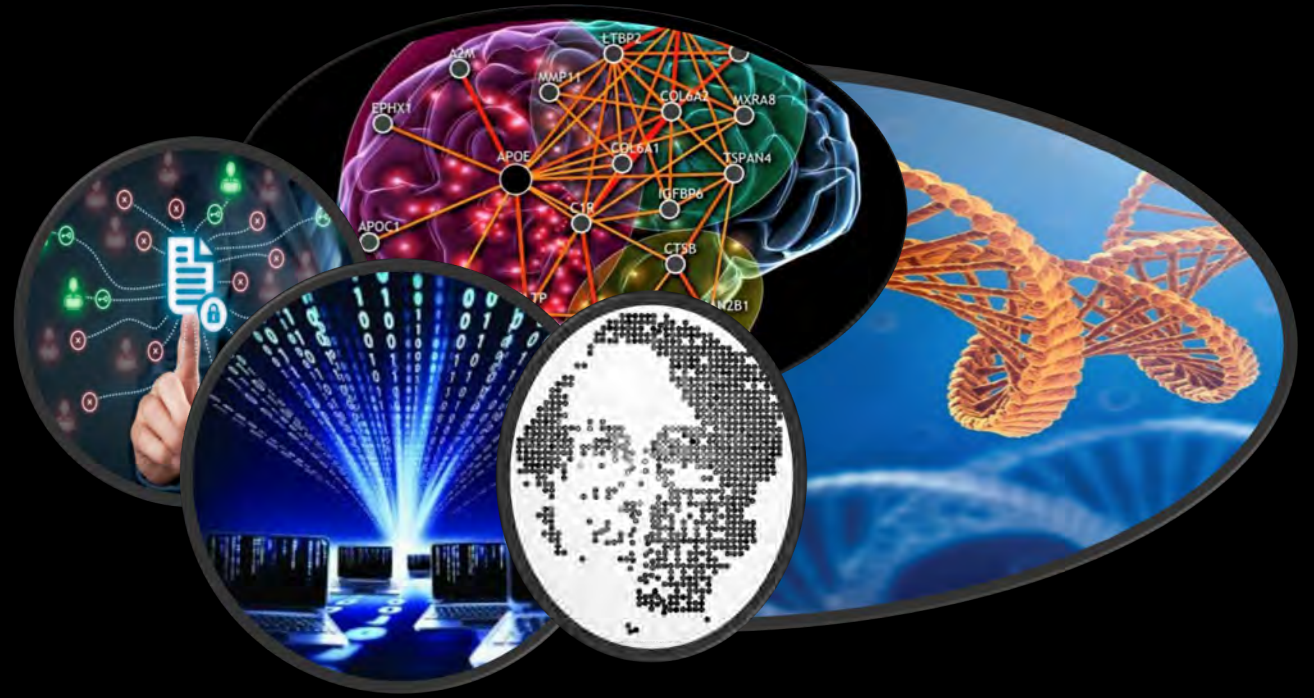


Advancing Knowledge Through Secondary Data Use



***NIDDK Data Management & Sharing
Webinar Series
03 March 2023***

***Vivian OTA WANG, Ph.D., CGC, FACMG
Office of Data Science Strategy
DPCPSI/Office of the Director
National Institutes of Health, DHHS***





- **The Drivers**

Human Rights and Open Science

- **The Data and Data Science**

Volumes of Varied and Complex Data

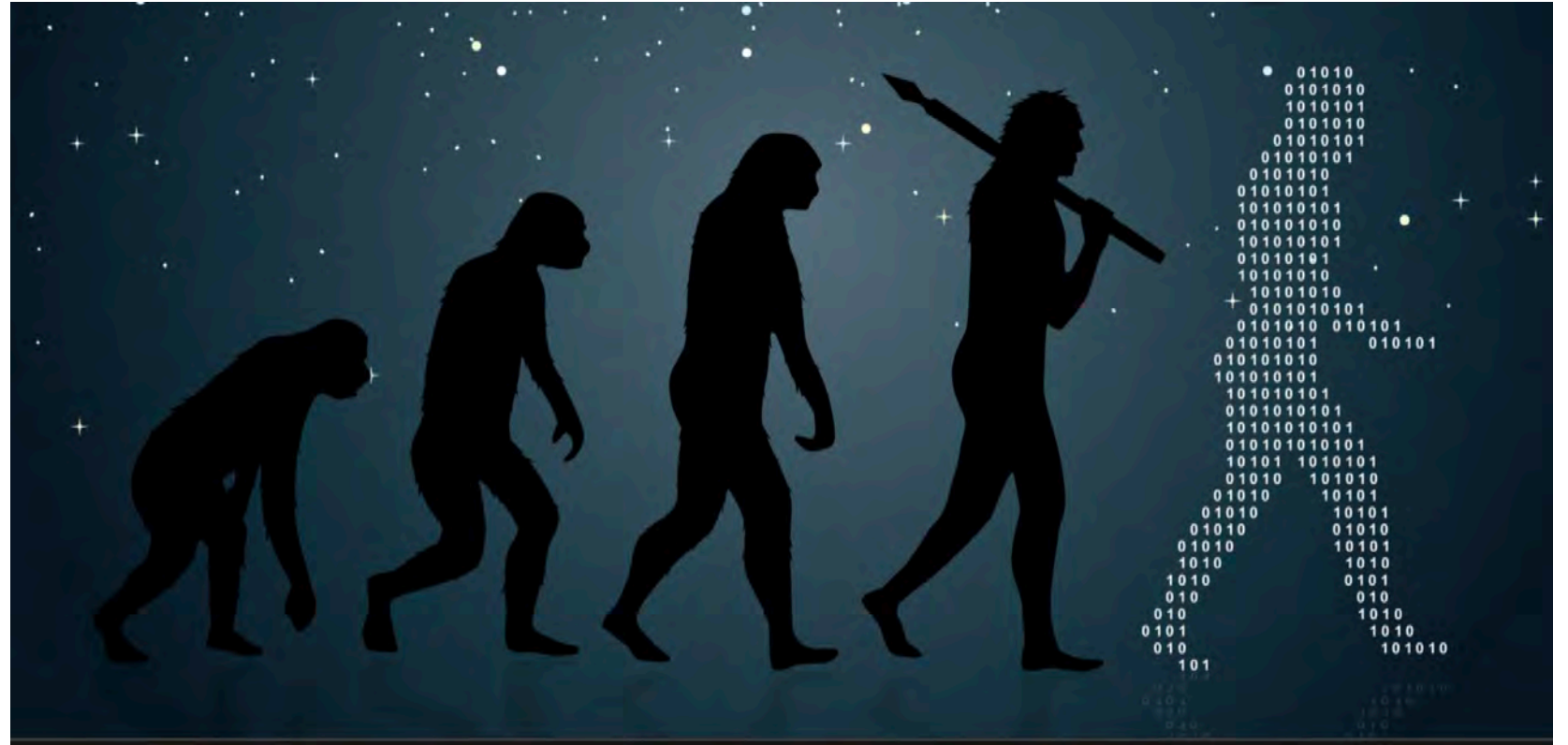
- **The Challenges**

Economic, Ethical, Legal, and Social Implications

- **Next Steps**

You

THE DRIVERS



Top Ten Leading Causes of Death (2020-2022)

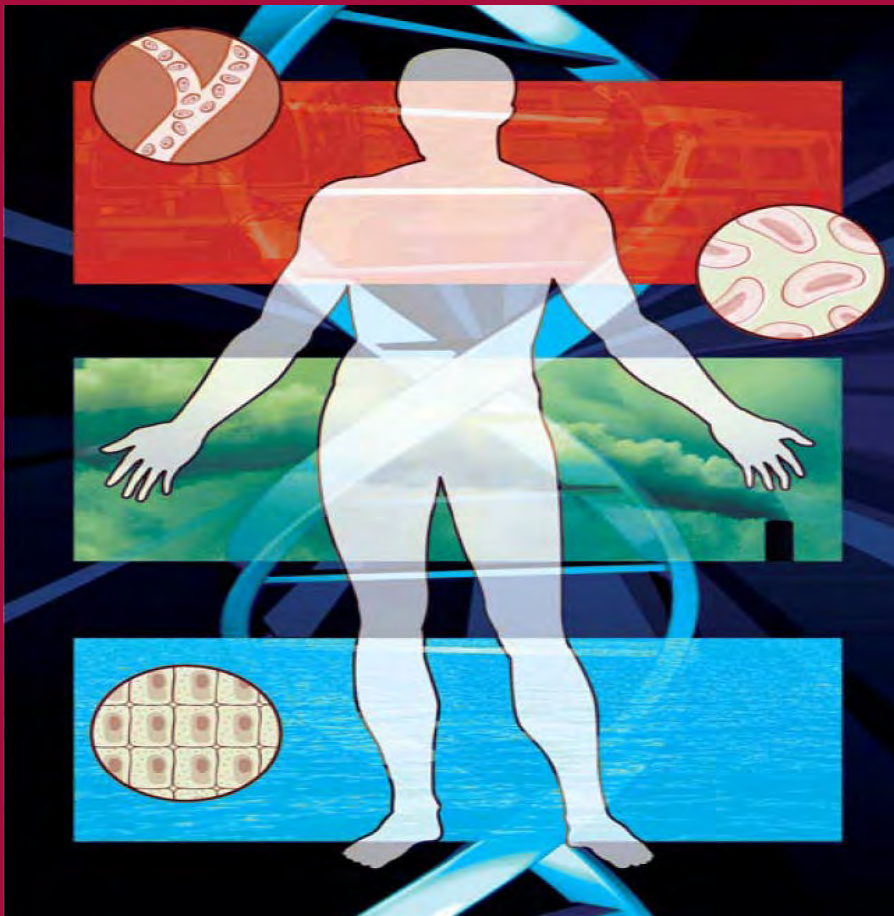
	Category	Total deaths (Jan.-Sept. 2022)	Total deaths (2021)	Total deaths (2020)
1	Heart disease	572,336	767,937	764,512
2	Cancer	454,176	604,358	599,607
3	COVID-19	234,434	475,059	343,566
4	Accidents	170,166	226,987	203,033
5	Stroke	123,215	162,769	159,248
6	Chronic respiratory	107,559	141,906	152,051
7	Alzheimer	87,866	119,442	134,271
8	Diabetes	74,716	103,197	101,355
9	Other respiratory	50,635	66,381	66,053
10	Renal failure	42,596	53,057	51,221

Notes: For 2022, the total death sum for each category is for January 1 - September 30, 2022, except deaths from accidents and suicides are from January - September 2021. Chronic respiratory is chronic lower respiratory disease.

<https://www.healthsystemtracker.org/brief/covid-19-leading-cause-of-death-ranking/>

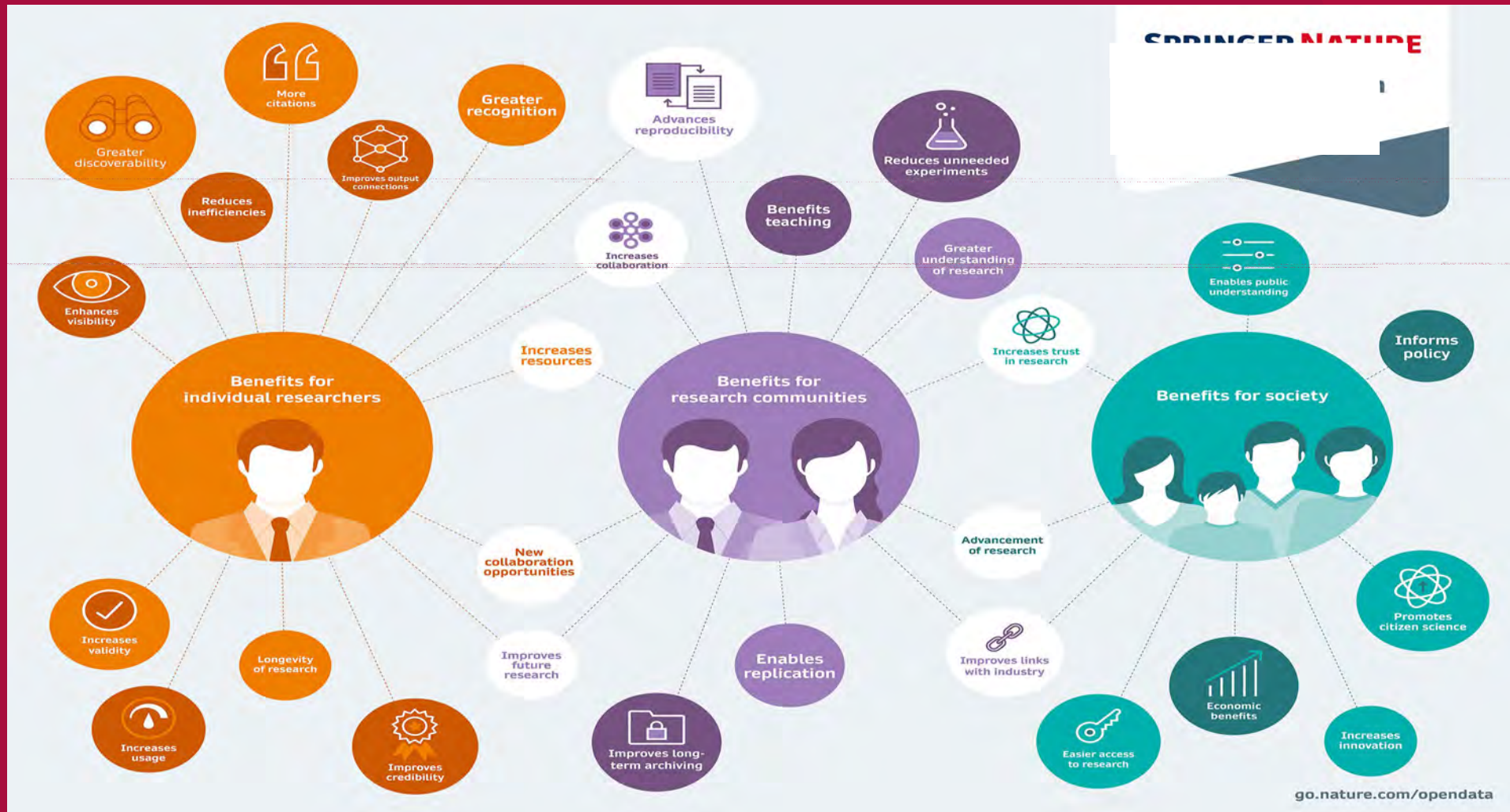


The People Factor: Top Ten Modifiable Behaviors Contributing to Mortality



- Tobacco use
- Diet
- Physical activity
- Alcohol misuse
- Microbial agents
- Toxic agents
- Firearms
- Sexual behavior
- Motor vehicle accidents
- Substance abuse

Human Rights and the Democratization of Knowledge



Open Science



National Academies of Sciences, Engineering, and Medicine. 2018. *Open Science by Design: Realizing a Vision for 21st Century Research*. Washington, DC: The National Academies Press. <https://doi.org/10.17226/25116>.

DATA SHARING AND INNOVATION

- Open access
 - Accessible research & data to all members of society (*e.g., public, citizen scientists, and professionals*)
- Open data
- Open sources



Open Science

- Facilitates innovation of research tools and methods
- Increases statistical power
- Improves research quality through validation and replication



Open Science

- Facilitates innovation of research tools and methods
- **Increases statistical power**
- Improves research quality through validation and replication



Open Science

- Facilitates innovation of research tools and methods

- Increases statistical power

- Improves research quality through validation and replication

Must try harder

Too many sloppy mistakes are creeping into scientific papers. Lab heads must look more rigorously at the data – and at themselves.

Error prone

Biologists must realize the pitfalls of massive amounts of data.

If a job is worth doing, it is worth doing twice

Researchers and funding agencies need to put a premium on ensuring that results are reproducible, argues Jonathan F. Russell.

The case for open computer programs

Six red flags for suspect work

C. Glenn Begley explains how to recognize the preclinical papers in which the data won't stand up

Know when your numbers are significant

Why Most Published Research Findings Are False

John P. A. Ioannidis

Summary
There is increasing concern that most current published research findings are false. The probability that a research claim is true may depend on study power and bias, the number of other studies on the same question, and, importantly, the ratio of true to no relationships among the relationships probed in each scientific field. In this framework, a research finding is less likely to be true when the studies conducted in a field are smaller, when effect sizes are smaller, when there is a greater number and lesser selection of tested relationships, when there is greater flexibility in designs, definitions, outcomes, and analytical models when

Modeling the Framework for False Positive Findings
Several methodologists have pointed out [9–11] that the high rate of nonreplication (lack of confirmation) of research discoveries is a consequence of the convenient, yet ill-founded strategy of claiming conclusive research findings solely on the basis of a single study assessed by formal statistical significance, typically for a p -value less than 0.05. Research is not most appropriately represented and summarized by p -values, but, unfortunately, there is a widespread

faces that influence this problem and some corollaries thereof.
is characteristic of the field and can vary a lot depending on whether the field urges highly likely relationships or searches for only one or a few true relationships among thousands and millions of hypotheses that may be postulated. Let us also consider, for computational simplicity, circumscribed fields where either there is only one true relationship (among many that can be hypothesized) or the power is similar to find any of the several existing true relationships. The presently probability of a relationship being true is $R/(R+N)$. The probability of a study finding a true relationship reflects the power $1-\beta$ (one minus the Type II error rate). The probability



Many landmark findings in preclinical oncology research are not reproducible, in part because of inadequate cell lines and statistical models.

Raise standards for preclinical cancer research

C. Glenn Begley and Lee M. Ellis propose how methods, publications and incentives must change if patients are to benefit.

Efforts over the past decade to characterize the genetic alterations in human cancers have led to a better understanding of molecular drivers of this complex of diseases. Although we in the cancer field boast that this would lead to

tools in oncology have the highest failure rate compared with other therapeutic areas. Given the high amount invested in oncology, it is undeniable that barriers to clinical development may be lower than for other therapeutic areas. A large number of drug

investigation must assess their approach to translating discovery research into practical success and impact. Many factors are responsible for the high failure rate, which is a reflection of the high

47/53
“landmark”
publications
could not be
replicated



Open Science and Data Sharing

Precision Health

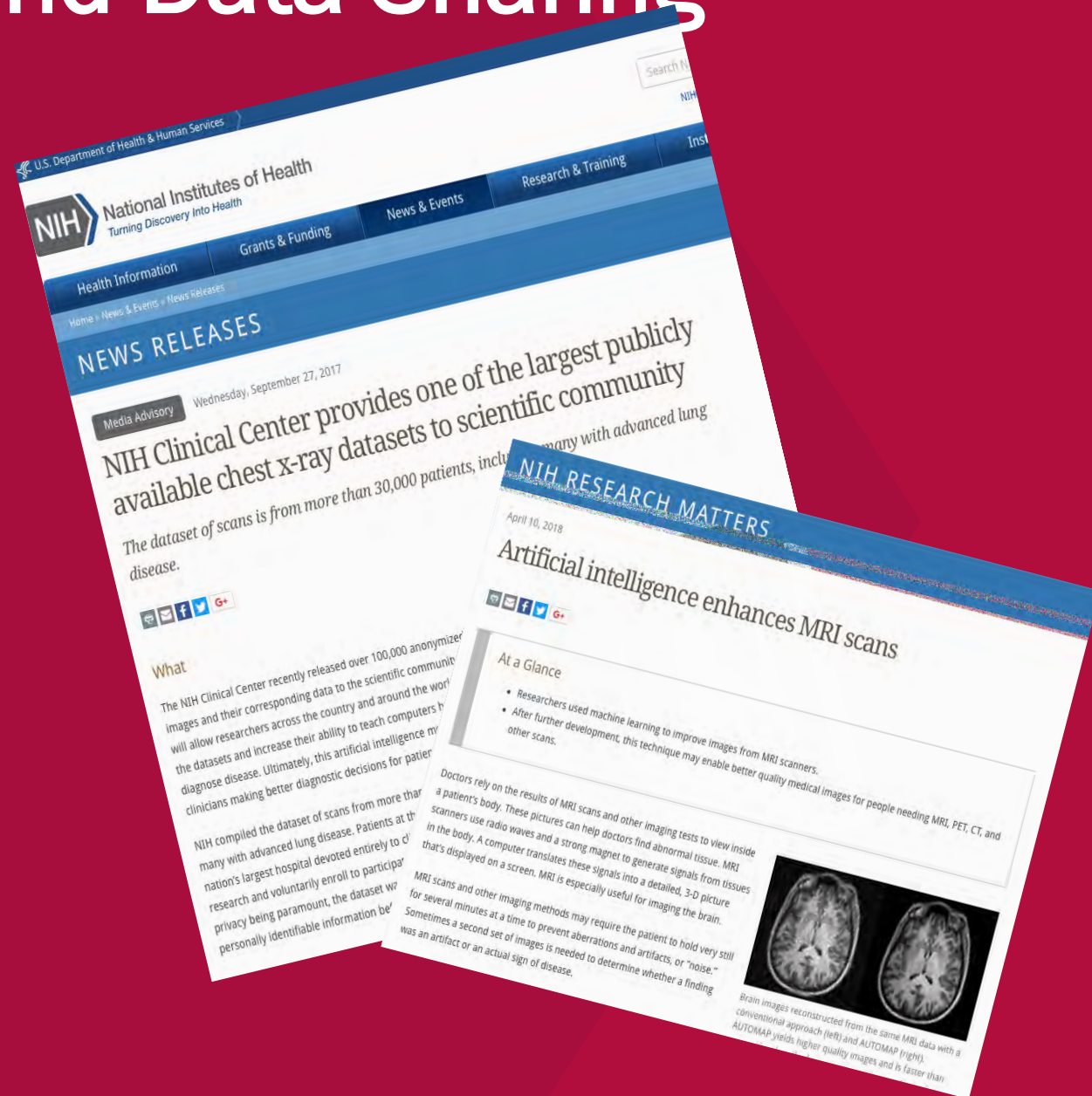


Courtesy of P. Kuhn (USC)

- Accounts for social and cultural complexity influencing underlying biology
- Requires
 - Biological understanding
 - Inclusion of social, cultural, and psychological factors
 - Scientific methods advancements
 - Instrumentation advancements
 - Technology advancements
 - Data management and computation advancements
- -omic, imaging, clinical, laboratory, etc data
- Can *change* disease classifications and treatments

Open Science and Data Sharing

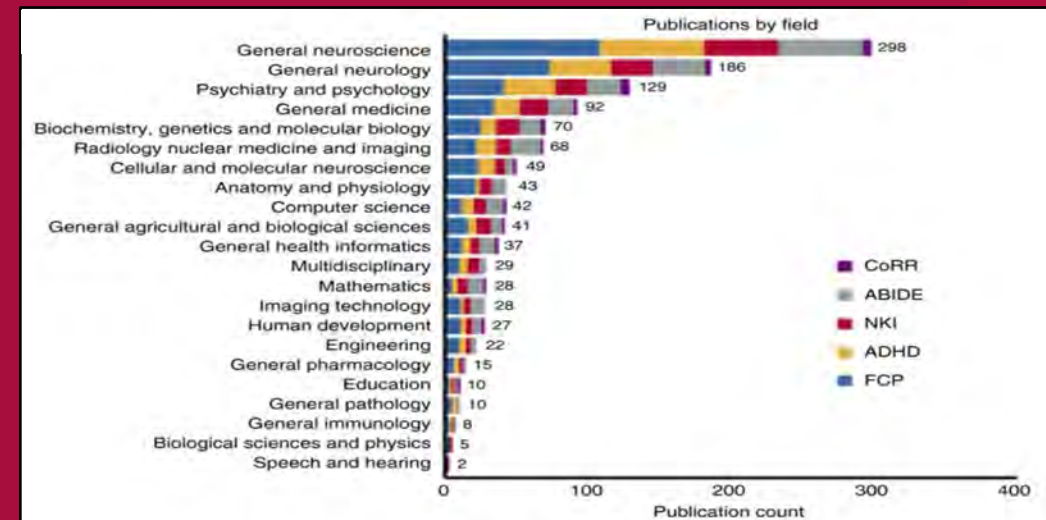
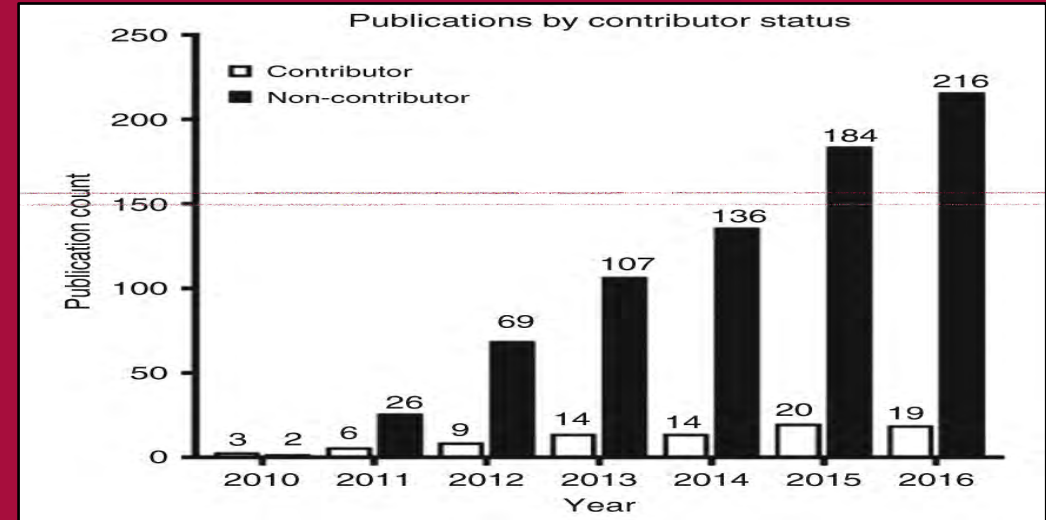
- Increases scientific value by exploring, combining, and analyzing data from multiple sources
- Increases scale of studies, # publications, and types of scientists from a broader range of disciplines



Open Science and Data Sharing

- Increases scientific value by exploring, combining, and analyzing data from multiple sources

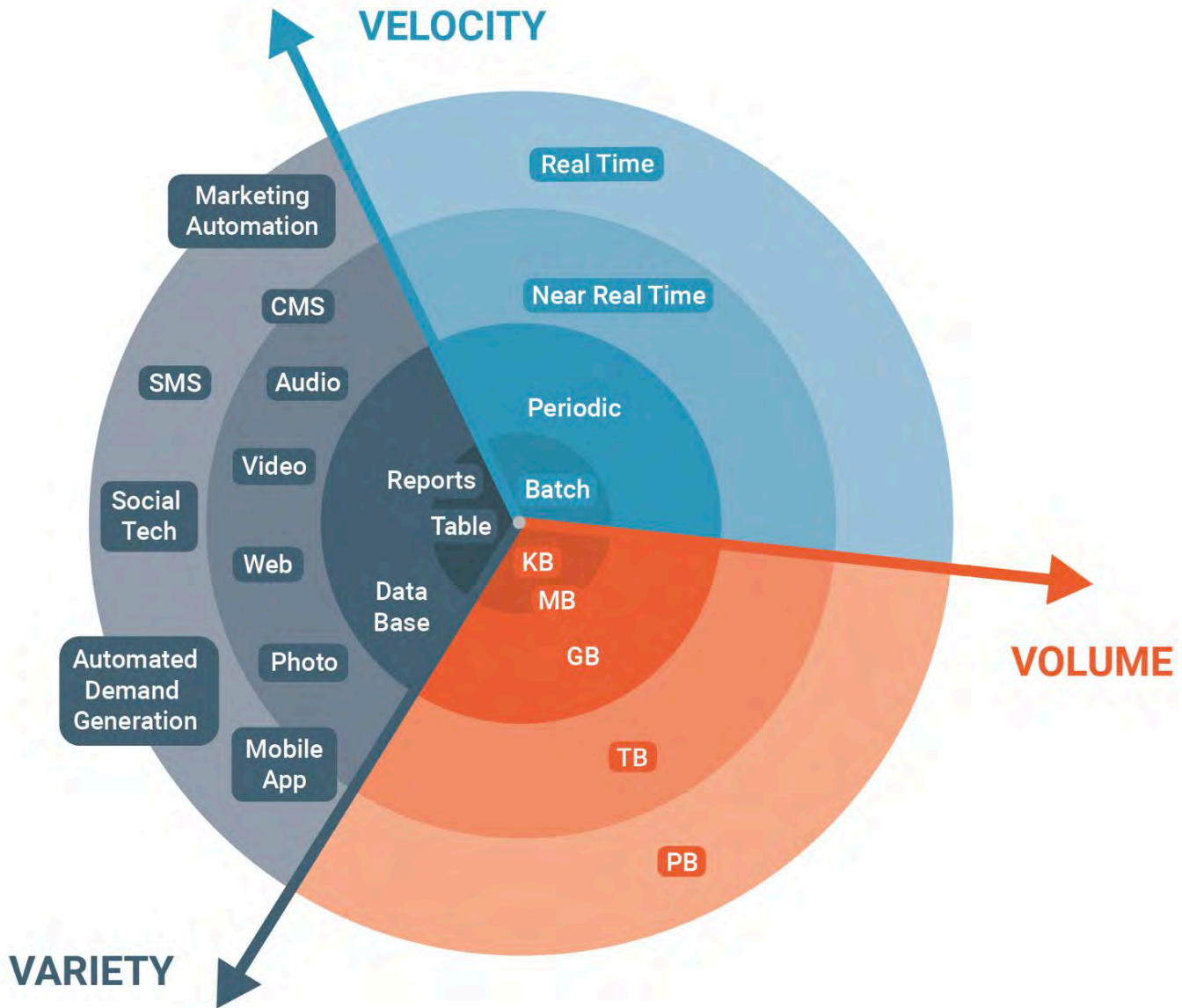
- Increases scale of studies, # publications, and types of scientists from a broader range of disciplines



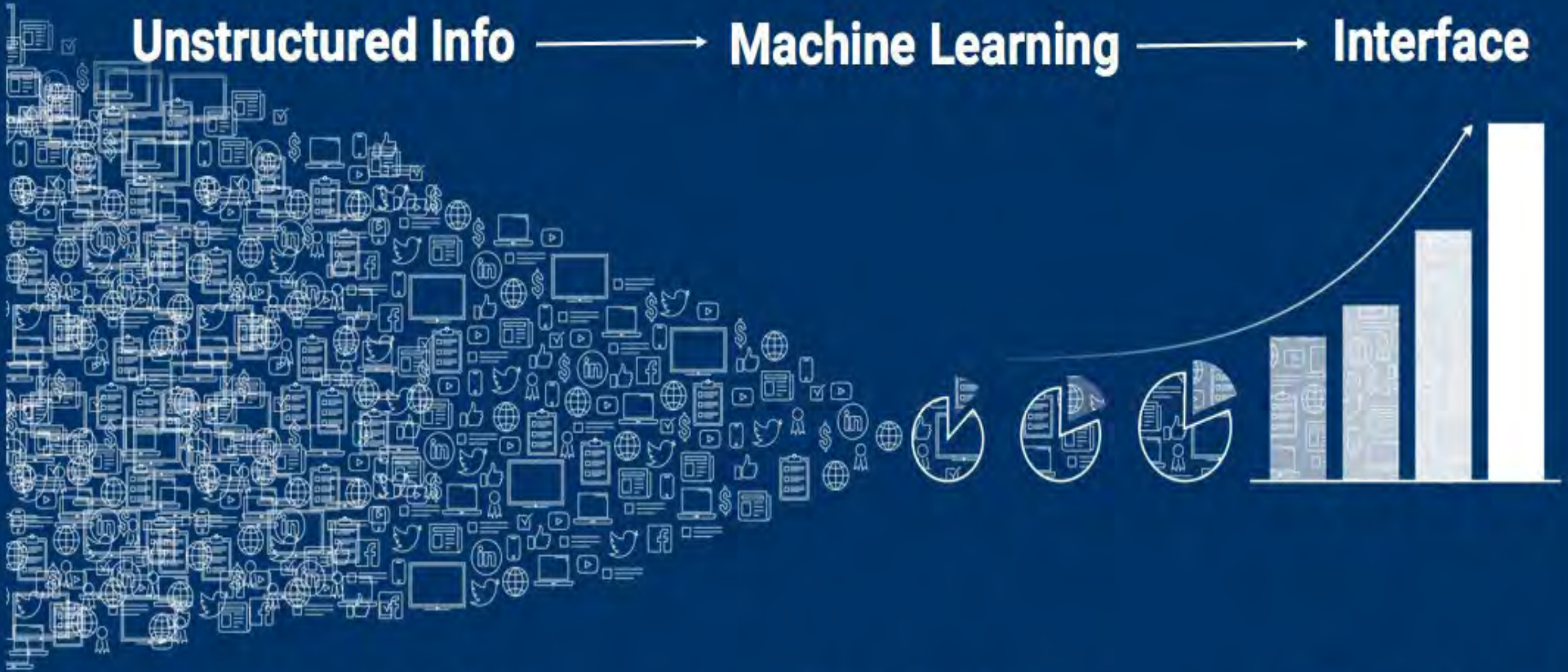
Milham, MP et al. (2018) Assessment of the impact of shared brain imaging data on the scientific literature. *Nature Communications*, 9, DOI: 10.1038/s41467-018-04976-1



THE DATA



Unstructured Info → Machine Learning → Interface



Machine learning technology analyzes millions of unstructured sources in real-time and...

selects and synthesizes that knowledge so you can...

see trends easily & quickly.



BIOECOLOGICAL SYSTEM

Societal and cultural beliefs,
attitudes and ideologies

Organizations, Schools

Neighborhoods, Communities

Family, group affiliations

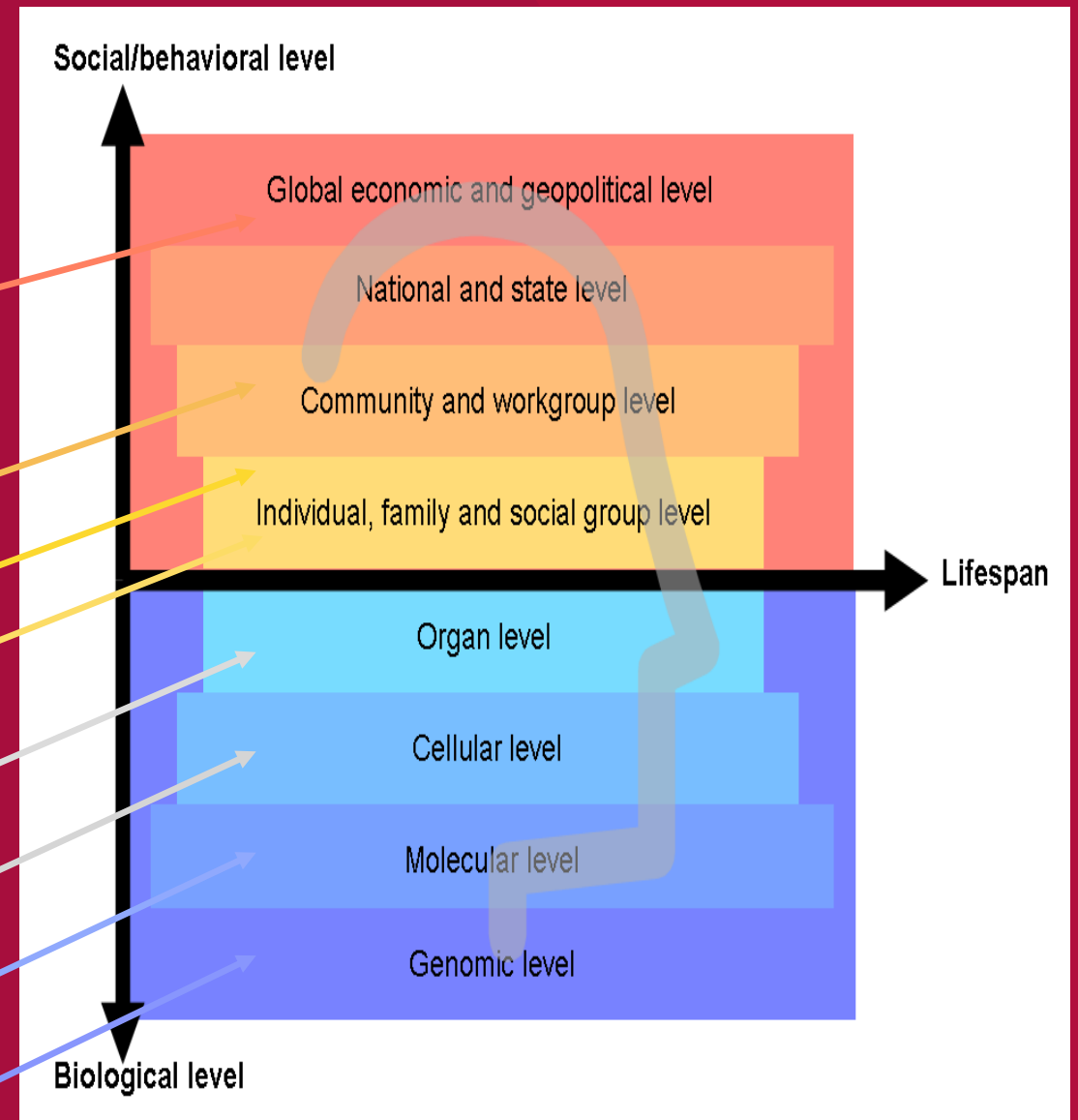
Individual

Disease/health phenotypes

Stem, white blood cells, germline

Biomolecules (proteins, lipids)

DNA, RNA, gene expression



(Adapted from Glass, TA & McAttee, MJ. (2006) *Social Science & Medicine*, 62, 1650-1671).

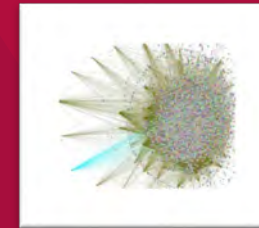
Data: **Variety**, Volume, Velocity, and Veracity

Real-time, Real-world Data Capacities

- Proteomics
- Metabolomics
- Microscopy
- Imaging
- Electronic Medical Records
- Mobile Devices
- Psychological/behavioral/
self-report
- Other technologies



Observational Phenotype



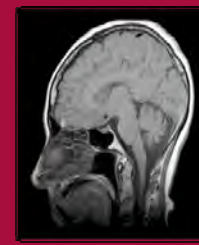
Genomic Other 'omic'



Location



Behavior



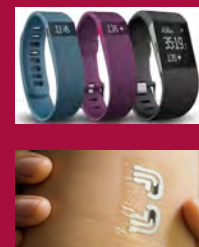
Imaging



Clinical/EMR



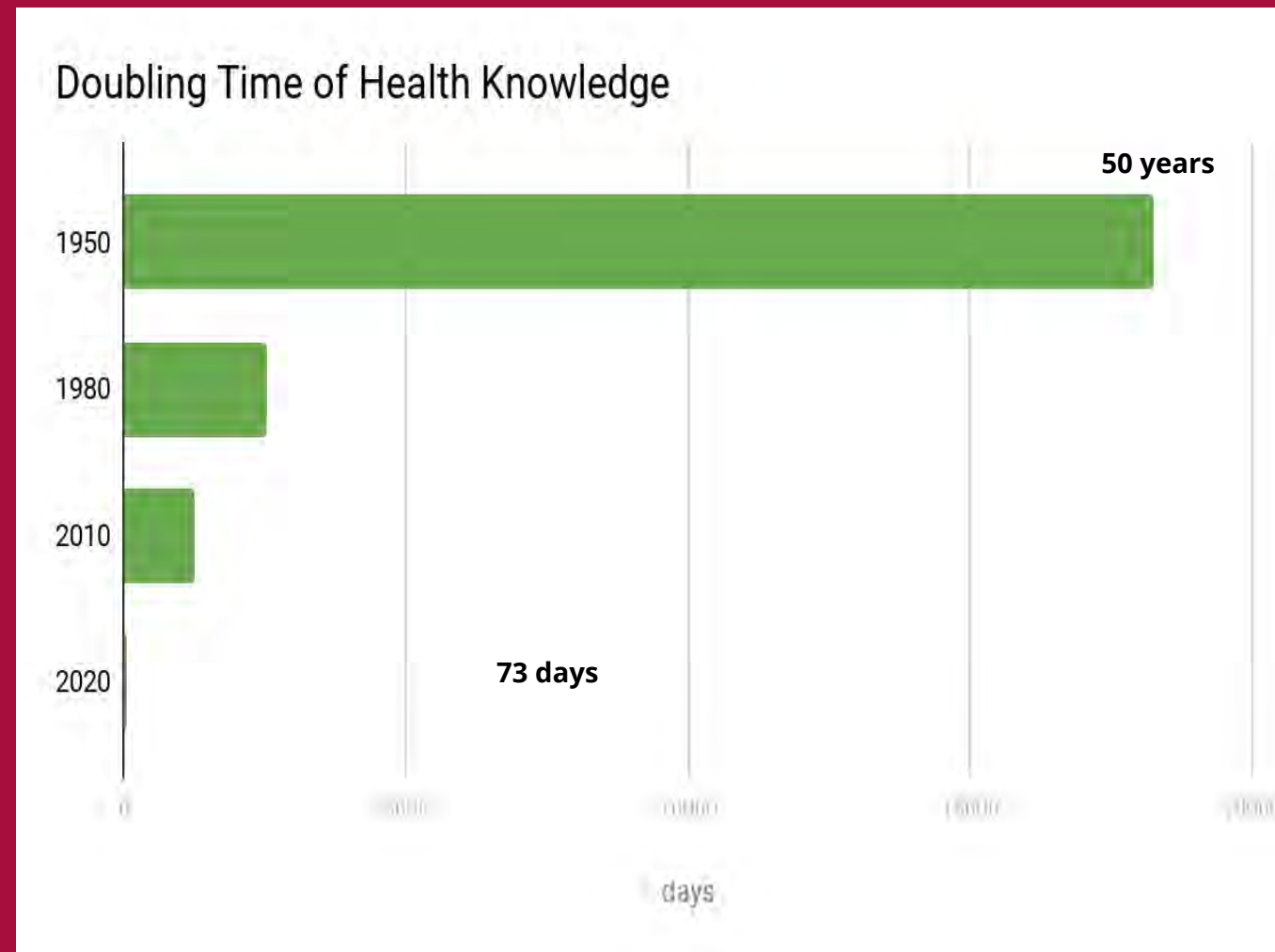
Exposures



**Mobile
Sensors**

Data: Variety, **Volume**, Velocity, and Veracity

Health Knowledge Doubling Time



(Densen, P. *Trans Am Clin Climatol Assoc* (2011))

Data: Variety, **Volume**, Velocity, and Veracity *Personal Health Data*

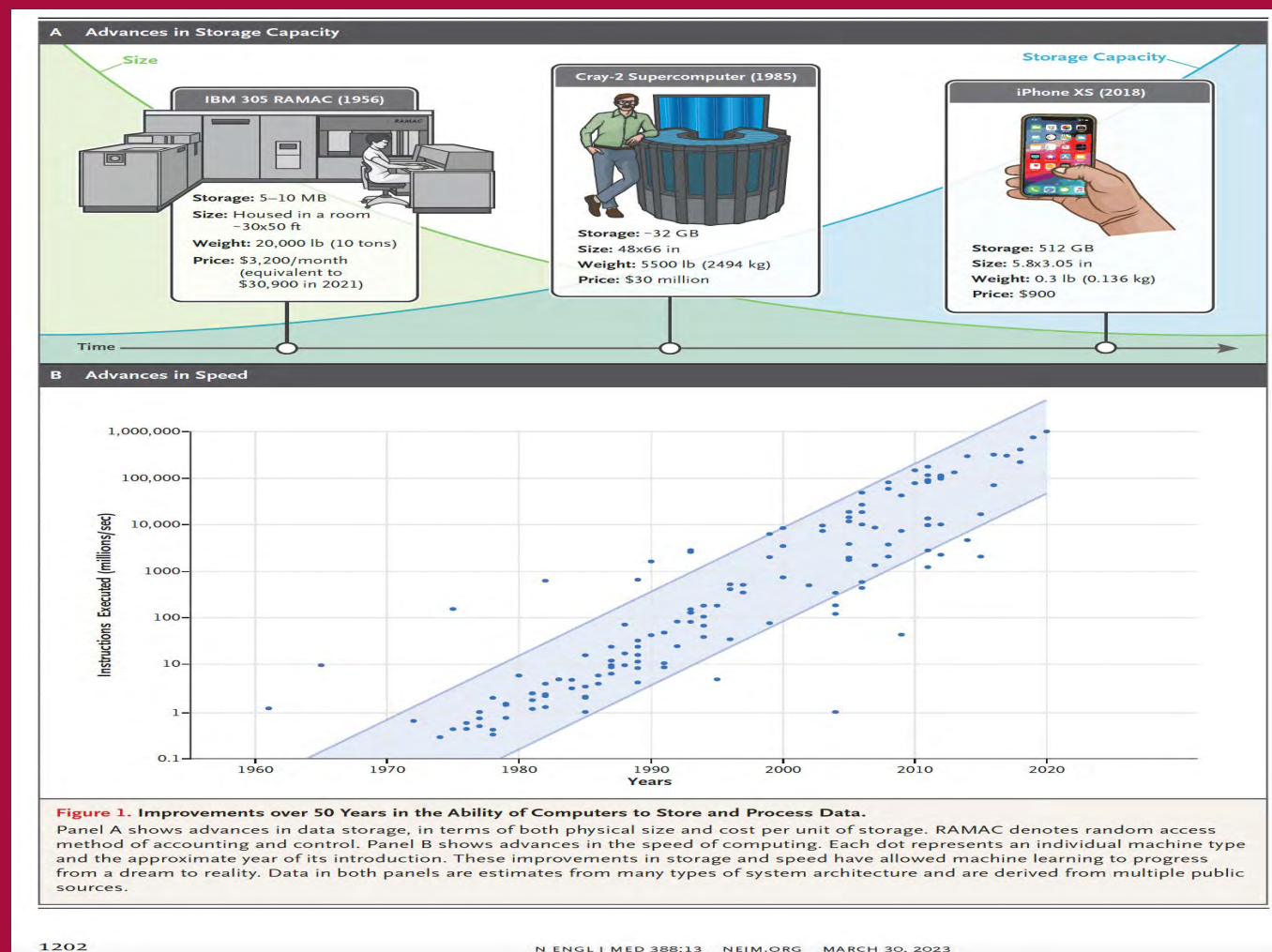
A single person is expected to generate over 1 million gigabytes of health data in their lifetime



<https://databricks.com/blog/2022/03/09/introducing-lakehouse-for-healthcare-and-life-sciences.html>

Data: Variety, Volume, **Velocity**, and Veracity

Improvements to Store and Process Data



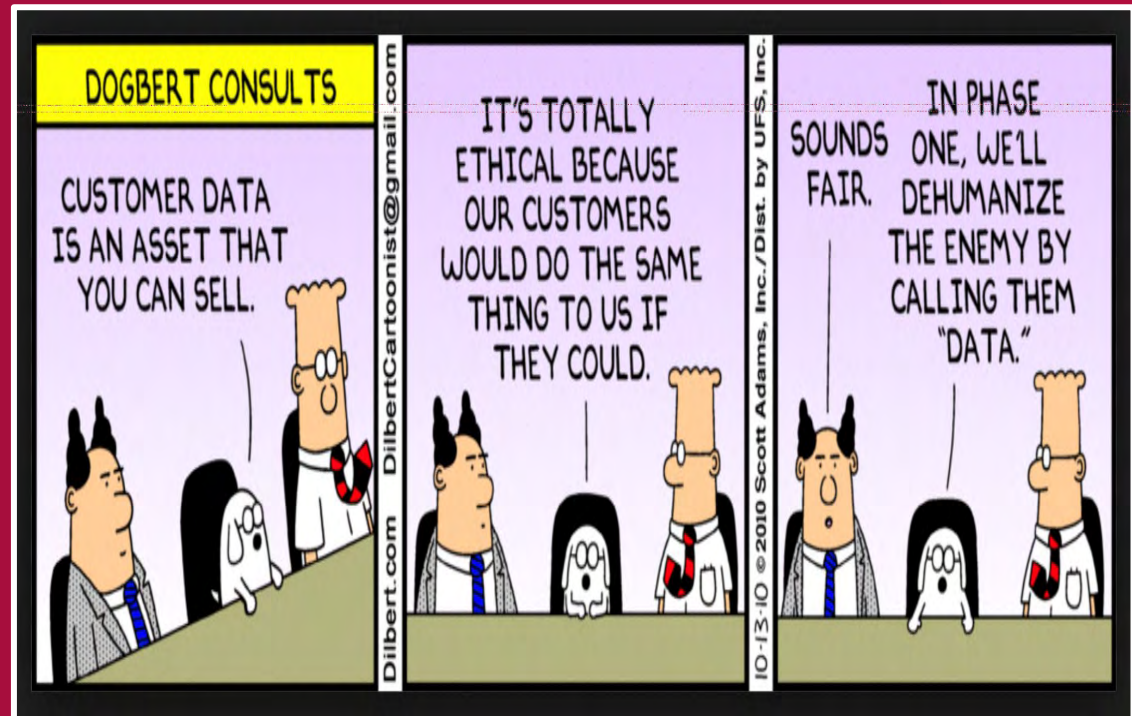
Data: Variety, Volume, Velocity, and **Veracity**

- Trustworthy
- Accurate
- Reliable

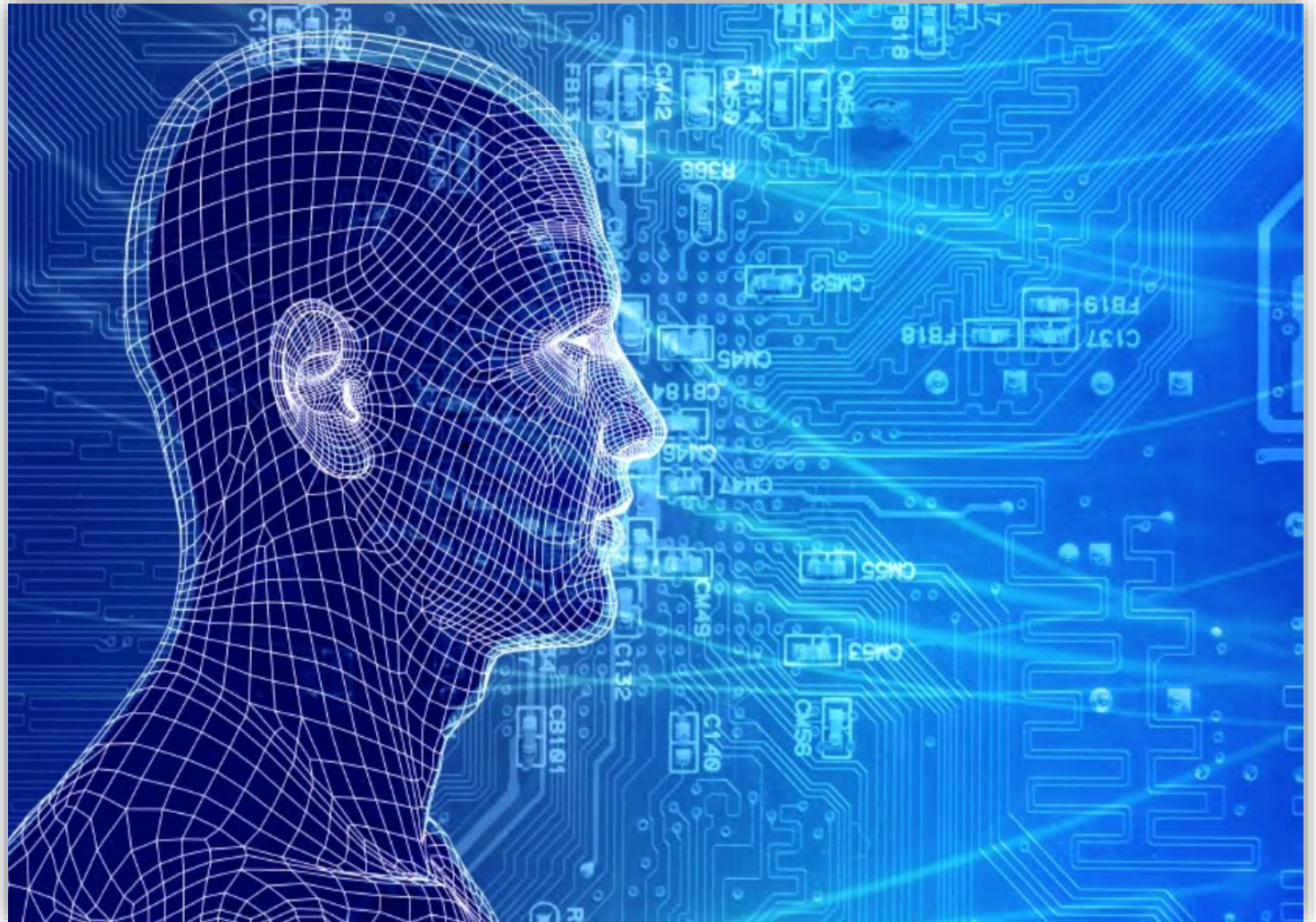


*[Information,
information uses],
and
“definitions
belong
to the definers,
not the defined*

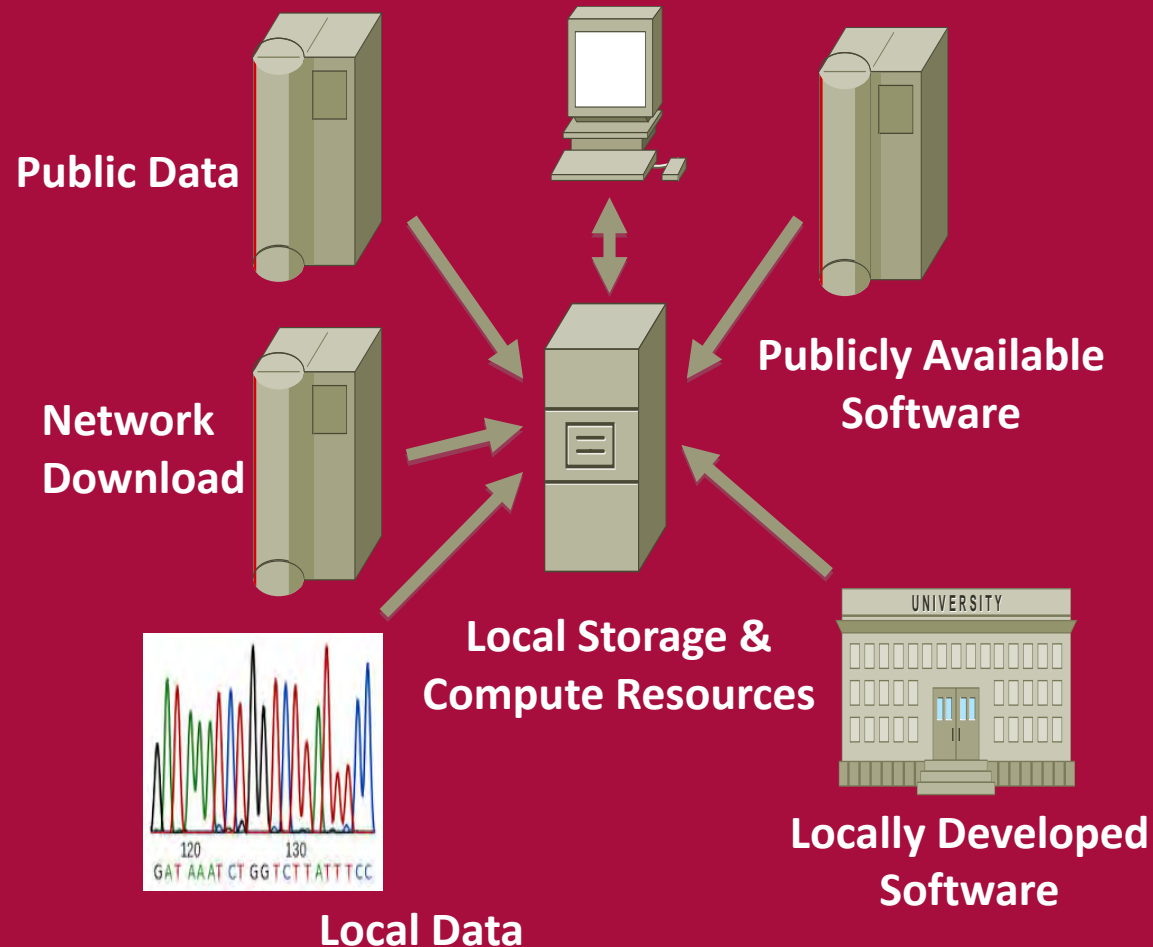
*- Toni Morrison
Beloved*



SOME
SCIENCE
DATA SCIENCE

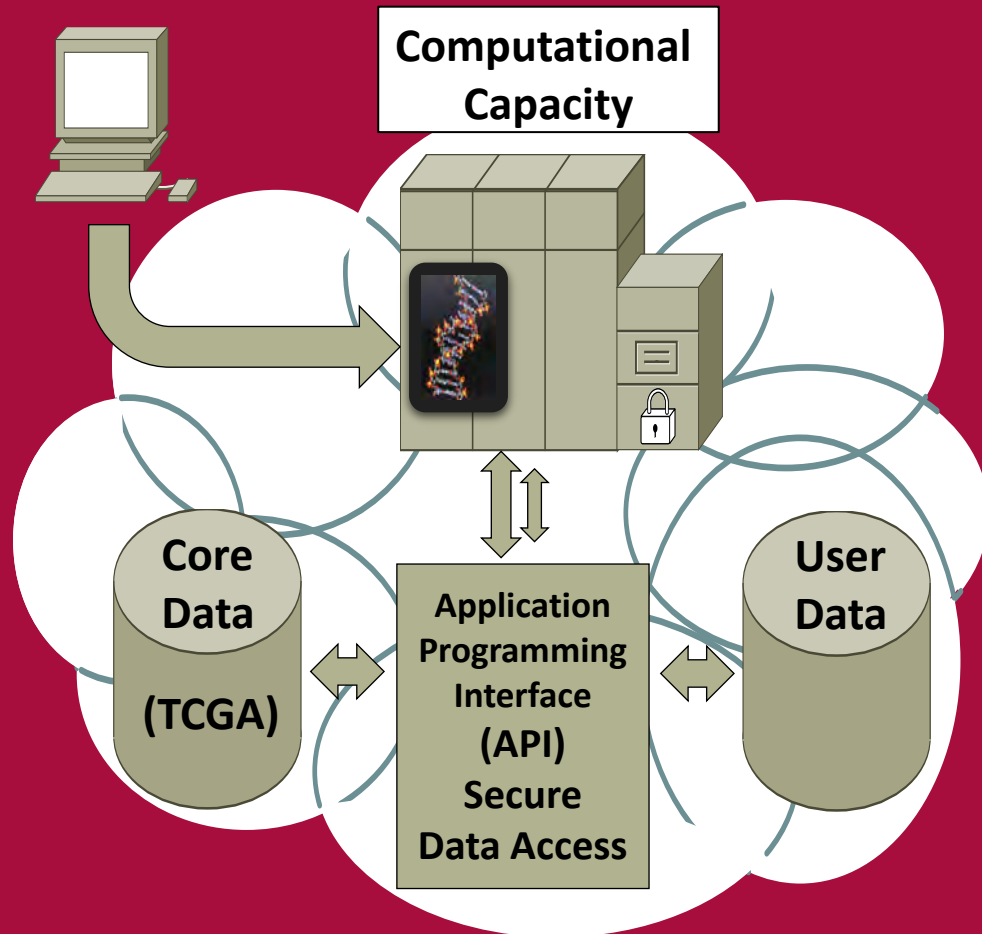


Download Computation Resources and Data (circa ~pre-2014)



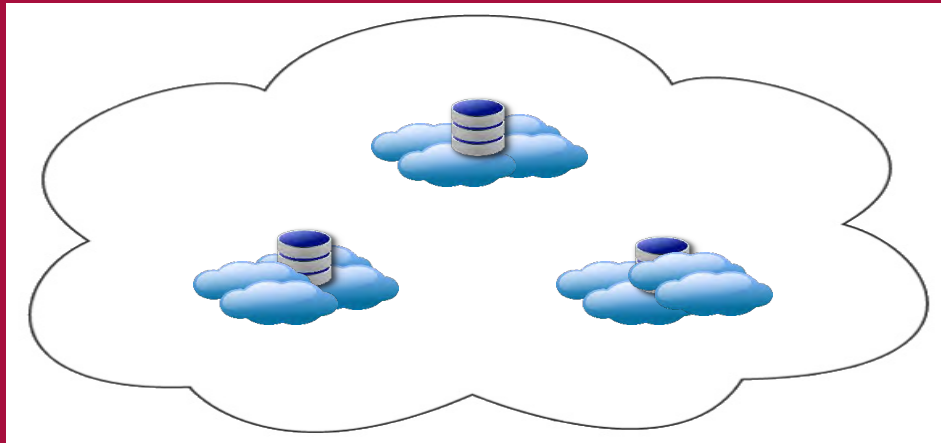
- Only large institutions had ability to utilize data
- Storage/data protection cost ~\$2M/yr
- Data download at 10 Gb/second (*23 days*)
- Increase rate of data generation

Co-Locate Computation Resources and Data (circa ~2014-2016)

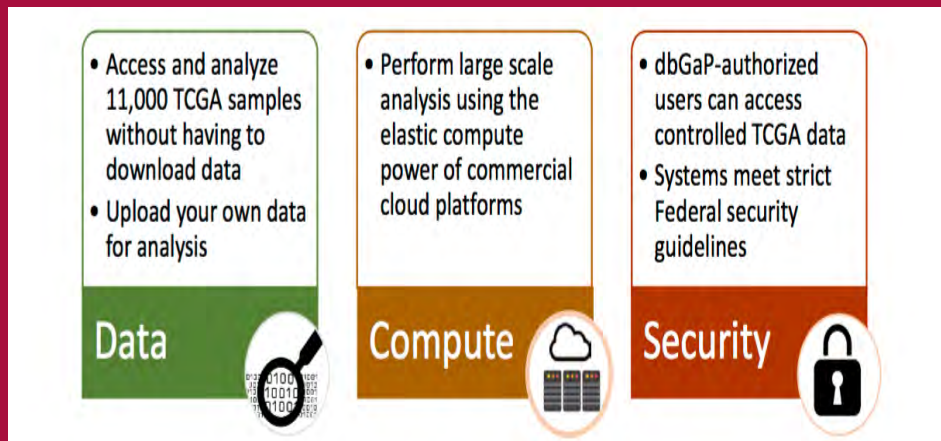


- Access large data sets without downloading data
- Bring tools and pipelines to data
- Combine own data and analyze with existing data
- Workspace to save, share, and analyze data

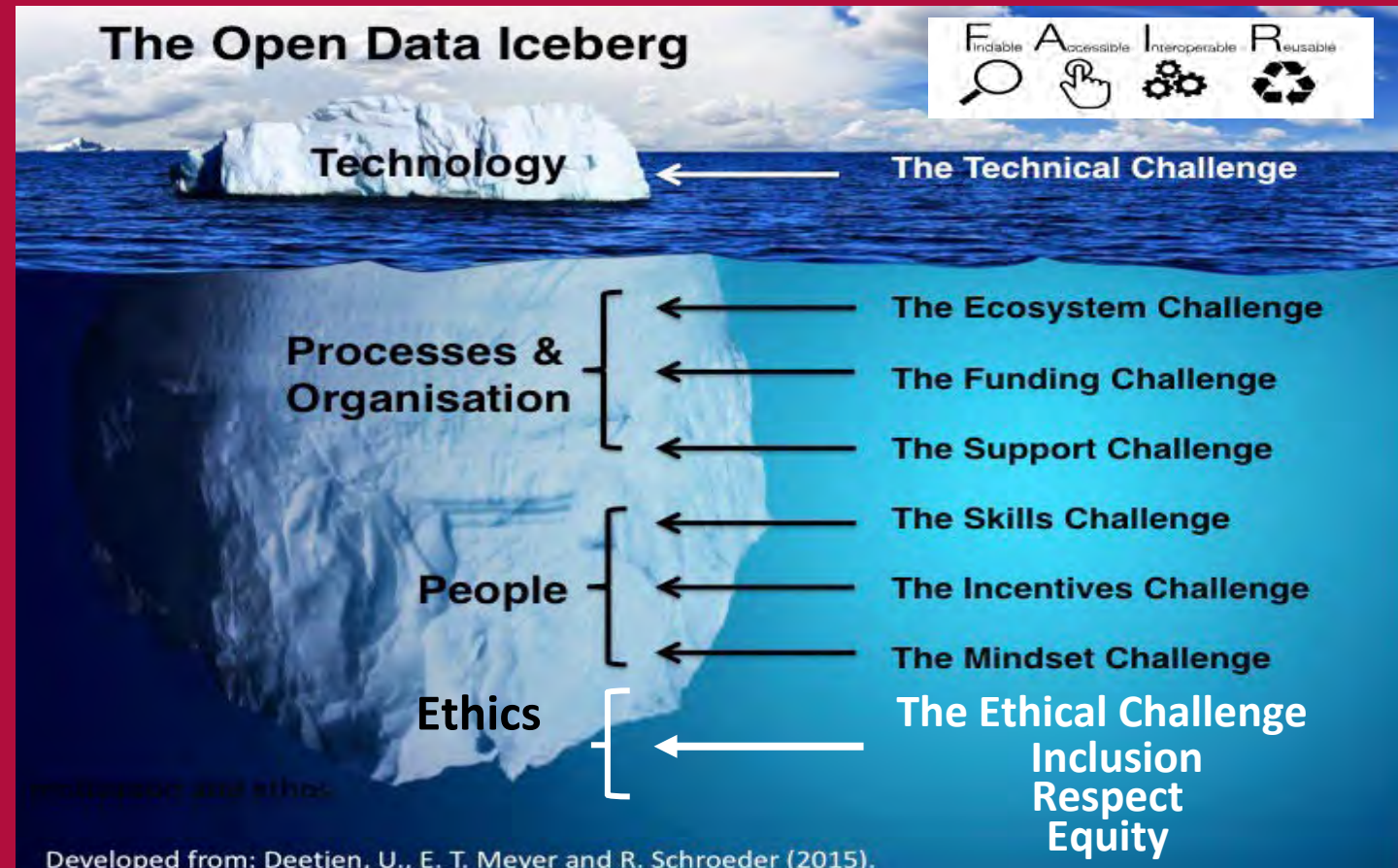
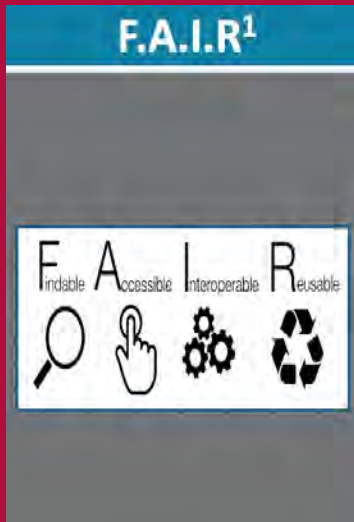
Co-Locate Computation Resources and Data *(circa 2017 – now)*



- Democratize data sharing and access
- Cost-effective
- Scalable
- Computational Capacity



Data Reuse: Isn't Only a Data and Technology Challenge



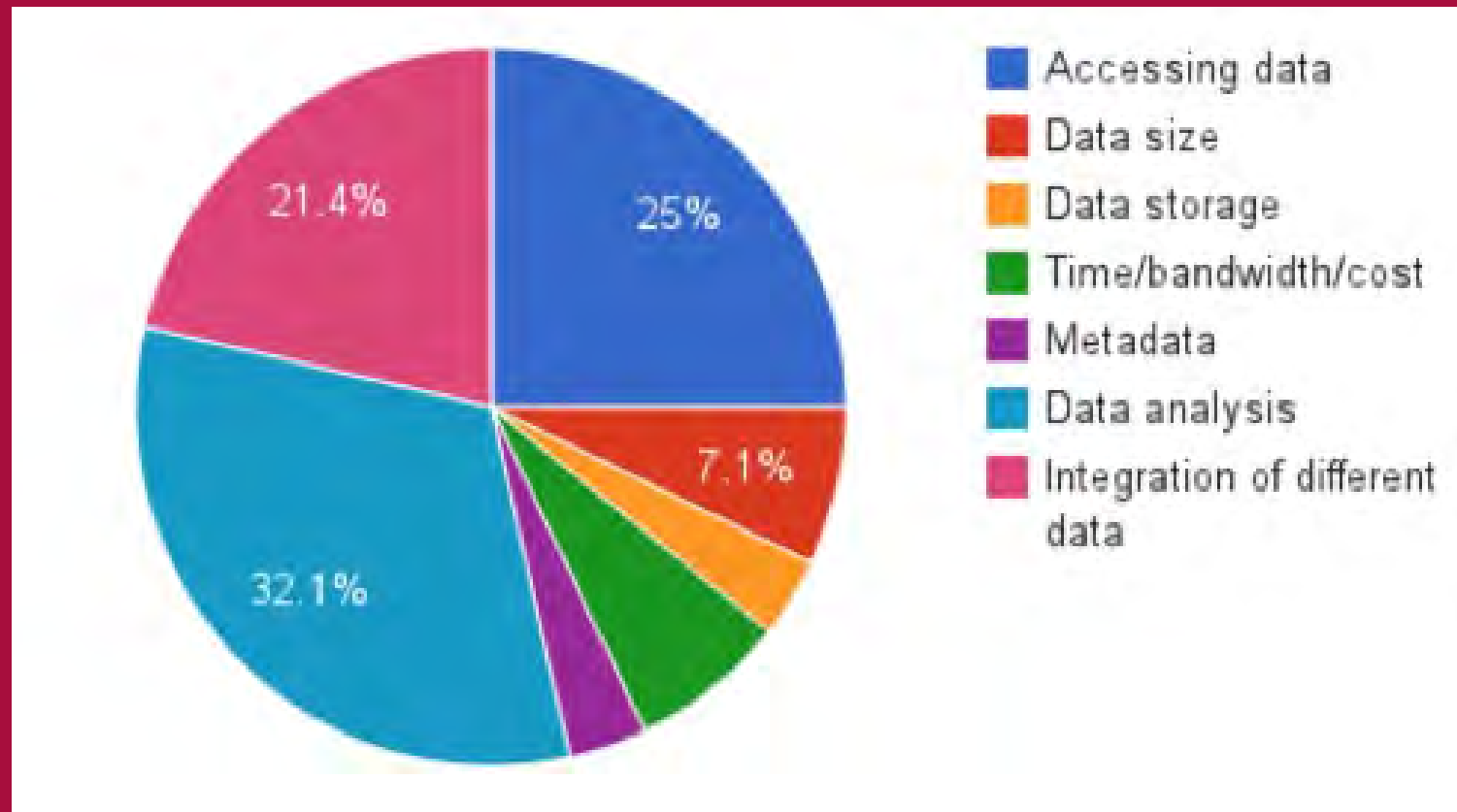
Wilkinson, M. D. *et al.* (2016). The FAIR Guiding Principles for scientific data management and stewardship. *Sci. Data*3:160018 doi: 10.1038/sdata.2016.18

¹ F.A.I.R. https://static1.squarespace.com/static/5d3799de845604000199cd24/t/5da9f4479ecab221ce848fb2/1571419335217/CARE+Principles_One+Paggers+FINAL_Oct_17_2019.pdf

² C.A.R.E. https://static1.squarespace.com/static/5d3799de845604000199cd24/t/5da9f4479ecab221ce848fb2/1571419335217/CARE+Principles_One+Paggers+FINAL_Oct_17_2019.pdf

Data Reuse: Isn't Only a Data and Technology Challenge

Difficulties Accessing, Analyzing, and Integrating Data



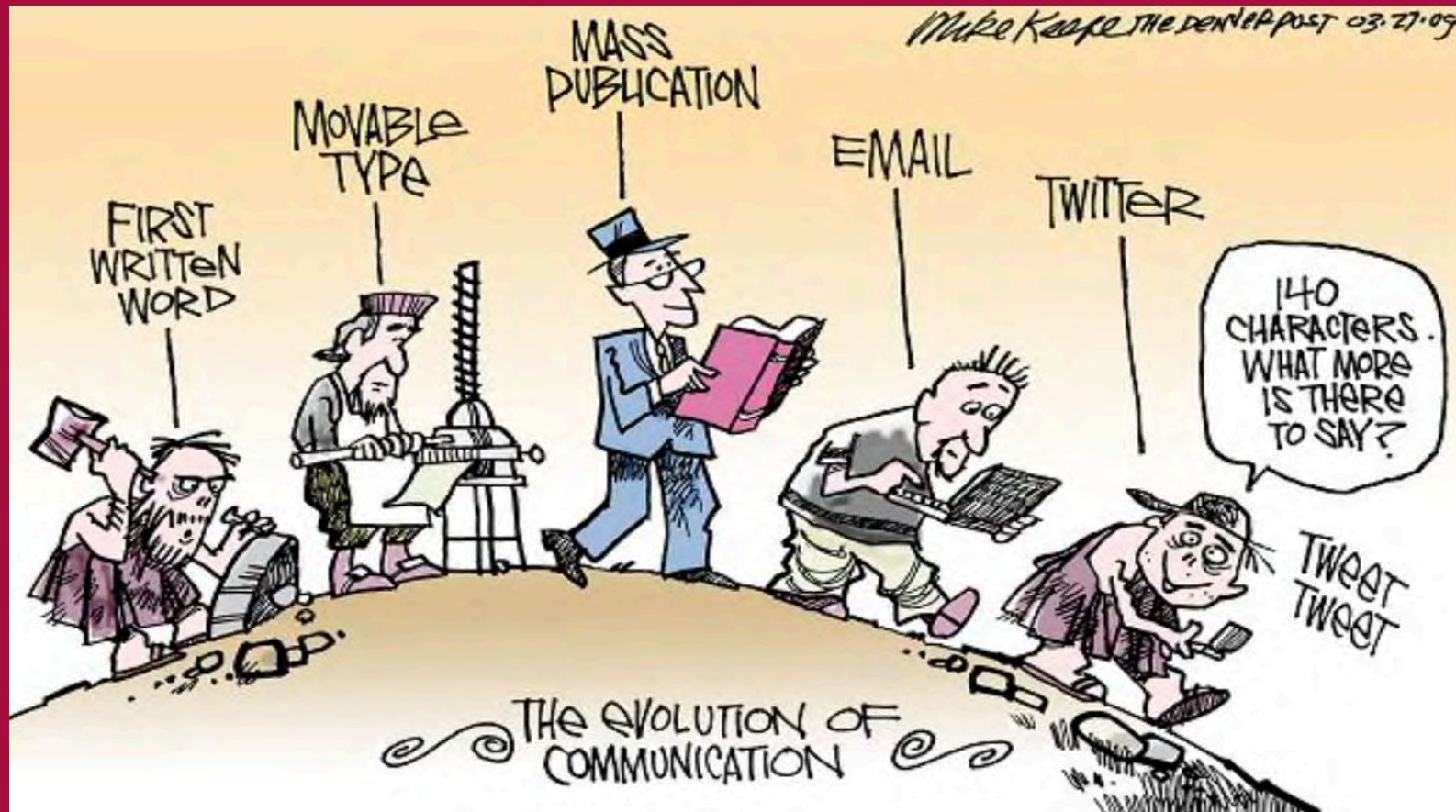
Data Reuse: Isn't Only a Data and Technology Challenge

Difficulties Accessing, Analyzing, and Integrating Data



Data Reuse: Isn't Only a Data and Technology Challenge

Communication

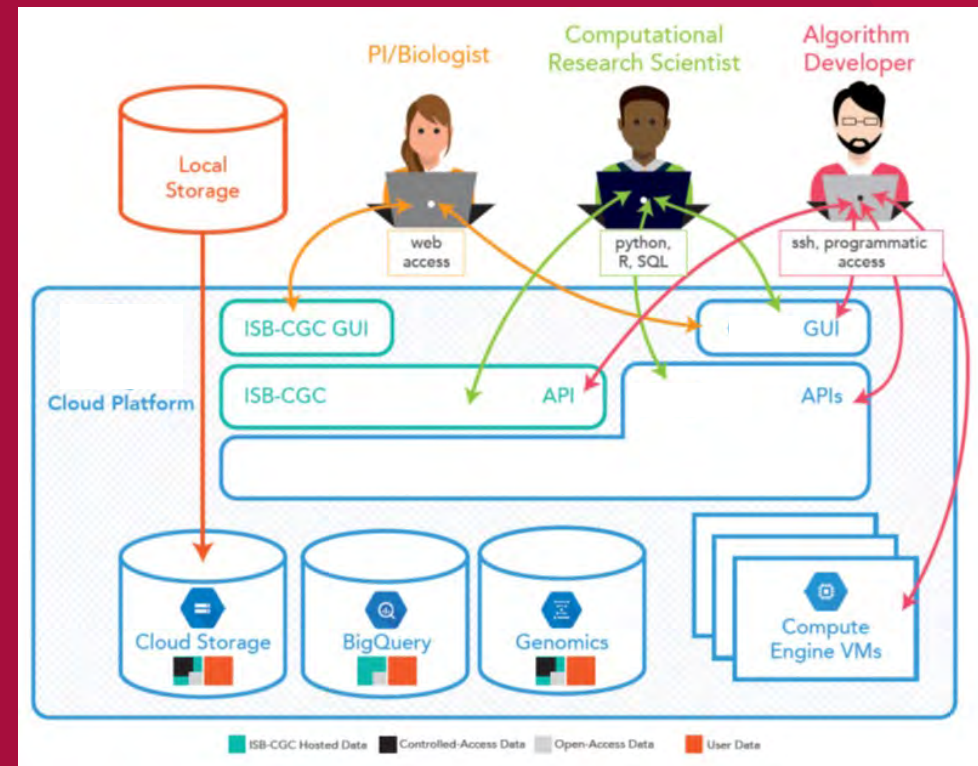


Data Reuse: Isn't Only a Data and Technology Challenge

Multidisciplinary Teams with Diverse Expertise and Resources

Biology/Social/Psychology Researcher

- select a data subset based on clinical, molecular, clinical characteristics
- explore all data for a specific pathways or models
- compare one cohort to another
- upload a small private dataset to analyze in conjunction with existing dataset



(Courtesy: Adapted from A. Kerlavage, CBIIT-NCI-NIH)

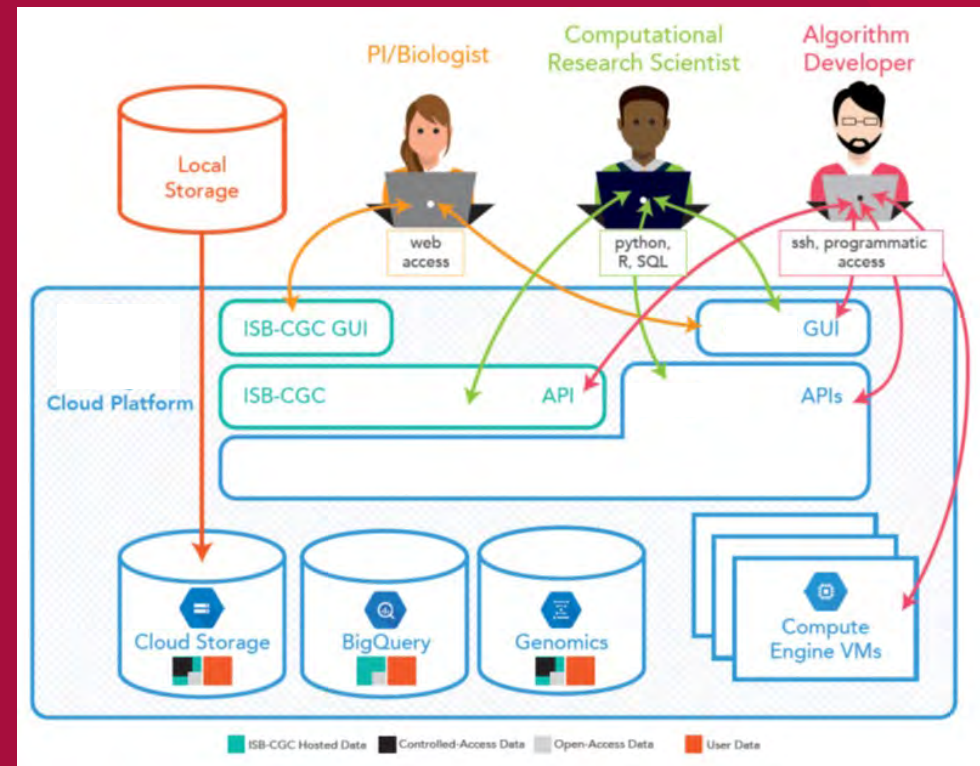
Data Reuse: Isn't Only a Data and Technology Challenge

Multidisciplinary Teams with Diverse Expertise and Resources

Biology/Social/Psychology Researcher

Computational Scientist

- interactive data exploration
- use R or Python to perform custom analyses
- develop new tools
- share new tools
- publish new tools (including interactive)
- develop/customize pipelines



(Courtesy: Adapted from A. Kerlavage, CBIIT-NCI-NIH)

Data Reuse: Isn't Only a Data and Technology Challenge

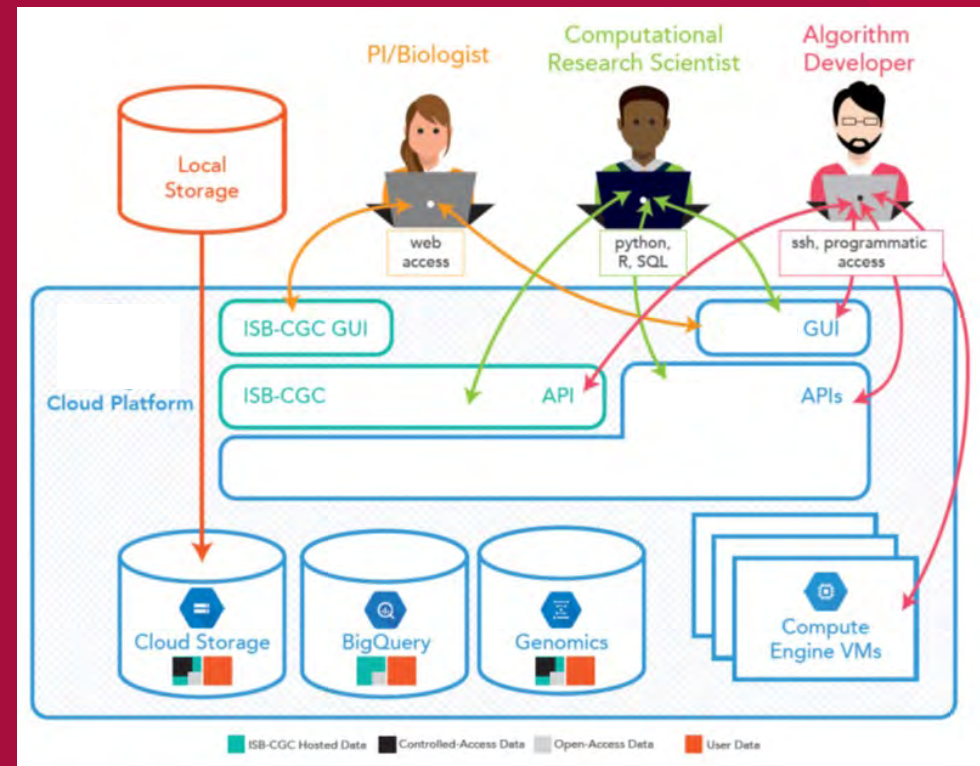
Multidisciplinary Teams with Diverse Expertise and Resources

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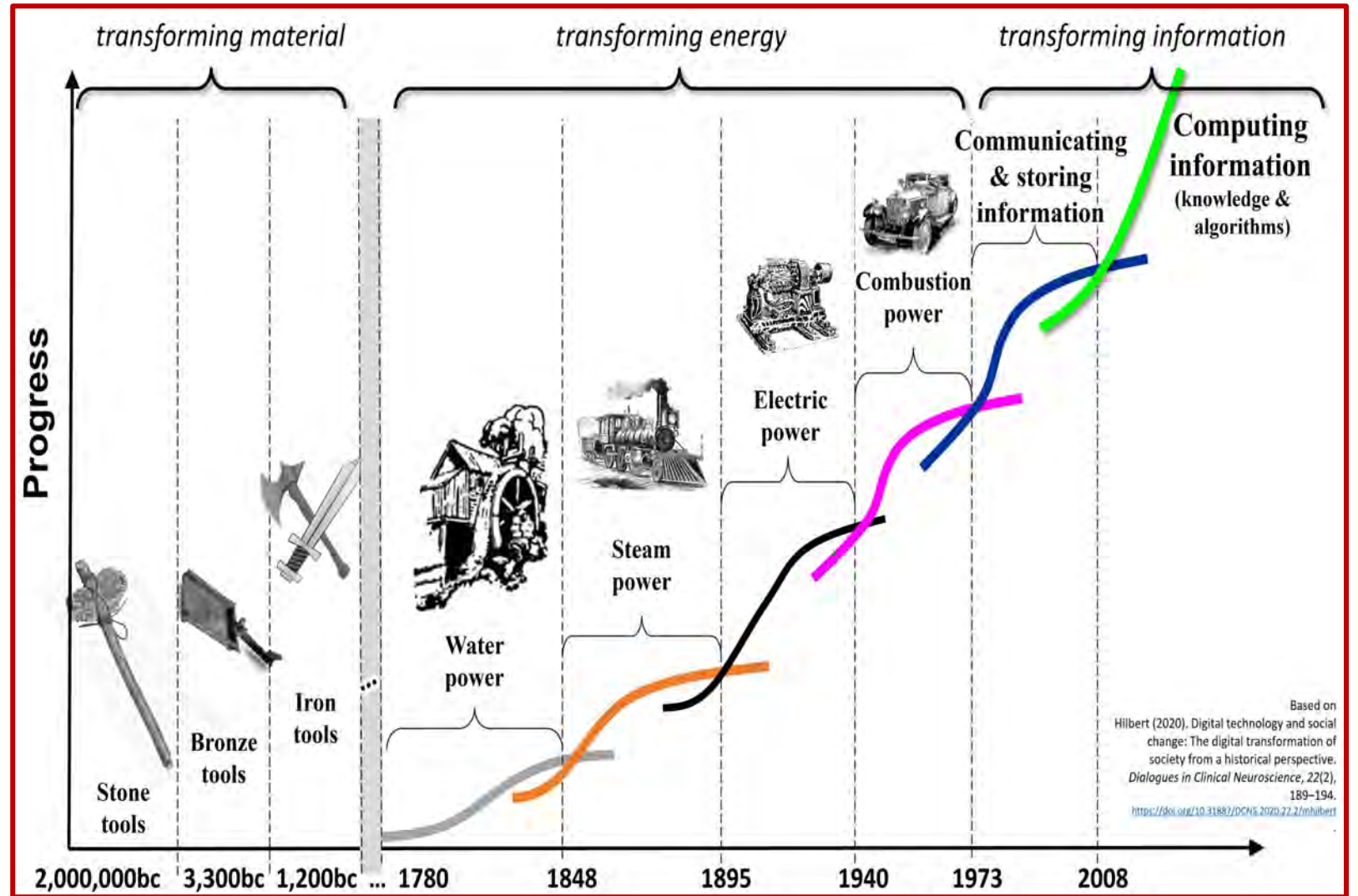
Algorithm Developer

- test new algorithm on hundreds or thousands of data files
- run novel image segmentation method across whole-slide images



(Courtesy: Adapted from A. Kerlavage, CBIIT-NCI-NIH)

INNOVATION AND REVOLUTION

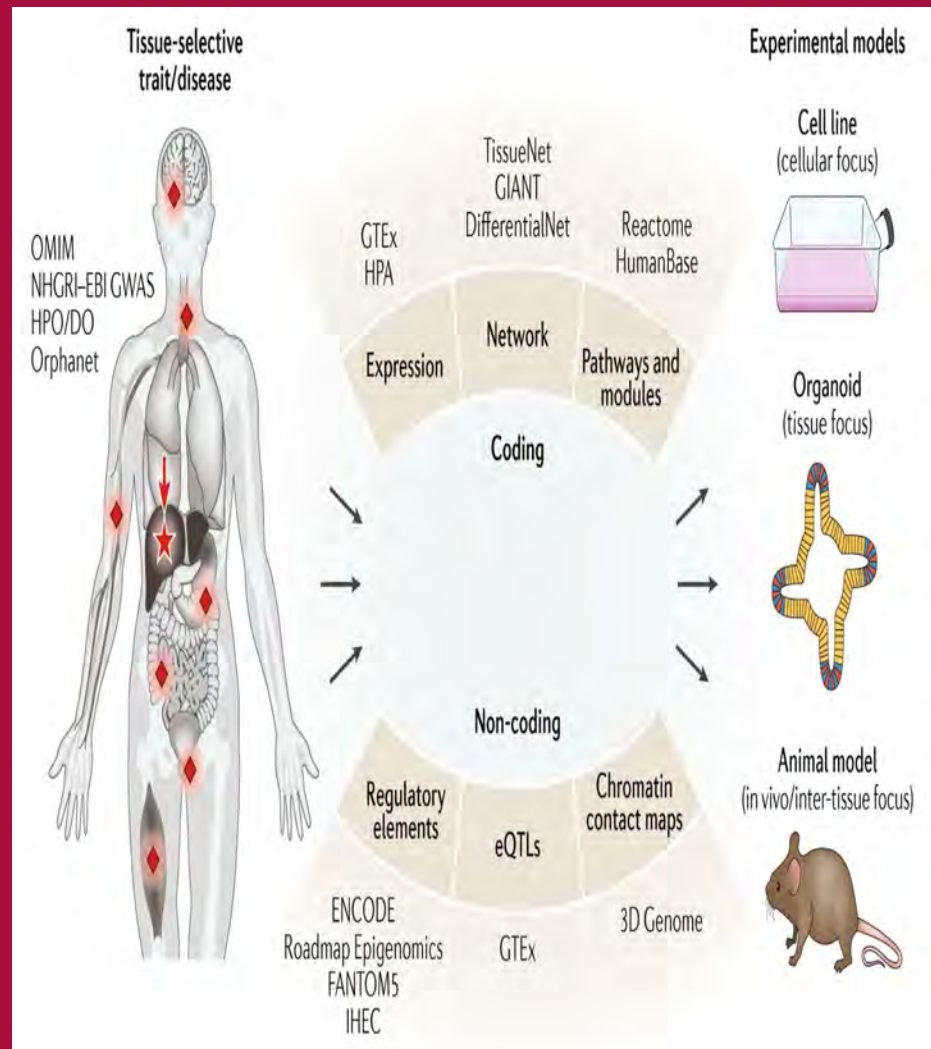


The Data Revolution



- Research is now a *data intensive enterprises*
- *Rapidly changing* scale
- Technology, *data computing & information technology (IT)* are *pervasive* in the *lab, clinics, and homes*

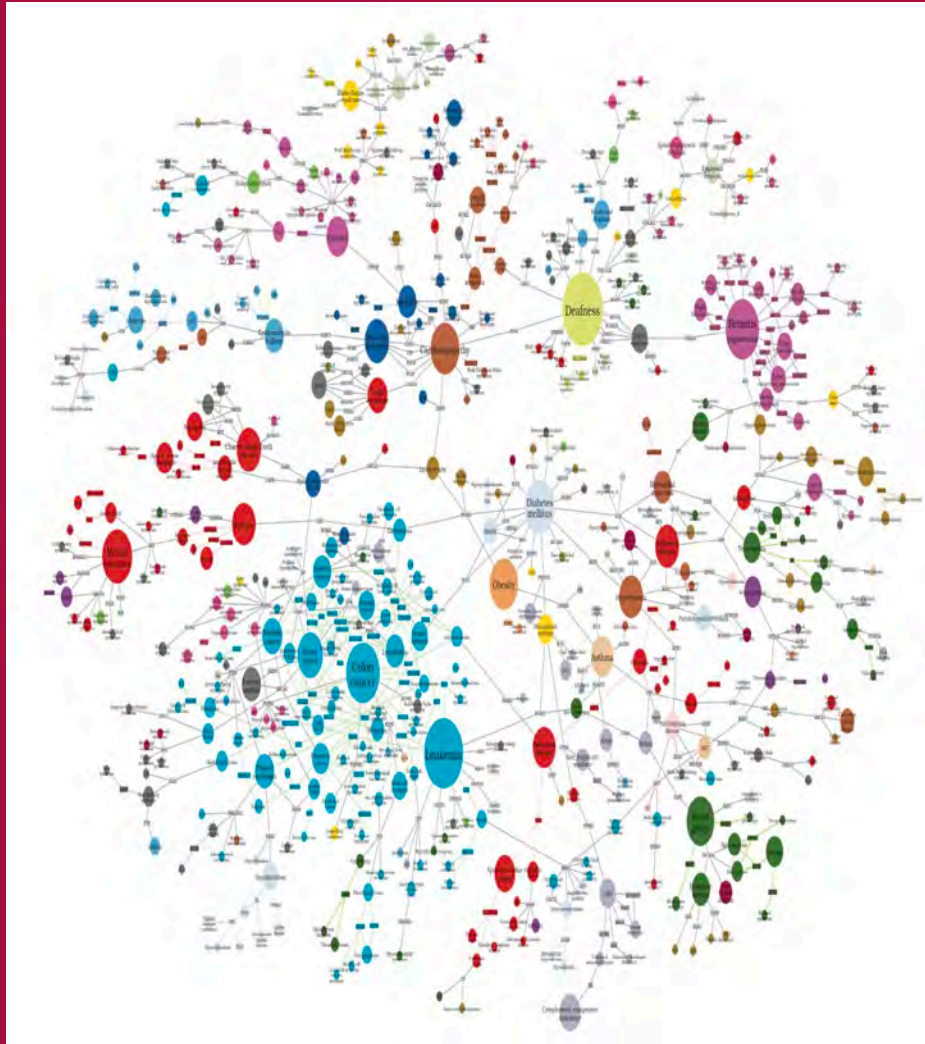
The Data Revolution



- *Changing functional roles of genes across tissues*
- *Relationships among diseases*
- *Relationships of behavior and health*

Hekselman, I. and Yeger-Lotem, E. (2020). *Nature Reviews Genetics*, (21) 137-150.
<https://doi.org/10.1038/s41576-019-0200-9>

The Data Revolution



- *Changing functional roles of genes across tissues*
- *Relationships among diseases*
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Goh, K., Cusick, ME, Valle, D., Childs, B., Vidal, M., and Barabási, A-L.

PNAS May 22, 2007 104 (21) 8685-8690; <https://doi.org/10.1073/pnas.0701361104>



The Data Revolution

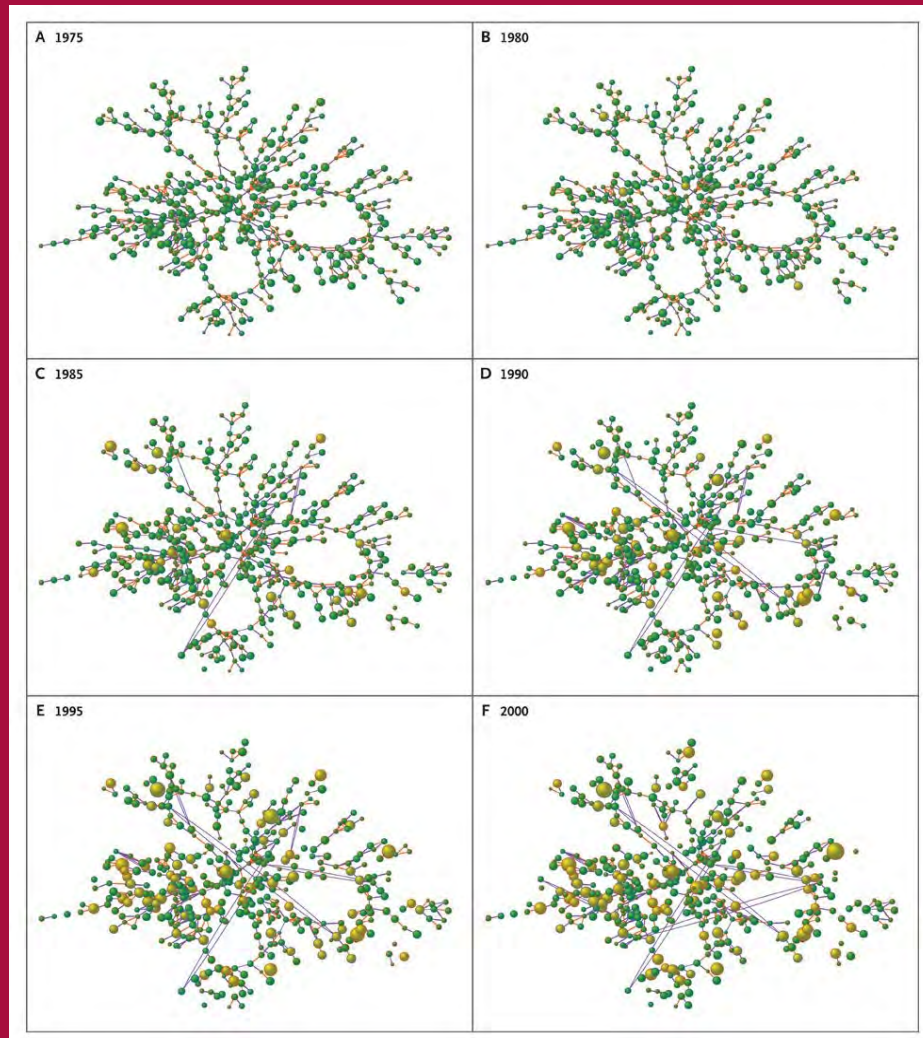


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Goh, K., Cusick, ME, Valle, D., Childs, B., Vidal, M., and Barabási, A-L.

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The Data Revolution



- *Changing functional roles of genes across tissues*
- *Relationships among diseases*
- *Relationships of behavior and health*

Christakis NA, Fowler JH. N Engl J Med 2007;357:370-379

THE BIG DATA
REVOLUTION

FiveThirtyEight q abc NEWS

Politics Sports **Science** Podcasts Video Interactives

Science Isn't Broken

It's just a hell of a lot harder than we give it credit for.

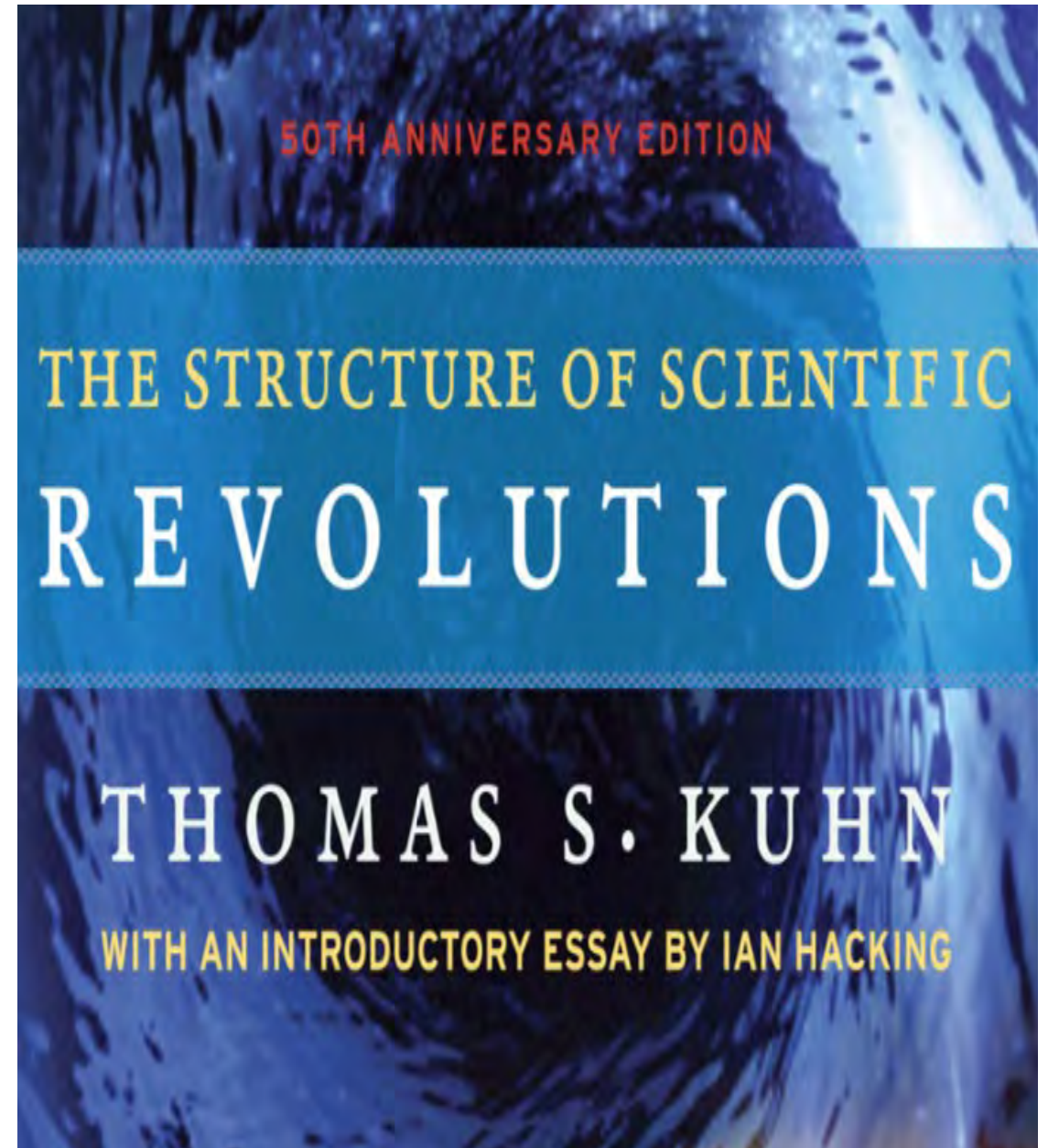
By [Christie Schwanden](#)
Graphics by [Ritchie King](#)
Filed under [Scientific Method](#)
Published Aug. 19, 2015



ILLUSTRATION BY SHOUT



The Paradigm Shift



The Paradigm Shift

The
Economist

JANUARY 14TH-20TH 2017

Trump v the spooks

The stain of Guantánamo

Pop stars and patronage in Congo

Inflation's welcome return

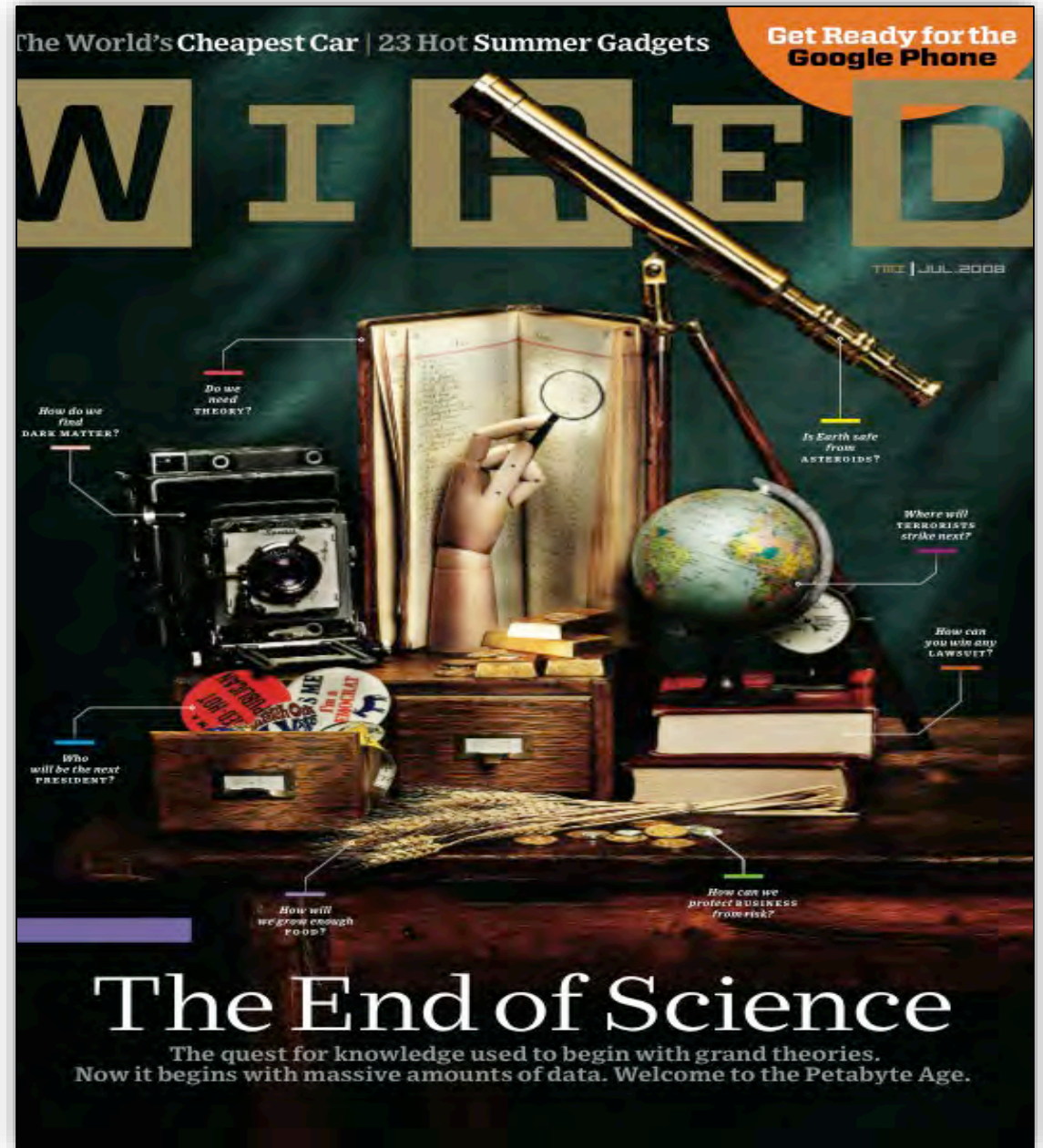
Lifelong learning

How to survive in the age
of automation

A SPECIAL REPORT



The Paradigm Shift



Hypothesis Confirmation TO The Paradigm Shift Hypothesis Generation

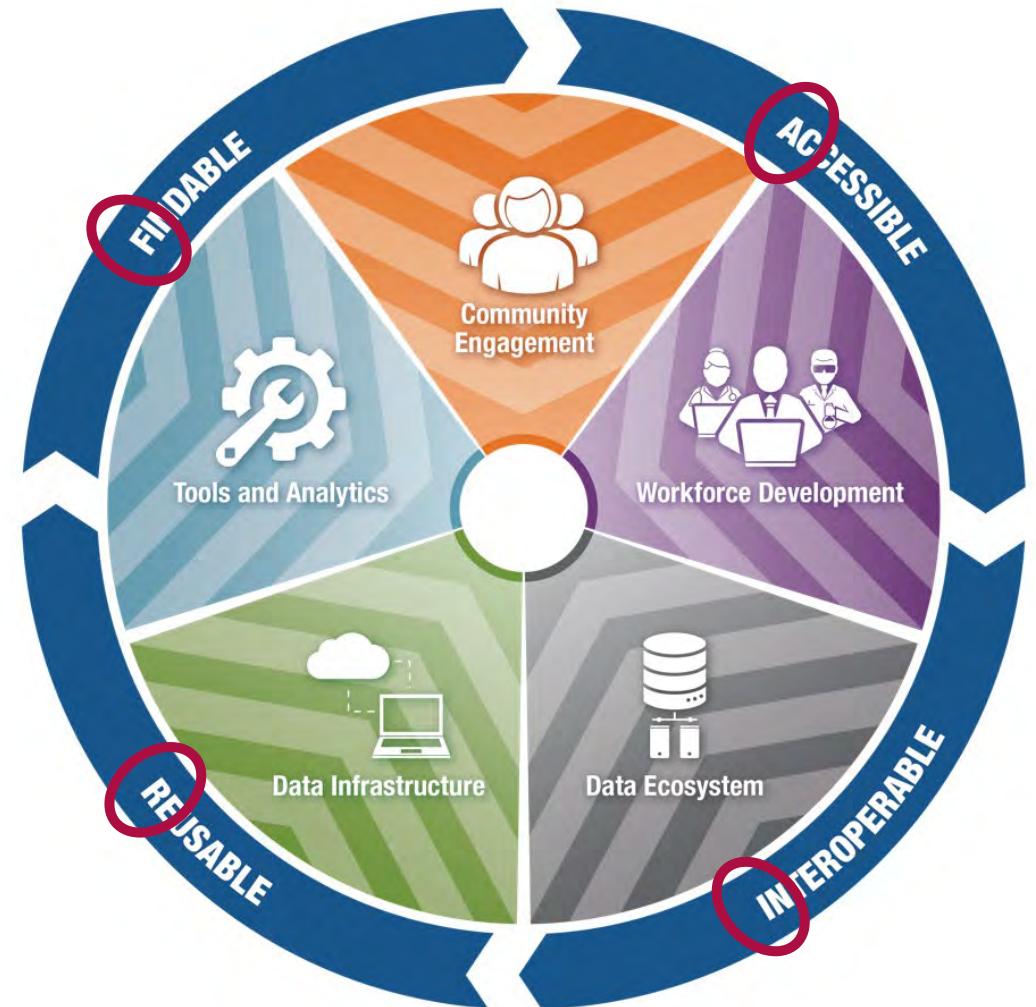


NIH Strategic Plan for Data Science (2018)

**VISION: A modernized, integrated,
and F.A.I.R. biomedical data
ecosystem**



Data Ecosystem Approach



Ethical, Economic, Legal, Social Implications (EELSI)

- Nature vs Nurture
 - Privacy and Confidentiality
- Research and other People Protections
 - Informed consent
- Risk Assessment/Decision-making
 - Benefits and Harms
 - Predictive/Prognostic Screening/Testing
 - Intellectual Property
- Dual Uses (*Forensics/Surveillance*)

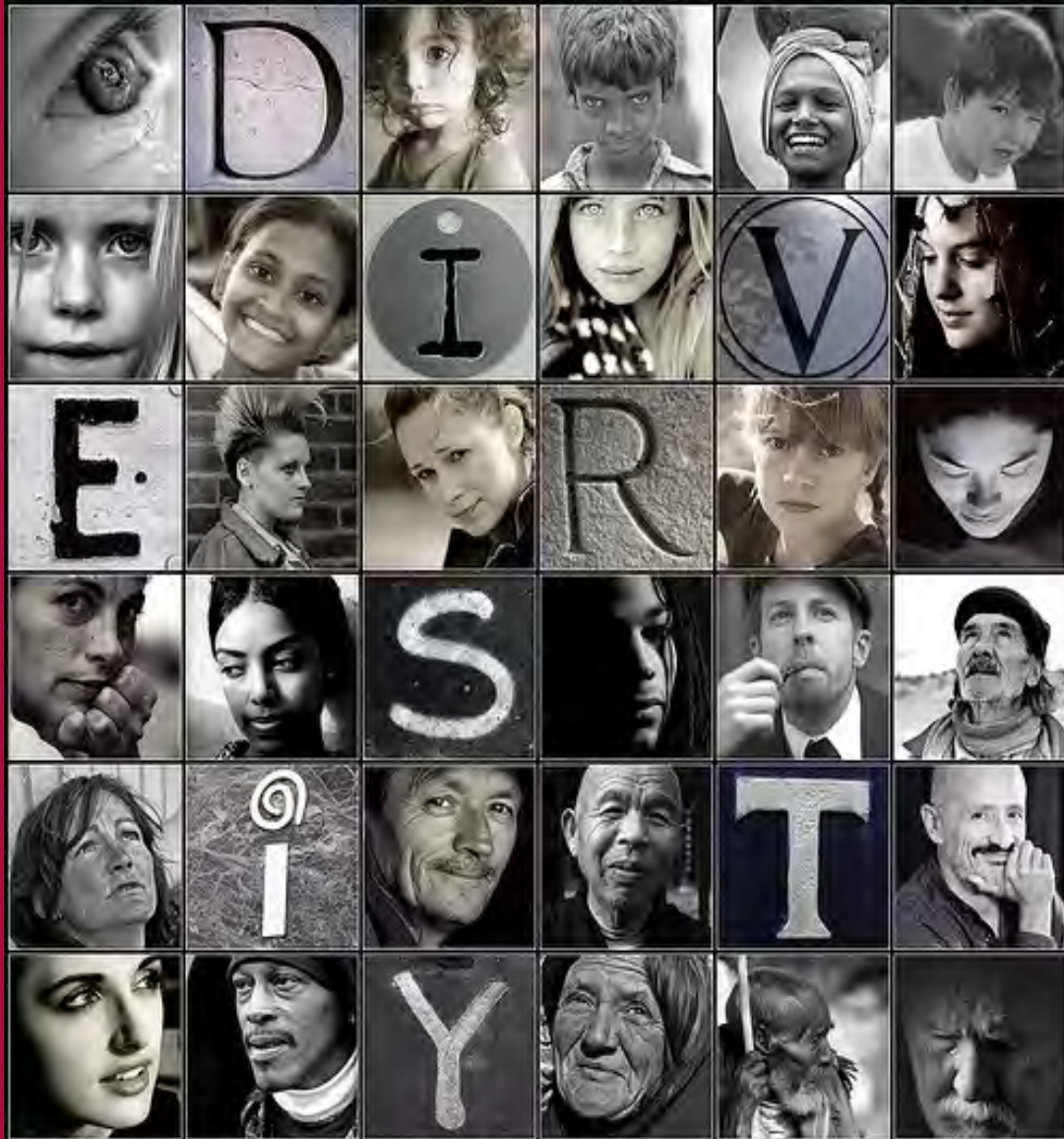


Equity and Disparity Issues

- **Data and Information are not Neutral**
 - **Stigma:** *People/Groups/Communities/Phenotypes*
 - **Inclusion:** *Basic/Applied/Clinical Trial Research*
 - **Diversity and Workforce Issues**
 - **Citizen Science and Community Engagement**
 - **Inclusion, Equity, and The Haves and Have Nots**

Data





If not designed
to address equity,
research (and data)
will perpetuate
disparities
and injustices

- me

