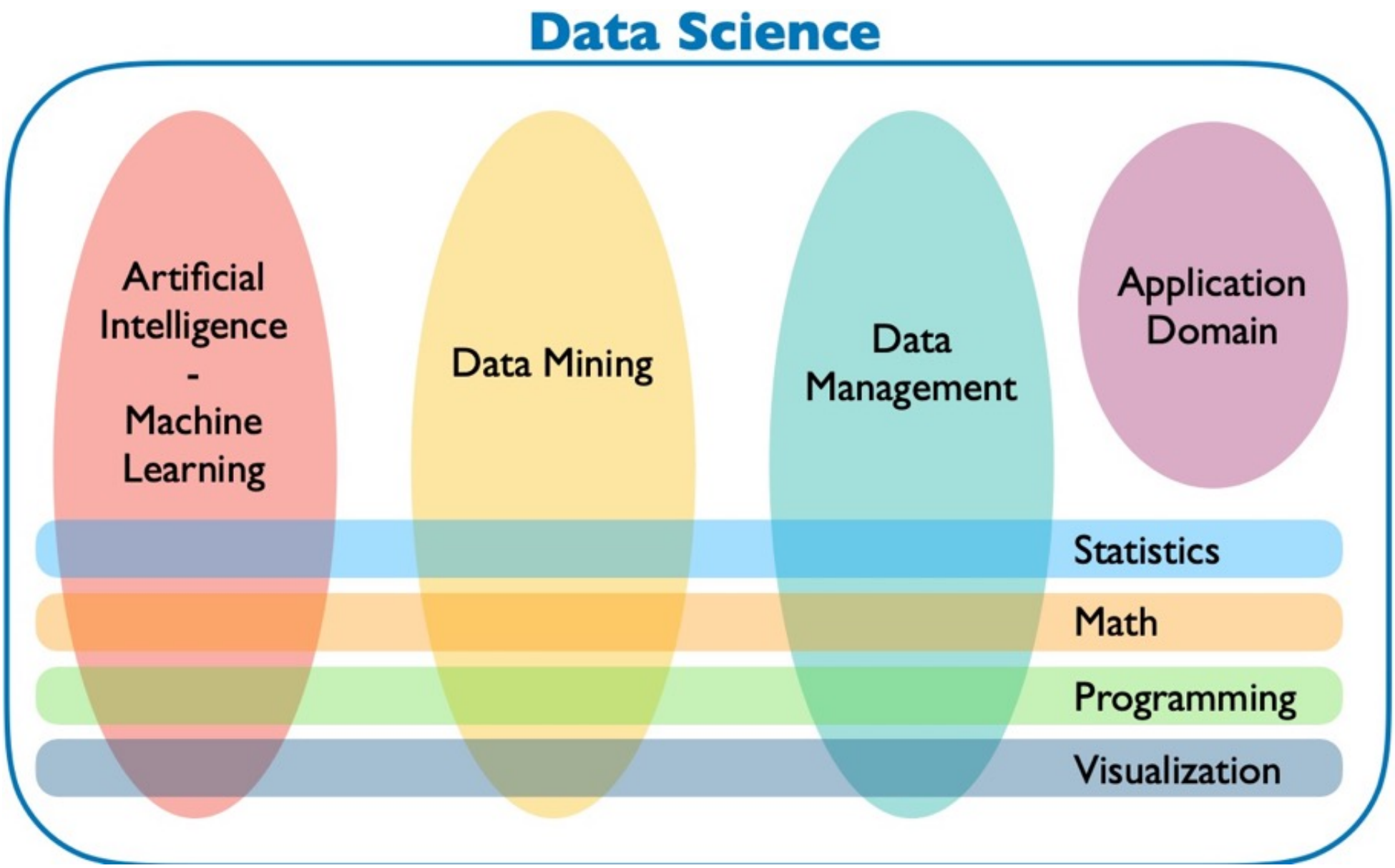
data
analysis
execution
support
programs
features
analyses
big
workflow
provenance
experiments
scientific
Scientific
activities
approaches
steering
view
different
results
SWfMS
Provenance
issues
process
may
cycle
talk
need
life
current
explorations
involve
Big
However
explore
lack
part
analysts
many
provide
manage
consistent
typically
parallel
experiment
workflows
useful
DBMS
Workflow
reproducible
interference
HPC
datasets
discuss
using
analyze
high
query
carefully
respond
component
heterogeneous
Scientists
scientists
trusted
performance
represent
critical
experimentation
scientist
flows
key
long
computer
Hadoop
pipelines
originally
long-term
information
managing
real-time
provided
steps
cleaning
present
greater
broader
distributed
supported
monitoring
modeling
providing
Data
like
produced
essential
web
represented
composition
especially
resulting
aggregate
dataflow
business
along
experimenting
tracks
several
manually
Cloud
easily
deal
presenting
revisit
Current
isolated
environments
performed
extract
activity
perform
must
core
make
designed
set
execute
require
interpret
goal
Many
rather
trace
legacy
followed
decision
sync
open
processing
trustworthy
optimized
dynamically
science
Parallel
Systems
Workflows
processed
Management
visualize
demand
Analyzing


?
Machine Learning
Big Data!
Data Science

Data Science ≠ Machine Learning



Jens Dittrich, VLDB 2017 (invited talk: “Deep Learning (m)eats Databases”



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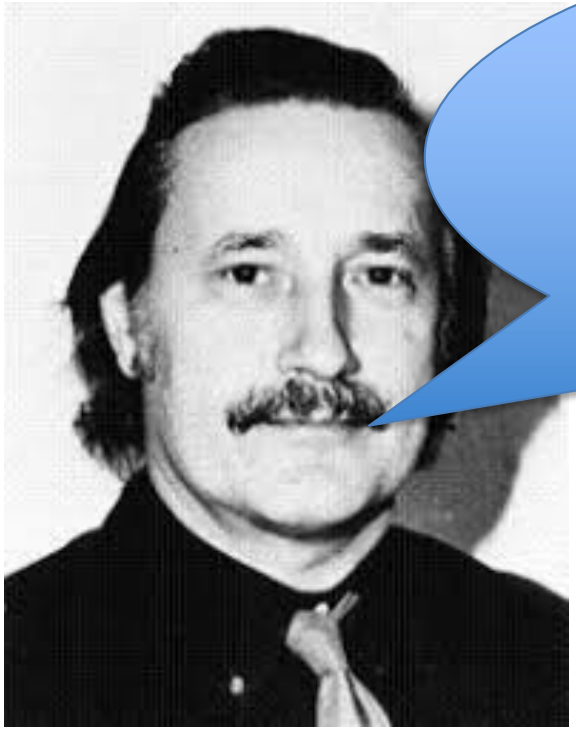


Christopher Strachey (1916-1975)

*"I am convinced that the crux of the problem of learning is **recognizing relationships** and being able to use them"*

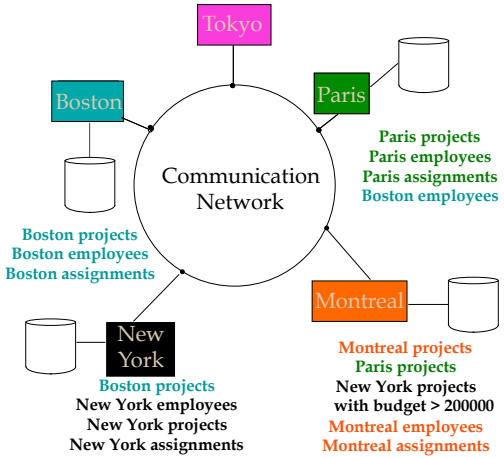
Carta a Alan Turing, 1954.

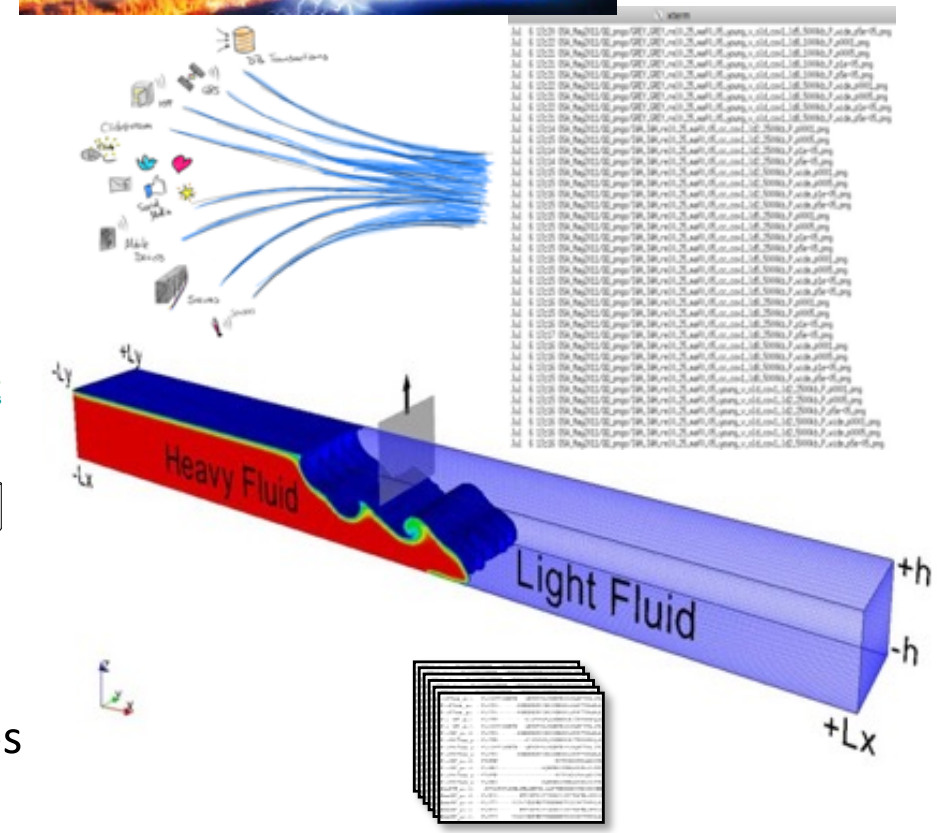
apud M. Nickel, K. Murphy, V. Tresp and E. Gabrilovich, "A Review of Relational Machine Learning for Knowledge Graphs," in *Proceedings of the IEEE*, v. 104 (1), pp. 11-33, 2016.

Análise de Dados

Como relacionar dados ?
Como seguir os relacionamentos ?


```
SELECT ENAME,SAL
FROM   EMP,ASG,PAY
WHERE  DUR > 12
AND    EMP.ENO = ASG.ENO
AND    PAY.TITLE = EMP.TITLE
```

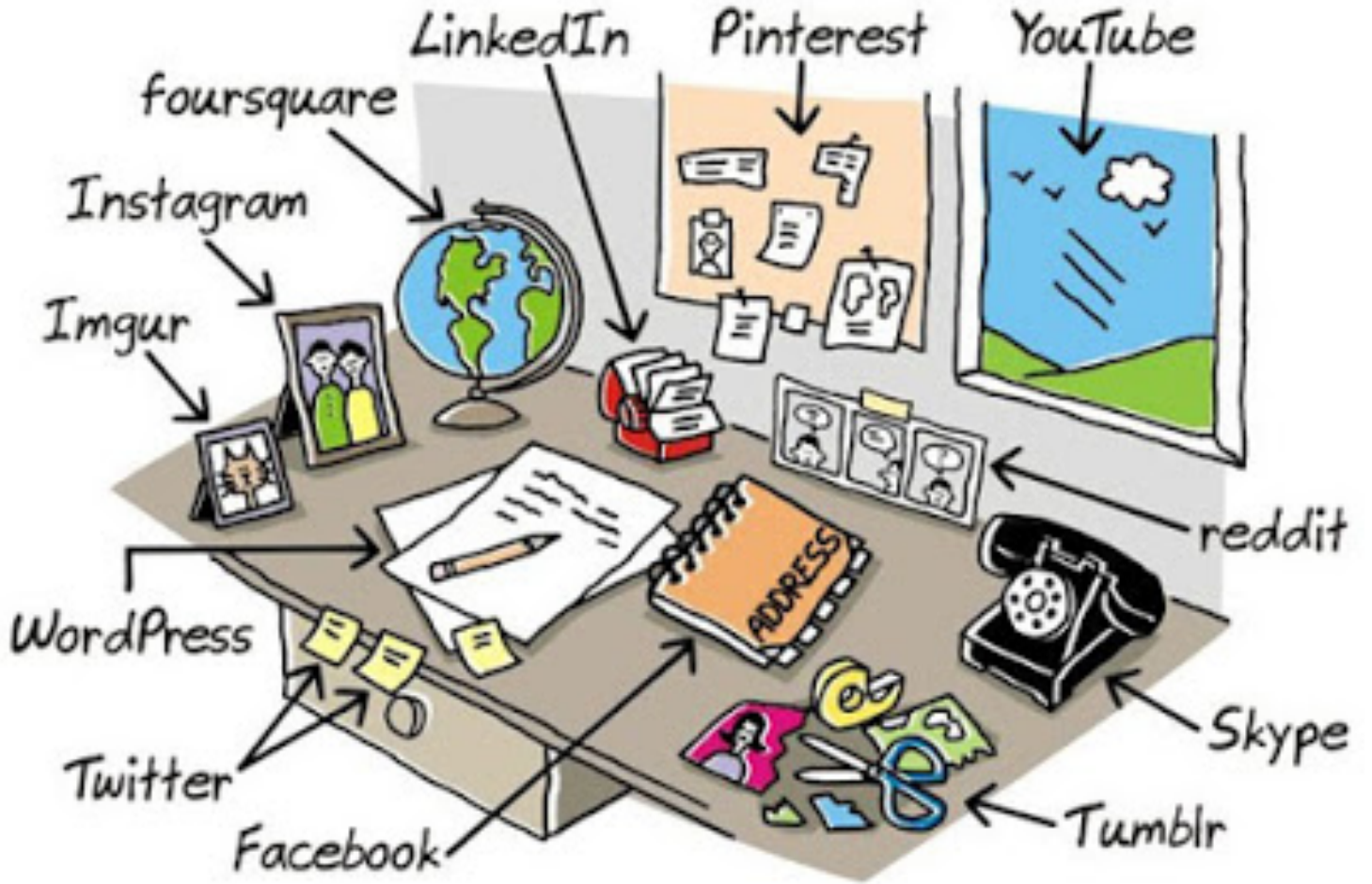




Bancos de Dados Distribuídos e Paralelos

Ter dados ≠ Analisar dados

Como relacioná-los?



Seguir ligações ≠ Analisar dados

Fonte: **7 Reasons Why You Need a Database Management System**
By David Scott Brown , May 26, 2016

What Data Management can do:

data modeling, replication, partition, indexing, joins, concurrency, consistency, fault tolerance

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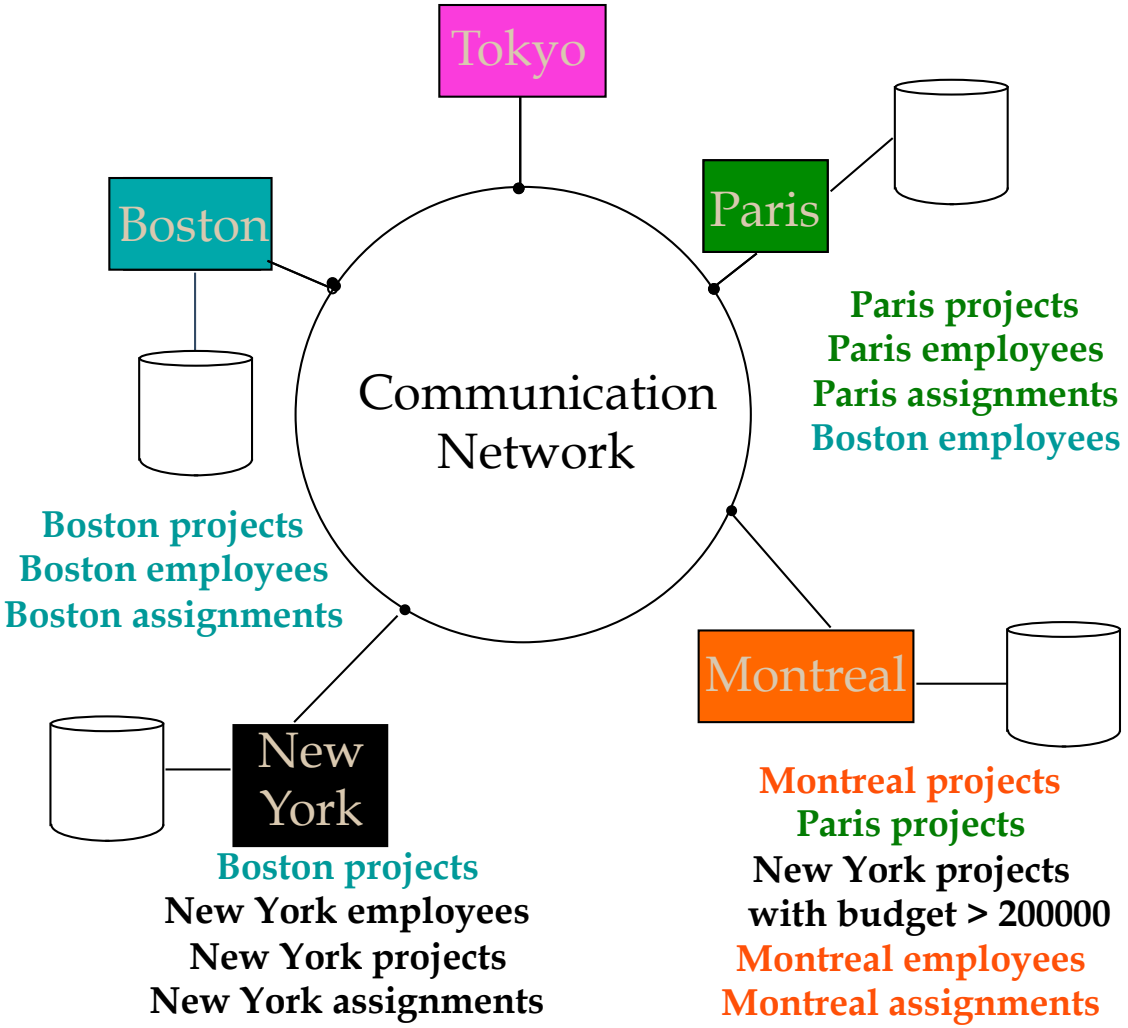
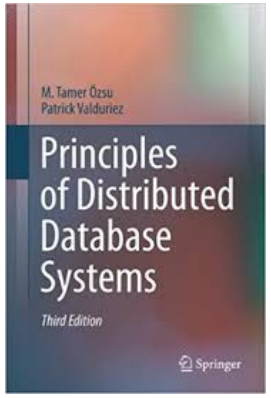
```





From M. T. Özsu & P. Valduriez "Principles of Distributed Databases", book by Springer

Big Data – Gerência de Dados

Super Eficiente

- percepção humana ~25ms
- TPC-C: executa ~ meio milhão de transações por segundo
- com controle de concorrência, cai para algumas centenas de milhares; ainda é muito rápido
- uma busca simples em um índice, tipo tabela hash, são 20 milhões de operatções por segundo

Database Management Systems

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```
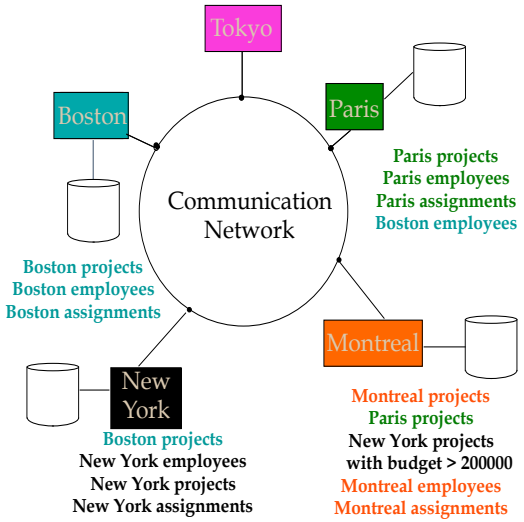



Dados Relacionados

EMP

ENO	ENAME	TITLE
E1	J. Doe	Elect. Eng.
E2	M. Smith	Syst. Anal.
E3	A. Lee	Mech. Eng.
E4	J. Miller	Programmer
E5	B. Casey	Syst. Anal.
E6	L. Chu	Elect. Eng.
E7	R. Davis	Mech. Eng.
E8	J. Jones	Syst. Anal.

ASG

ENO	PNO	RESP	DUR
E1	P1	Manager	12
E2	P1	Analyst	24
E2	P2	Analyst	6
E3	P3	Consultant	10
E3	P4	Engineer	48
E4	P2	Programmer	18
E5	P2	Manager	24
E6	P4	Manager	48
E7	P3	Engineer	36
E7	P5	Engineer	23
E8	P3	Manager	40

PROJ

PNO	PNAME	BUDGET
P1	Instrumentation	150000
P2	Database Develop.	135000
P3	CAD/CAM	250000
P4	Maintenance	310000

PAY

TITLE	SAL
Elect. Eng.	40000
Syst. Anal.	34000
Mech. Eng.	27000
Programmer	24000

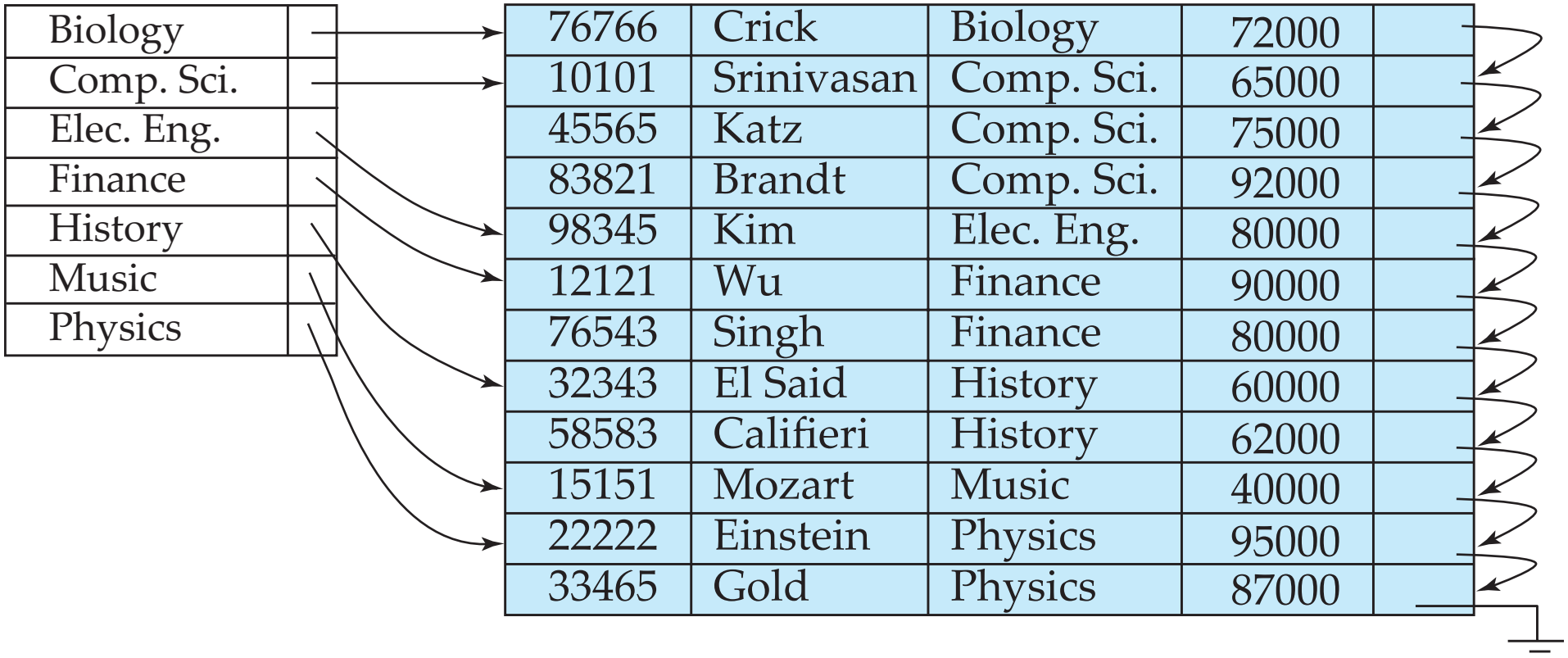
Exemplo de uma consulta

Quais os funcionários com registro > 4000 e idade menor que 40?

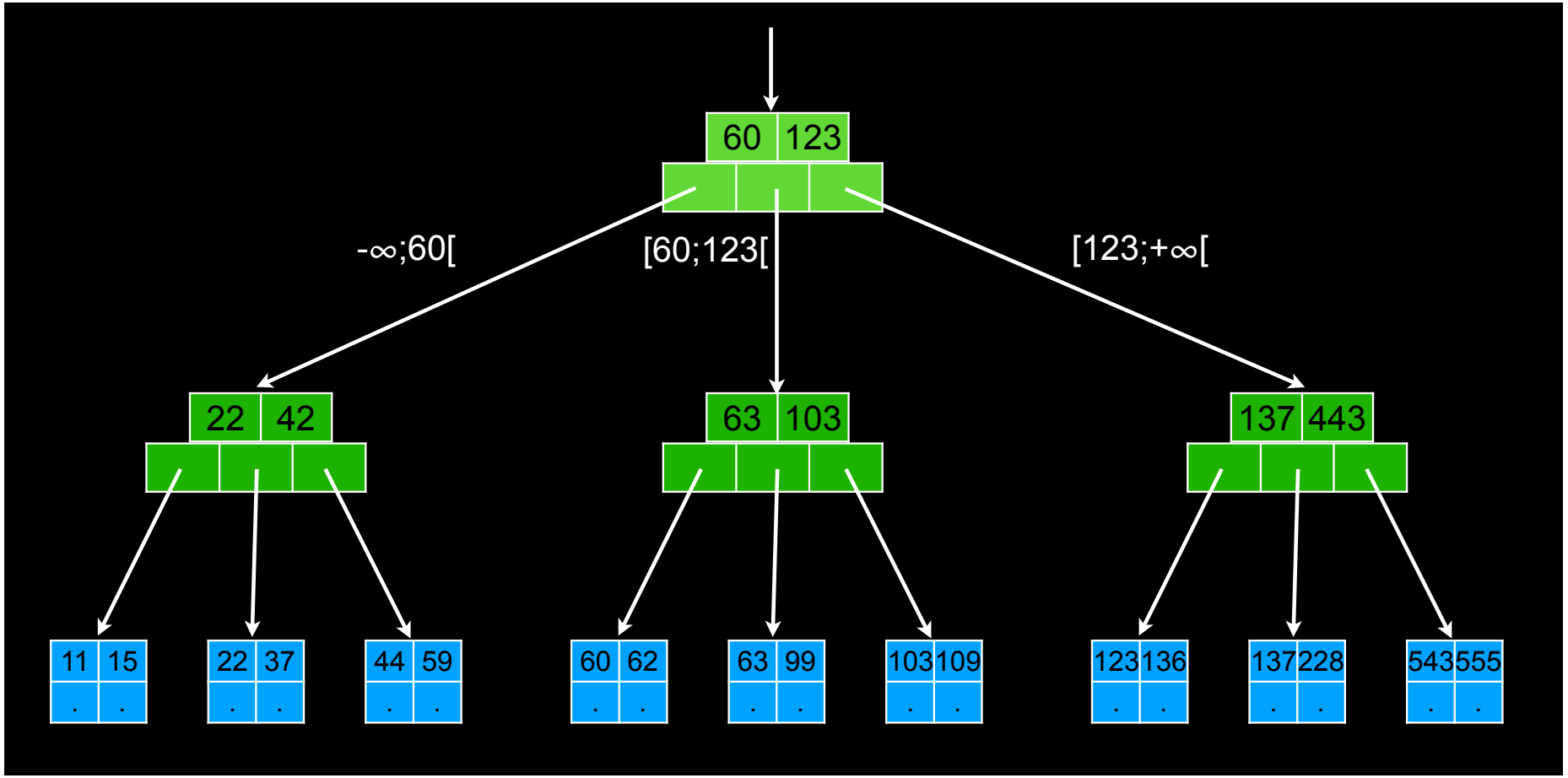
Funcionários

ID	Register	Name	Age
RH1	0962	Jane	30
RH2	7658	John	45
RH3	3589	Jim	20
RH4	5523	Susan	52

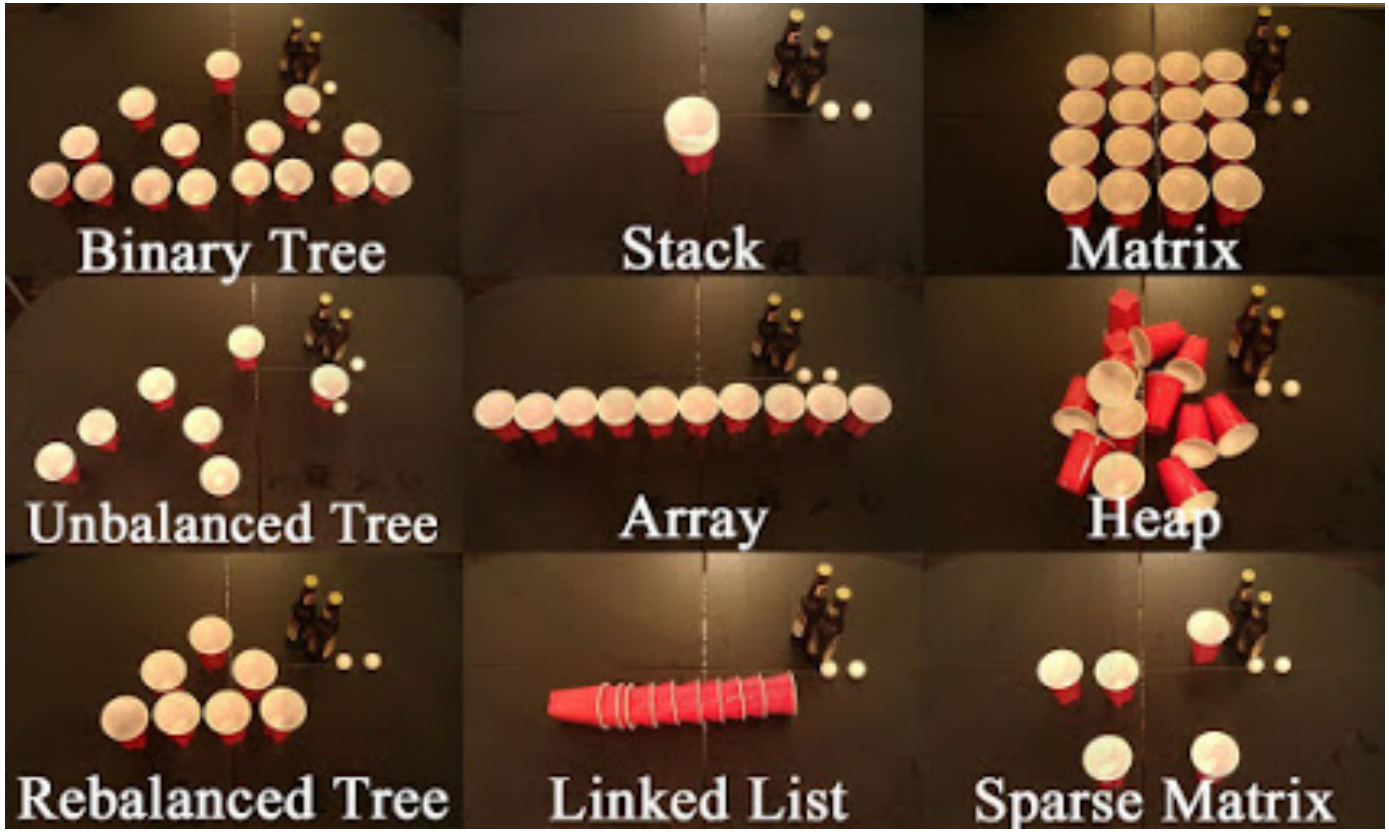
E se a tabela for muito grande ?
Índices



E se a tabela for muito grande ?
Índices – Arvore B

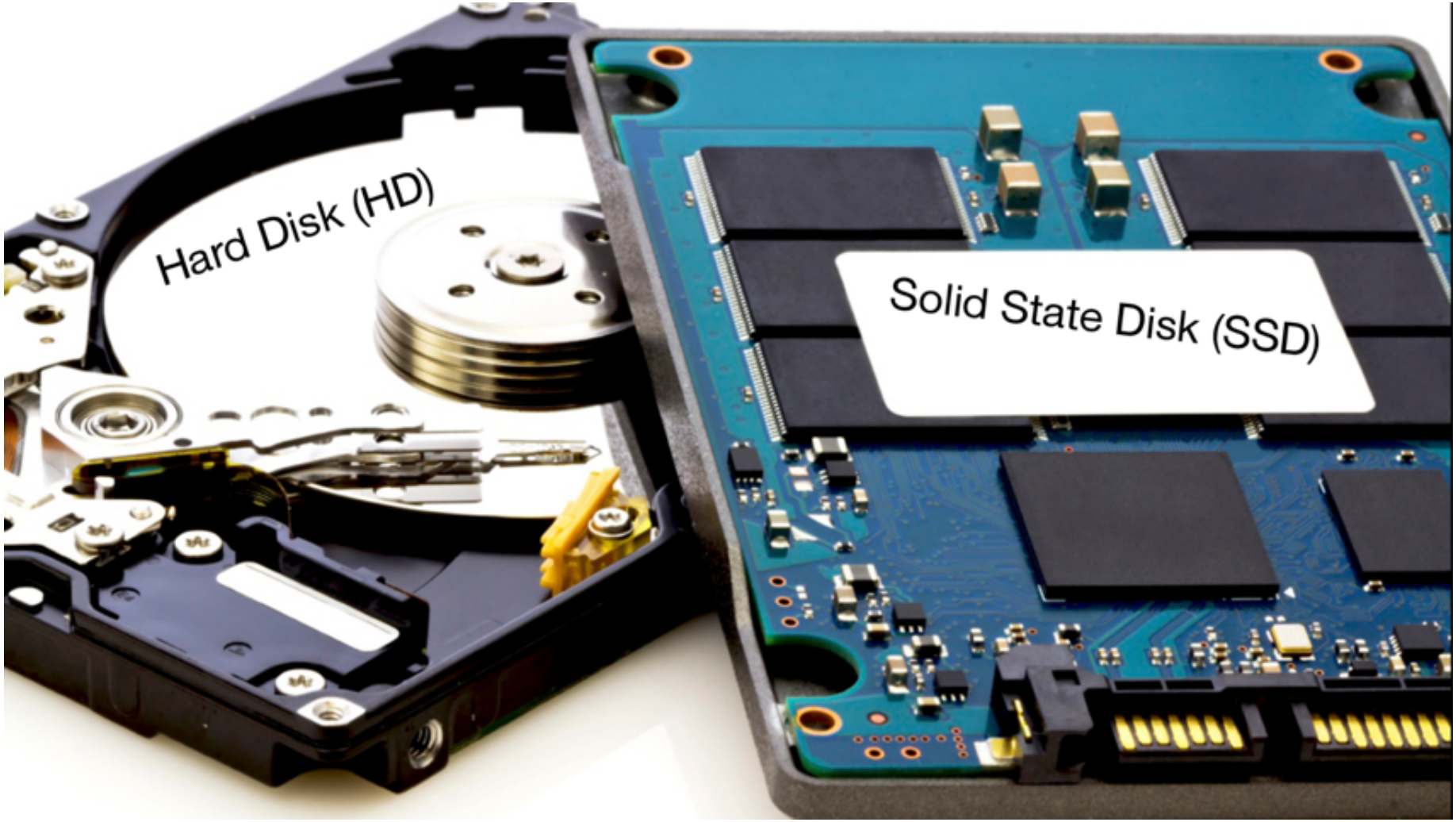


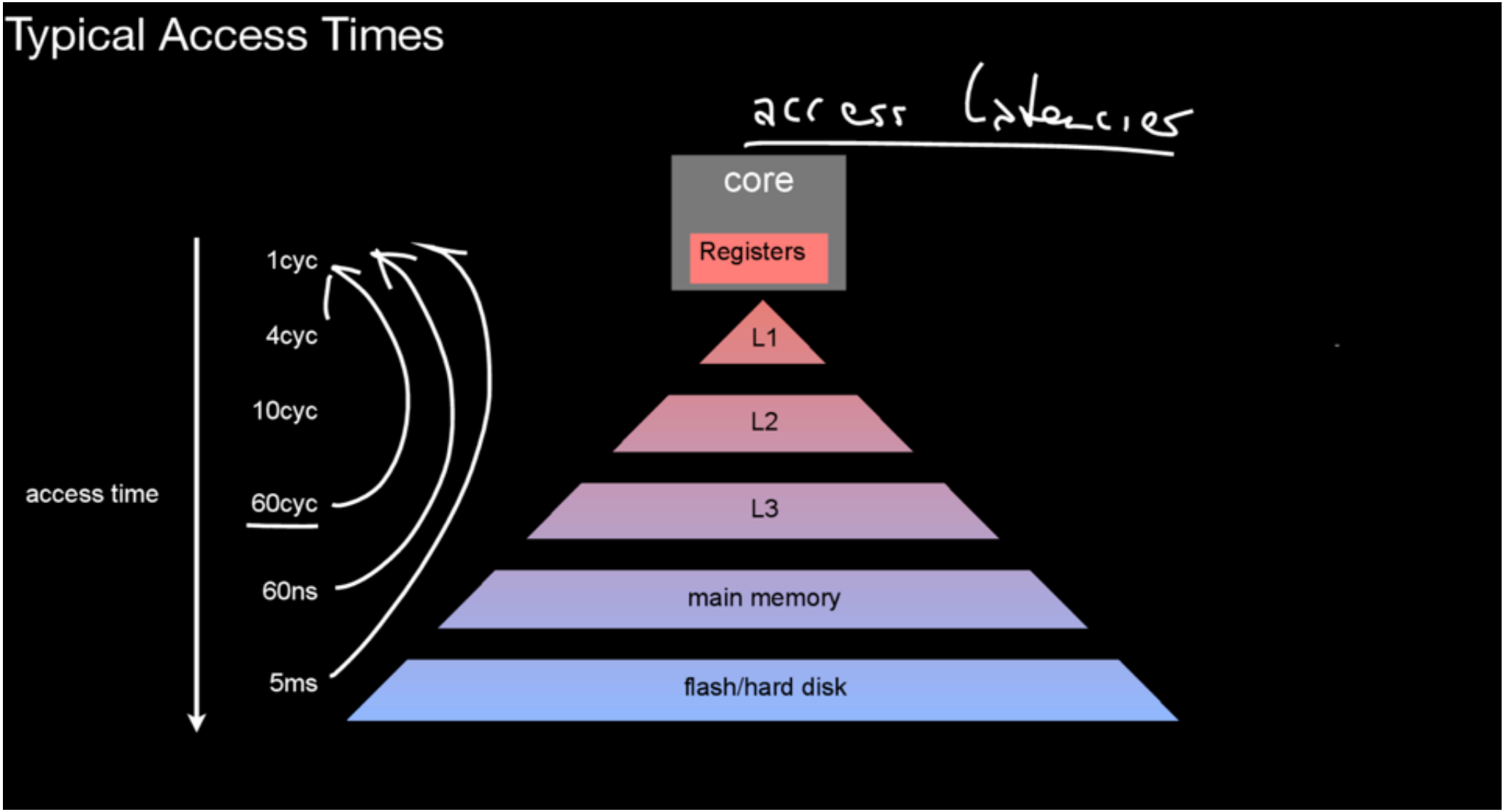
Uma vez organizado e relacionado, como acessar ?

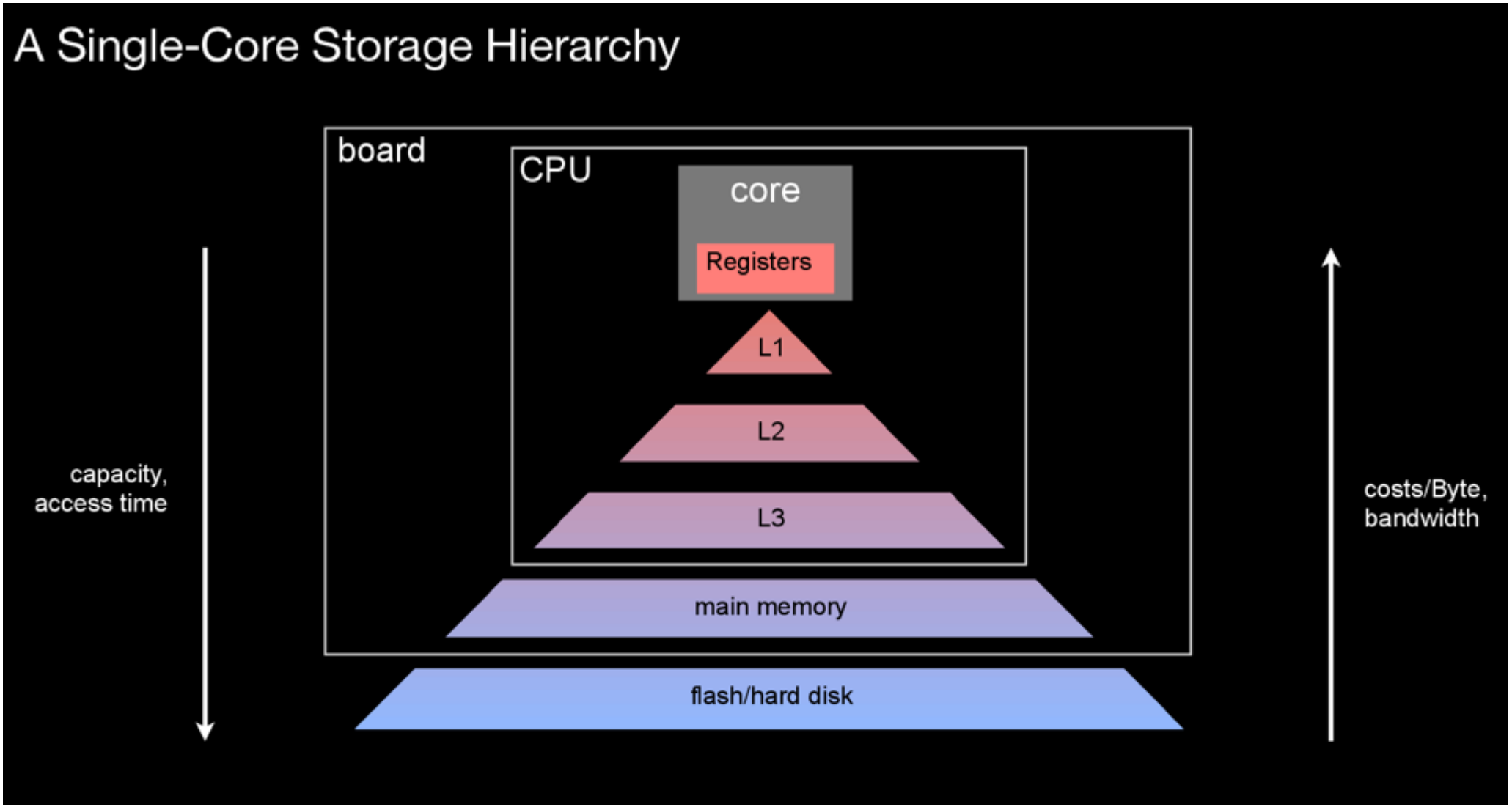


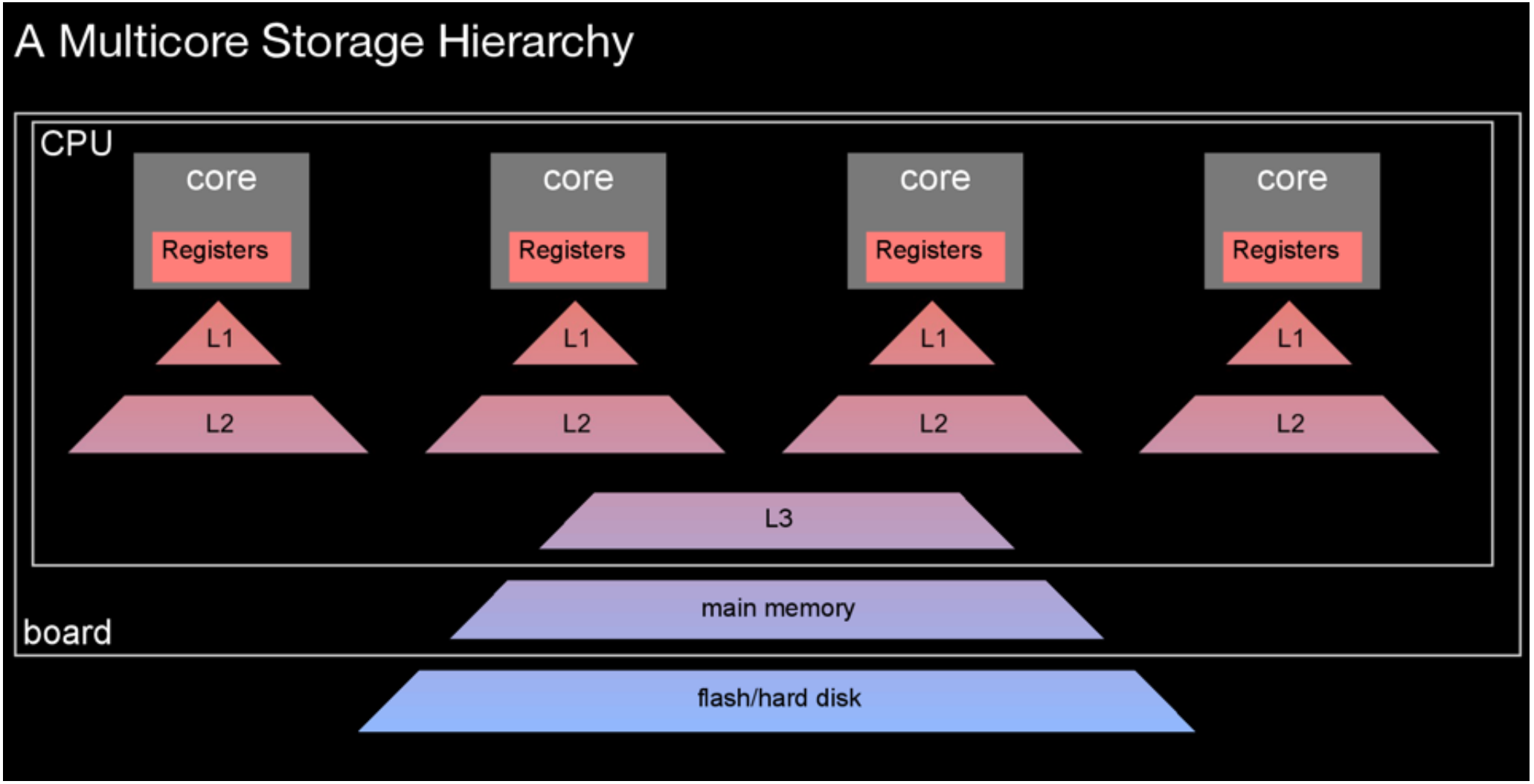
Estruturas de Dados fazem parte de um Sistema de Banco de Dados

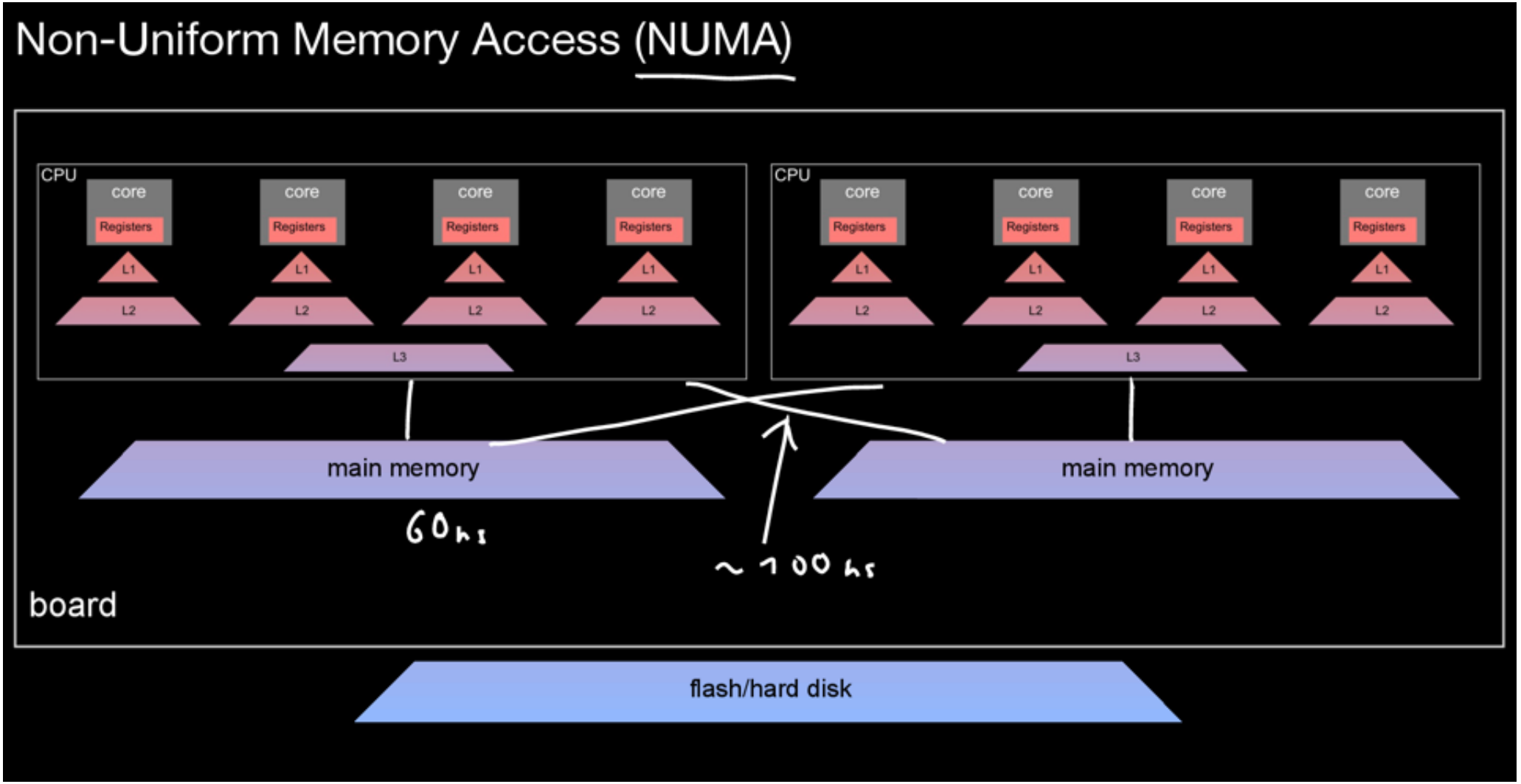
Onde armazenar ?











“One size fits all”

Super Eficiente

- O mesmo software DBMS
- Diversas aplicações
- Grande Volume de dados
- Leitura X Escrita
- OLAP x OLTP

Database Management Systems

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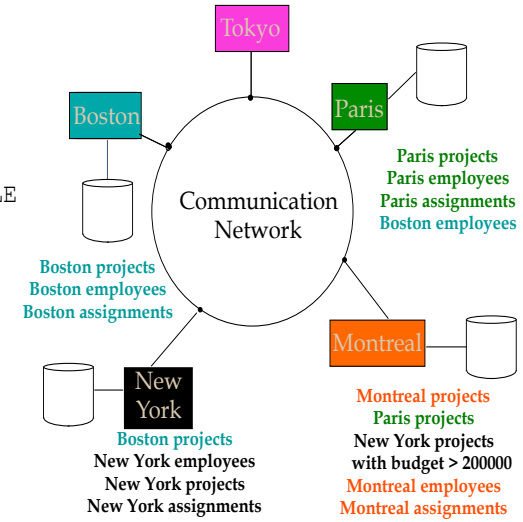


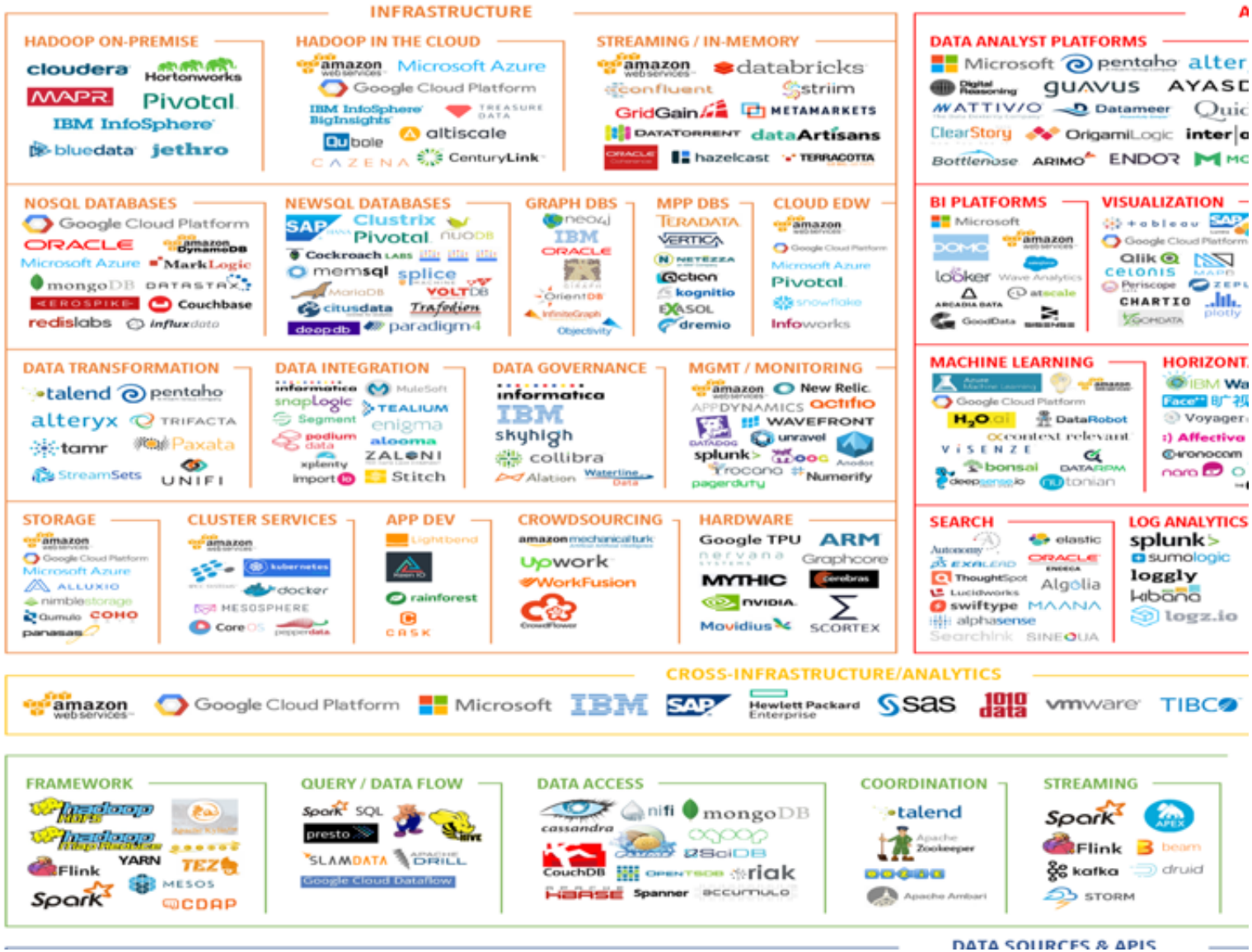
Michael Stonebraker recebeu em junho, o prêmio Turing da ACM de 2014.

"For fundamental contributions to the concepts and practices underlying modern database systems."

Stonebraker

"no size fits all" (2005)

“One size **does not** fit all”

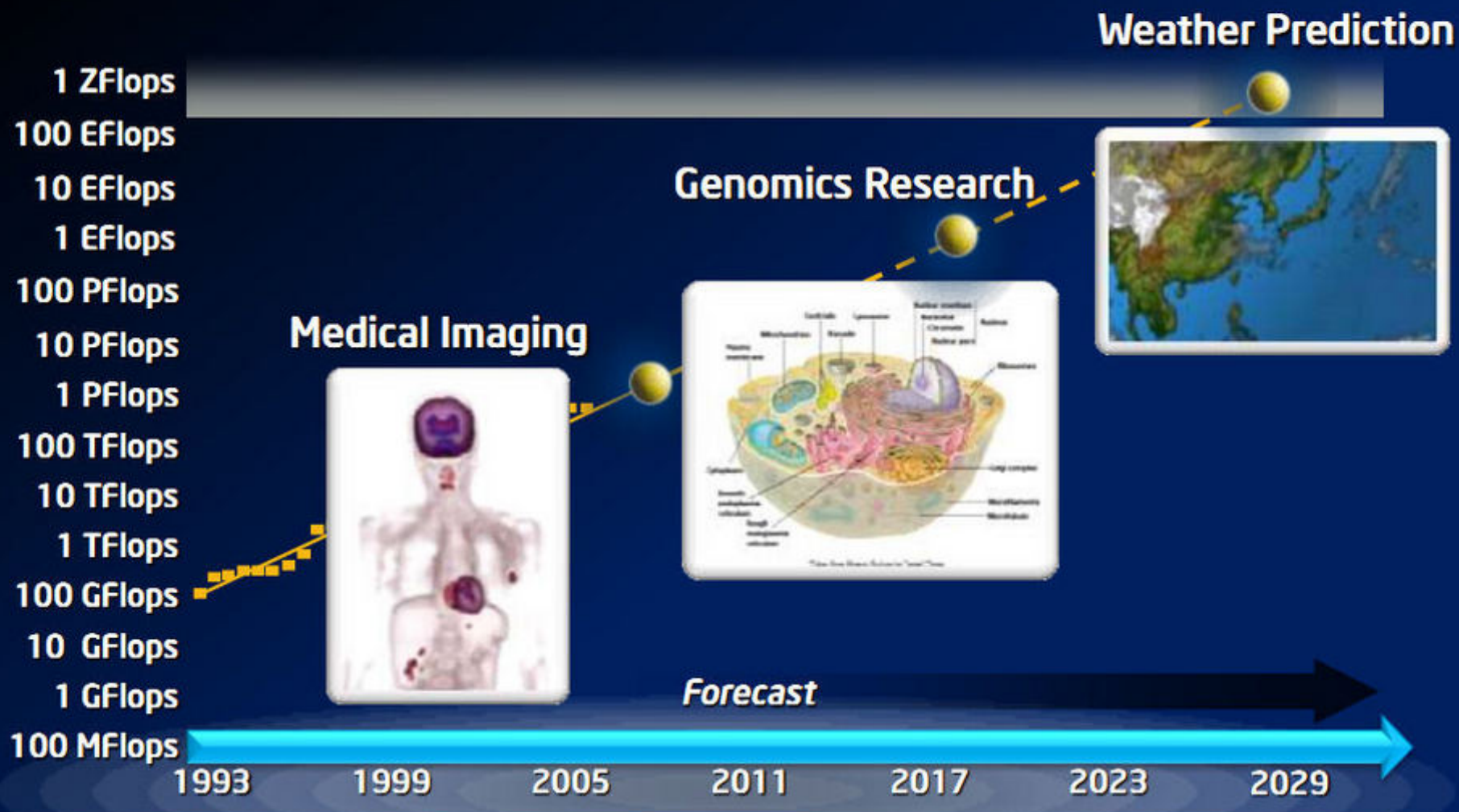


Especialização: extremos

Tamanho único

Sob medida

An Insatiable Need For Computing



Exascale Problems Cannot Be Solved Using the Computing Power Available Today

Source: www.top500.org

intel

Especialização: extremos

"a set of special-purpose appliances"

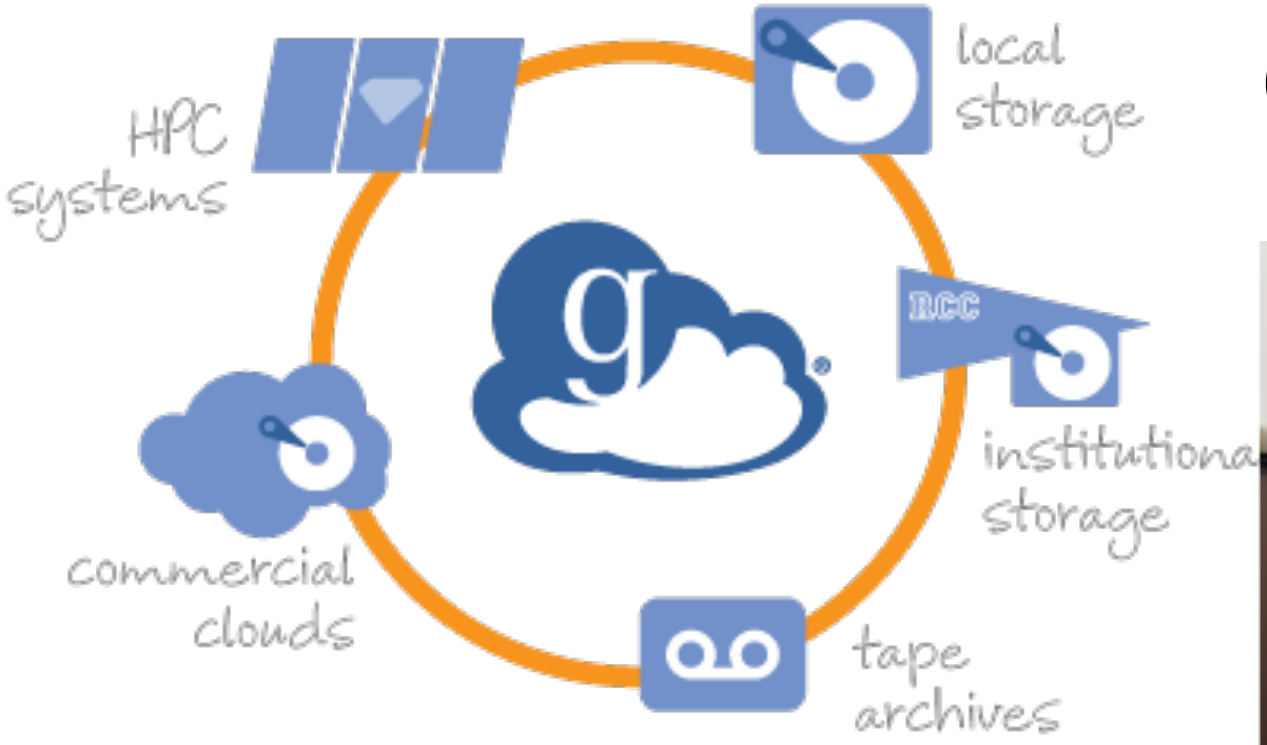
		Perf/W			
More Flexible / Homogeneous	CPUs	1X	Today's standard, most programmable, good for services changing rapidly	Conventional programming	C/C++
	Manycore CPUs	3X	Many simple cores (10s to 100s per chip), useful if software can be fine-grain parallel, difficult to maintain.		
	GPUs	5-30X	Good for data parallelism by merged threads (SIMD), High memory bandwidth, power hungry	Alternative programming	CUDA
	FPGAs	5-30X	Most radical fully programmable option. Good for streaming/irregular parallelism. Power efficient but currently need to program in H/W languages.		Verilog
Specialized / More Efficient	Structured ASICS	20-100X	Lower-NRE ASICs with lower performance/efficiency. Includes domain-specific (programmable) accelerators.	Can't change functionality	Verilog
	Custom ASICs	> 100X	Highest efficiency. Highest NRE costs. Requires high volume. Good for functions in very widespread use that are stable for many years.		

Source: http://bit.ly/2SDGHzT

http://www.ianfoster.org/wordpress/presentations/ (Code in Continuum)

Code in continuum

Globus

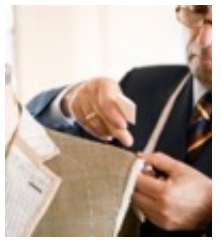


Ian Foster

(IPDPS'2019)

https://www.slideshare.net/ianfoster/coding-the-continuum

Exascale “sob medida”



- Google designed its own tensor processing unit (TPU), designed for high throughput of low-precision arithmetic.
  - TPU accelerates their neural network computations behind Google Search, Street View, Google Photos and Google Translate.

Exascale – Google's TPU

- How fast are these new chips?
  - "To put this into perspective, our new large-scale translation model takes a full day to train on 32 of the world's best commercially available GPU's—while one 1/8th of a TPU pod can do the job in an afternoon," Google wrote in a statement.

Ciência de Dados

Jens Dittrich, VLDB 2017 (invited talk: “Deep Learning (m)eats Databases”

Data Science ≠ Machine Learning

Definition (Data Science)

Data Science =

1/3 Artificial Intelligence ($\supset$ Machine Learning) +

1/3 Data Mining +

1/3 Data Management.

Venham fazer os cursos de BD (= Data Management)

Acknowledgements