



CIÊNCIA DE DADOS E SUA APLICAÇÃO EM SAÚDE

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Universidade Federal da Bahia (UFBA)

Salvador, 22 de março de 2018

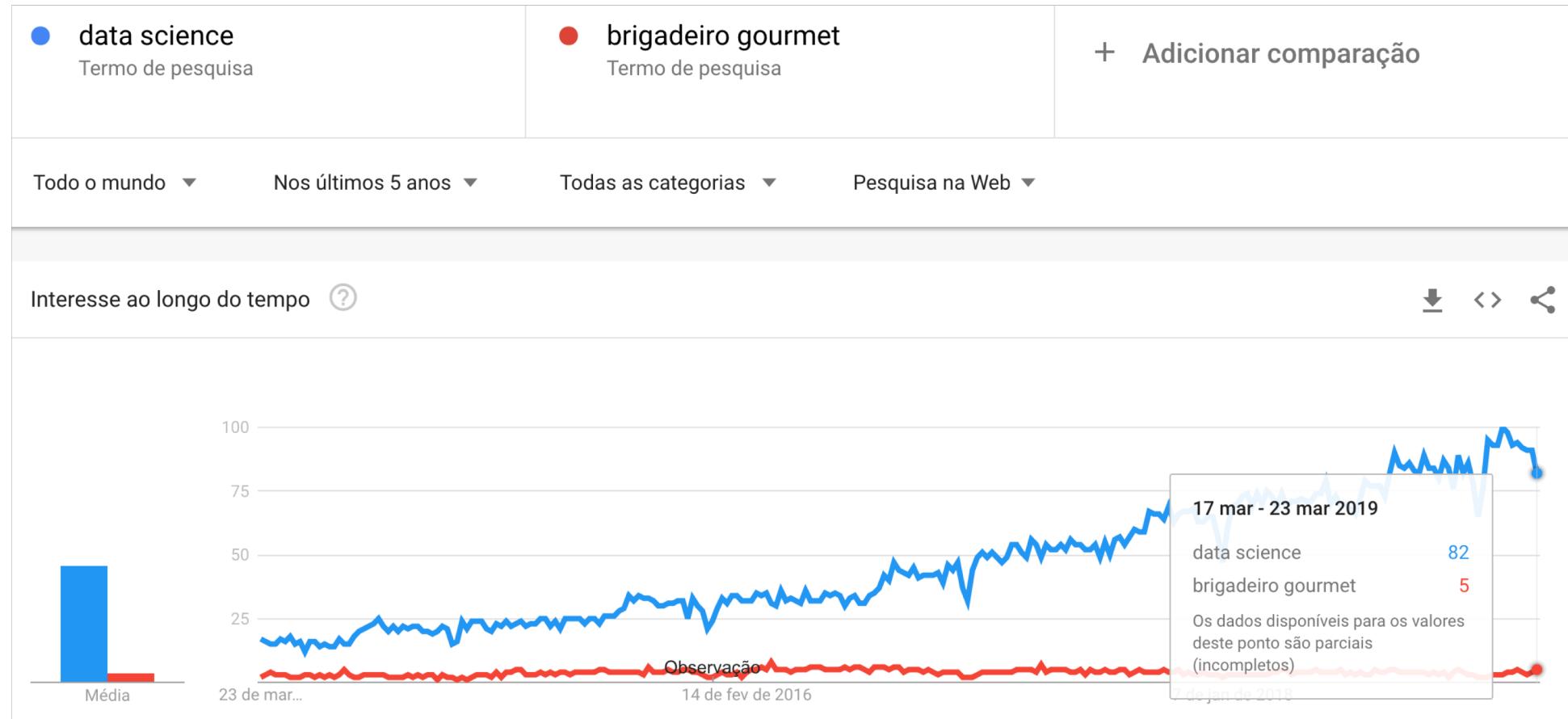
Popularização da Ciência de Dados

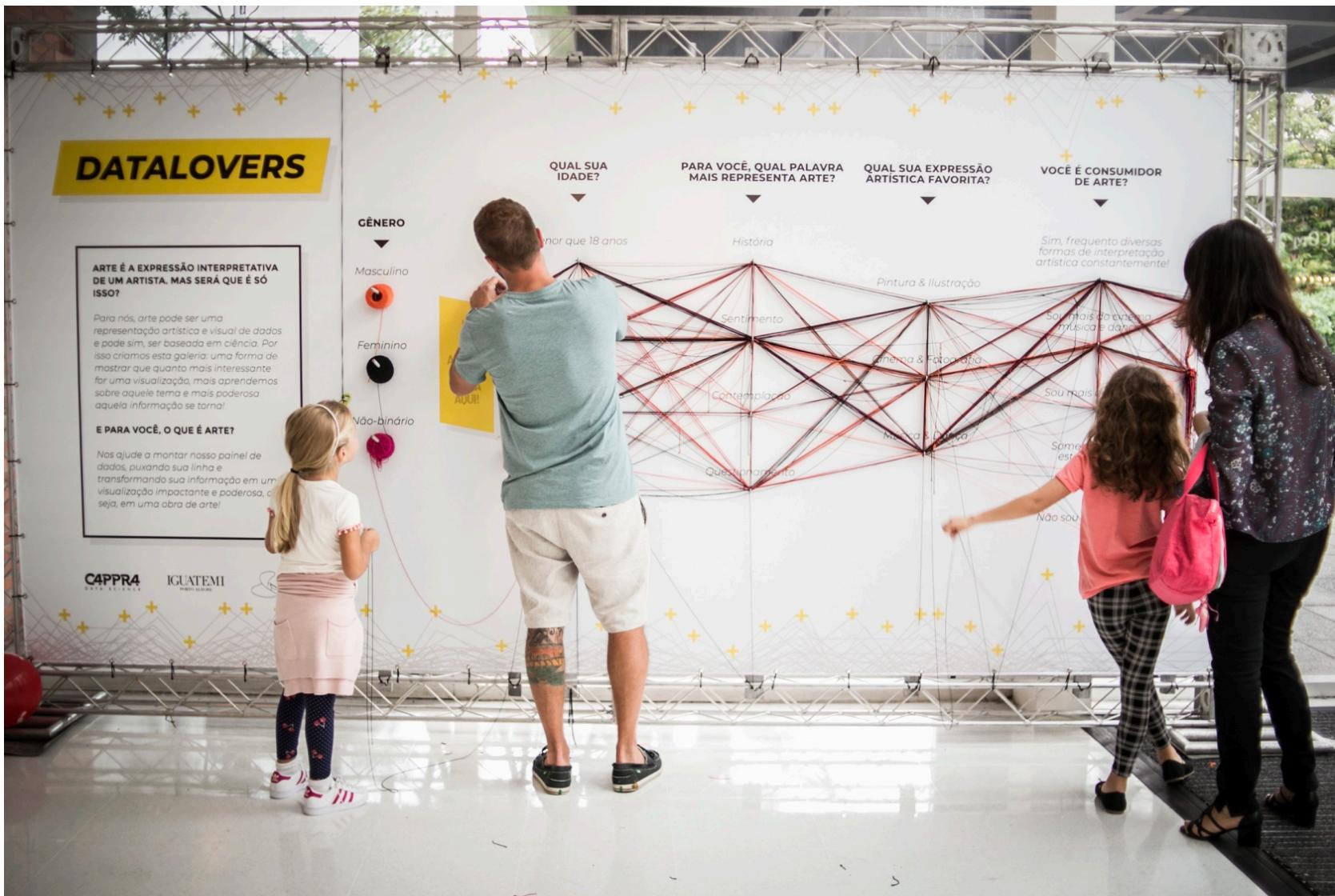


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Popularização da Ciência de Dados





<https://cappra.com.br/2018/04/26/apaixonados-por-dados-datalovers/>

Ciência de dados

[ocultar]

Origem: Wikipédia, a enciclopédia livre.

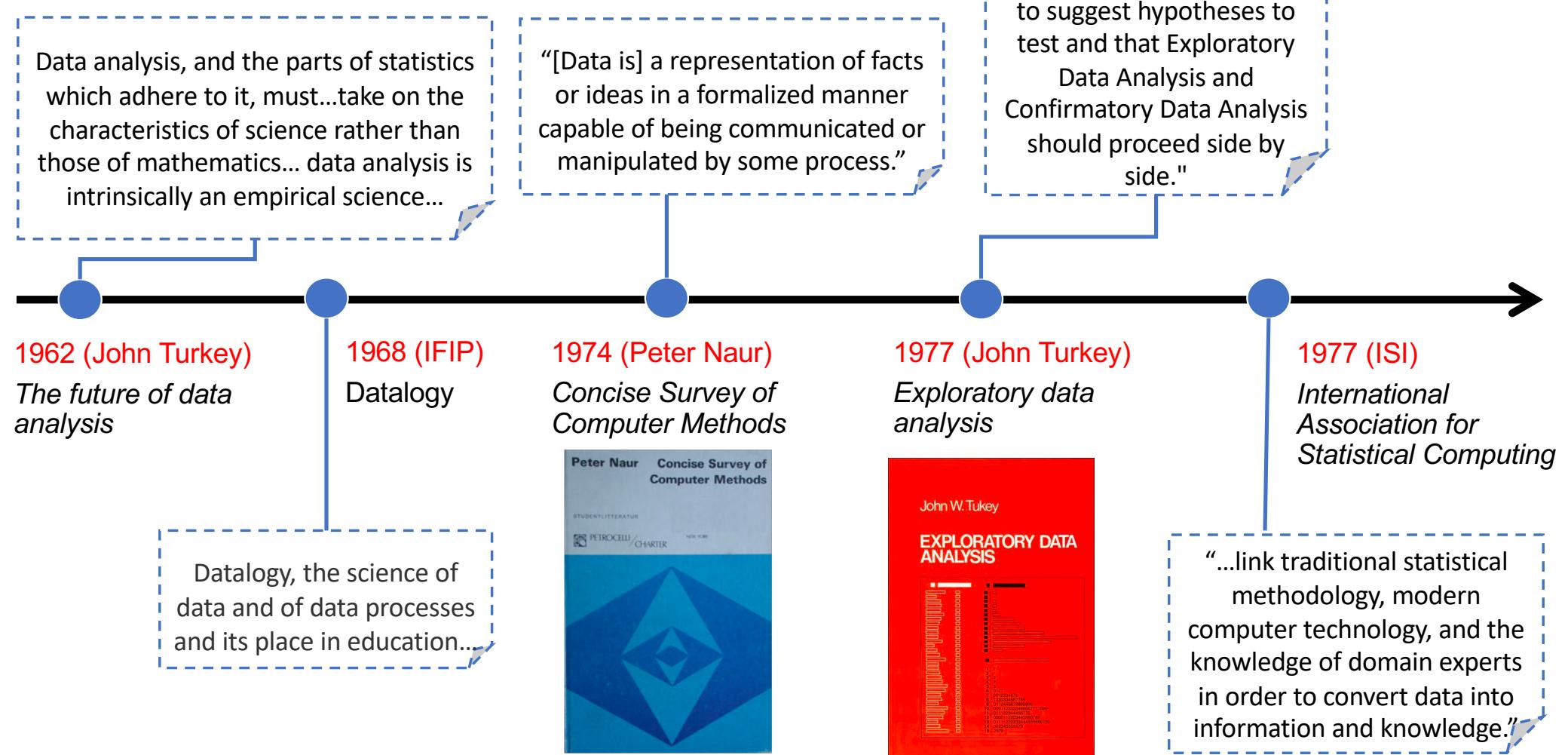
Ciência de dados (em inglês: *data science*) é uma área interdisciplinar voltada para o estudo e a análise de dados, estruturados ou não, que visa a extração de conhecimento ou *insights* para possíveis tomadas de decisão, de maneira similar à **mineração de dados**. Ciência de dados alia **big data** e **machine learning**, além de técnicas de outras áreas interdisciplinares como estatística, economia, engenharia e outros subcampos da **computação** como: **banco de dados** e **análise de agrupamentos** (*cluster analysis*). A ciência de dados é um campo que já existe há 30 anos, porém ganhou mais destaque nos últimos anos devido a alguns fatores como: o surgimento e popularização do Big Data e o desenvolvimento de áreas como o machine learning. A ciência de dados pode, por exemplo, transformar essa grande quantidade de dados brutos em *insights* de negócios, e com isso, auxiliar empresas em tomadas de decisões para atingir melhores resultados.^[1]



Is Data Science a science?

<https://towardsdatascience.com/data-science-and-ai-for-business-data-analysts-64f28a5d7ff2>

História (base Estatística)



<https://www.forbes.com/sites/gilpress/2013/05/28/a-very-short-history-of-data-science/#78699be255cf>

História (base Computação + BI)

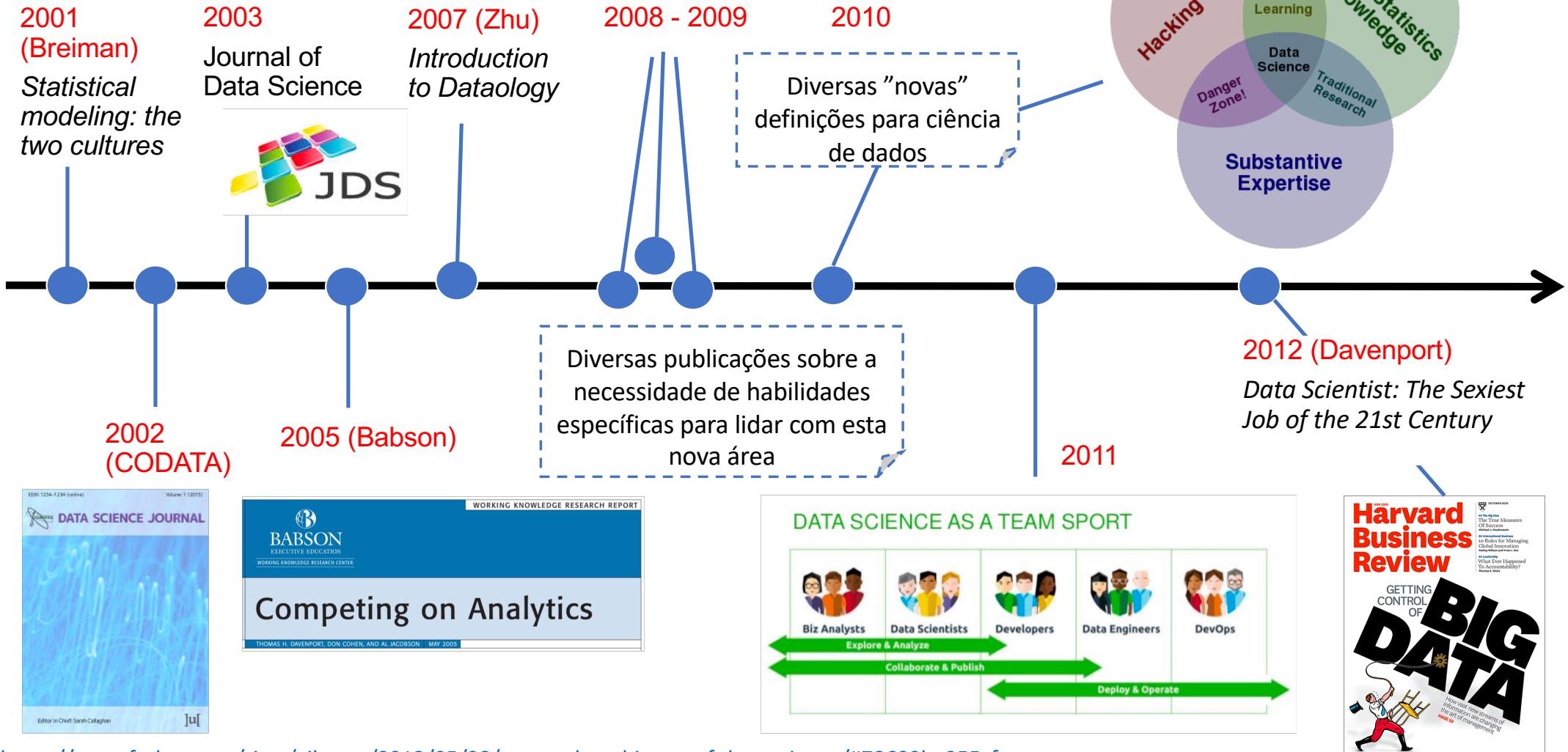
“Companies are collecting mountains of information about you, crunching it to predict how likely you are to buy a product, and using that knowledge to craft a marketing message precisely calibrated to get you to do so...”

The classification societies have variously used the terms data analysis, data mining, and data science in their publications.

“Historically, the notion of finding useful patterns in data has been given a variety of names, including data mining, knowledge extraction, information discovery, information harvesting, data archeology, and data pattern processing...”

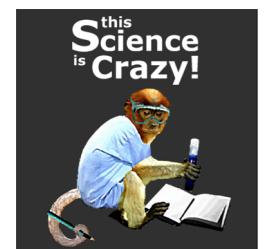
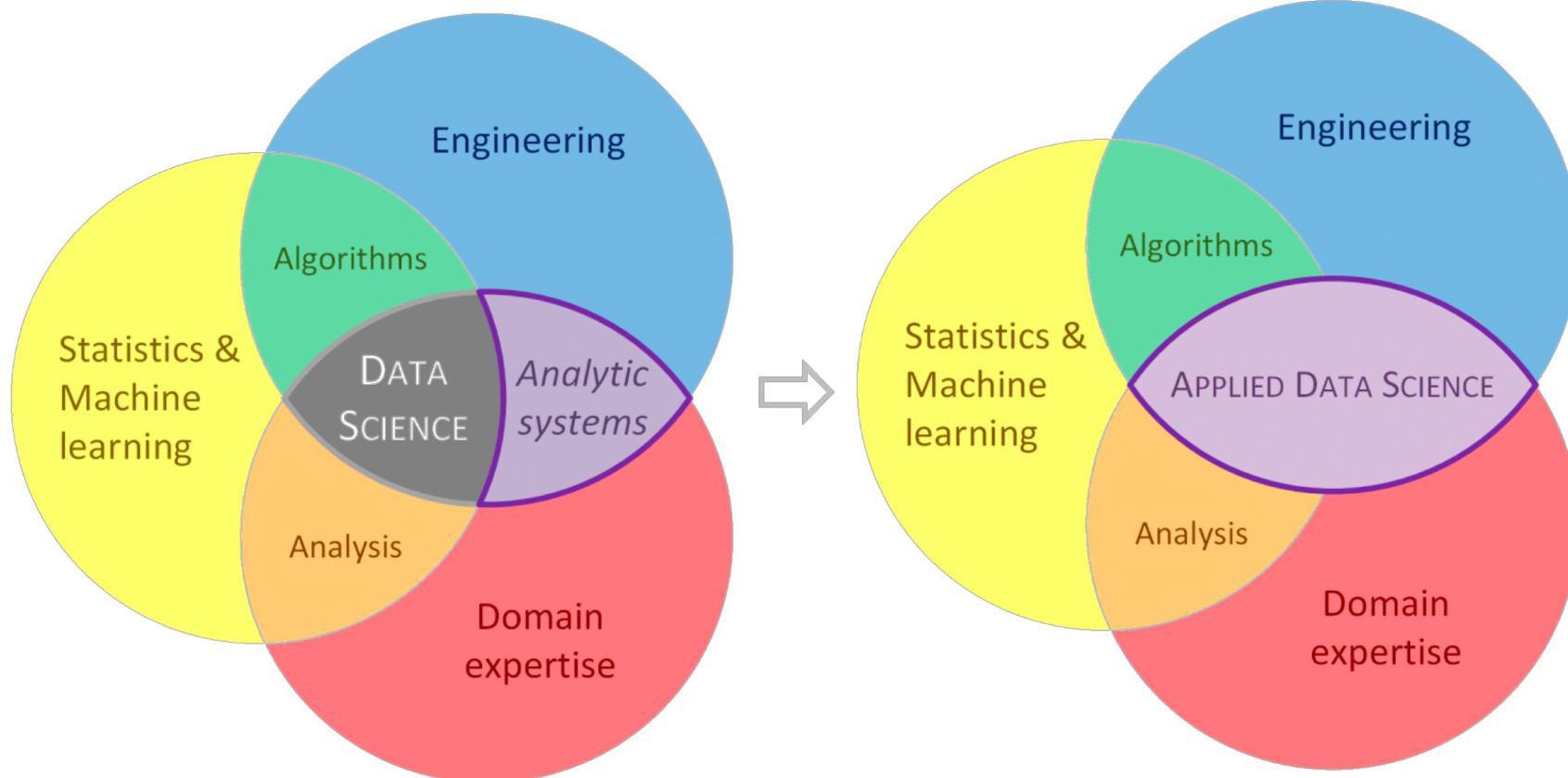


História (base Computação + BI)



<https://www.forbes.com/sites/gilpress/2013/05/28/a-very-short-history-of-data-science/#78699be255cf>

Definindo Ciência de Dados



BIG DATA



Big Data

1. Volume stands for scale of data
2. Velocity denotes the analysis of streaming data
3. Variety indicates different forms of data
4. Veracity focuses on trustworthiness of data sources
5. Variability refers to the complexity of data set. In comparison with “Variety” (or different data format), it means the number of variables in data sets
6. Visibility emphasizes that you need to have a full picture of data in order to make informative decision

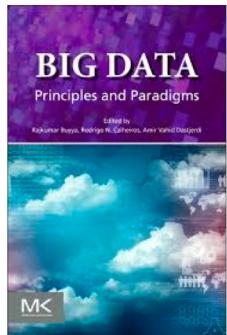
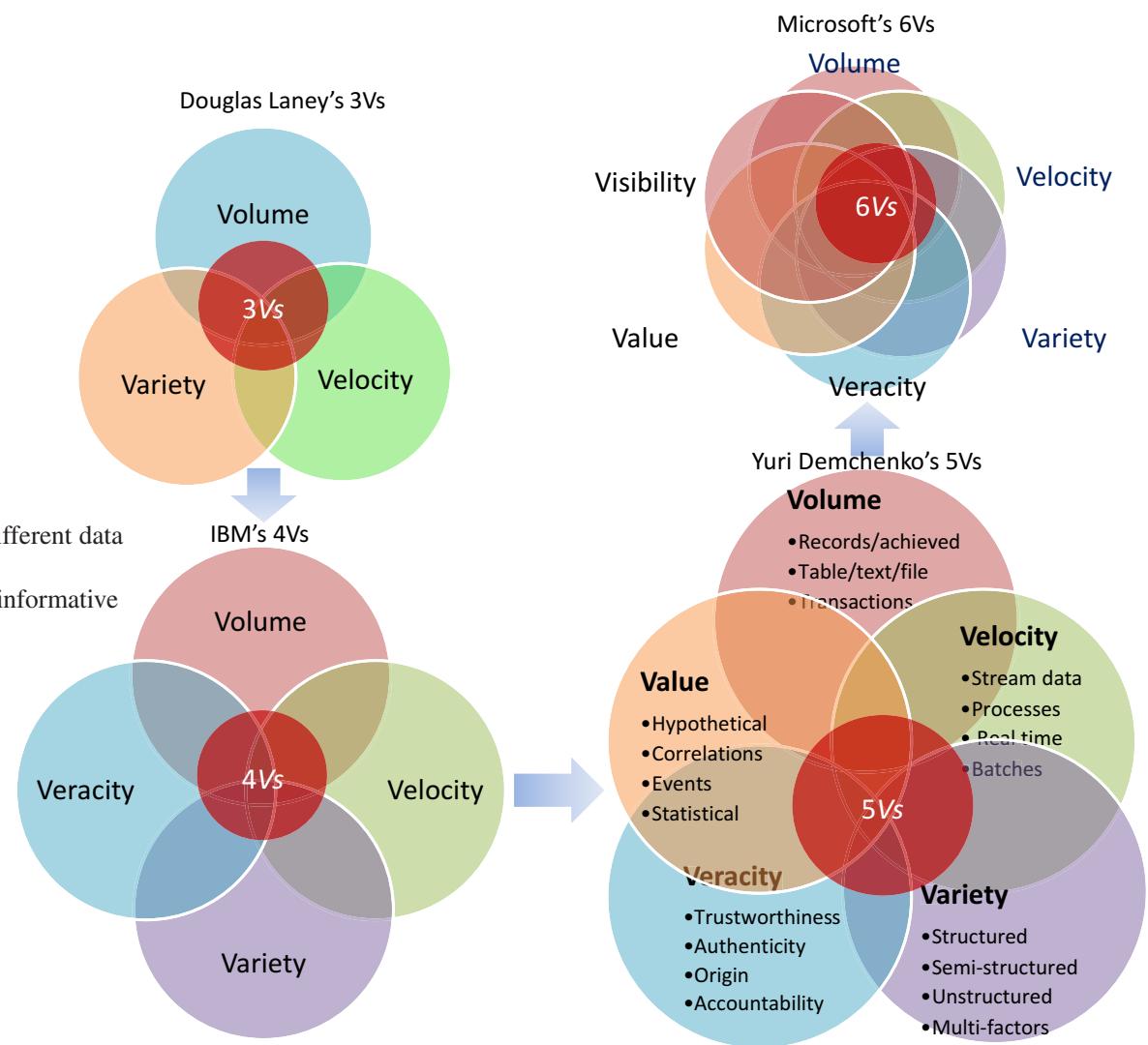


FIG. 3

From 3Vs, 4Vs, 5Vs, and 6Vs big data definition.



Big Data

- Data domain (searching for patterns)
- Business intelligence domain (making predictions)
- Statistical domain (making assumptions)

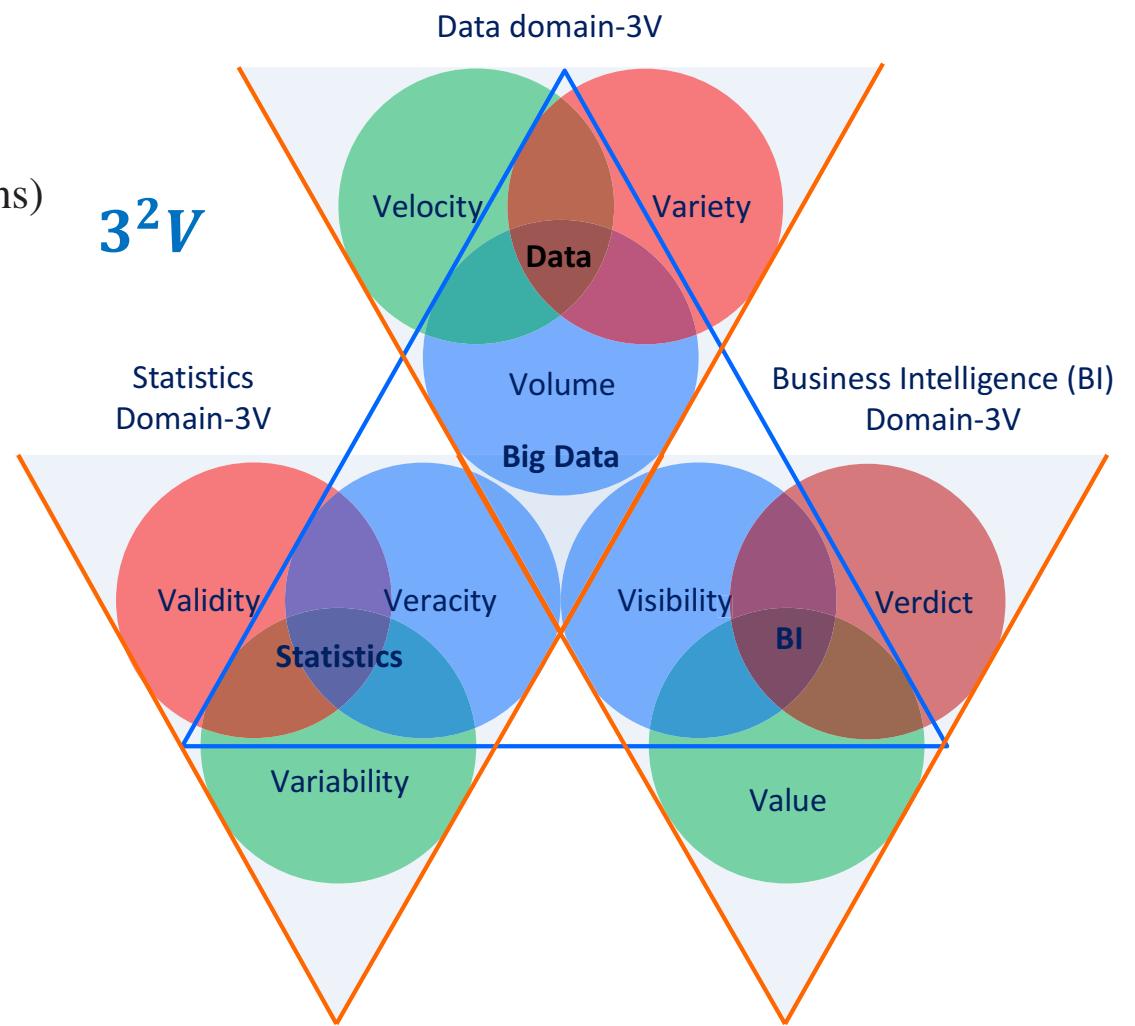
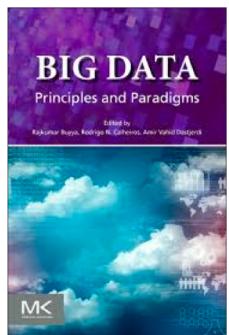
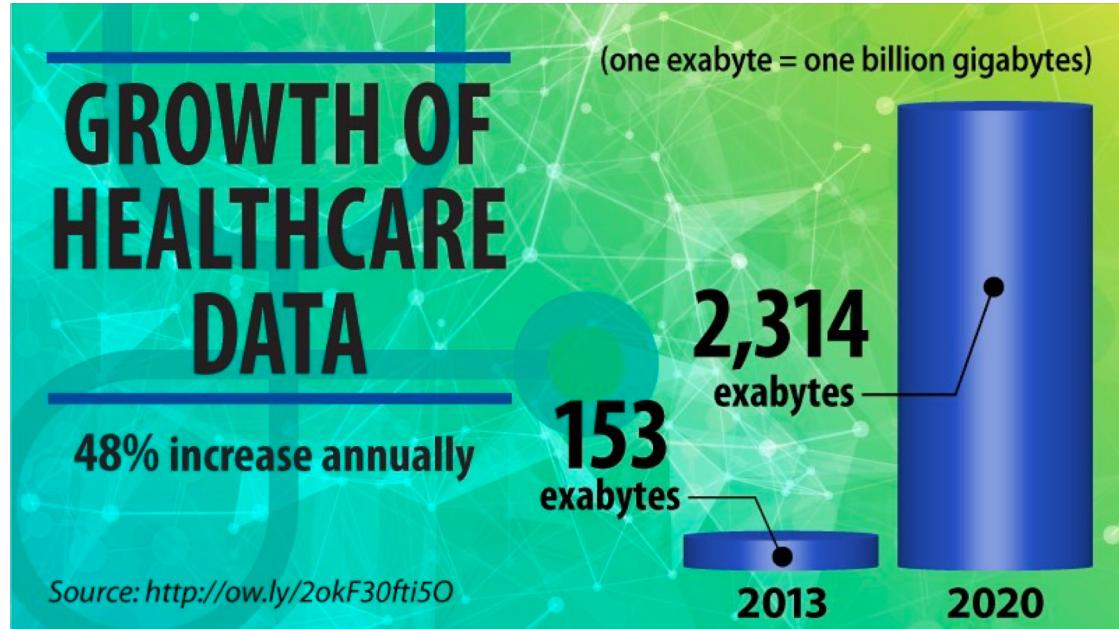


FIG. 5

3²Vs Venn diagrams in hierarchical model.

Big Data em Saúde



<http://sites.ieee.org/futuredirections/2018/05/18/the-future-of-health-care-is-tied-to-big-data/>

The Power of Healthcare Data

The Body as a Source of Big Data

Today data storage is essential for healthcare providers to see a patient's complete story of care, make the most informed decisions and enhance treatment and outcomes.

The human genome requires approximately **3GB** of data storage.^{*}

X-RAY **30MB**

0.5MB is generated

It is estimated that by 2015, the average hospital will generate **665TB** of data.^{*}

PACS (picture archiving and communication systems) applications were cited as the primary reason for healthcare data growth, at 63 percent, followed by files held in the electronic health record (54 percent) and scanned documents such as proof of insurance (51 percent).^{*}

The Medicare and Medicaid Electronic Health Record Incentive Program now includes a measure for recording imaging results via certified EHR technology.*

Medical image archives are increasing by **20-40%** annually.*

Access to electronic patient data beyond the desktop

3D MRI **150MB**

MAMMOGRAMS **120MB**

3D CT SCAN **1GB**

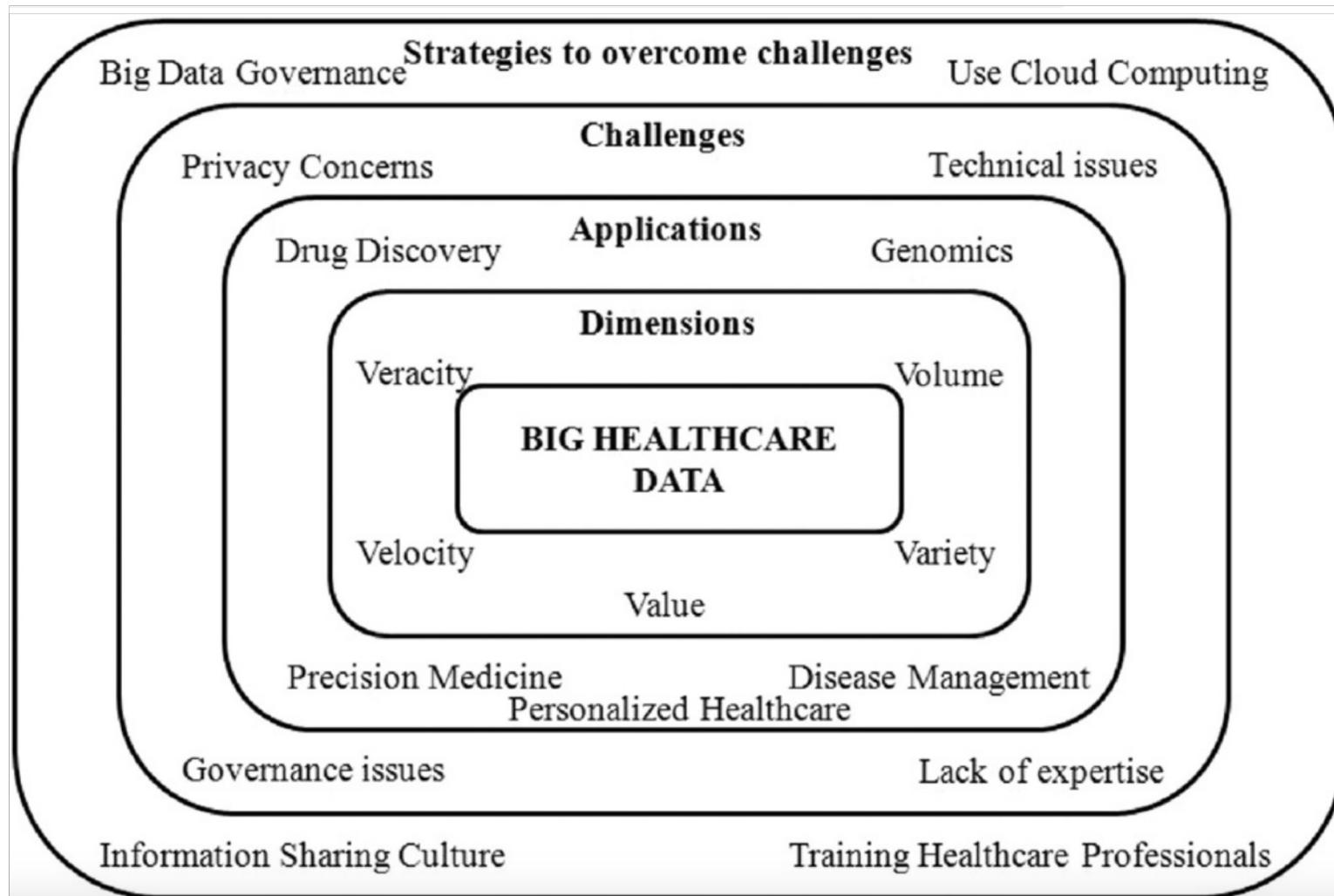
There are currently **425K** telehealth providers in the U.S.*

Common uses of health care analytics: More accurate diagnoses, streamlining the cost of care, revenue reimbursement, outcomes and business analysis to manage populations*

36.6M Total admissions in U.S. registered hospitals, according to the American Hospital Association*

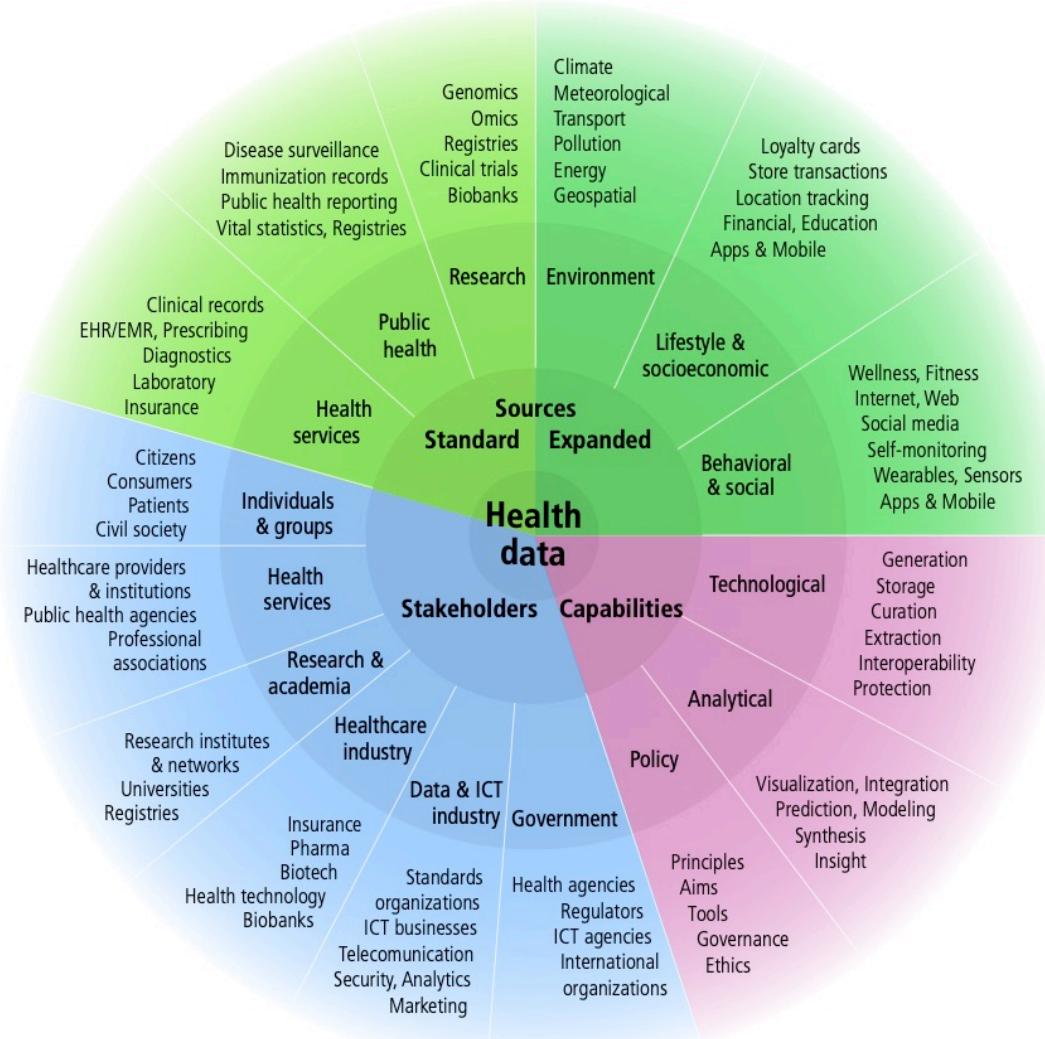
Today, **80%** of data is unstructured, such as images, video and email.*

Big Data em Saúde



DADOS DE SAÚDE

Evolving health data ecosystem



Dados de saúde

1738.00 663v100,
 J45, J44, 66YL.11,
 G20.00, 662O.00,
 1738.00 1682.00,
 I50, 06,
 116676008, I21.00

Structured

Orientation plus
 Stabilized plus

Make rs174546(C;C)

Make rs174546(C;T)

Make rs174546(T;T)

Reference GRCh38 38.1/141

Chromosome 11

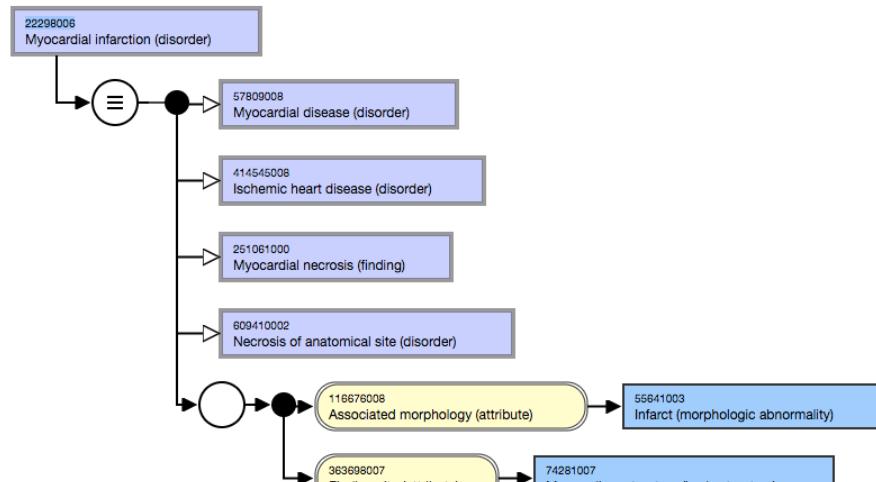
Position 61802358

Gene FADS1

is a snp

is mentioned by

dbSNP rs174546



0 Heart failure

Excl.: complicating:
 • abortion or ectopic or molar pregnancy (000-007, 008.8)
 • obstetric surgery and procedures (075.4)
 due to hypertension (I11.0)
 • with renal disease (I13.-)
 following cardiac surgery or due to presence of cardiac prosthesis (I97.1)
 neonatal cardiac failure (P29.0)

0.0 Congestive heart failure

Congestive heart disease
 Right ventricular failure (secondary to left heart failure)

0.1 Left ventricular failure

Cardiac asthma
 Left heart failure
 Oedema of lung
 Pulmonary oedema | with mention of heart disease NOS or heart failure

0.9 Heart failure, unspecified

Cardiac, heart or myocardial failure NOS

Dados de saúde

1738.00 663v100,
J45, J44, 66YL.11,
G20.00, 662O.00,
1738.00 1682.00,
I50, 06,
116676008, I21.00

Structured

220, 110, 0.002, 1,
200, 3, 2, 2.1, 2.01,
20, 1, 99092, 1.2,
99, 123, 6, 23.2,
878, 9901, 11,
203.1

Semi-structured

Local Code

OBX|1|NM|123^RBC^MyHosp|26453-1^Erythrocytes [#/volume] in Blood^LN|4.82|10*6/uL

LOINC Code

Dados de saúde

1738.00 663v100,
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G20.00, 662O.00,
1738.00 1682.00,
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220, 110, 0.002, 1,
200, 3, 2, 2.1, 2.01,
20, 1, 99092, 1.2,
99, 123, 6, 23.2,
878, 9901, 11,
203.1

Semi-structured

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Unstructured

76 yo man with h/o HTN, DM, and sleep apnea who presented to the ED complaining of chest pain. He states that the pain began the day before and consisted of a sharp pain that lasted around 30 seconds, followed by a dull pain that would last around 2 minutes. The pain was located over his left chest area somewhat near his shoulder. The onset of pain came while the patient was walking in his home. He did not sit and rest during the pain, but continued to do household chores. Later on in the afternoon he went to the gym where he walked 1 mile on the treadmill, rode the bike for 5 minutes, and swam in the pool. After returning from the gym he did some work out in the yard, cutting back some vines. He did not have any reoccurrences of chest pain while at the gym or later in the evening. The following morning (of his presentation to the ED) he noticed the pain as he was getting out of bed. Once again it was a dull pain, preceded by a short interval of a sharp pain. The patient did experience some tingling in his right arm after the pain ceased. He continued to have several episodes of the pain throughout the morning, so his daughter-in-law decided to take him to the ED around 12:30pm. The painful episodes did not increase in intensity or severity during this time.

# Dados de saúde

1738.00 663v100,  
J45, J44, 66YL.11,  
G20.00, 662O.00,  
1738.00 1682.00,  
I50, 06,  
116676008, I21.00

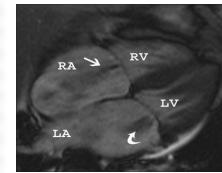
Structured

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878, 9901, 11,  
203.1

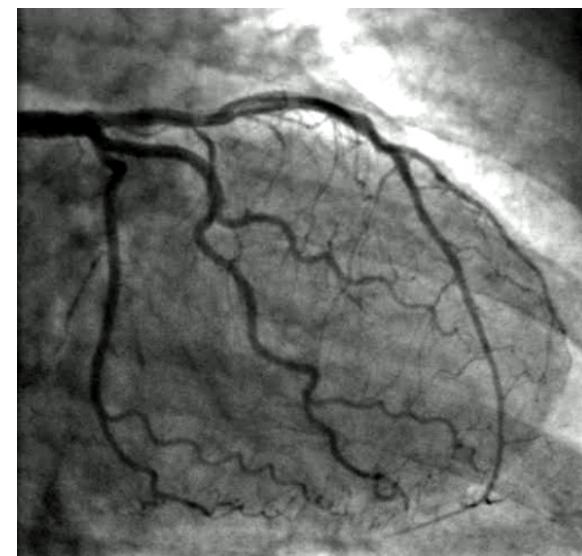
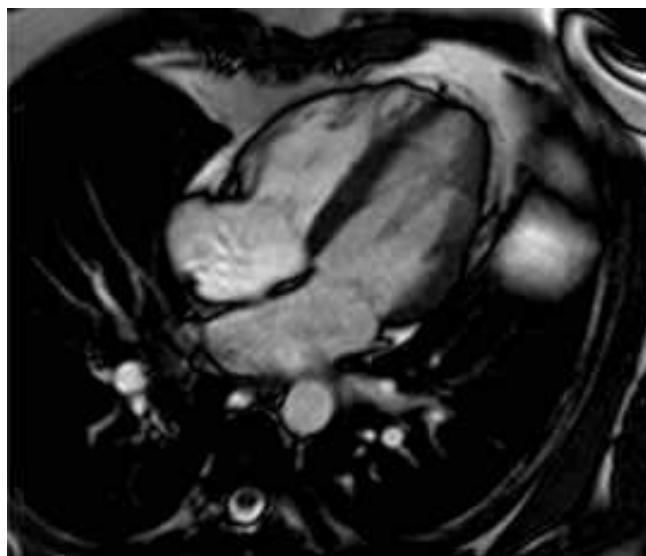
Semi-structured

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Unstructured



Binary



# Dados de saúde

1738.00 663v100,  
J45, J44, 66YL.11,  
G20.00, 662O.00,  
1738.00 1682.00,  
I50, 06,  
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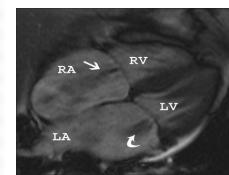
Structured

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878, 9901, 11,  
203.1

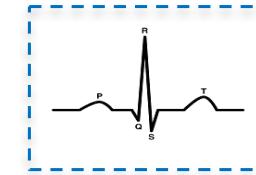
Semi-structured

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Unstructured



Binary



Streaming

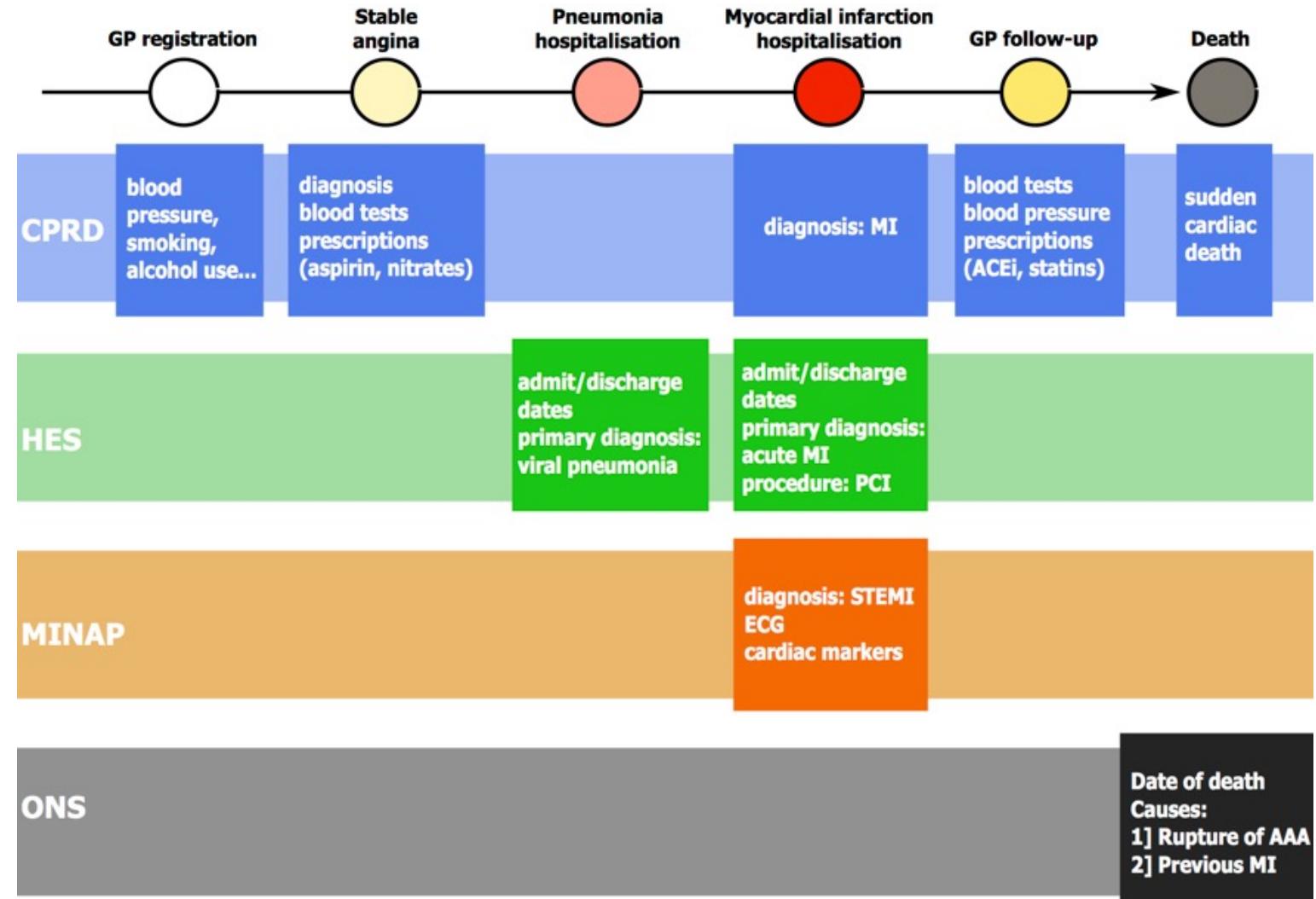


## APLICAÇÕES

- ✓ Estudos epidemiológicos de base populacional (coorte)
- ✓ Análises clínicas
- ✓ Descoberta de novos fármacos
- ✓ Cura de doenças / resistência antimicrobiana
- ✓ Medicina personalizada
- ✓ Prevenção de visitas desnecessárias ao médico
  
- ✓ Análise preditiva em saúde
- ✓ Registros eletrônicos (*electronic health records – EHR*)
- ✓ Monitoramento em tempo real
- ✓ Sistemas de suporte à decisão
- ✓ Medicina assistida por computação / *mobile health (m-Health)*

# Aplicações

## Population-based clinical epidemiology



# Aplicações

## Type-2 Diabetes and 12 CVDs

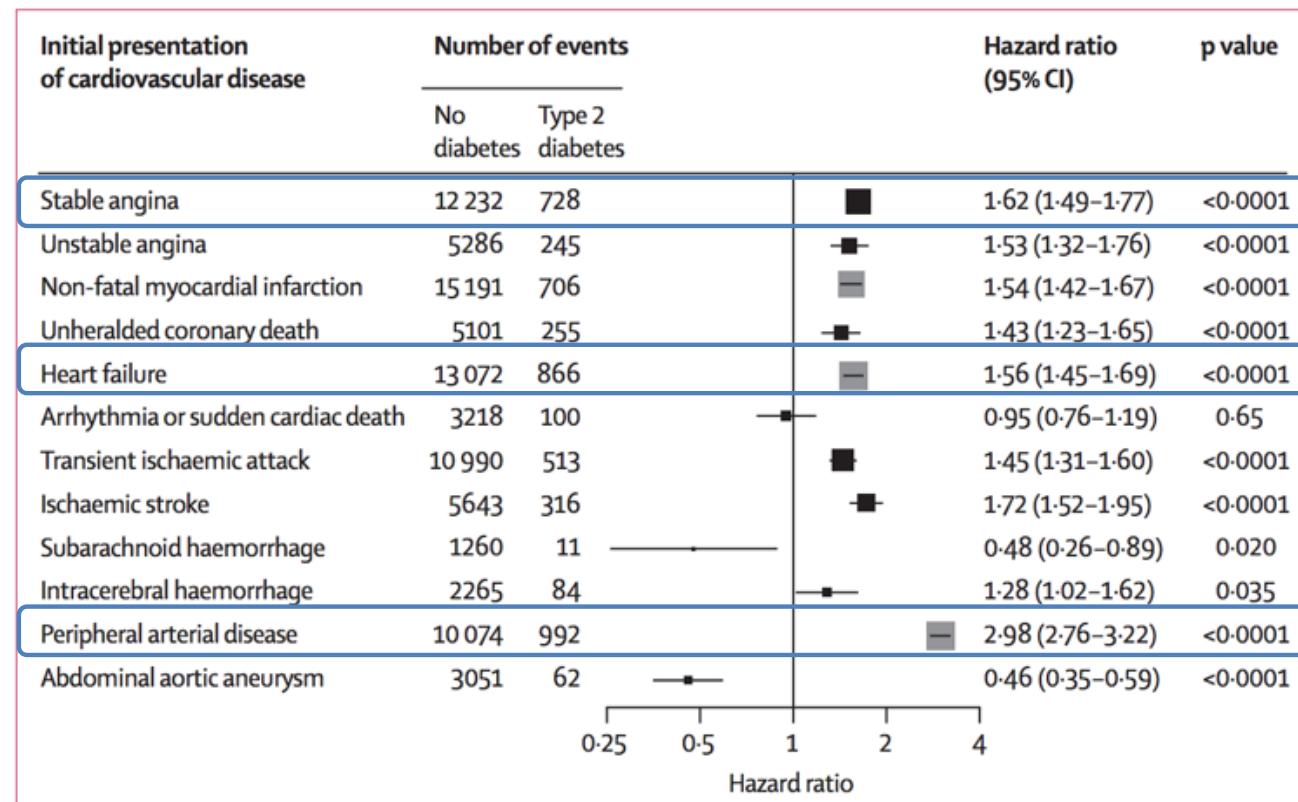


Figure 3: Association of type 2 diabetes with 12 cardiovascular diseases in patients aged  $\geq 30$  years

# Aplicações

# Clinical trials pipelines

**Problem:** A lot of medical care is educated guesses

**Opportunity:** Decisions based on what happened to people like you.

## My Patient

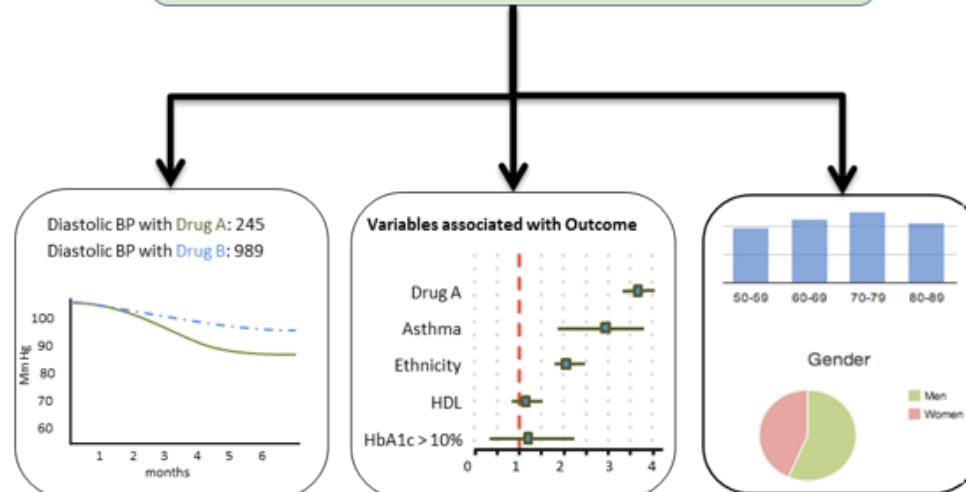
A 55 year old female of Vietnamese heritage with known asthma presents to her physician with new onset moderate hypertension

## Intervention

antihypertensives

## Outcome

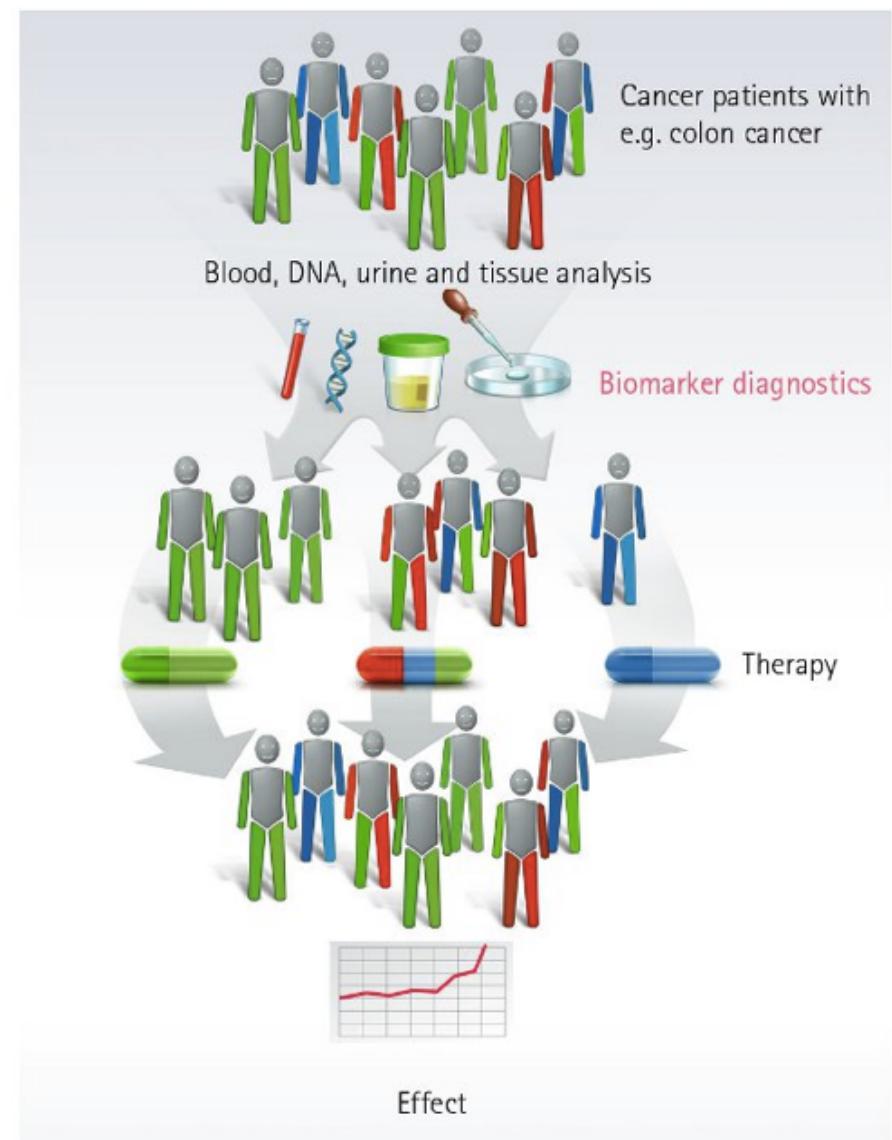
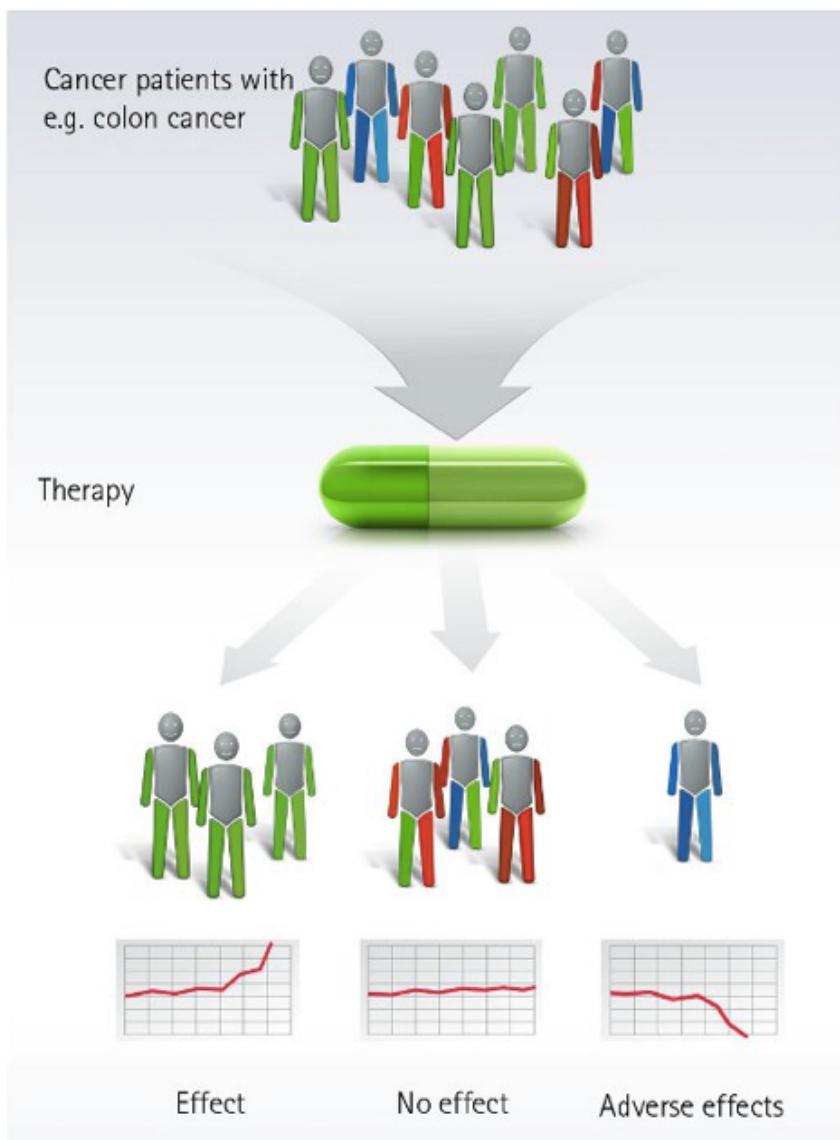
Diastolic pressure < 90 mm Hg



Longhurst A. A. et al., Health Affairs, 2014, doi:10.1377/hlthaff.2014.0099

# Aplicações

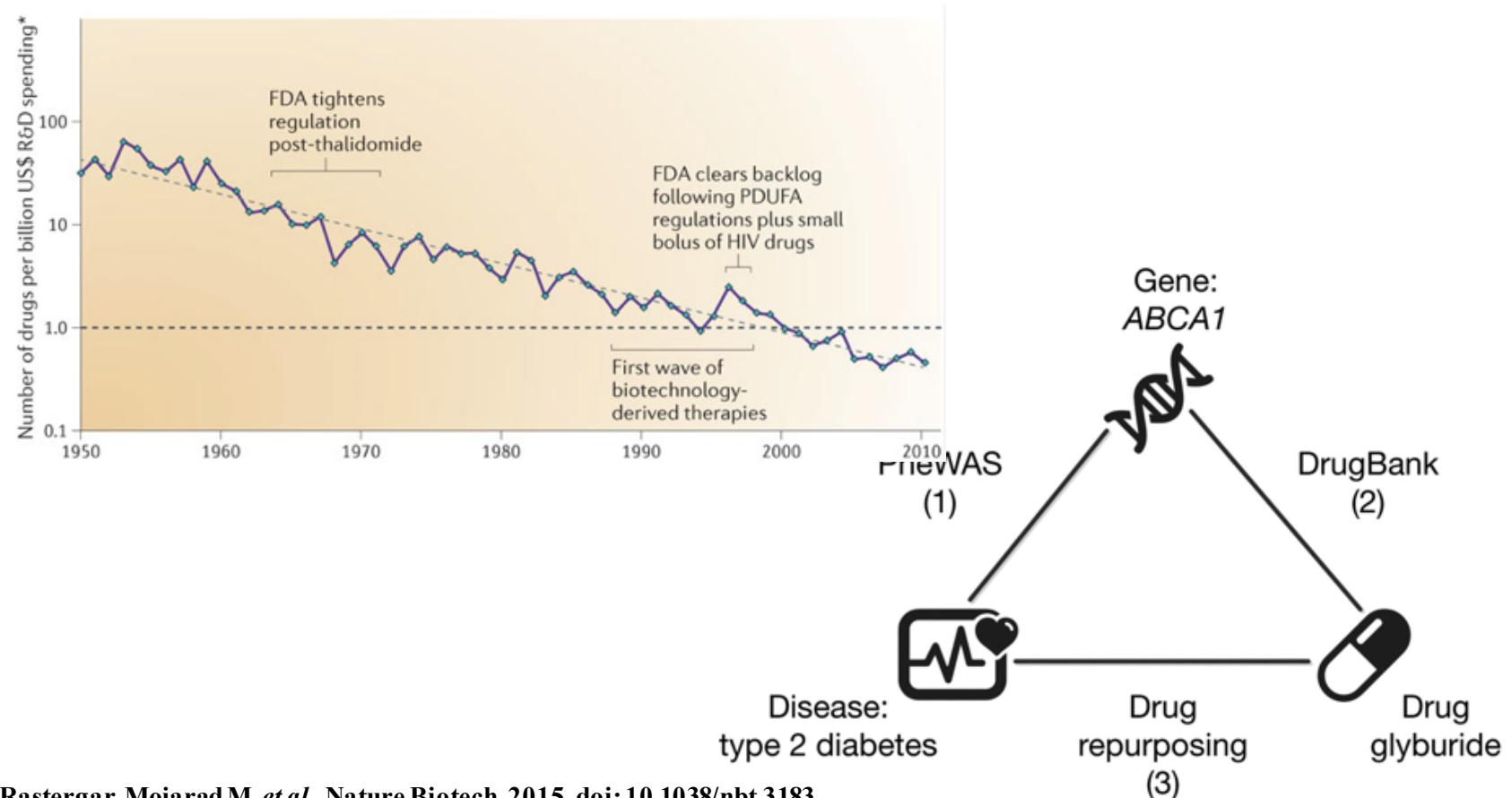
Precision  
medicine



# Aplicações

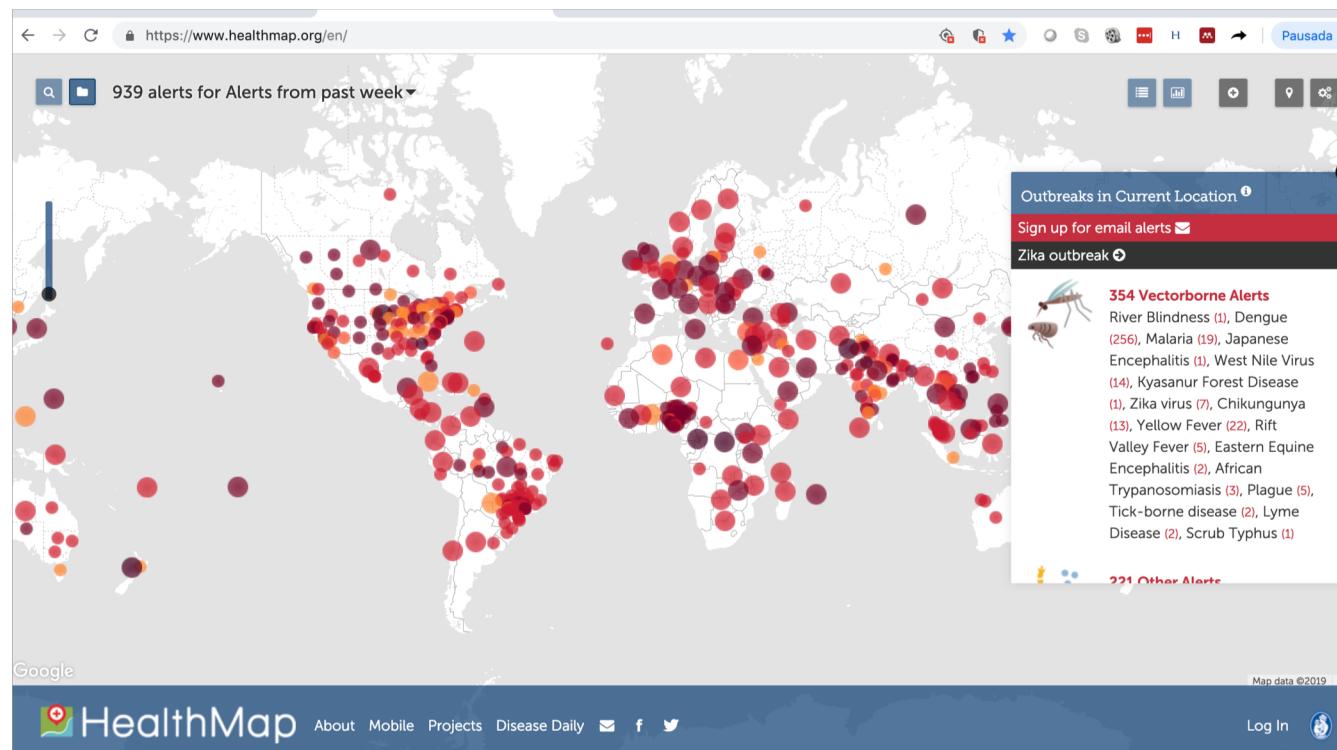
# Drug discovery and repositioning

**Challenge:** costs (5-11bn USD), time (17 years)



Rastegar-Mojarrad M. et al., Nature Biotech, 2015, doi: 10.1038/nbt.3183  
Scannell J.W. et al., Nat Review Drug Discovery, 2012, doi: 10.1038/nrd3681

# Aplicações



The Journal of Infectious Diseases

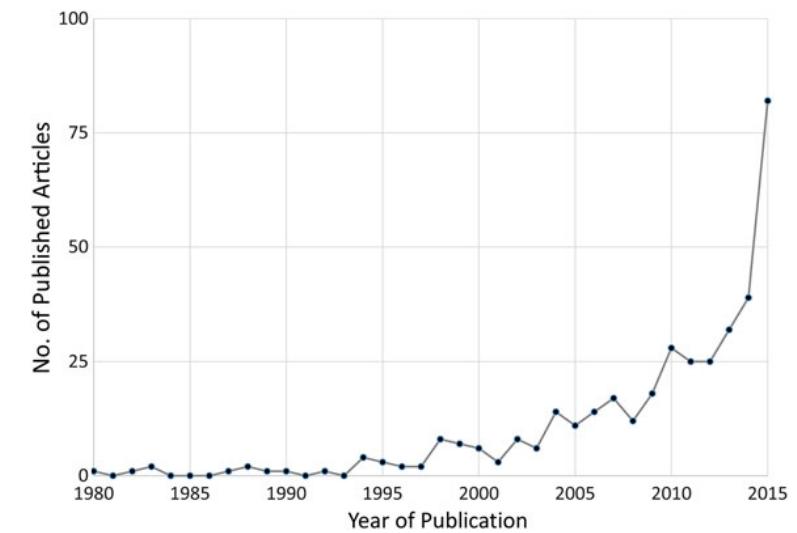
SUPPLEMENT ARTICLE



## Big Data for Infectious Disease Surveillance and Modeling

Shweta Bansal,<sup>1,2</sup> Gerardo Chowell,<sup>1,3</sup> Lone Simonsen,<sup>1,4</sup> Alessandro Vespignani,<sup>5</sup> and Cécile Viboud<sup>1</sup>

<sup>1</sup>Fogarty International Center, National Institutes of Health, Bethesda, Maryland; <sup>2</sup>Department of Biology, Georgetown University, Washington D.C.; <sup>3</sup>School of Public Health, Georgia State University, Atlanta; <sup>4</sup>Department of Public Health, University of Copenhagen, Denmark; and <sup>5</sup>Network Science Institute, Northeastern University, Boston, Massachusetts

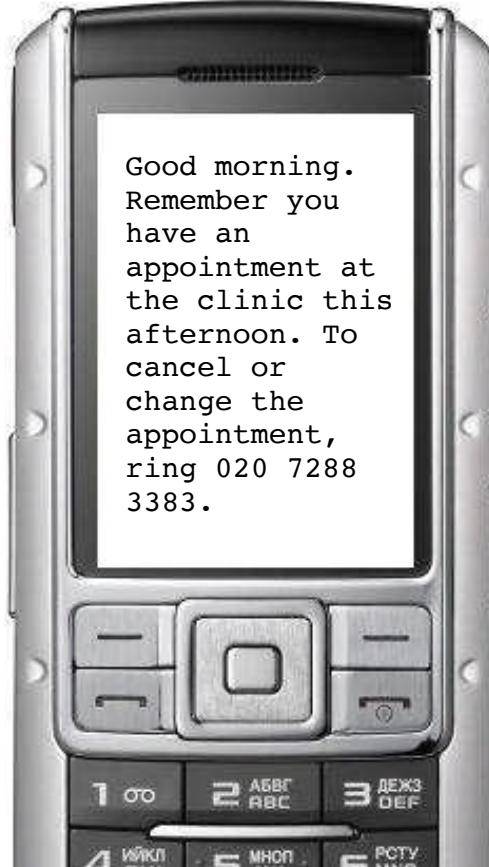


**Figure 1.** Exponential increase since the early 2000s in publications at the intersection of big data and infectious diseases. Annual trends in the number of publications were identified through a Scopus search for articles published between 1980 and 2015, using the following keywords: (big data AND infectious diseases) OR (big data AND epidemics) OR (digital epidemiology AND infectious diseases).

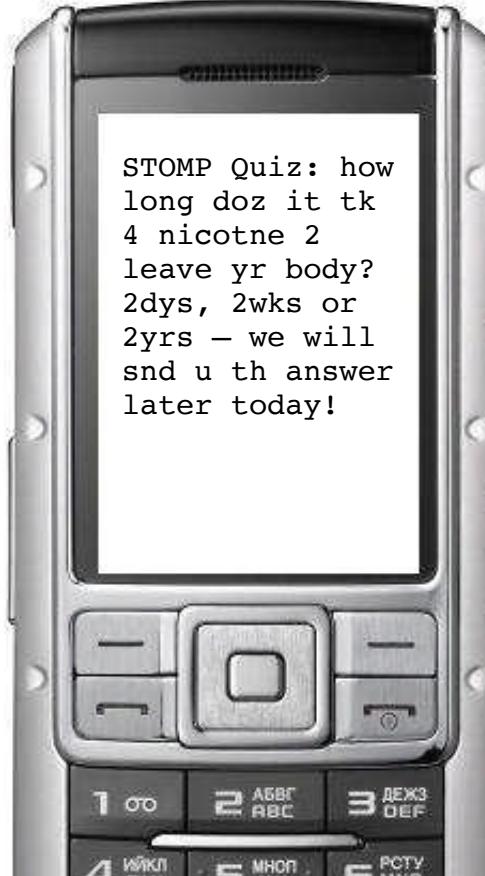
# Aplicações

## m-Health

Dr Henry Potts: h.potts@ucl.ac.uk



Appointment  
reminder



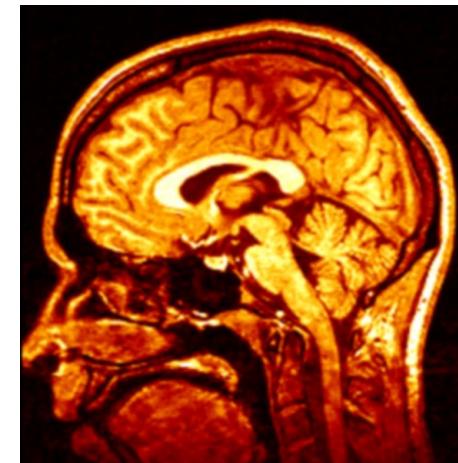
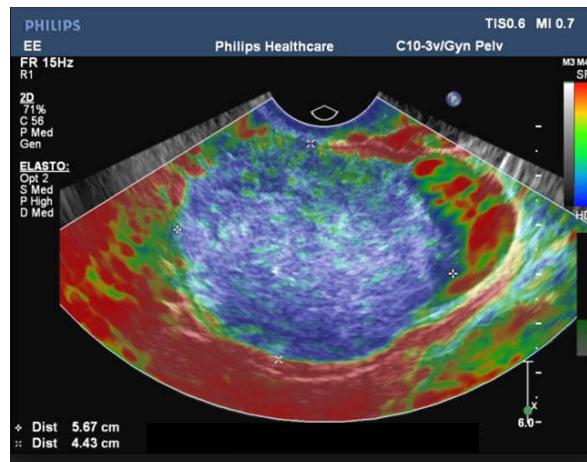
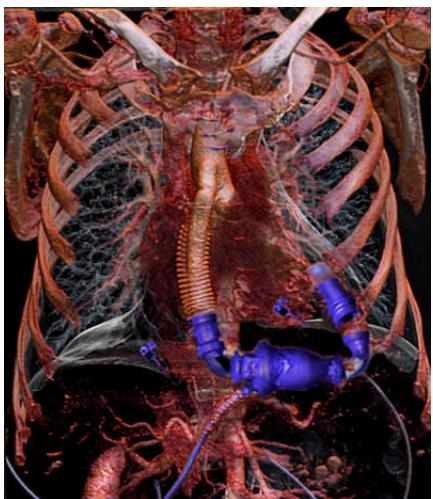
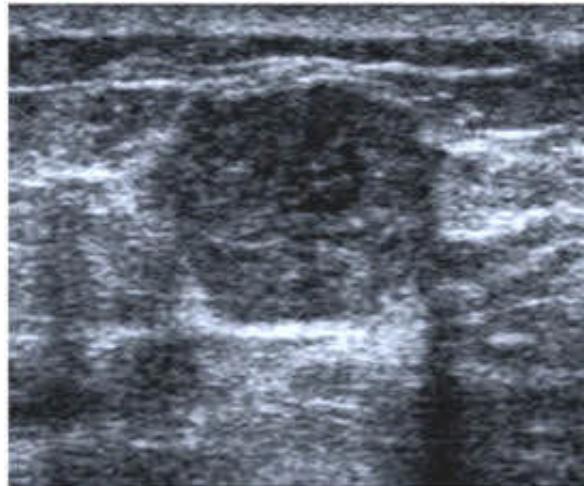
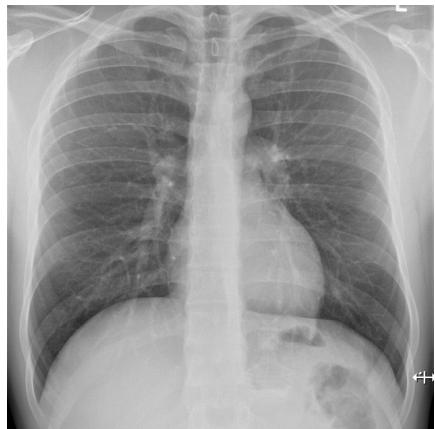
Behaviour  
change



Personal  
health record

# Aplicações

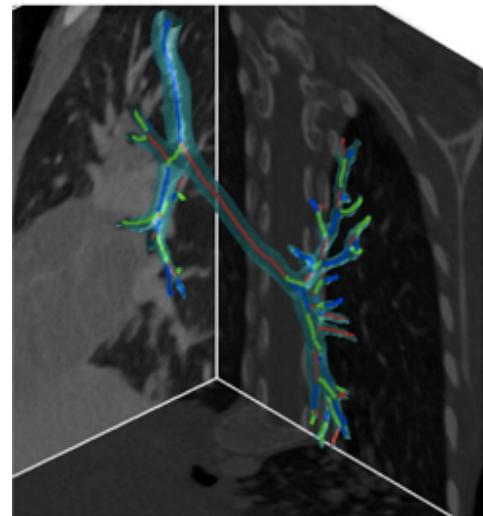
## Medical image processing



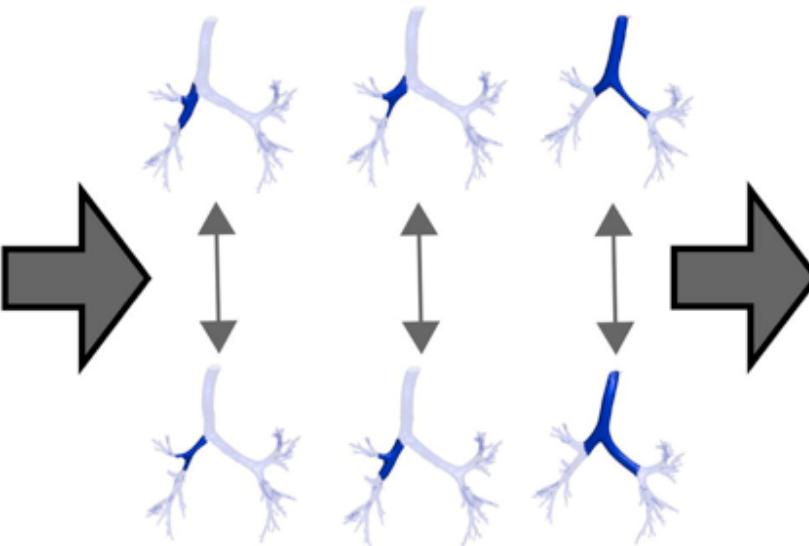
# Aplicações

## Medical image processing

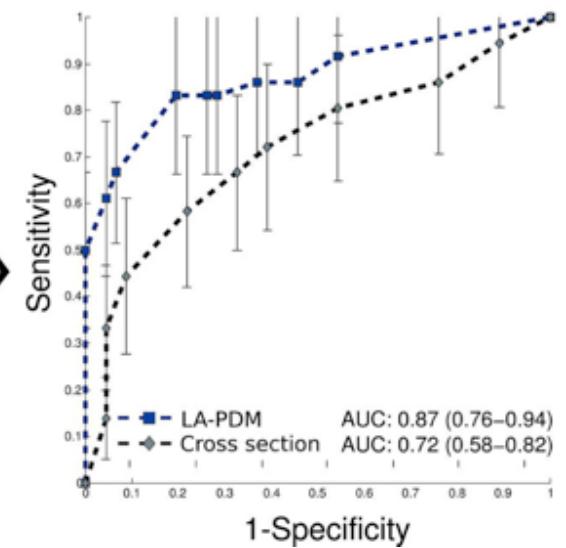
Airway segmentation  
from CT



Population analysis of  
airway regions

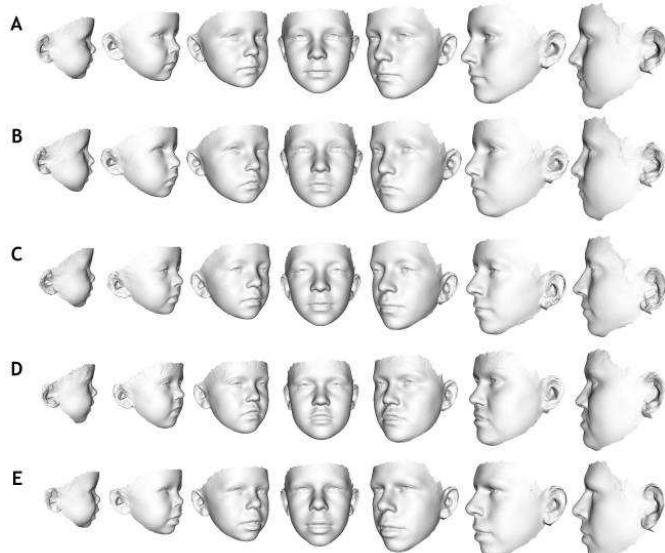


Classification of  
pathological variation

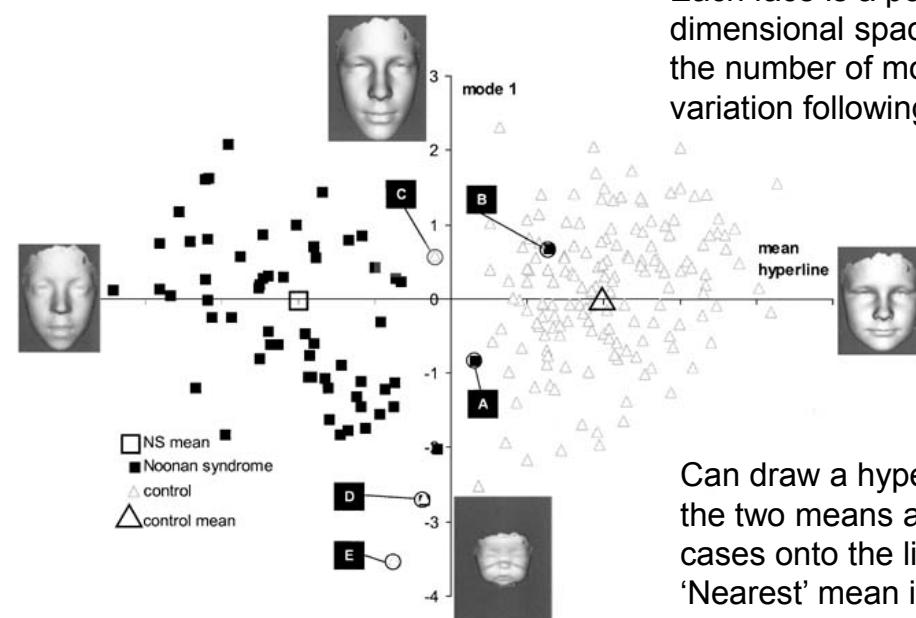


# Aplicações

Each row shows a series of views of the mean face for a different syndrome



## Hammond et al. Using a database of 3D facial scans to identify genetic disorders



Each face is a point in n dimensional space where n is the number of modes of variation following PCA

Can draw a hyperline between the two means and project cases onto the line  
'Nearest' mean is one classifier

# DESAFIOS

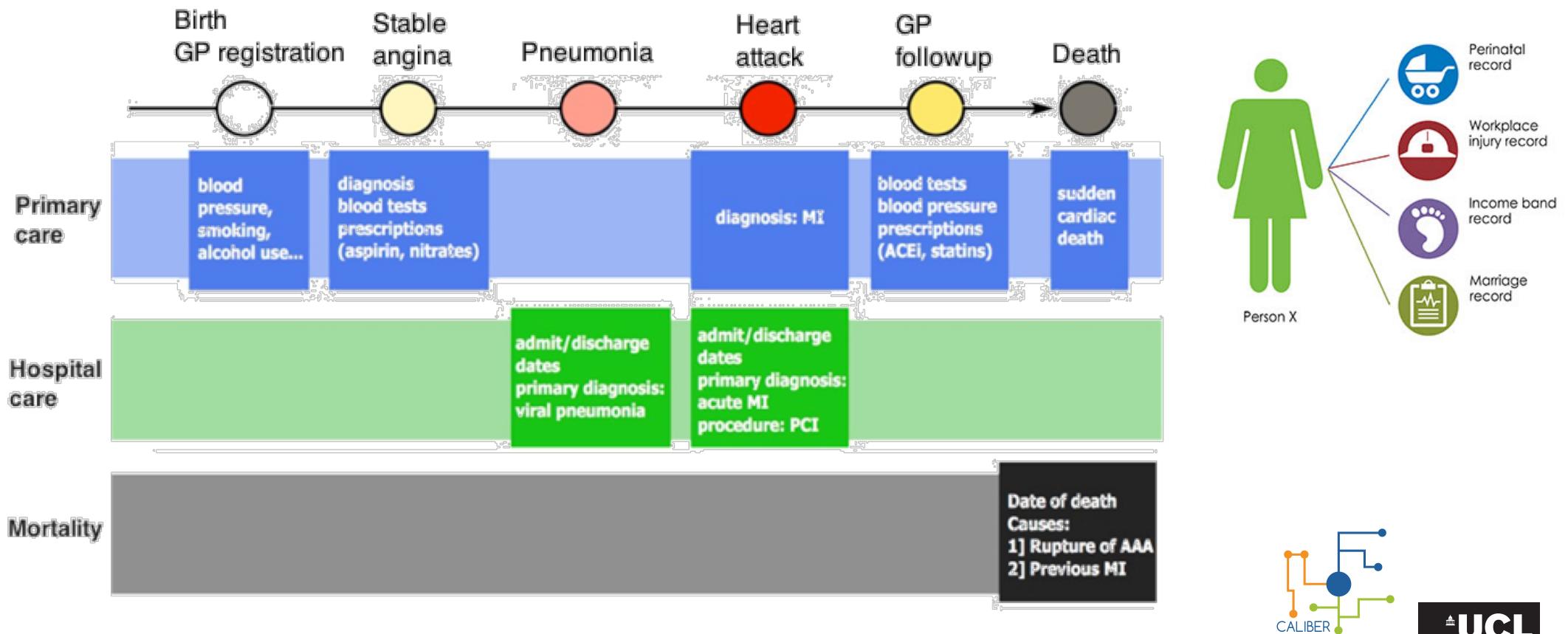
## CASO CLÍNICO

### ► Caminho do Paciente



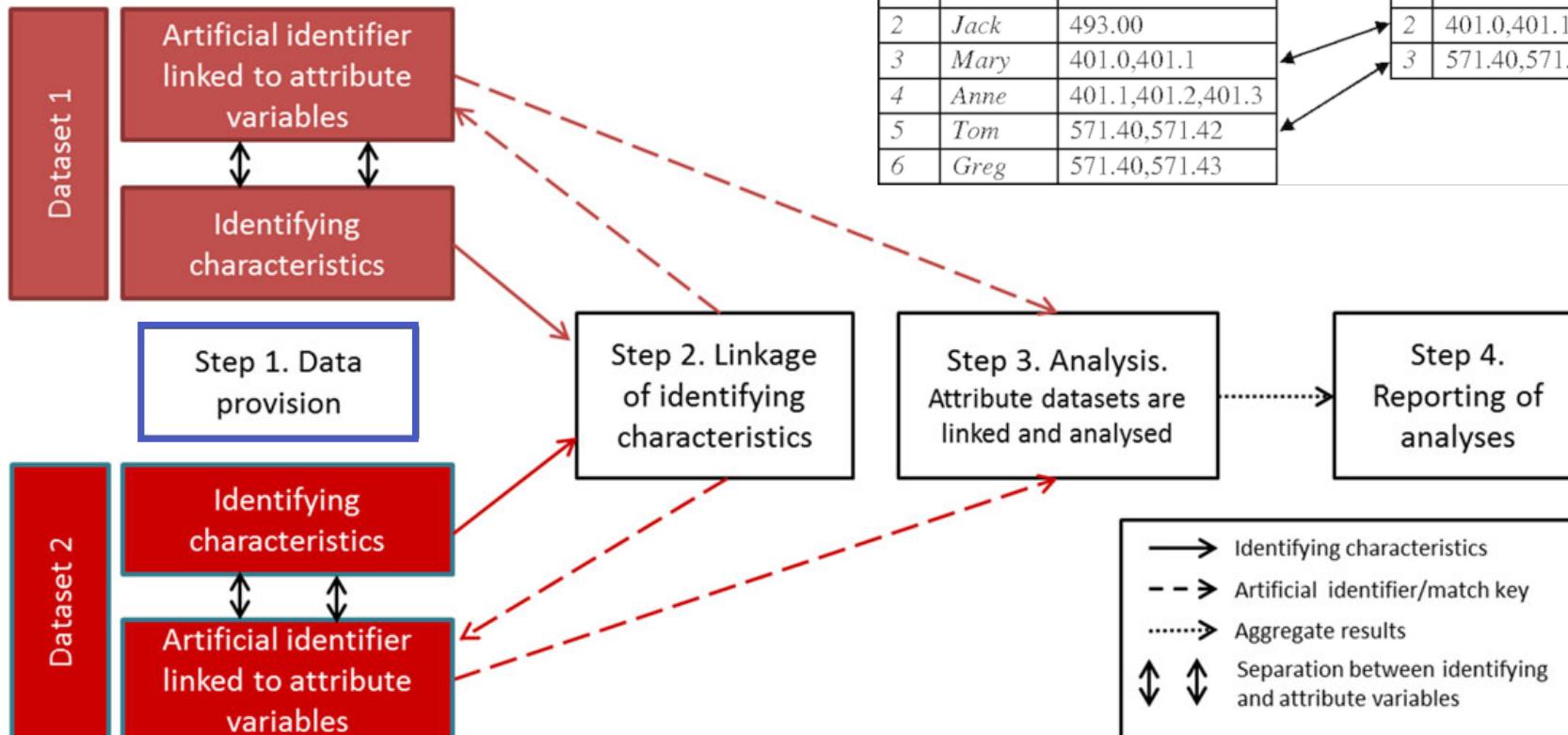
# Vinculação de dados (*data linkage*)

- To bring together electronic records containing information from different sources about an entity (individual, organisation, location etc).



# Vinculação de dados (*data linkage*)

- Basic pathway

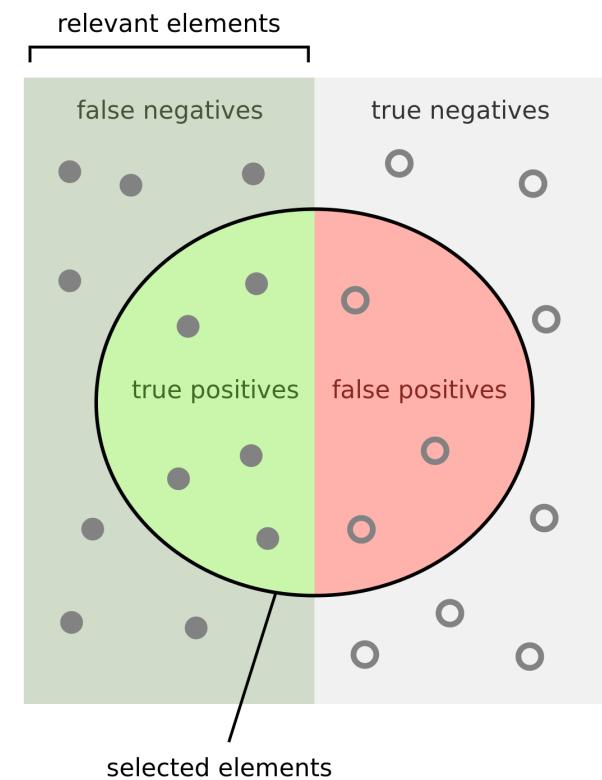
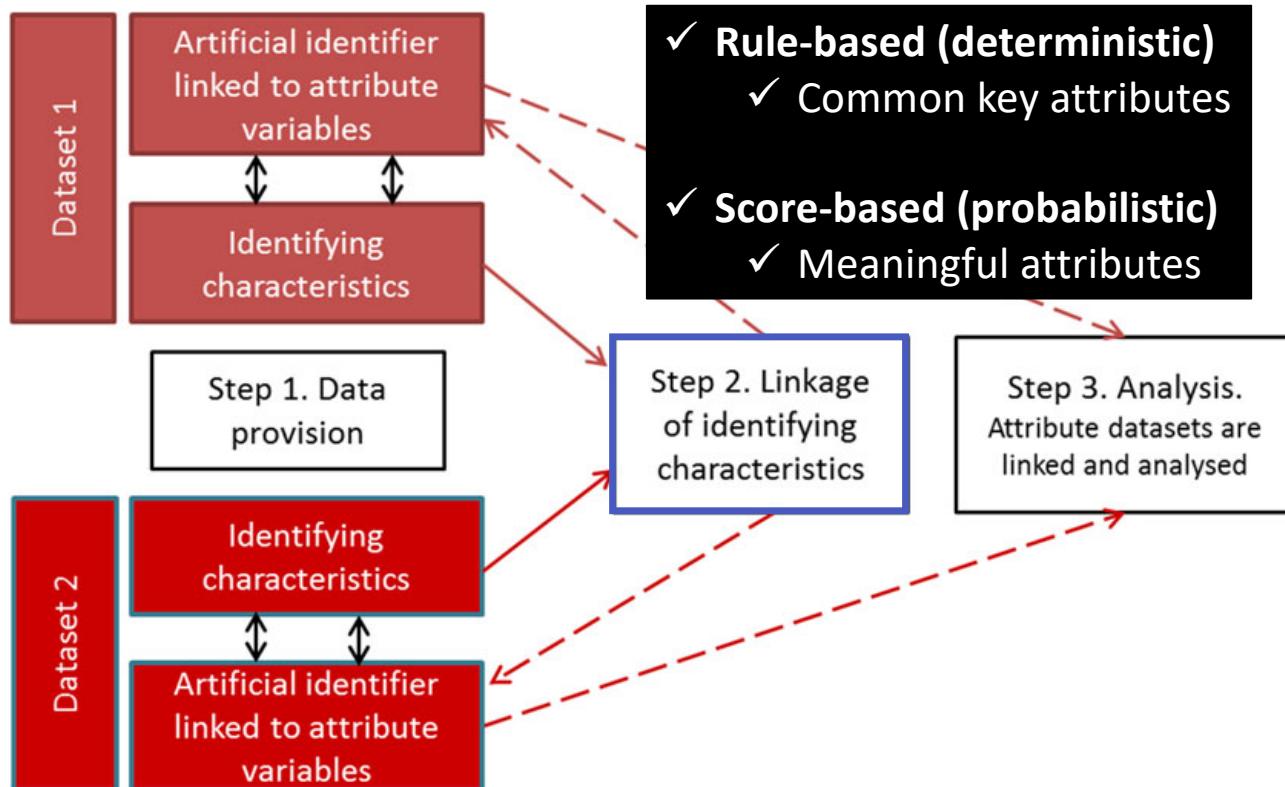


| Identified EMR data (P) |      |                   | De-identified Research data (S) |               |        |
|-------------------------|------|-------------------|---------------------------------|---------------|--------|
| i                       | ID   | ICD9              | j                               | ICD9          | DNA    |
| 1                       | Jim  | 493.00            | 1                               | 493.00        | CT...A |
| 2                       | Jack | 493.00            | 2                               | 401.0,401.1   | AC...T |
| 3                       | Mary | 401.0,401.1       | 3                               | 571.40,571.42 | GC...A |
| 4                       | Anne | 401.1,401.2,401.3 |                                 |               |        |
| 5                       | Tom  | 571.40,571.42     |                                 |               |        |
| 6                       | Greg | 571.40,571.43     |                                 |               |        |

GUILD: *GU*idance for *I*nformation about *L*inking *D*a<sup>t</sup>sets  
*Journal of Public Health*, doi:10.1093/pubmed/fdx037

# Vinculação de dados (*data linkage*)

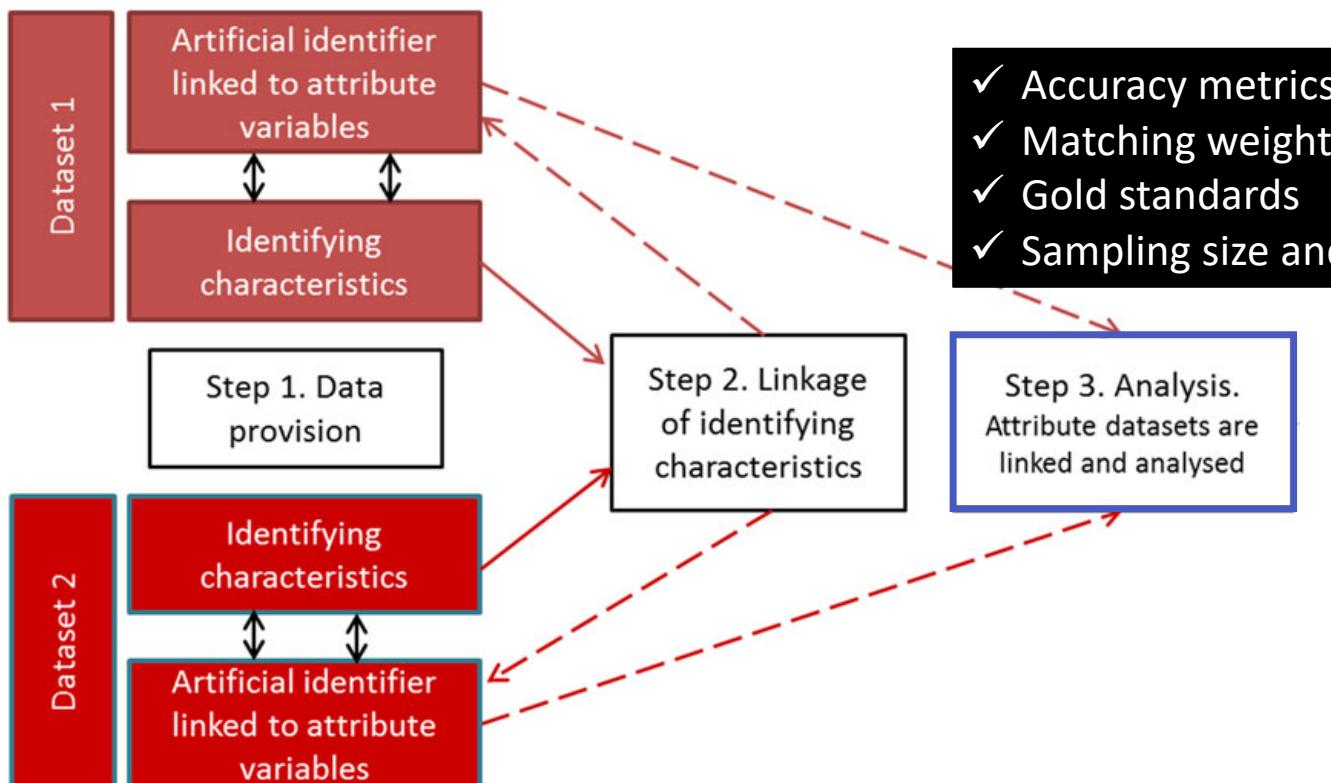
- Pairwise comparison



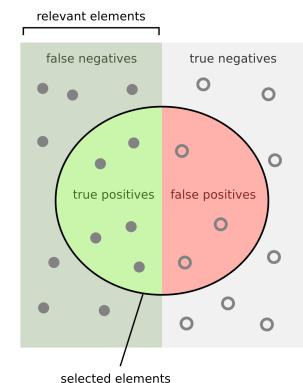
GUILD: *GUIDance for Information about Linking Data sets*  
Journal of Public Health , doi:10.1093/pubmed/fdx037

# Vinculação de dados (*data linkage*)

- Accuracy ascertainment



- ✓ Accuracy metrics
- ✓ Matching weights
- ✓ Gold standards
- ✓ Sampling size and expressiveness



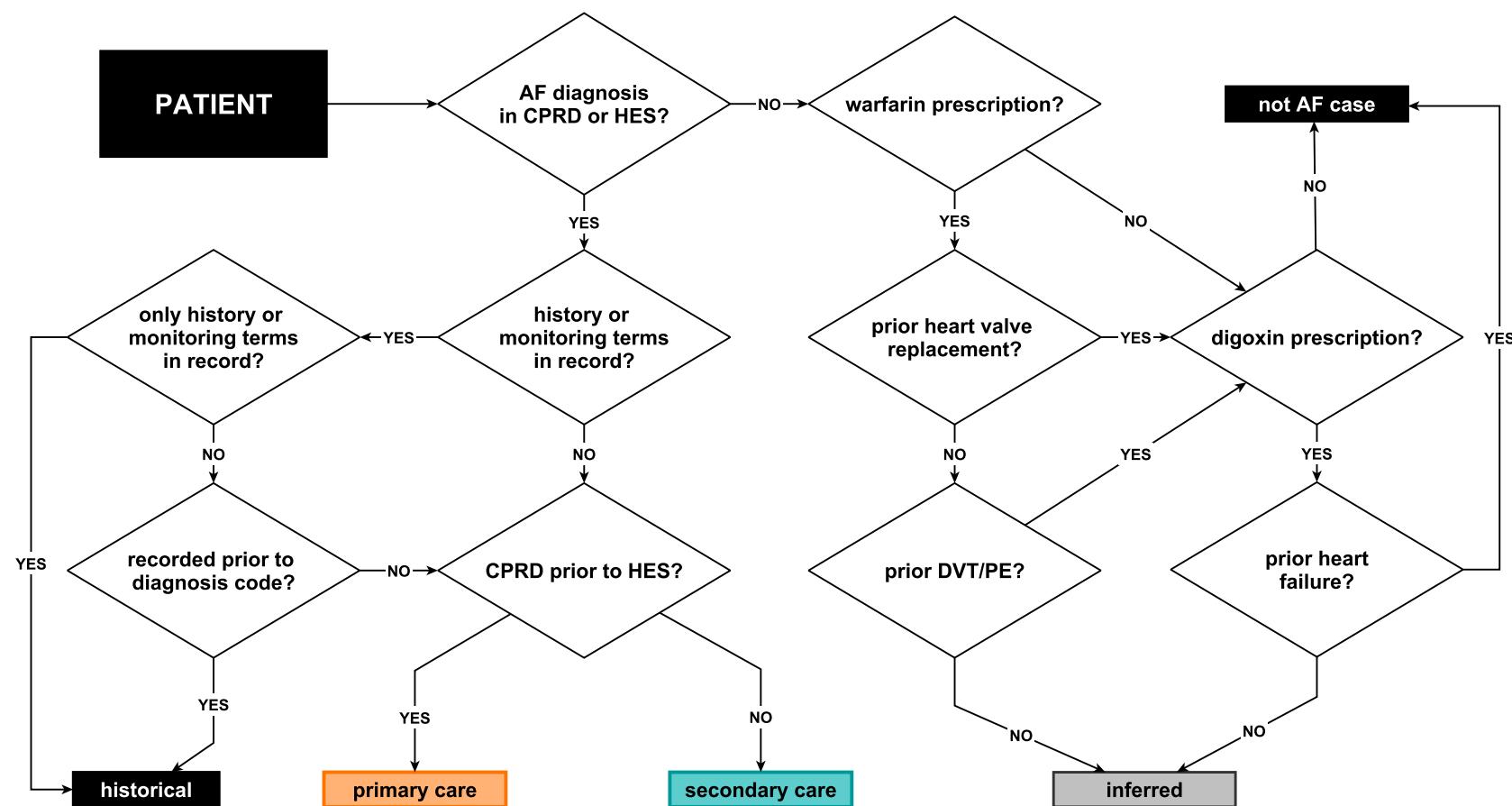
How many selected items are relevant?

$$\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

How many relevant items are selected?

$$\text{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

# Extratificação de pacientes (*phenotyping*)



# Análise de dados temporais



Review

## A Systematic Review on Healthcare Analytics: Application and Theoretical Perspective of Data Mining

Md Saiful Islam<sup>1</sup>, Md Mahmudul Hasan<sup>1</sup>, Xiaoyi Wang<sup>1</sup>, Hayley D. Germack<sup>1,2,3</sup> and Md Noor-E-Alam<sup>1,\*</sup>

### Big Data Analytics in Healthcare – Pattern Mining of Temporal Clinical Events

Svetla Boytcheva<sup>1</sup>, Galia Angelova<sup>1</sup>, Dimitar Tcharaktchiev<sup>2</sup>, Zhivko Angelov<sup>3</sup>

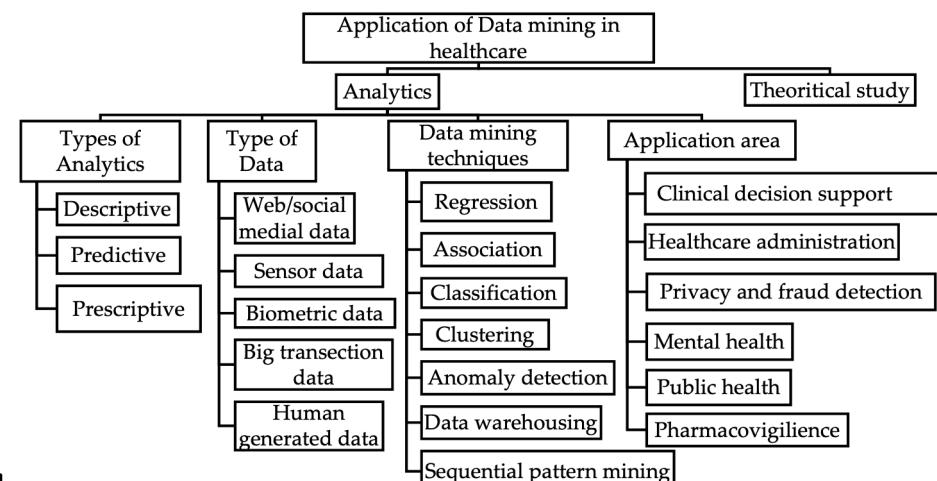
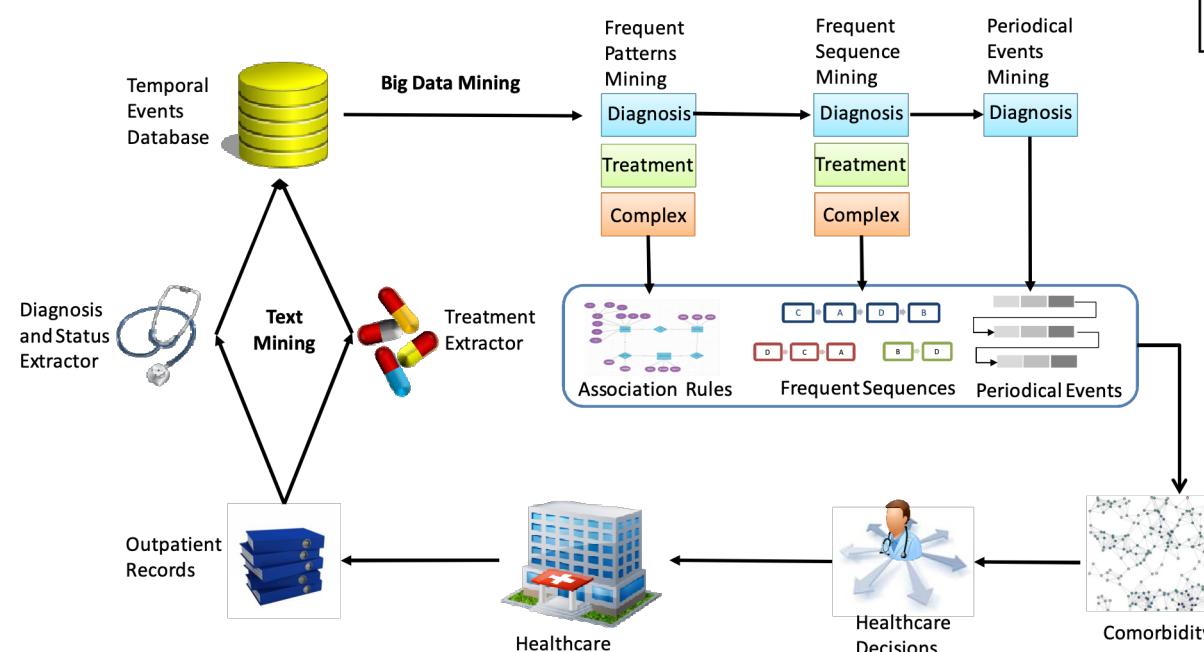


Figure 3. Classification scheme of the literature.

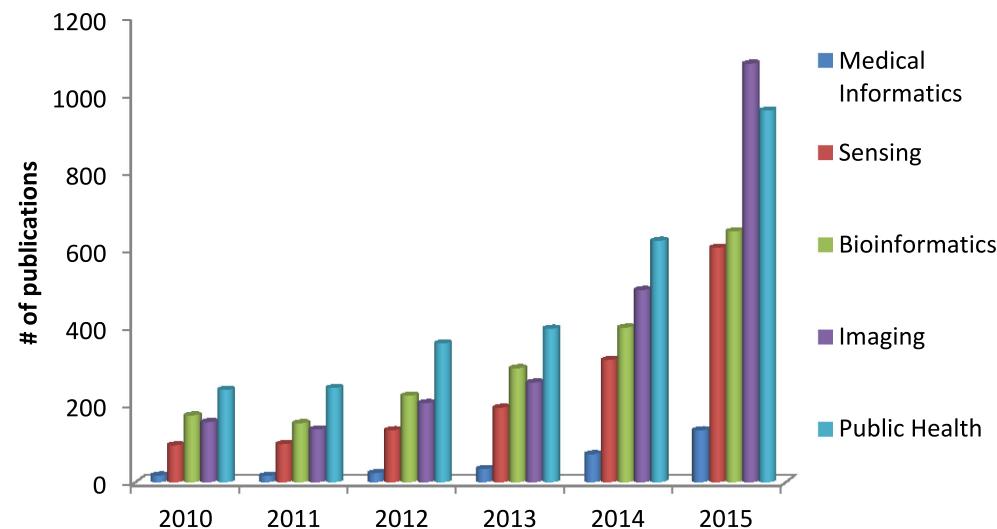
# Análise preditiva

IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS, VOL. 21, NO. 1, JANUARY 2017



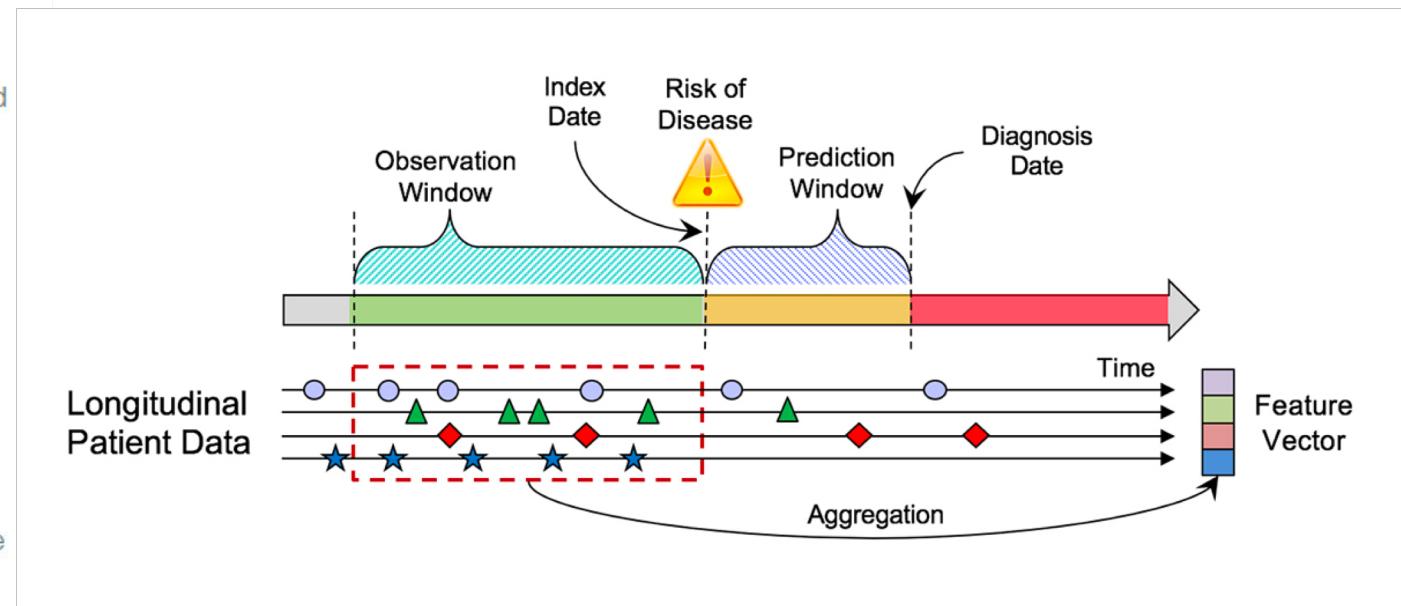
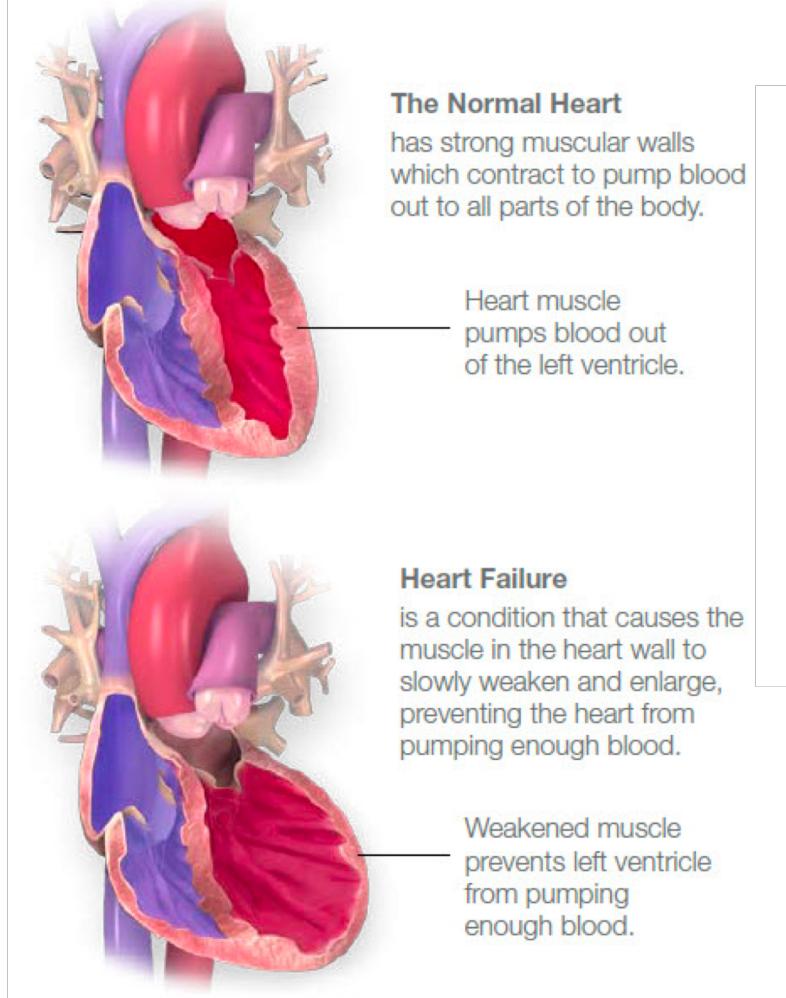
## Deep Learning for Health Informatics

Daniele Ravì, Charence Wong, Fani Deligianni, Melissa Berthelot, Javier Andreu-Perez, Benny Lo,  
and Guang-Zhong Yang, *Fellow, IEEE*

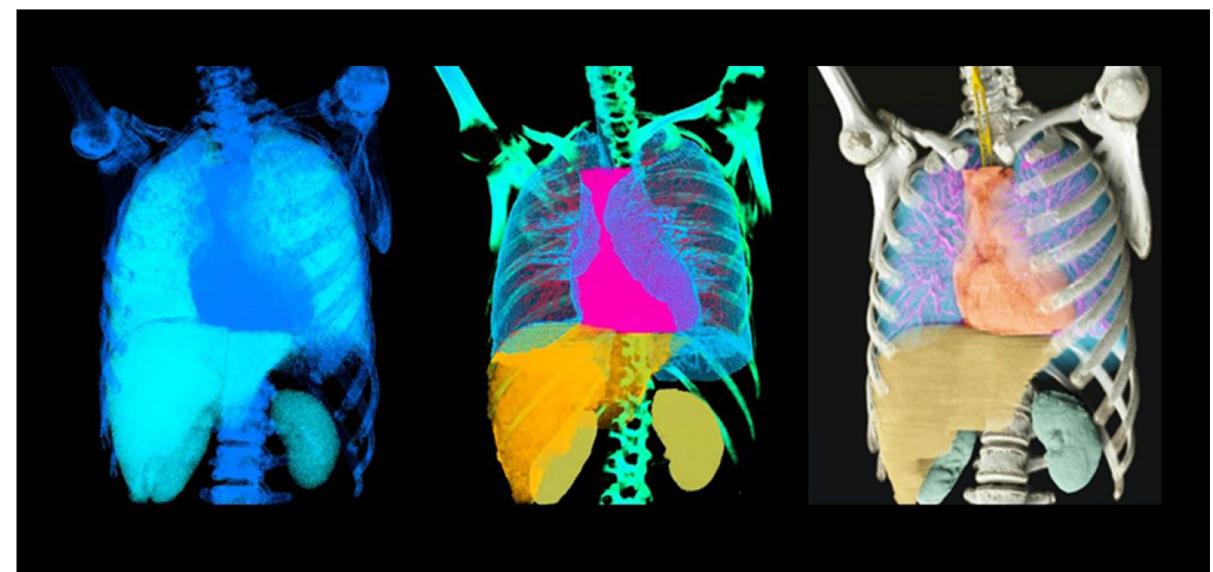
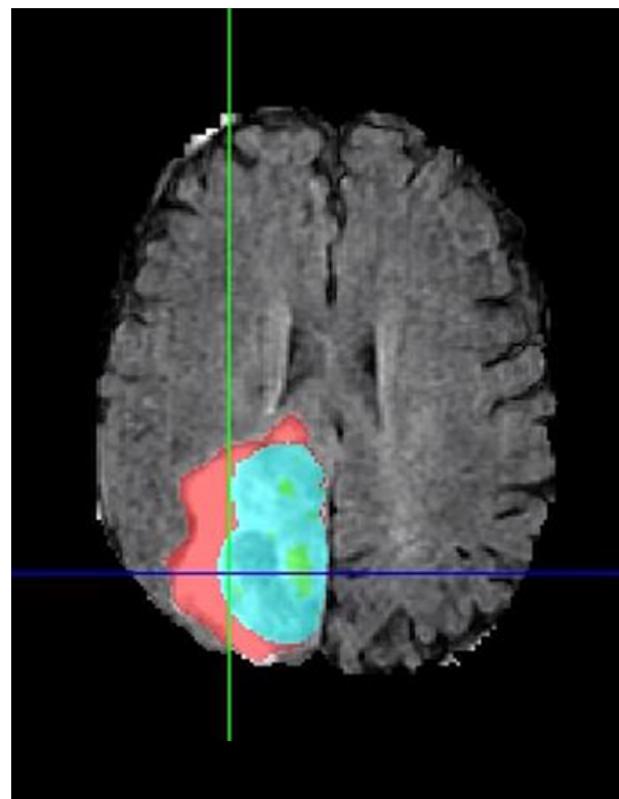


**Fig. 1.** Distribution of published papers that use deep learning in subareas of health informatics. Publication statistics are obtained from Google Scholar; the search phrase is defined as the subfield name with the exact phrase *deep learning* and at least one of *medical* or *health* appearing, e.g., “public health” “deep learning” medical OR health.

# Análise preditiva



# Processamento de imagens



NVIDIA CLARA PLATFORM

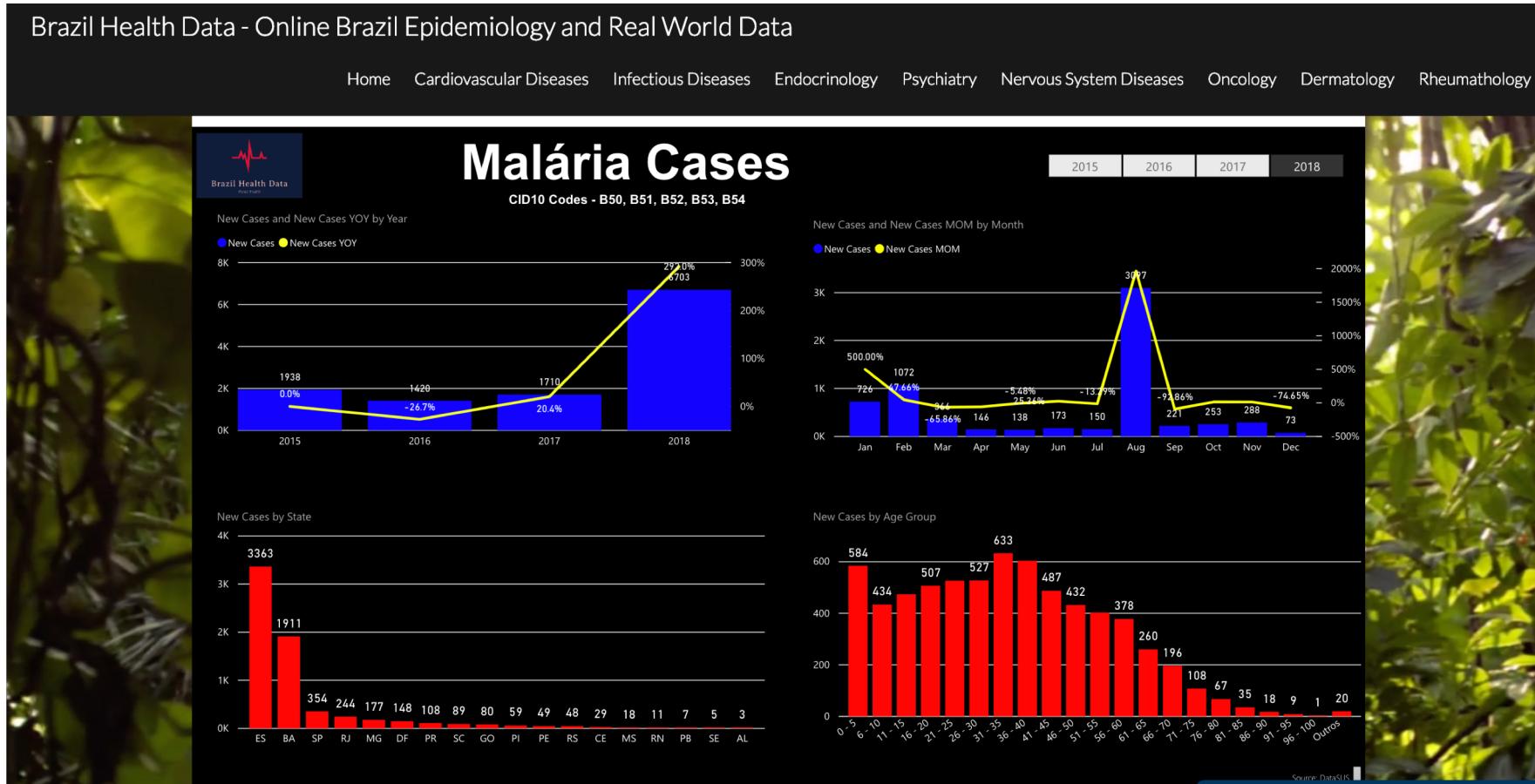
Intelligent Compute Platform for Medical Imaging

[DOWNLOAD NOW](#)

A small, dark rectangular graphic featuring a stylized white and red shape that resembles both a brain and a computer processor, positioned to the right of the text.

# Mineração visual de dados

<https://www.brazilhealthdata.com/>



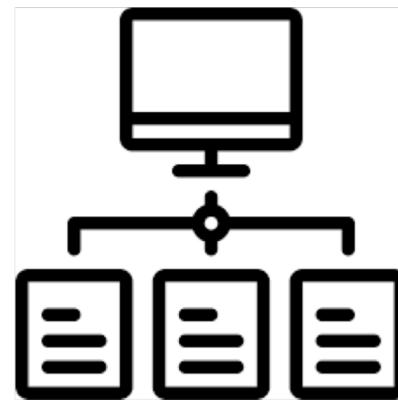


[www.atyimolab.ufba.br](http://www.atyimolab.ufba.br)

## What we do



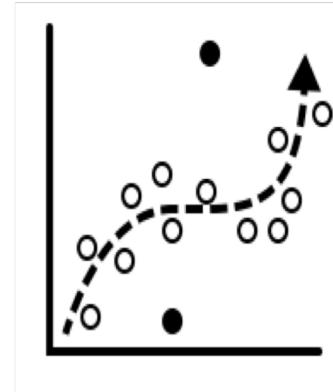
cloud  
robotics



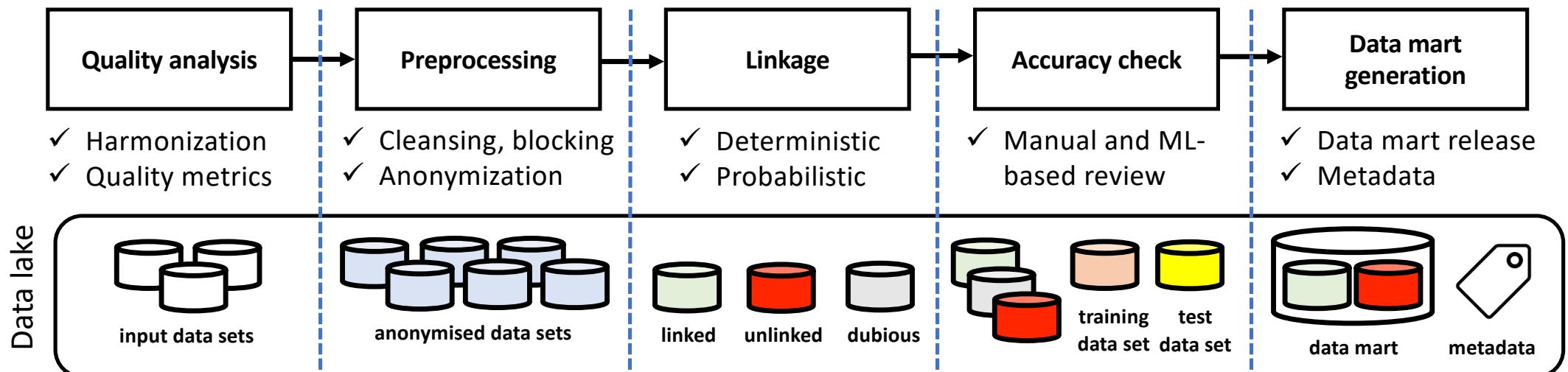
hybrid  
parallel  
computing



big data  
linkage &  
analytics



# AtyImo – Data linkage platform



- ✓ Harmonization
- ✓ Data imputation
- ✓ Deep + Machine learning
- ✓ Statistical tools
- ✓ Visual modelling, storyboards
- ✓ Geospatial data



Data analytics pipeline

# Brazilian governmental databases

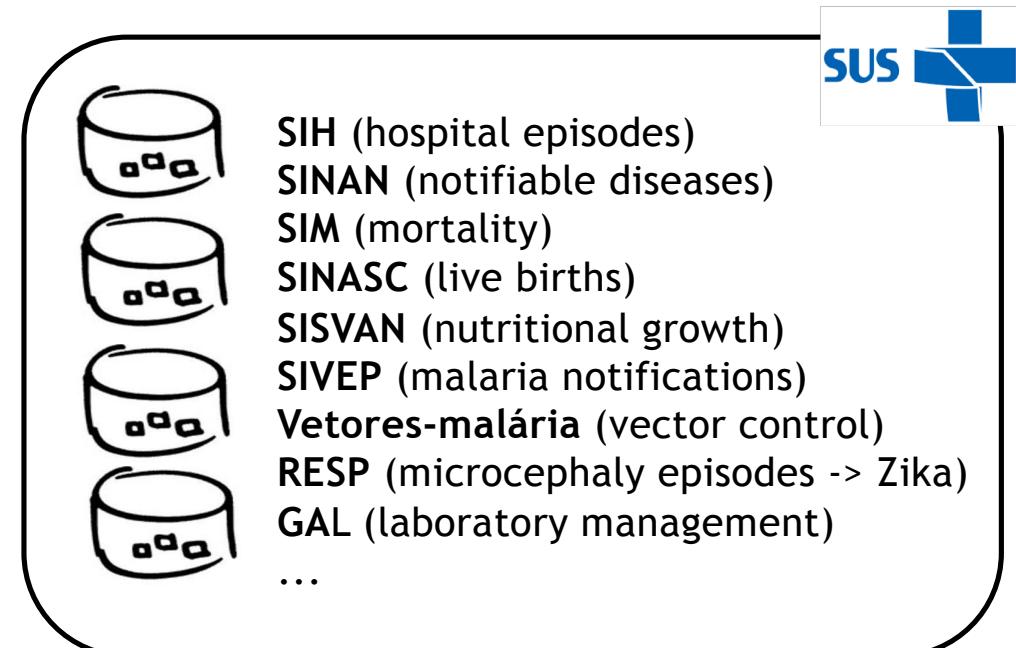
## Social programmes

- ✓ Targeted to poor and extremely poor families.
- ✓ Cadastro Único: central registrar for all programmes.



## Public health system (SUS)

- ✓ Big and complex public health system.
  - from primary care to specialised transplantations.
- ✓ Used by approximately 77% of the Brazilian population (164 million people).



# Existing research platforms we contribute to

## ✓ The 100 Million Cohort



- ✓ Baseline: CadastroÚnico, 2001–2015, **114 million individuals** x 367 attributes.
- ✓ Cohort: baseline + Bolsa Família (cash transfers) + Housing (MCMV), 2001 – 2015, **400 million records**, 3,000 attributes.
- ✓ Used by +20 projects assessing the effects of social programmes on health outcomes.



## ✓ Zika surveillance (+ microcephaly)



- ✓ Birth cohort, 2001 – 2030,  $\cong 80$  million records.
- ✓ Morbidity, mortality, socioeconomic and service data.
- ✓ Focus on the triple epidemic (Zika, Dengue and Chikungunya) and health/educational outcomes related to microcephaly.

## ✓ Malaria linkage & analytics



- ✓ Malaria episodes (>5 million records) + mortality + socioeconomic + climate data, 2000 – 2018.
- ✓ Focus on i) data aggregation and ii) epidemic forecasting.



BILL & MELINDA GATES foundation



# Example results



## Exploring hybrid parallel systems for probabilistic record linkage

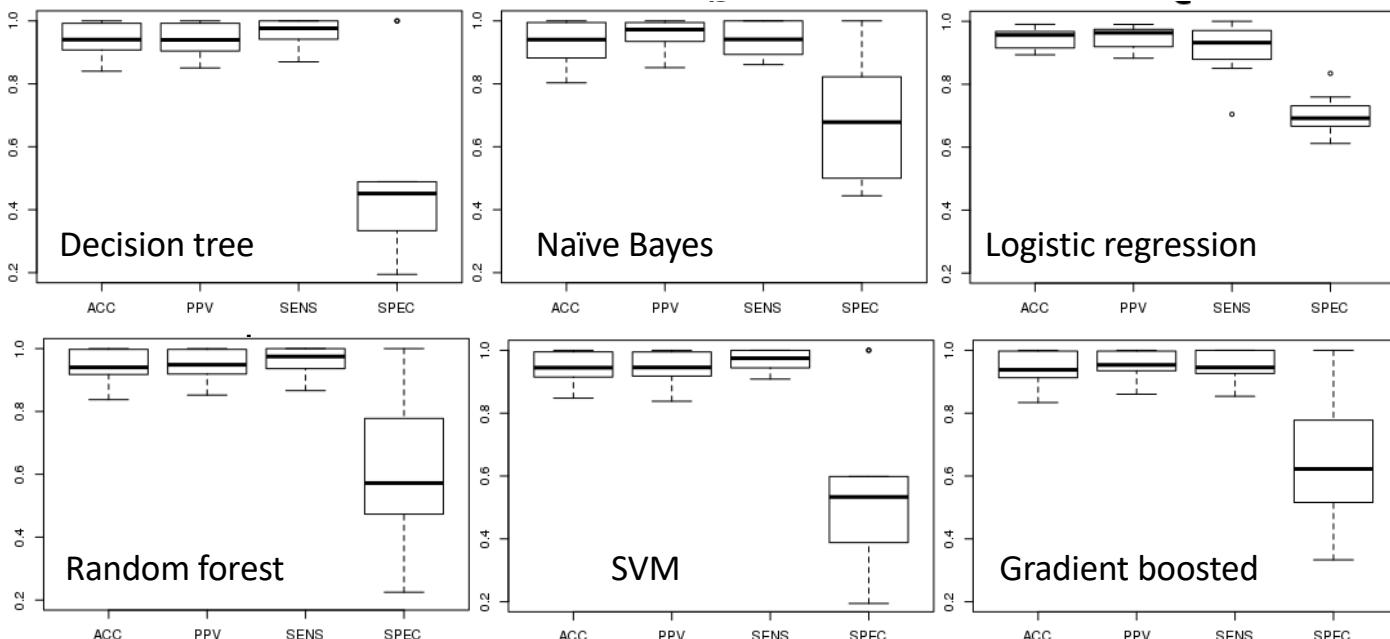
Murilo Boratto<sup>1</sup> · Pedro Alonso<sup>2</sup> ·  
Cíclia Pinto<sup>3</sup> · Pedro Melo<sup>3</sup> · Marcos Barreto<sup>3</sup> ·  
Spiros Denaxas<sup>4</sup>

J Supercomput  
<https://doi.org/10.1007/s11227-018-2328-3>

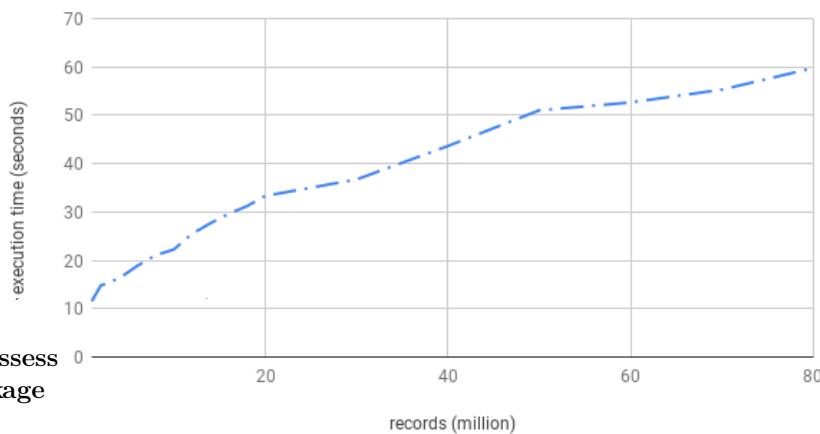
DOI: 10.1007/978-3-319-64283-3\_16

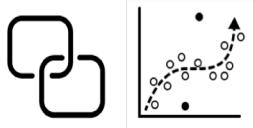
## A Machine Learning Trainable Model to Assess the Accuracy of Probabilistic Record Linkage

Robespierre Pita<sup>1</sup> , Everton Mendonça<sup>1</sup>, Sandra Reis<sup>2</sup>, Marcos Barreto<sup>1,3</sup>,  
and Spiros Denaxas<sup>3</sup>



## Hybrid Execution Time





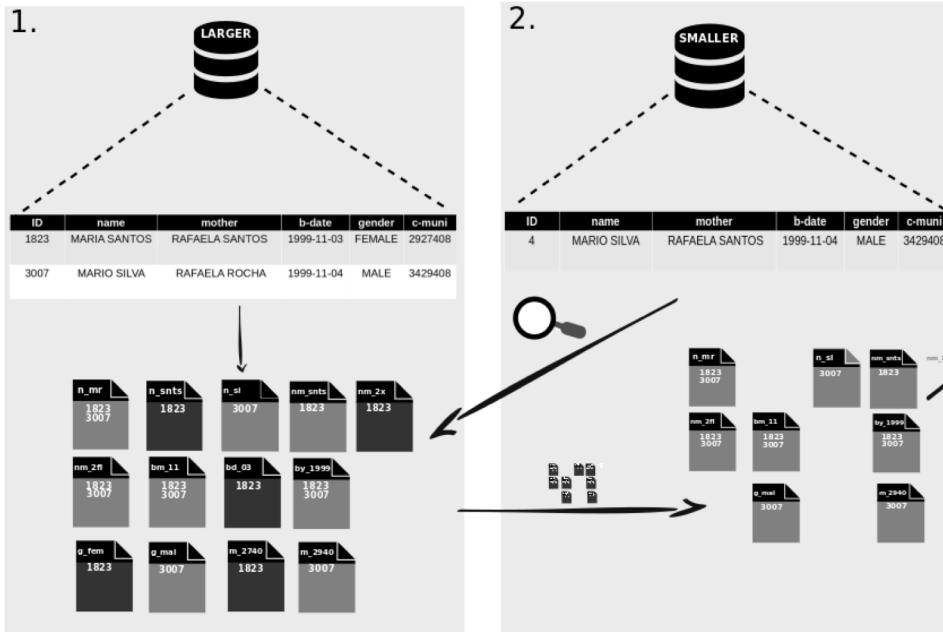
# data linkage & analytics

Latin America Data Science Workshop  
AUGUST 27TH - VLDB 2018 WORKSHOP - RIO DE JANEIRO, BRAZIL

## Applying term frequency-based indexing to improve scalability and accuracy of probabilistic data linkage

Robespierre Pita<sup>1,2</sup>, Luan Menezes<sup>1,2</sup>, Marcos E. Barreto<sup>1,2</sup>

**Figura 2.** Term frequency-based approach used in Atylmo.



**Tabela 1.** Gold standard data set used for validation.

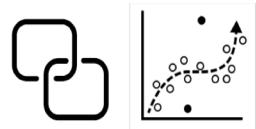
|                         |                    |
|-------------------------|--------------------|
| SIM                     | 6,458 records      |
| SINASC                  | 13,046 records     |
| Total of comparisons    | 84,251,068 records |
| Expected true positives | 3,030 records      |

**Tabela 2.** Size of generated blocks for each indexing technique

| method | predicate 1 |       | predicate 2 |       | term frequency |     |
|--------|-------------|-------|-------------|-------|----------------|-----|
|        | sb          | lb    | sb          | lb    | sb             | lb  |
| min    | 1           | 1     | 1           | 1     | 1              | 100 |
| med    | 24          | 51    | 2           | 2     | 1              | 100 |
| mean   | 43          | 88.38 | 8.289       | 11.57 | 1              | 100 |
| max    | 1855        | 41528 | 87          | 611   | 1              | 100 |

**Tabela 3.** Results of each indexing technique used.

|                        | predicate 1 | predicate 2 | term frequency |
|------------------------|-------------|-------------|----------------|
| true matches retrieved | 2,382       | 3,018       | 3,020          |
| number of blocks       | 5,806       | 6,432       | 6,458          |
| number of comparisons  | 44,406,049  | 29,111,755  | 645,800        |
| reduction ratio        | 0.472       | 0.654       | 0.992          |
| pair completeness      | 0.786       | 0.996       | 0.996          |



data linkage & analytics

✓ **Integrating socioeconomic and healthcare data to combat malaria**

✓ Phase I: November 2016 - October 2018

✓ Focus on i) data aggregation and ii) epidemic forecasting.



**SIVEP**

- ✓ Coverage: 2003-2018
- ✓ Records: 5,340,564
- ✓ Attributes: 52



**SIM**

- ✓ Coverage: 2003-2018
- ✓ Records: 1,004
- ✓ Attributes: 37



**SINAN**

- ✓ Coverage: 2003-2018
- ✓ Records: 46,170
- ✓ Attributes: 20



**Climate**

- ✓ Coverage: 2003-2018
- ✓ Records: 5,570
- ✓ Attributes: 5



**UFBA**



Fundação Oswaldo Cruz



Fundação  
de Vigilância  
em Saúde



**BILL & MELINDA GATES foundation**

## Malaria GCE

- Informações Gerais
- Base de dados
- Dicionário de dados
- Mineração de dados
- Mineração Visual de dados
- Estatística
- Análise Univariada
- Séries Temporais
- Graficos de Controle
- Análise Bivariada
- Operacional
- Analytics

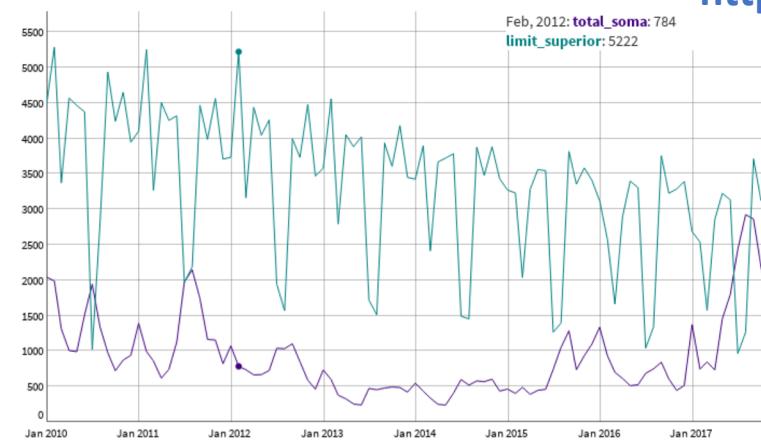
### Input

Select the Variable:

3º Quartil

Manaus-AM

### Grafico de controle



## Descriptive analytics

### Estatística

- Análise Univariada
- Séries Temporais
- Graficos de Controle
- Análise Bivariada

### Operacional

### Analytics

### Climate Variable:

Umidade do Ar

### Coloring by:

Estado

### Year:

2015

### More Inputs

#### Transparency:

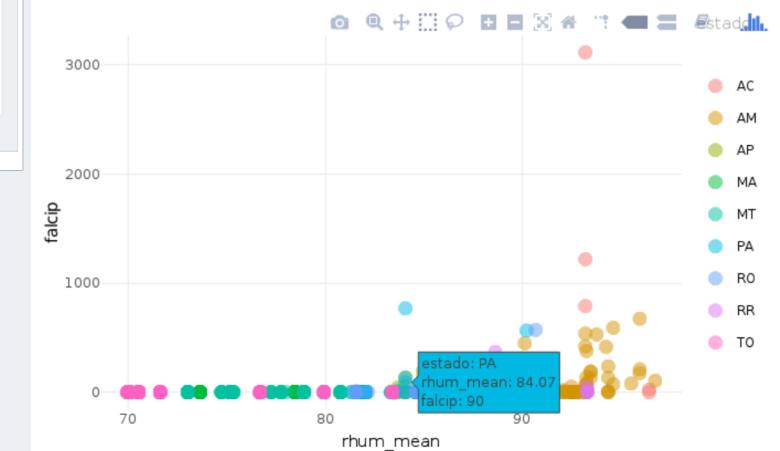
0

0.5

1

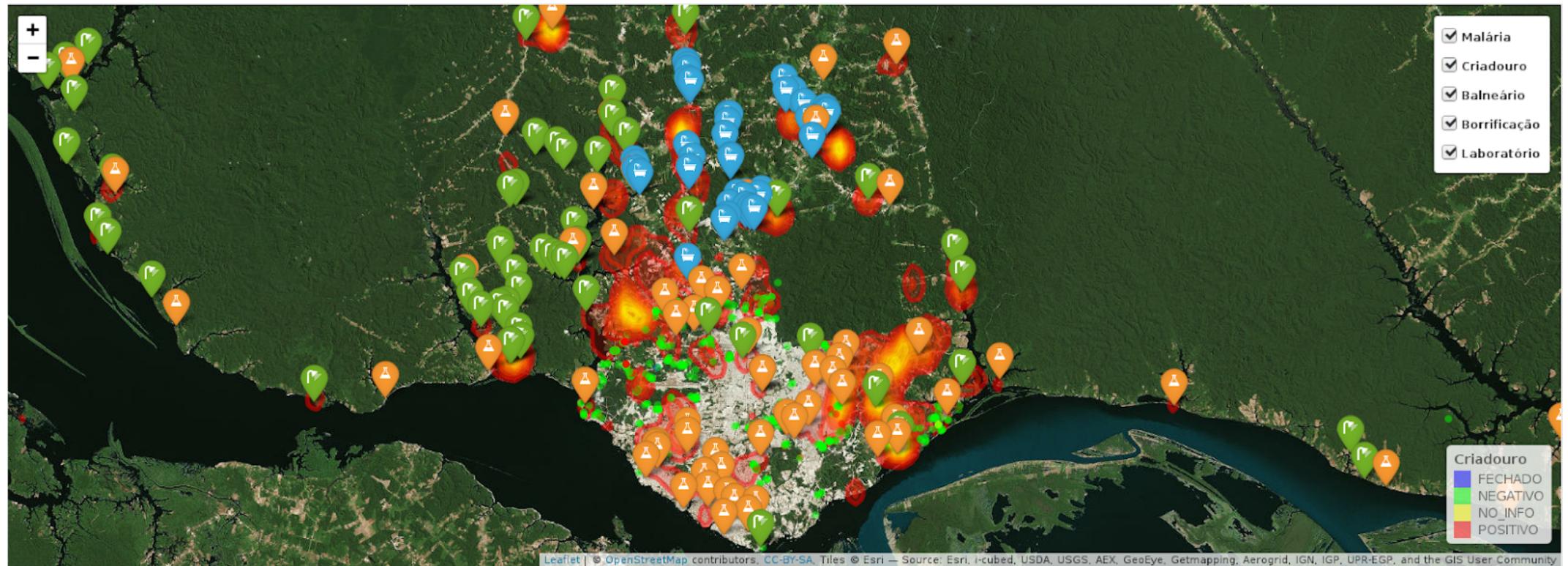
[http://200.128.60.86:3838/shiny\\_integracao/](http://200.128.60.86:3838/shiny_integracao/)

### Scatterplot



## Descriptive analytics

## Example: multilayer visual mining



# Existing results



**MEDTROP**  
54º CONGRESSO DA SOCIEDADE BRASILEIRA  
DE MEDICINA TROPICAL  
32 a 05 Setembro 2018 - Centro de Convocações de Pernambuco | Olinda PE

**INTEGRAÇÃO E MINERAÇÃO VISUAL DE DADOS PARA ESTUDO DA MALÁRIA NO BRASIL**

ALBERTO SIRONI<sup>1</sup>, JURACY BERTOLDO JUNIOR<sup>1</sup>, MARCOS E. BARRETO<sup>1</sup>, VANDERSON SAMPAIO<sup>2</sup>, ANDRÉ SIQUEIRA<sup>3</sup>  
<sup>1</sup> DEPARTAMENTO DE CIÊNCIA DA COMPUTAÇÃO, UNIVERSIDADE FEDERAL DA BAHIA (SALVADOR, BA), <sup>2</sup> FUNDAÇÃO DE VIGILÂNCIA  
EM SAÚDE DO AMAZONAS (MANAUS, AM), <sup>3</sup> INSTITUTO NACIONAL DE INFECTOLOGIA EVANDRO CHAGAS (RIO DE JANEIRO, RJ)

International Journal of Population Data Science (2018) 3:3:453

## International Journal of Population Data Science



Swansea University  
Prifysgol Abertawe

### Linking surveillance and climate data to combat malaria

Sironi, A<sup>1</sup>, Barreto, M<sup>1</sup>, Bertoldo, J<sup>1</sup>, Conceição, D<sup>1</sup>, and Sampaio, V<sup>2</sup>



#### Título

INTERACTIVE DATA VISUALIZATION OF MALARIA USING R SHINY

#### Resumo

Data visualization consists in representing data in some systematic form including attributes and variables for the unit of information. A simple and quick information can highlight possible errors with data just as it helps uncover interesting trends. There are traditional and new approaches for visualization methods. Data coming from different sources (SIVEP, IBGE, NOAA, MDS) were considered and are potentially useful for the effective understanding of malaria in the Amazon region. Using data of malaria, we illustrated the process of exploratory analysis and traditional visualization tools that can make the evaluation of high dimensional data available and feasible. Exploratory analysis tools (univariate and bivariate) were used to enhance the data visualization techniques. We believe that data integration and the exploration of visualization tools, such as those available using R Shiny, can assist decision making, provide significant contribution for understanding several processes and make massive amounts of available data in several systems become useful.

#### Autores

André Alves Ferreira Mendes, Rosemeire Leovigildo Fiaccone, Leila Denise Alves Ferreira Amorim, Marcos Ennes Barreto, Juracy Bertoldo Santos Junior, Alberto Sironi, Marcos Aurelio Eustorgio Filho



## Frontiers of Engineering for Development symposium:

### Engineers as healthcare practitioners

Ho Chi Minh City, Vietnam

30 October to 2 November 2018



**CLOSER 2019**  
9<sup>th</sup> INTERNATIONAL CONFERENCE ON CLOUD COMPUTING AND SERVICES SCIENCE  
HERAKLION, CRETE - GREECE  
2 - 4 MAY, 2019

# Current research / projects

## • The 100 million Brazilian cohort

- Principal investigators: Maurício Barreto (FIOCRUZ BA), Gerson Penna (FIOCRUZ DF), Laura Rodrigues (London School of Hygiene and Tropical Medicine), Liam Smeeth (London School of Hygiene and Tropical Medicine).
- Period: 2015-2019
- Scope: i) integration of socioeconomic data from Cadastroúnico and Bolsa Família (conditional cash transfer programme) databases to build a huge population-based cohort covering the period 2007-2015. [Current cohort size is 114 million records](#); ii) design a probabilistic data linkage tool ([AtyImo](#)) to link this cohort with Public Health databases and generate domain-specific data from several epidemiological studies on HIV, tuberculosis, leprosy etc; iii) propose and validate statistical approaches to probabilistic linkage of huge datasets; iv) promote technology transfer and capacity building on big data integration.

More information [here](#).

Funding:



## • Long-term surveillance platform for Zika virus and microcephaly

- Principal investigators: Maurício Barreto (FIOCRUZ/BA), Maria Glória Teixeira (UFBA), Cláudio Henriques Maierovisch (Ministry of Health).
- Period: 2016-2020
- Scope: i) Design a cohort based on live births (from SINASC database) from 2001 to 2030; ii) assessment of health and educational outcomes related to Zika virus and microcephaly.

More information [here](#).

Funding:



## • The 100 million Brazilian linked data and datacentre.

Funding:



- Principal investigators: Mauricio Barreto (FIOCRUZ/BA), Laura Rodrigues (London School of Hygiene and Tropical Medicine).
- Period: 2017-2022
- Scope: i) link electronic health records from Brazilian governmental databases; ii) build the **CIDACS** datacentre and its public interface.

More information [here](#).

# Current research / projects

- **Design of a scientific repository (data lake) for big data applications**

Funding:



- Principal investigator: Marcos Barreto (UFBA).
- Period: 2016-2019
- Scope: Design and deployment of a data repository (data lake) for big data applications. The first prototype comprises malaria surveillance data to support predictive analytics.

- **Treating heterogeneity and uncertainty in data integration: case study on Brazilian databases.**

Funding:



- Principal investigators: Marcos Barreto (UFBA), Spiros Denaxas (Farr Institute of Health Informatics Research).
- Period: 2016-2018
- Scope: i) design and validation of a data integration model and related computing tools addressing heterogeneity, uncertainty and scalability targeted to big data integration; ii) support for some Brazil-UK ongoing projects: the 100 million cohort, the surveillance platform for Zika and microcephaly, and predictive analytics methods applied to Malaria data (Post-doctoral proposal).

More information [here](#).

# Current research / projects

- **Integrating socioeconomic and health data to combat malaria.**

Funding:

BILL & MELINDA  
GATES foundation

- Principal investigator: Marcos Barreto (UFBA), Spiros Denaxas (Farr Institute of Health Informatics Research).
  - Period: 2016-2018
  - Scope: i) develop a platform to integrate surveillance data from Malaria with other sources (socioeconomic and public health data); ii) design and validate predictive analytics methods to help on Malaria elimination.
- More information [here](#).



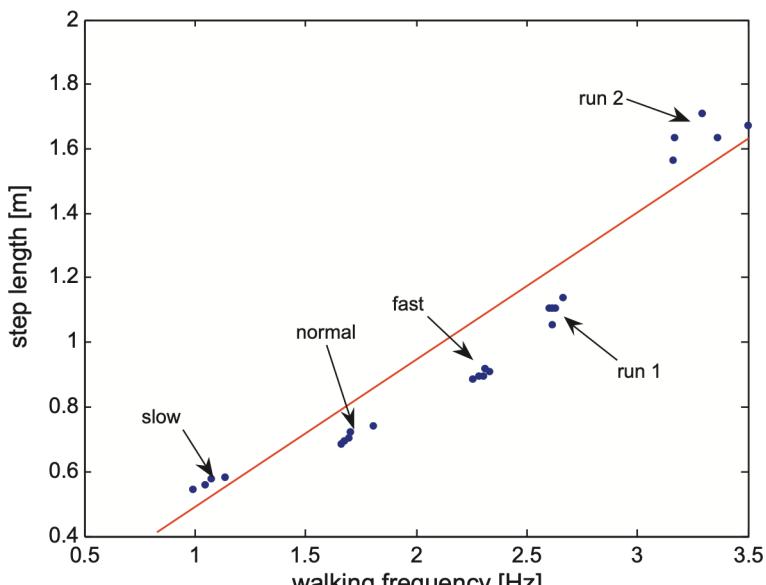
- **Early childhood development friendly index: assessing the enabling environment for Nurturing Care.**

Funding:

BILL & MELINDA  
GATES foundation



- Principal investigator: Muriel Gubert (UnB).
- Team: Marcos Barreto (UFBA), Gabriela Buccini (Yale School of Public Health), Rafael Perez-Escamilla (Yale School Of Public Health), Sonia Isoyama Venancio (Health Institute of São Paulo)
- Period: 2018-2020
- Scope: This project aims to develop an ECD (Early Childhood Development) friendly index (ECD-FI), based on a core set of evidence-based Nurturing Care indicators, to assess the enabling environment and promote ECD at the municipality level by monitoring and identifying opportunities to scale up ECD programs locally. More information [here](#).



(a) Walking frequency versus step length

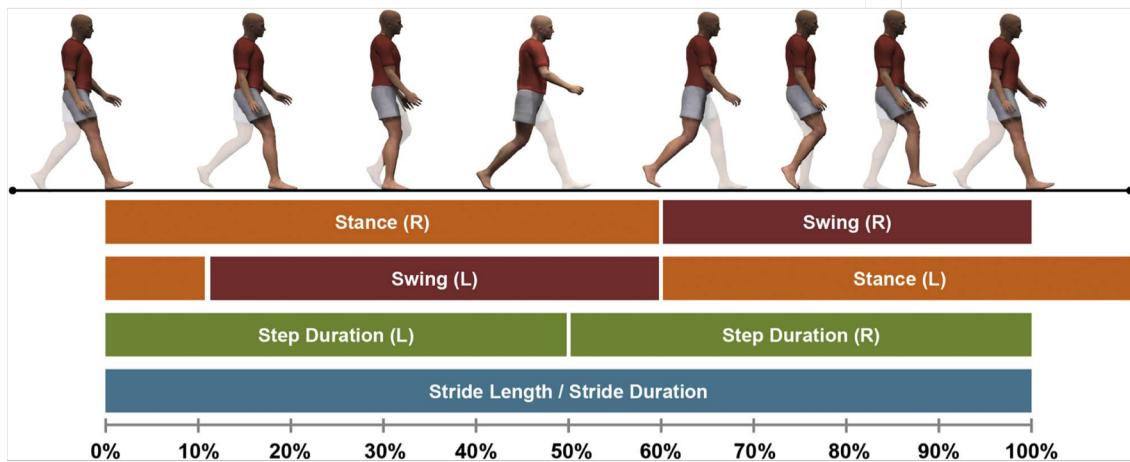


Fig. 1. Schematic of the human gait cycle and the spatiotemporal parameters validated in this study. Specifically, we validated the IMU system's ability to measure the stance percent, swing percent, stride duration (gait cycle time), stride length, and step duration in addition to the speed and cadence of the cycle.

## Current research / projects

- Standardisation of wearable-based algorithms for healthcare applications in developing countries.

- Principal investigator: Alan Godfrey (Northumbria University, Newcastle-upon-Tyne, UK).
- Team: Rodrigo Vitorio (UNESP), Marcos Barreto (UFBA), Azad Hussain (University of Birmingham), Clara Aranda-Jan (University College London)
- Period: 2018-2019
- Scope: This proposal aims to develop a novel standardised framework to better inform algorithms for a more harmonised gait assessment in Parkinson's disease (PD), particularly for developing countries where guidance is lacking. This project will lead to the design of an online simulation to test algorithms. Additionally, it will outline an educational process for all clinicians to better understand the functionality of wearables/algorithms and resulting outcomes. This will better guide PD assessment for sustainable health, promoting and encouraging low-cost wearables as routine diagnostics in developing countries. This framework will also be adapted to the needs of those in developed regions.



Funding:

# Current research

- **Stratification of patients suffering from myalgic encephalomyelitis/chronic fatigue syndrome.**

Support:



CUREME



- Principal investigator: Marcos Barreto (UFBA).
- Team: Nuno Sepulveda (London School of Hygiene & Tropical Medicine), Robespierre Pita (UFBA)
- Period: 2019-2020
- Scope: This study aims at to stratify ME/CFS patients into different clusters (or symptom subtypes). The respective objectives are the following: i) to distinguish ME/CFS patients from those suffering from multiple sclerosis (MS); ii) to identify sets of clinical symptoms that could characterize different clusters of ME/CFS patients; iii) to identify the best (or exclusive) predictive symptoms for CFS and compare the results with those obtained from different statistical/computational methods; (iv) to compare the stability of patients stratification using baseline and follow-up data.



OBRIGADO!

Contato:  
[marcosb@ufba.br](mailto:marcosb@ufba.br)  
[www.atyimolab.ufba.br](http://www.atyimolab.ufba.br)