LaCCAN

Laboratório de Computação Científica e Análise Numérica

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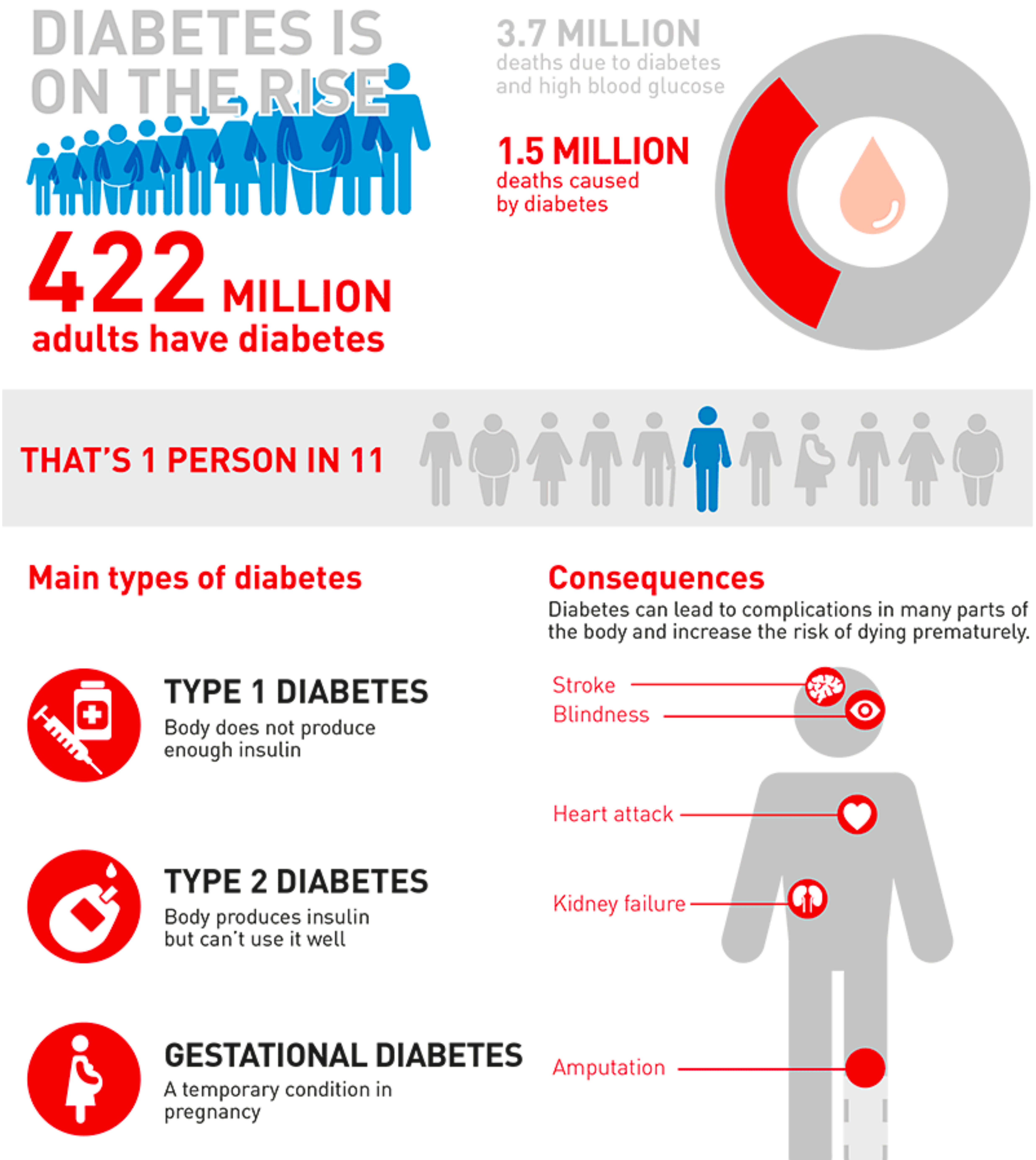
Pesquisas

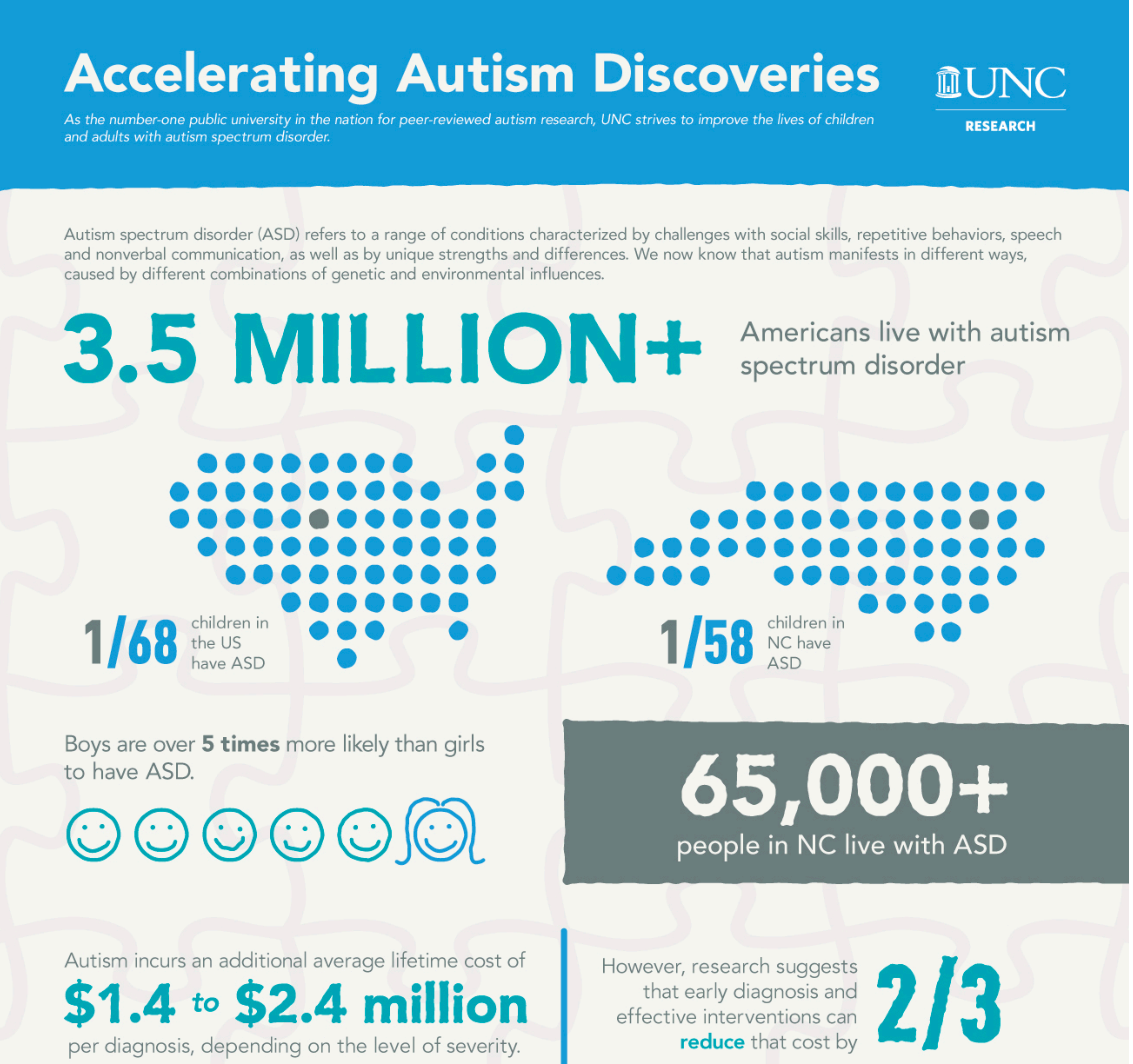
Microbiota Intestinal

Estado da Arte



https://www.who.int/diabetes/global-report/en/

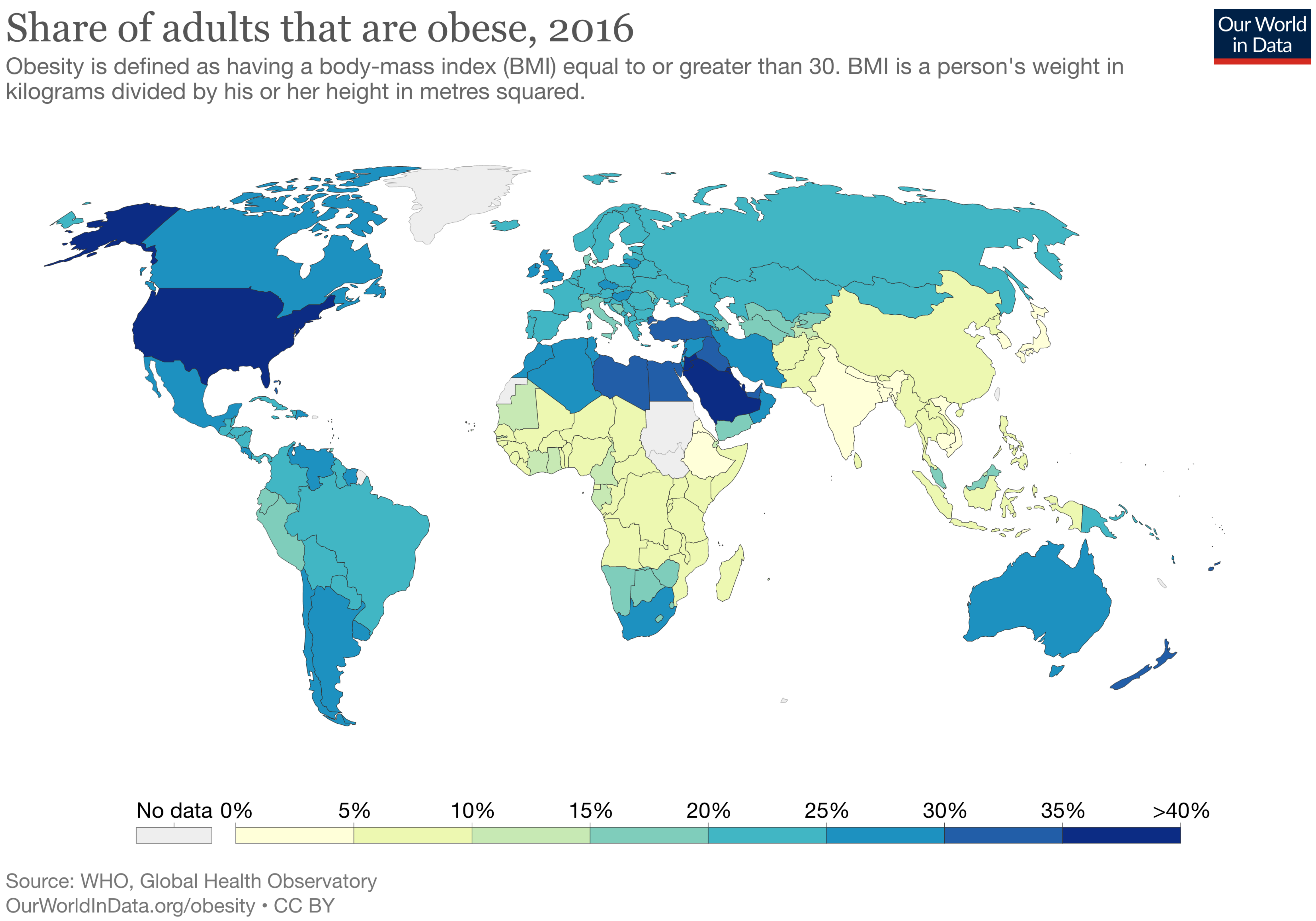
Microbiota Fecal de Pacientes com Diabetes Mellitus tipo 2 após uso de probióticos: Revisão Sistemática e Metanálise de ensaios clínicos



https://endeavors.unc.edu/autism-research-infographic/

Caracterização molecular do Microbioma gastrointestinal de pessoas Autistas e neurotípicas: Revisão Sistemática e Metanálise de ensaios clínicos

O efeito de probióticos na microbiota intestinal de pacientes obesos: Revisão Sistemática e Metanálise



http://view.infografz.com:8000/shared/infograph/?b=2f71bcee3ec170853615e09905af3b255f30b813

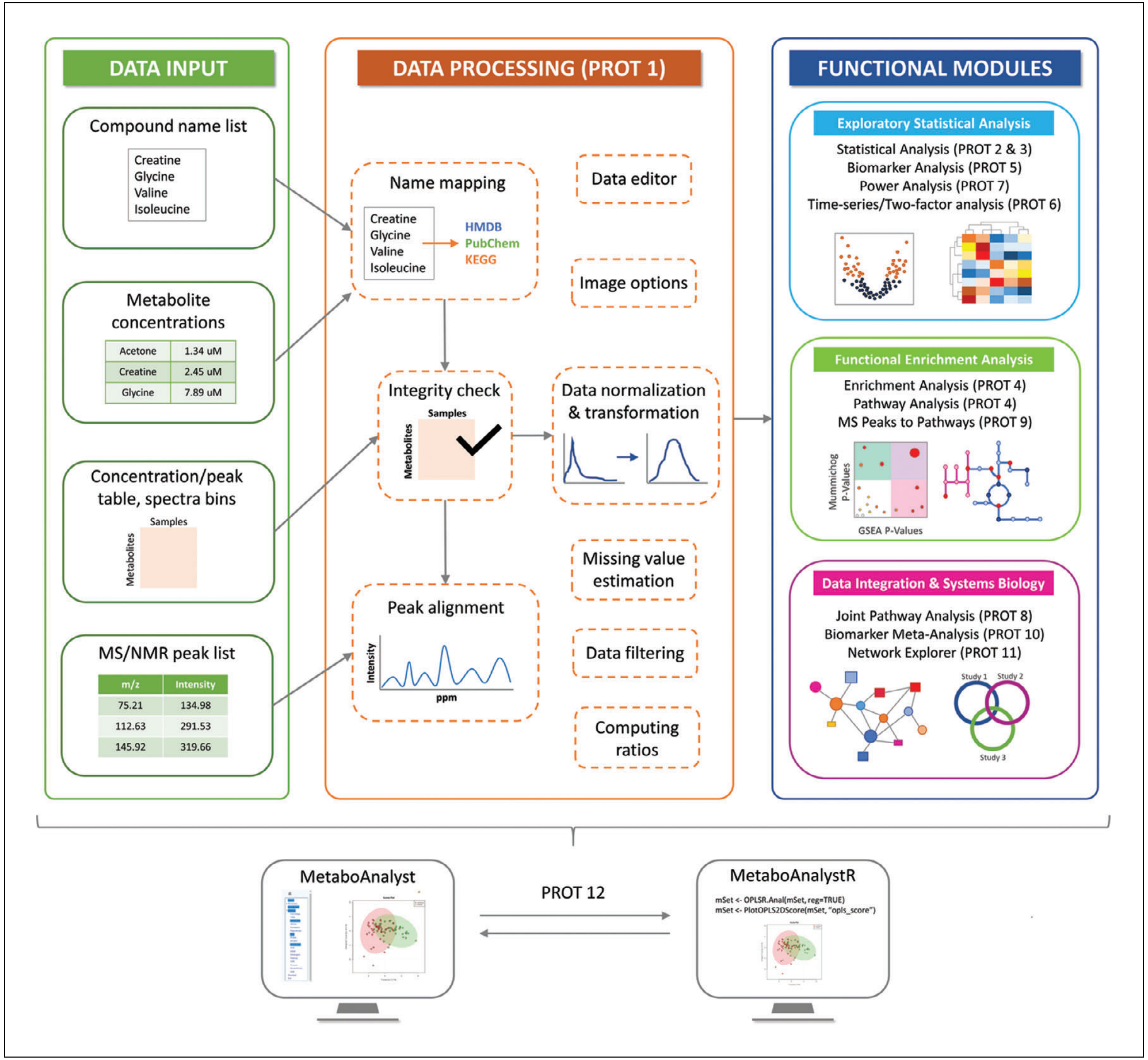
https://return2health.nz/articles/endurance-activities-boost-your-performance-with-natural-supplements

O efeito dos exercícios de endurance na microbiota intestinal: Revisão Sistemática e Metanálise

Microbiota Intestinal

Análise de Dados

Pipeline de processamento e análise de dados



análises univariadas básicas [testes t, análise de variância (ANOVA)];

multivariadas [PCA (principal component analysis); PLS-DA (partial least squares discriminant analysis); orthogonal partial least-squares discriminate analysis (OPLS-DA); análise de agrupamento e visualização; MSEA (metabolite set enrichment analysis); MetPA (metabolic pathway analysis); seleção de biomarcadores por meio de Curva ROC (receiver operating characteristic); séries temporais e power analysis; pathway activity prediction directly from mass peaks; biomarker meta-analysis e network-based multiomics data integration.

aprendizagem de máquina [random forest e support vector machine (SVM) classification.

Considerando as boas práticas de análise de dados e tendo em vista a reprodutibilidade da pesquisa, adotar-se-á o MetaboAnalyst que foi implementado utilizando a livraria PrimeFaces (v6.1) com base no JavaServer Faces Technology. A maioria dos cálculos e visualização de back-end é realizada por mais de 600 funções escritas em R (v3.4.3). A comunicação entre Java e R é estabelecida por TCP / IP usando o programa Rserve. Trata-se de aplicação open source.

Chong, J., Wishart, D. S., & Xia, J. (2019). Using metaboanalyst 4.0 for comprehensive and integrative metabolomics data analysis. *Current protocols in bioinformatics*, *68*(1).

P&D

Psicometria

TMFN-CAD1

Teste de Memória de Faces e Nomes

cespe

Cebraspe

Centro Brasileiro de Pesquisa em Avaliação e Seleção e de Promoção de Eventos

Interactive activation and competition (IAC) model (Burton e Bruce)

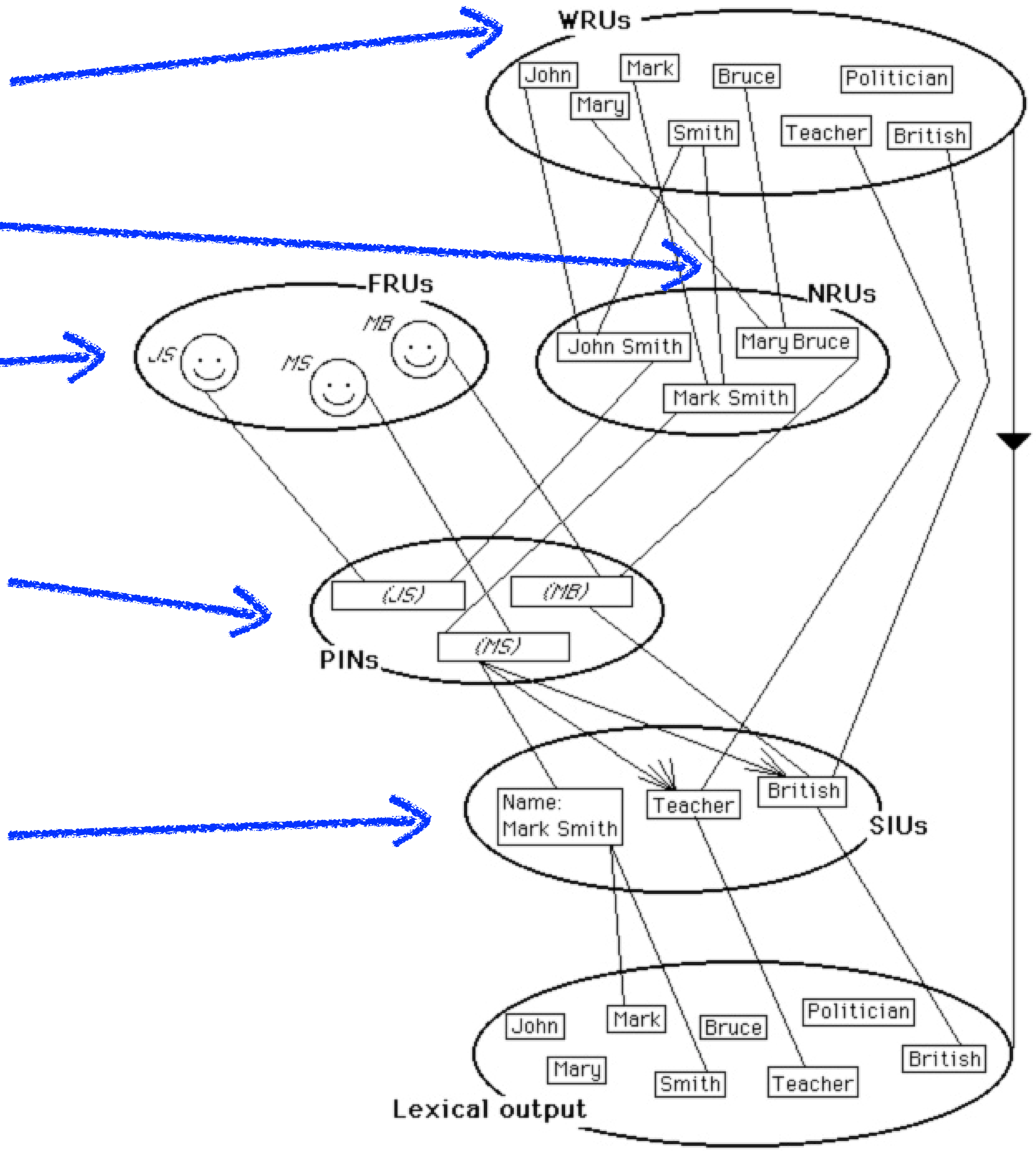
Unidades de reconhecimento de palavras (**WRUs**)

Unidades de reconhecimento de nomes (**NRUs**)

Unidades de reconhecimento de faces (**FRUs**)

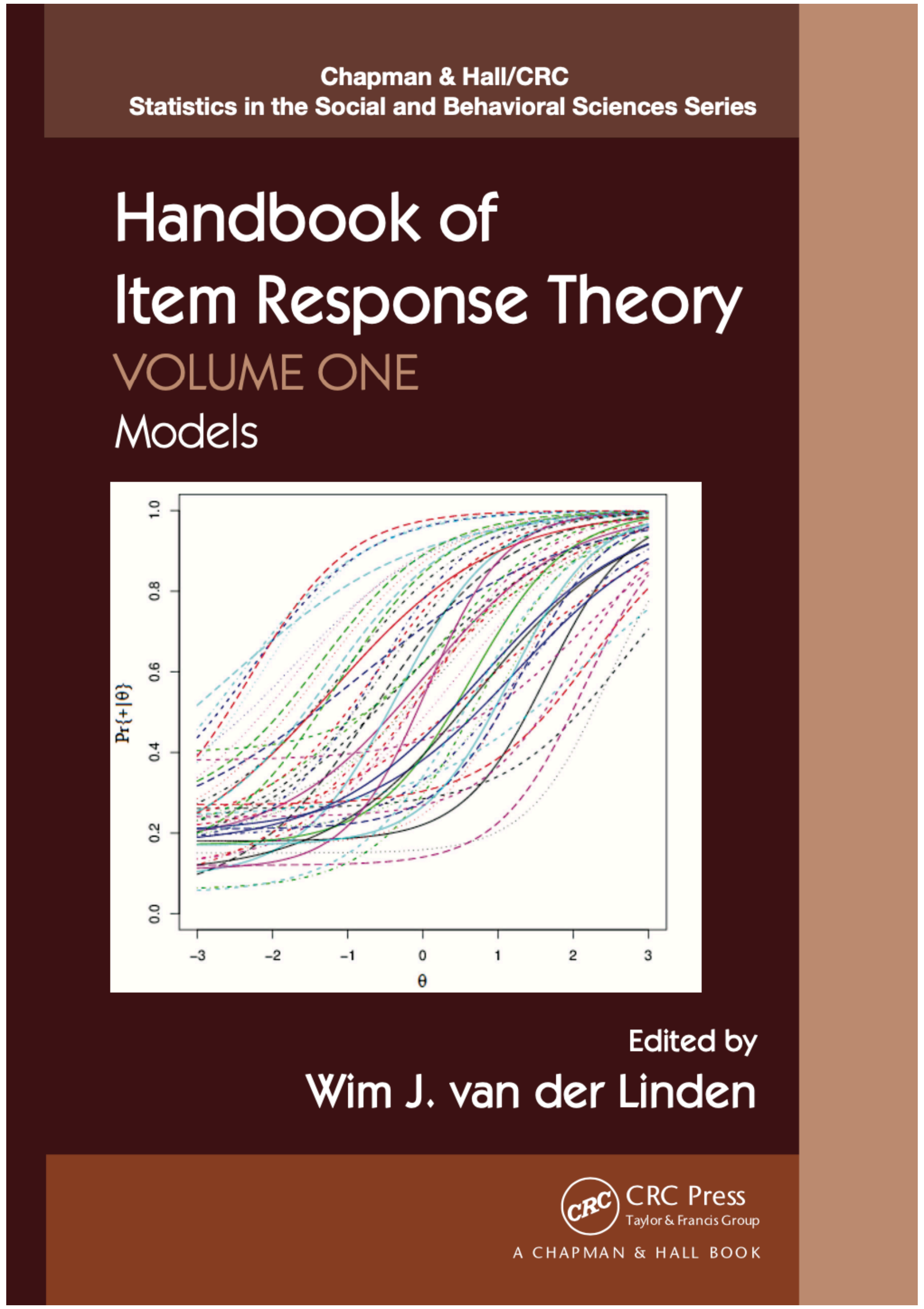
Nós de identidade da pessoa (**PINs**) são portas de entrada para as informações – *input* verbal sobre os nomes das pessoas ou *input* facial.

Unidade de informações semânticas (**SIUs**) - nomes e outras informações sobre o indivíduo, por exemplo, ocupação.



Unidimensional Logistic Response Models

Wim J. van der Linden



Making the usual assumption of independence between the responses by the same test taker ("local independence"), and assuming they all worked independently, the probability function of the joint distribution of a complete response matrix, $\mathbf{U} \equiv (U_{pi})$, is the product of each of these Bernoulli distributions:

$$f(\mathbf{u};\pi) = \prod_{p=1}^{P}\prod_{i=1}^{I}\pi_{pi}^{u_{pi}}(1-\pi_{pi})^{1-u_{pi}} \tag{2.2}$$

with parameter vector $\boldsymbol{\pi} \equiv (\pi_{11}, \ldots, \pi_{1I}, \ldots, \pi_{P1}, \ldots, \pi_{PI})$.

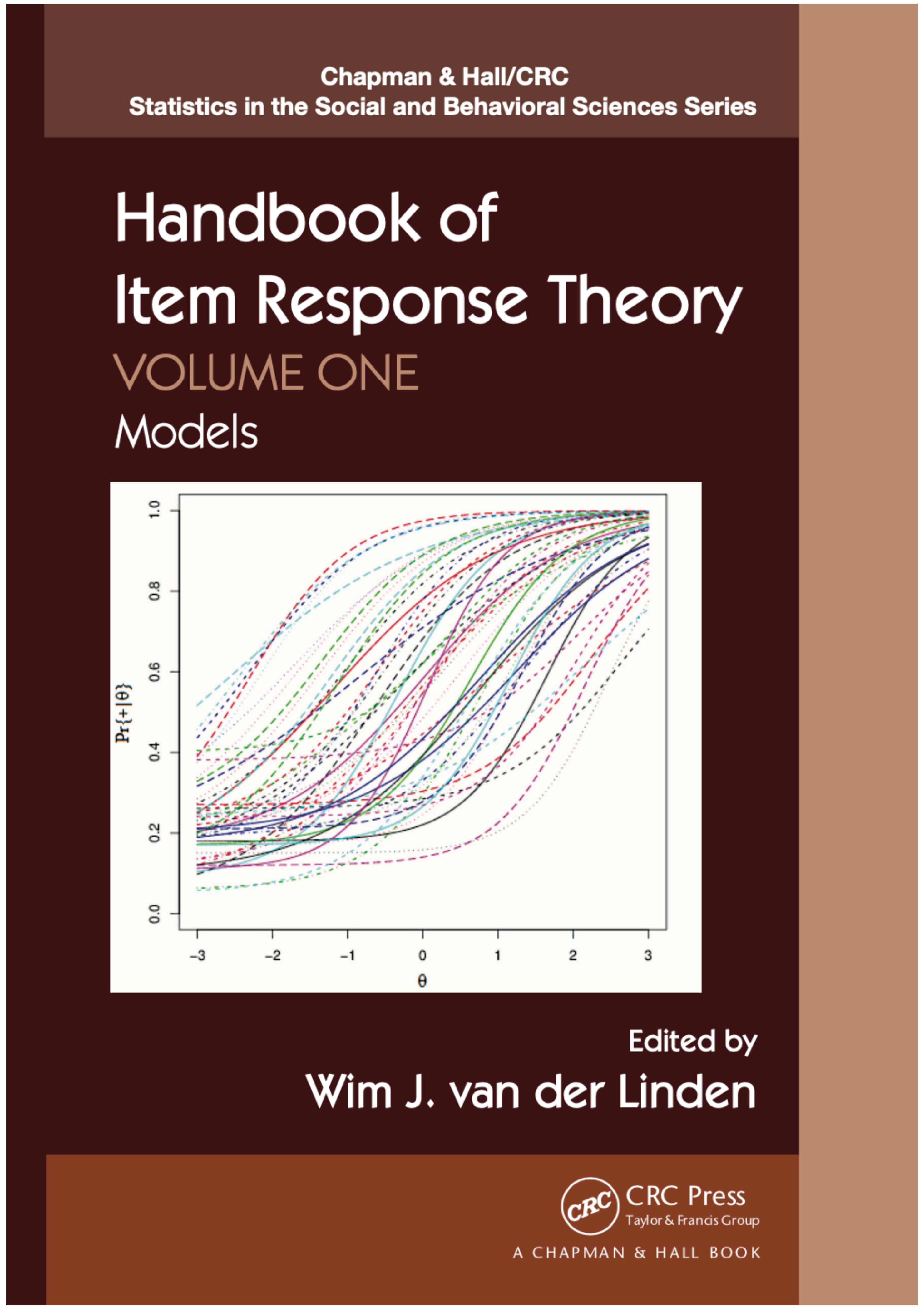
The 3PL model explains each π_{pi} as a function of parameters for the effects of the test taker's ability and the properties of the item. More specifically, let θ_p denote the parameters for the effects of the individual abilities of the test takers and a_i, b_i, and c_i the effects of the items generally interpreted as representing their difficulties, discriminating power, and success probabilities when guessing randomly on them, respectively. For a given response matrix, the 3PL model equations are

$$\pi_{pi} = c_i + (1-c_i)\frac{\exp[a_i(\theta_p - b_i)]}{1+\exp[a_i(\theta_p - b_i)]}, \quad p = 1,\ldots,P; \quad i = 1,\ldots,I \tag{2.3}$$

with $\theta_p \in (-\infty, \infty)$, $a_i \in (0, \infty)$, $b_i \in (-\infty, \infty)$, and $c_i \in [0,1]$ as ranges for the values of their parameters. The model thus consists of $P \times I$ nonlinear equations, one for each of the success parameters. In other words, rather than a single-level probabilistic model, it is a system of second-level mathematical equations. (The statistical literature is somewhat ambiguous in its assignments of the number of levels to a model; some sources count the levels of parameters as we do here, while the others count the levels of randomness that are modeled.)

Rasch Model

Matthias von Davier



The following notational conventions are used: Let $\boldsymbol{U} = (U_1, \ldots, U_I)$ denote a vector of discrete observed variables, with $U_i \in \{0,1\}$ and 1 indicating success and 0 indicating failure. For each test taker $p = 1, \ldots, P$, let $U_{pi} \in \{0,1\}$ denote the test taker's response in terms of success or failure on item i. Rasch (1966a) introduces the model using the following assumptions:

1. The probability that an examinee p succeeds in trial i is

$$Pr\{U_i = 1 \mid p\} = \frac{\lambda_{pi}}{1 + \lambda_{pi}}, \tag{3.1}$$

   which is equivalent to

$$Pr\{U_i = 0 \mid p\} = \frac{1}{1 + \lambda_{pi}}. \tag{3.2}$$

2. Parameter $\lambda_{pi} = (Pr\{U_i = 1 \mid p\} / Pr\{U_i = 0 \mid p\})$ can be written as

$$\lambda_{pi} = \frac{\tau_p}{\xi_i}, \tag{3.3}$$

   which implies that $Pr\{U_i = 1|p\} = (\tau_p/\xi_i + \tau_p)$ and $Pr\{U_i = 0|p\} = (\xi_i/\xi_i + \tau_p)$.
3. Stochastic independence of these probabilities holds for examinee p attempting multiple trials $i = 1, \ldots, I$.

Note that with the transformation $\theta_p = \ln(\tau_p)$ and $\beta_i = \ln(\xi_i)$, we obtain an equivalent form of the Rasch model:

$$Pr\{U_i = u \mid p\} = \frac{\exp(u(\theta_p - \beta_i))}{1 + \exp(\theta_p - \beta_i)}, \tag{3.4}$$

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STATISTICAL FOUNDATIONS FOR COMPUTERIZED ADAPTIVE TESTING WITH RESPONSE REVISION

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HUA-HUA CHANG

PURDUE UNIVERSITY

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2.1. The IRT Model

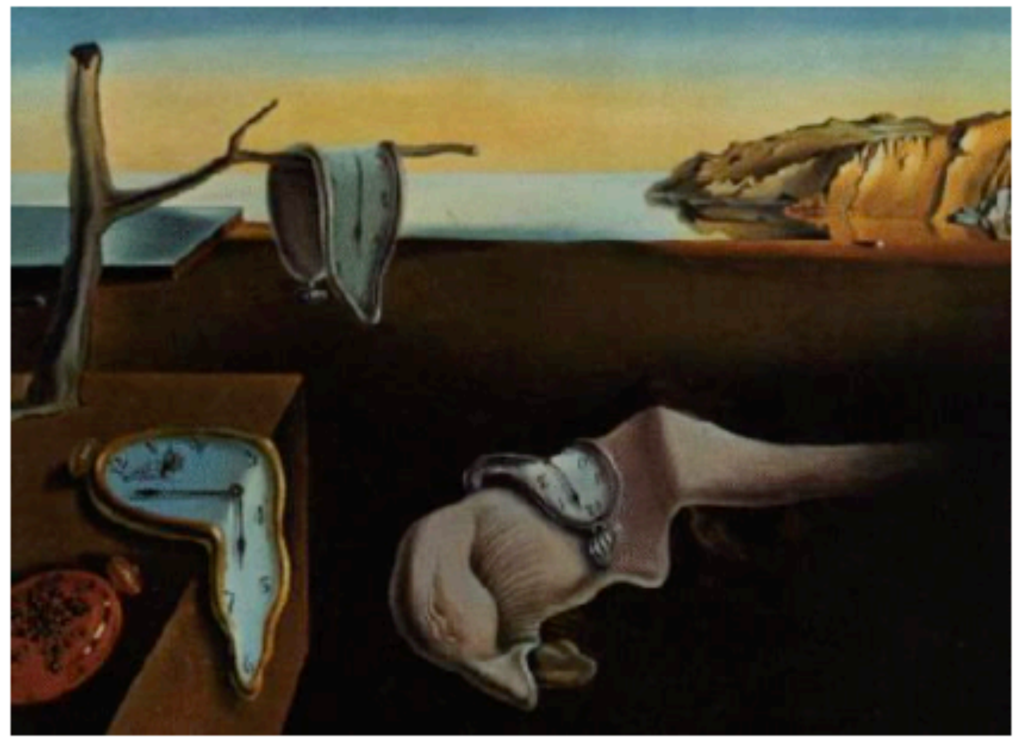
First of all, we assume that an item bank is available and that an item response theory (IRT) model has been calibrated to it. According to this model, the ability of a test taker is described by an unknown parameter $\theta \in \mathbb{R}$ and each item in the pool is described by a known parameter vector d, which takes values in a subset $\mathcal{D}$ of some Euclidean space. For simplicity, we assume that each item has the same number, $m \geq 2$, of possible answers. We denote by $\mathcal{Y}$ the set of effective responses according to the IRT model. Thus, $\mathcal{Y} = \{1, \ldots, m\}$ when the IRT model is polytomous, either nominal or ordinal, and $\mathcal{Y} = \{0, 1\}$ when the IRT model is a dichotomous one that aggregates wrong answers.

We denote by $p(\theta; y, d)$ the probability that a test taker with ability θ selects response $y \in \mathcal{Y}$ to an item with parameter vector $d \in \mathcal{D}$. We assume that for any given $y \in \mathcal{Y}$ and $d \in \mathcal{D}$, $p(\theta; y, d)$ is twice differentiable as a function of θ. For any given $\theta \in \mathbb{R}$ and $d \in \mathcal{D}$, we denote by $s(\theta; y, d)$ the corresponding *score function*, i.e.,

$$s(\theta; y, d) := \frac{\partial}{\partial \theta} \log p(\theta; y, d), \quad y \in \mathcal{Y}, \tag{1}$$

and by $j(\theta; d)$ the corresponding *Fisher information*, i.e.,

$$j(\theta; d) := \sum_{y \in \mathcal{Y}} p(\theta; y, d)\, s^2(\theta; y, d). \tag{2}$$



Journal of Statistical Software

May 2012, Volume 48, Issue 1. *http://www.jstatsoft.org/*

Psychoco: Psychometric Computing in R

Florian Wickelmaier
Universität Tübingen

Carolin Strobl
Universität Zürich

Achim Zeileis
Universität Innsbruck

Journal of Statistical Software

January 2017, Volume 76, Code Snippet 1. *doi: 10.18637/jss.v076.c01*

Computerized Adaptive Testing with R: Recent Updates of the Package catR

David Magis
University of Liège

Juan Ramon Barrada
Universidad de Zaragoza

Business Intelligence

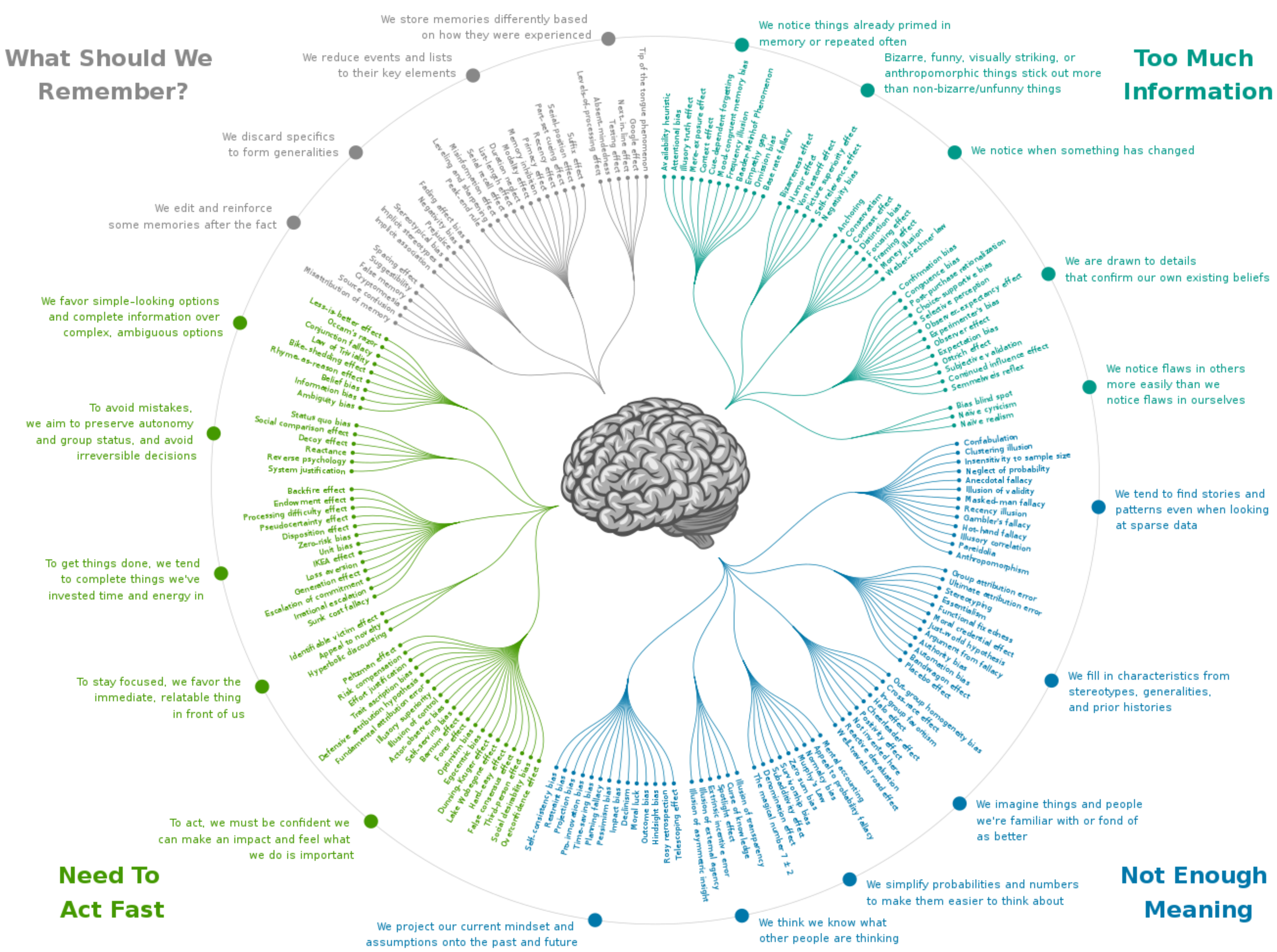
Fase 1	**Fase 2**	**Fase 3**	**Fase 4**
Dados	Stage	DW	Análise
			
Processo transacional	Processo analítico		Análise e Visualização
Ambiente 1	Ambiente 2		Ambiente 3

Inteligência Computacional para mitigar e compensar muitas das heurísticas da cognição humana

Viés de ancoragem
Viés de disponibilidade
Viés de confirmação
Viés de apresentação
Viés de otimismo
Viés da falácia do planejamento
Viés de custos irrecuperáveis ou aversão a perdas

Neil Jacobstein Chairs the AI and Robotics Track at Singularity University

THE COGNITIVE BIAS CODEX



https://busterbenson.com/piles/cognitive-biases/

Valdez, A. C., Ziefle, M., & Sedlmair, M. (2017). A framework for studying biases in visualization research.

I. Too Much Information

a. We notice things already *primed* in memory or repeated often
1. Availability Heuristic
2. Attentional Bias
3. Illusory truth effect
4. Mere exposure effect
5. Context effect
6. Cue-dependent forgetting
7. Mood-congruent memory bias
8. Frequency illusion
9. Baader-Meinhof Phenomenon
10. Empathy gap
11. Omission bias
12. Base rate fallacy

b. Bizarre/funny/ visually-striking/ *anthropomorphic* things stick out more than non-bizarre/unfunny things
1. Bizarreness effect
2. Humor effect
3. Von Restorff effect
4. Picture superiority effect
5. Self-relevance effect
6. Negativity Effect

c. We notice when something has *changed*
1. Anchoring
2. Conservatism
3. Contrast effect
4. Distinction bias
5. Focusing effect
6. Framing effect
7. Money illusion
8. Weber-Fechner law

d. We are drawn to details that *confirm* our own existing beliefs
1. Confirmation bias
2. Congruence bias
3. Post-purchase rationalization
4. Choice-supportive bias
5. Selective perception
6. Observer-expectancy effect
7. Experimenter's bias
8. Observer effect
9. Ostrich effect
10. Subjective validation
11. Continued influence effect
12. Semmelweis reflex

e. We notice *flaws in others* more easily than flaws in ourselves
1. Bias blind spot
2. Naive cynicism
3. Naive realism

II. Not Enough Meaning

a. We find stories and *patterns* even in sparse data
1. Confabulation
2. Clustering illusion
3. Insensitivity to sample size
4. Neglect of probability
5. Anecdotal fallacy
6. Illusion of validity
7. Masked man fallacy
8. Recency illusion
9. Hot-hand fallacy
10. Illusory correlation
11. Pareidolia
12. Anthropomorphism

b. We fill in characteristics from *stereotypes*, generalities, and prior histories
1. Group attribution error
2. Ultimate attribution error
3. Stereotyping
4. Essentialism
5. Functional fixedness
6. Moral credential effect
7. Just-world hypothesis
8. Argument from fallacy
9. Authority bias
10. Automation bias
11. Bandwagon effect
12. Placebo effect

c. We imagine things and people we're *familiar* with or fond of as better
1. Halo effect
2. In-group bias
3. Not invented here
4. Cross-race-effect
5. Cheerleader effect
6. Well-traveled road effect
7. Out-group homogeneity bias
8. Reactive devaluation
9. Positivity effect

d. We *simplify probabilities* and numbers make them easier to think about
1. Mental accounting
2. Normalcy bias
3. Magic number 7 + 2
4. Murphy's law
5. Subadditivity effect
6. Survivorship bias
7. Zero sum bias
8. Denomination effect
9. Appeal to probability fallacy

e. We *think we know* what other people are thinking
1. Curse of knowledge
2. Illusion of transparency
3. Spotlight effect
4. Illusion of external agency
5. Illusion of asymmetric insight
6. Extrinsic incentive error

f. We *project* our current mindset and assumptions onto the past and future
1. Self-consistancy bias
2. Restraint bias
3. Projection bias
4. Pro-innovation bias
5. Time-saving bias
6. Planning fallacy
7. Pessimism bias
8. Impact bias
9. Rosy retrospection
10. Telescoping effect
11. Declinism
12. Moral luck
13. Outcome bias
14. Hindsight bias

III. Need to act fast

a. To act, we must be *confident* we can make an impact and feel what we do is important
1. Peltzman effect
2. Risk compensation
3. Effort justification
4. Trait ascription bias
5. Defensive attribution hypothesis
6. Fundamental attribution error
7. Actor-observer bias
8. Self-serving bias
9. Lake Wobegone effect
10. Illusory superiority
11. Hard-easy effect
12. Dunning-Kruger effect
13. False consensus effect
14. Illusion of control
15. Barnum effect
16. Forer effect
17. Third-person effect
18. Social desirability bias
19. Optimism bias
20. Egocentric bias
21. Overconfidence effect

b. To stay focused, we favor the *immediate*, relatable thing in front of us
1. Identifiable victim effect
2. Appeal to novelty
3. Hyperbolic discounting

c. To get things done, we tend to *complete* things we've invested time & energy in
1. Backfire effec
2. Endowment effect
3. Pseudocertainty effect
4. Unit bias
5. Disposition effect
6. Zero-risk bias
7. Generation effect
8. Processing difficulty effect
9. IKEA effect
10. Loss aversion
11. Escalation of commitment
12. Irrational escalation
13. Sunk cost fallacy

d. To avoid mistakes, we're motivated to preserve our *autonomy* and status in a group, and to avoid irreversible decisions
1. Status quo bias
2. Social comparison bias
3. Decoy effect
4. Reverse psychology
5. Reactance
6. System justification

e. We favor *simple*-looking *options* and complete information over complex, ambiguous options
1. Less-is-better effect
2. Occam's razor
3. Conjunction fallacy
4. Delmore effect
5. Law of Triviality
6. Belief bias
7. Bike-shedding effect
8. Rhyme as reason effect
9. Information bias
10. Ambiguity bias

IV. What Should We remember?

a. We *edit* and reinforce some *memories* after the fact
1. Spacing effect
2. Suggestibility
3. False memory
4. Cryptomnesia
5. Source confusion
6. Misattribution of memory

b. We discard *specifics* to form *generalities*
1. Fading affect bias
2. Negativity bias
3. Prejudice
4. Stereotypical bias
5. Implicit stereotypes
6. Implicit associations

c. We reduce events and lists to their *key elements*
1. Suffix effect
2. Serial position
3. Recency effect
4. Primacy effect
5. Past-list cueing effect
6. Memory inhibition
7. Modality effect
8. List-length effect
9. Serial recall effect
10. Duration neglect
11. Misinformation effect
12. Leveling and sharpening
13. Peak-end rule

d. We store memories differently based on how they were *experienced*
1. Tip of the tongue phenomenon
2. Google effect
3. Next-in-line effect
4. Testing effect
5. Absent-mindedness
6. Levels of processing effect

Legend

The reason **why** a bias occurs is given at the top and with roman numerals. → I. Cause

How humans cope with this reason is given with bold letters. → **x.** Strategy

The bias name is **addressed** using arabic numerals. → 1. Bias a 2. Bias b 3. Bias c

Derived from John Manoogian III "Cognitive Bias Codex 2016
Categorization by Buster Benson - Visualization by ACV

Obrigado!

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