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Best Practices to Solve Data Science Problems that Slow Down Scientific Research

Ari E. Berman, Ph.D. & Simon Twigger, Ph.D.



Introductions and outline



Ari E. Berman, Ph.D., CEO, BioTeam, Inc.

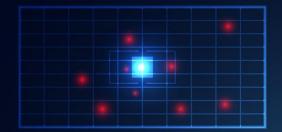
- Neuroscientist/Molecular Biologist/Computational Biologist
- 30 years building HPC for science
- BioTeam for 12 years Bio-IT World for 12 years



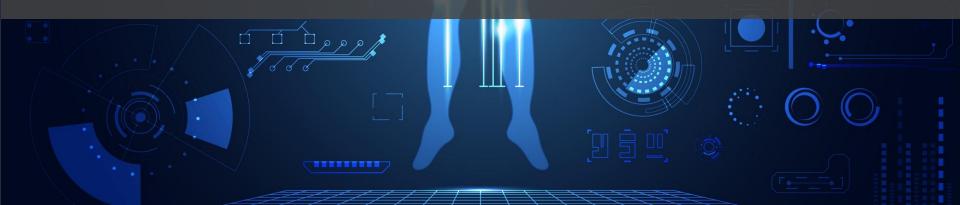
Simon Twigger, Ph.D., Principal Consultant, BioTeam, Inc.

- Biochemist then Bioinformatics, Genomics, Proteomics, Clinical informatics.
- 25+ years building software and systems for the life sciences
- BioTeam for 11 years





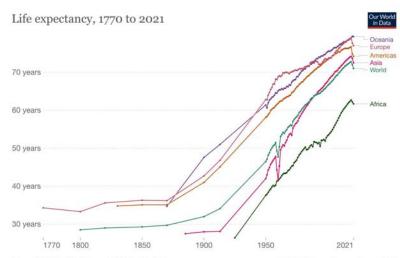
The Big Picture: Why are we all here?



Scientific Discovery Drives Modern Medicine

Science: the systematic study of the structure and behavior of the physical and natural world through observation and experiment

- Human lifespan hit a maximum in 2019 (76.7 years US)
- First major inflection in 1865 Germ Theory, antiseptics in surgery, washing hands (doubled lifespans)
- Vaccinations, epidemiology, anesthesia, antibiotics are others
- All driven by basic life sciences research and applied to human health



Source: UN WPP (2022); Zijdeman et al. (2015); Riley (2005) OurWorldinData.org/life-expectancy • CC BY Note: Shown is the 'period life expectancy'. This is the average number of years a newborn would live if age-specific mortality rates in the current year were to start the same throughout its life.

Long Lifespan and Healthspan Now Out of Sync

- Healthspan the percentage of life that one is considered healthy
- "Healthy" means different things to different people
- Average age of health decline in US is 63yo vs. 76.7-year lifespans
- Live nearly 20% of our lives unhealthy – with lower quality of life
- Resulted in soaring healthcare costs and increased burden on medical and economic systems as the population ages poorly

| Disease | Deaths per year | Age of 1 st occurrence |
|--|-----------------|-----------------------------------|
| Heart Disease | 610,000 | 65 |
| Lung cancer | 158,060 | 60 |
| Chronic obstructive pulmonary disease (COPD) | 147,101 | 45 |
| Stroke | 140,000 | 65 |
| Lower respiratory infections | 131,800 | 75 |
| Alzheimer's disease | 93,541 | 65 |
| Type 2 diabetes | 69,071 | 54 |
| Colorectal cancers | 50,260 | 70 |
| Breast cancer | 40,000 | 62 |
| Prostate cancer | 25,000 | 66 |

Table 1: Top ten causes of death in the US and their average or median age of first occurrence.

Medical Science Needs a New Focus

- Historically, medicine has focused on reducing risk of death as an outcome
- Medical science has advanced to the point where that focus isn't as relevant anymore
- Need new breakthroughs and renewed focus on being healthy for longer, vs being alive longer (likely linked)
- Modern diagnostic and computational methods have already started driving towards this reality



Drive Towards Precision Medicine is Data Intensive

- Move away from the "one-size-fits-all" approach to health care delivery and to instead tailor treatment and prevention strategies to people's unique characteristics, including environment, lifestyle, and biology
- Medical decisions, practices, interventions and/or products being tailored to the individual patient based on their predicted response or risk of disease
- Goal of increased Healthspan
- Foundational data initiatives like All of Us, CANDLE, TCGA, InsightRX, and many more
- Involves a large amount of data collection, modeling, and classification to pull off

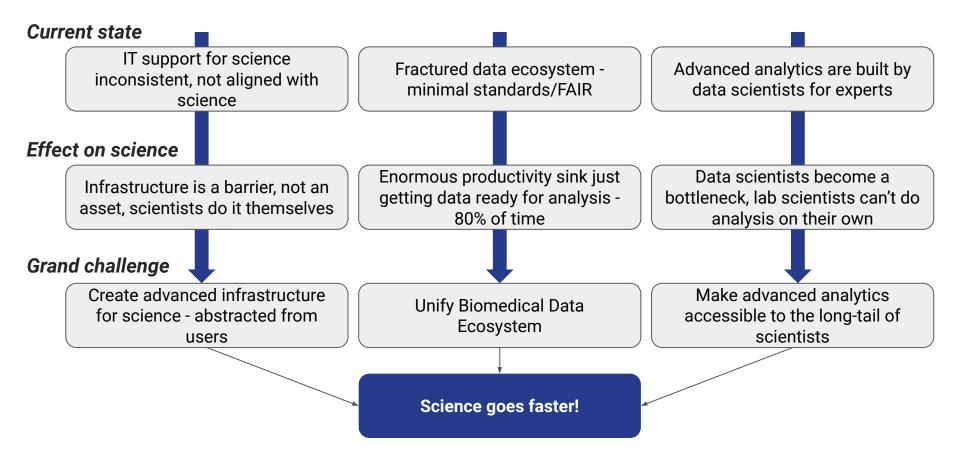


Biomedical Research Grand Challenges

Context for this workshop, driven by what we're trying to help the community do better



Grand Challenges



Infrastructure in Life Sciences and Healthcare: Scoping the problem

Data Generation: All-time high Estimated 120 ZB of total data collected to date

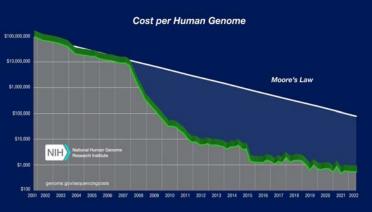
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23 ZB last year – 10GB/person/day

Laboratory and Health Diagnostics Innovation Accelerating

Rate of innovation in data generating equipment in life sciences far outpaces Moore's Law

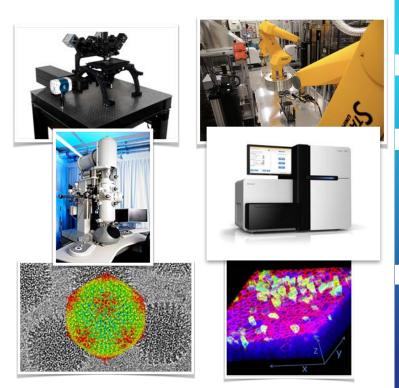
- Laboratory technology changing on the order of months
- HPC and IT tends to move on the order years – equipment lifecycles are 3-6 years
- Cloud has enabled more rapid cycling, but at increased cost and complexity
- Health diagnostics and IoT sensor data pushes amount and complexity of data

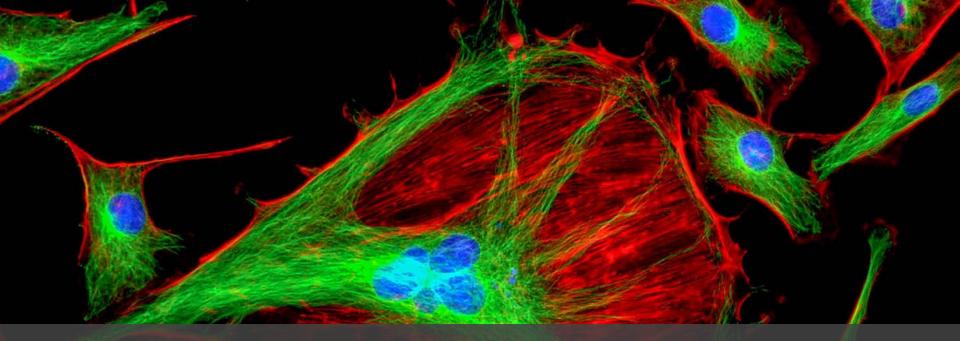




Laboratory Data Generation at an All-time High

- Sequencers were just the beginning
- Life sciences and Healthcare among the top data generators of all the sciences
- Most labs have equipment that can generate 10s TB of data/week
- Bioinformatics/Data Science have taken over biomedical analytics space
- Computational sophistication required to compete
- Clinical informatics becoming a major health diagnostics tool





Life sciences research in the 21st century: Computation as a laboratory tool



Infrastructure for Biomedical Research

Infrastructure a Critical Issue in 2024

- Big Data era led to huge data generation and now AI/ML
- Sophistication needed for data intensive science is high
- Backlog in data to be analyzed, slow to interpret due to state of data
- Stress on existing resources
- Led to a decrease in discovery and productivity



The pandemic changed the game

- Everyone went home into isolation
- Labs shut down researchers started remotely analyzing data
- On-premises HPC and compute systems ramped up usage a lot – users that wouldn't use it that often were now clamoring for access and hours on systems
- On-premises infrastructure became expensive, hard to manage remotely
- Supply chain drove up prices, slowed delivery – local IT barely maintaining status quo (still)





On-prem Compute: Increasing in Complexity



Modern Scientific Computing

- Used to be "figured out", not so simple anymore
- Explosion of Data Science, huge datasets, accelerators and co-processors (GPUs!!!!!), cloud
- AI/ML in particular
- Caused a previously simple set of decisions to become extremely complex
- Also, diversification of CPU, back-end network options, matched to use cases





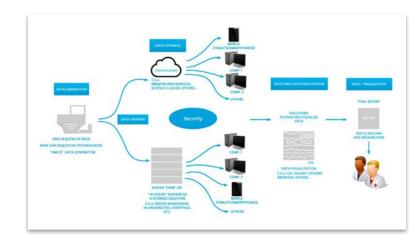
Networking Challenges



You have to move the data!

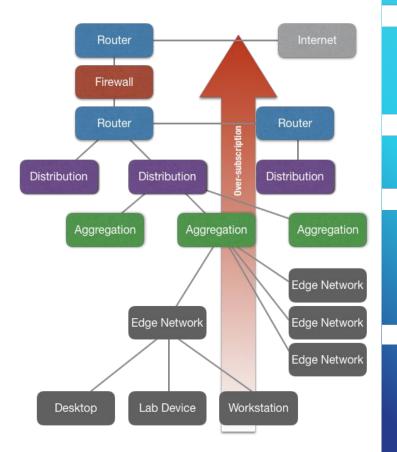
A lot of talk about moving compute to data, but you always have to move it at least once

- Laboratory equipment only able to store last few experiments
- Not designed for any analysis past initial data reduction
- Have to move it to compute storage for processing
- Many labs can generate 1PB/year or more – Non-trivial network requirements
- Data is valuable, needs to be protected, replicated, or backed up
- Data sharing is a standard requirement



Enterprise Networks

- Viewed as a cost to be controlled
- IT in general has flat budget, tight fiscal control
- Networks optimized for web/email traffic, not for large sustained data transfers
- Results in highly under- provisioned and oversubscribed network deployments
- Expertise split and siloed networking org isolated
- Really need at least 10Gb from local data storage to Cloud for data intensive science
- Security designed for risk, not science



More on Security...

- Enterprise security usually universally applied to all use cases
 - Security designed for highest risk data in network
 - Usually smallest percentage of data
- Malware in a genome file is extremely unlikely – packet scanners don't know what a BAM file is
- Slows down transfer, scans every packet for 300GB files with no useful outcome
- Takes the sledgehammer approach, then all is covered
- Seriously hampers data sharing, movement, reference datasets, etc.



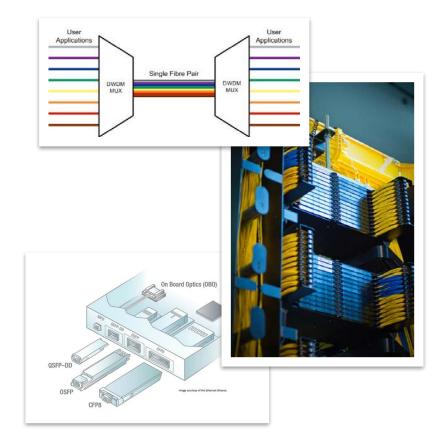
Most common high-speed network - STILL

FPA

Express

Networking: key for modern biomedical science

- Modern science requires 100Gb data speeds (1TB transfer in 1.5min*)
- Next-gen filesystems require 100Gb networking to function
- 400Gb current standard
- 600-800Gb Optical Transport Networks are out now
- 1 Tb networks in early release
- If you aren't thinking of high-speed science for your network, you are hampering the science of your org





Cloud Challenges



Cloud providers launched a BRILLIANT marketing campaign: convinced decision makers to go cloud.

People Tend to Think in Absolutes

- A solution can only be this or that
- If cloud, then ALL cloud
- Abandon things that work well, because this will be better!
- Reasons:
 - Everyone's doing it
 - It's cool so people will invest in it, support it
 - People like to talk about it a lot
- Reality:
 - Very nuanced situation, there are no absolutes, and it isn't simple



Aggressive Cloud Migration Programs were Started

- Most science organizations started planning for cloud-first or all-cloud transitions away from local infrastructure
- Cloud providers gave deep discounts and a lot of direct support during the planning and the migrations to cloud
- Stopped planning on local infrastructure: storage, HPC, even networking
- All future planning was for cloud-based architectures
- We've seen this movie before...



A Look Back: The Last Wave of Cloud Migrations

- 2008 2014: we helped several orgs migrate to the cloud and close their datacenters (AWS)
- The draw: cheap, easier to manage, endless supply of compute power, less staff needed
 - Better shared access for external collaborations
 - Better access to public datasets
- The reality:
 - 10-50x the cost of operating datacenters
 - Cloud couldn't replace all local infrastructure
 - Required specialized skillsets in IT, harder to use
 - Didn't meet scientists' requirements
- The Result: Cloud sobriety massive pullback

Ah, what short memories we have



Now it's Happening Again...

- ...for slightly different reasons this time:
 - There are more cloud providers, way more sophisticated, clouds are largely designed to handle enterprise needs now
 - Competition has forced huge innovation in cloud services
 - There are aspects of cloud that you can't reproduce locally
 - Deep learning applications and specialized hardware/services are huge draws
 - There's so much data now, that storing it locally is non-trivial
 - Promise of it being somehow cheaper to operate
- Flexibility of cloud architectures combined with supply chain issues for local hardware made moving that direction more attractive

Also: Cloud business model locks your data/operations into their platforms

- The most successful ransom scheme in history
- Free to put data in, charged to get it out
- Save money by using proprietary (and very useful) services like:
 - Serverless
 - Bulk operations services
 - Specific analytics services
- Locks you into using their services can't reproduce them yourself (e.g. – Parler)



Advantages of the Cloud

- Large capacity, automatic upgrades, reliability
- Virtual orchestration and serverless technologies
 - Can architect very sophisticated environments more easily
- Containerization and portability of workloads
- Share data more easily, and in more sophisticated ways
- Shared standards in architecture, great way to prototype
- Availability of accelerators, like GPUs
 - Though, they aren't so available, really
- Specialized services that can speed up deployments



Relevant Questions: To Cloud or not to Cloud?

- Can you do real HPC in the cloud?
 - Yes, now you can, but depends on what kind you need
- Can you create a secure environment?
 - Absolutely, but it's yours to mess up. The models are different than on-prem
- Can scientists use it out of the box?
 - Absolutely not: requires set up of services, user interfaces, platforms
 - Even the sophisticated users need to architect their environments
 - Some things are there out of the box, but they're basic
- Can we use it for storage?
 - Definitely: but storage in the cloud is complex, hard to price, and easy to overdo
 - Once your data is in the cloud, it costs money to get it out again



So, Why not All Cloud?

- Fundamental mismatch between cloud business model and long-term research goals
- These are private, for-profit companies, not public utilities. They offer services that they can change at any point (and do!)
- Shortest full scientific study, 5-10 years. Some 100s of years
- Clouds don't even disclose time period if they shut down to get your data back this should concern you
- Hybrid computing model preserves data ownership source of truth kept locally
 - Copy data to the cloud for analysis (ingress no charge)
 - Only copy results of analyses back delete source data (minimize data egress fees)
 - Still not solved!!



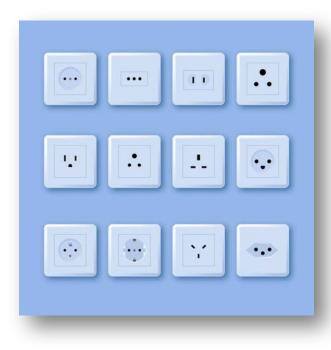
Let's Talk About Data



How are we doing with FAIR so far? Not great—limited pockets of excellence

What's blocking FAIR?

- Short answer: people, not technology
- Long answer—it's complicated:
 - 1. It's really hard to do, extremely complex—lots of historical data—but it can be done
 - 2. Lack of unified data standards in the field
 - 3. Lots of distraction, lack of sophistication, lack of tools and training, lack of accessibility of solutions
 - 4. No incentive to make the effort—all incentives are individual (i.e., NIH grants), this is a community effort (some EU efforts towards open data)
 - 5. It pays to do your own thing—your funding gets diluted if you join with groups of collaborators
 - 6. No clear vision, leadership, or directives from funding organizations to get there



Lack of unified data standards

- Biomedicine and life sciences research lack unified data standards
 - Very difficult to combine data from multiple sources for deeper analysis
- Clinical information largely contained in electronic health records (EHR) systems
 - Not designed for analytics, designed for compliance
 - Different systems store and make data available differently—far from FAIR
 - Deidentifying data is difficult and loses key information, while improving access
- Historical data locked in publications
- Each domain and each project has its own format/standards







HL7 FHIR

MIAME and ArrayExpress

OHDSI OBSERVATIONAL HEALTH DATA SCIENCES AND INVOMMATICS

Collaborate. Innovate. Accelerate.



THE NATIONAL CENTER FOR BIOMEDICAL ONTOLOGY



Data platforms—they're everywhere!

- Another buzz-loaded space:
 - Data Lakes, Oceans, Fogs, Swamps, Islands, Universe, Warehouse, Commons, Ecosystem, Mesh, Fabric...
- Truth: just building more silos of excellence—and not accessible to long tail of scientists (laboratory)
- Need a diversity of tools and approaches, but they aren't cross-compatible
- Lack of data standards and interoperability lose the power of the data in collaboration

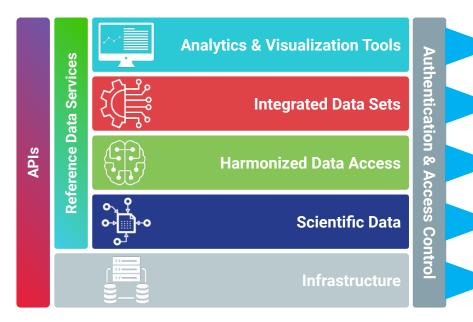


Data value in life sciences: key for digital transformation

- In general—no understanding of scientific data value
 - Investment—how much is data worth, what did it cost to generate
 - Scientific value—will this data ever be reused, how long do we keep it, what's the impact of each unit of data?
- Without this understanding, everything is high value so we just keep everything
- Infinitely expand storage—hoarding
- Can't prioritize investments in data that are aligned with strategy
- FAIR also doesn't contemplate data quality



Scalable data structure strategy



- Data Analytics, Discovery, Development, Safety, Trials, Manufacturing Interfaces
- Data Sharing, Data Commons, Collaboration
- Data Harmonization, Hygiene, Governance

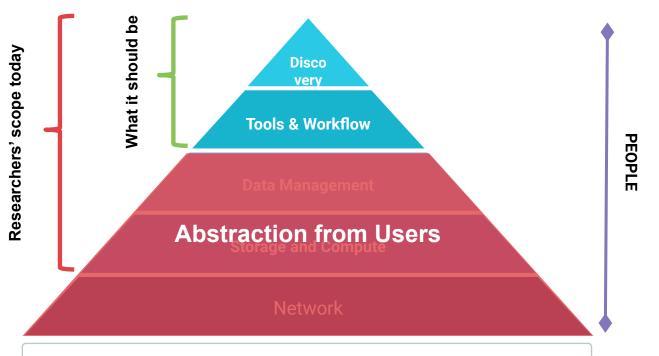
Data Standards (FAIR), Value, Lifecycle Management, Citizenship

Next-generation architectures to support science



Making Science Accessible

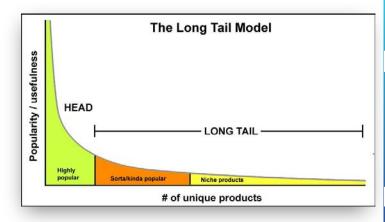
Maslow's hierarchy of IT needs



Research IT: Integrated spectrum of infrastructure, software, services and support, focused on science

Accessible Advanced Analytics

- Most life sciences researchers and clinicians lack computational sophistication (can barely print and use email). Systems need to be designed to be accessible by that population.
- Most infrastructure and analytics platforms target people who have a lot of expertise (i.e., know APIs, how to code, understand how to use HPC).
- This creates a barrier for the long tail of science, and a bottleneck for efficient discovery.
- Funding organizations need to incentivize and require data standards.
- Design systems that non-sophisticated users can use – (e.g. – Jupyter Notebooks = not accessible)

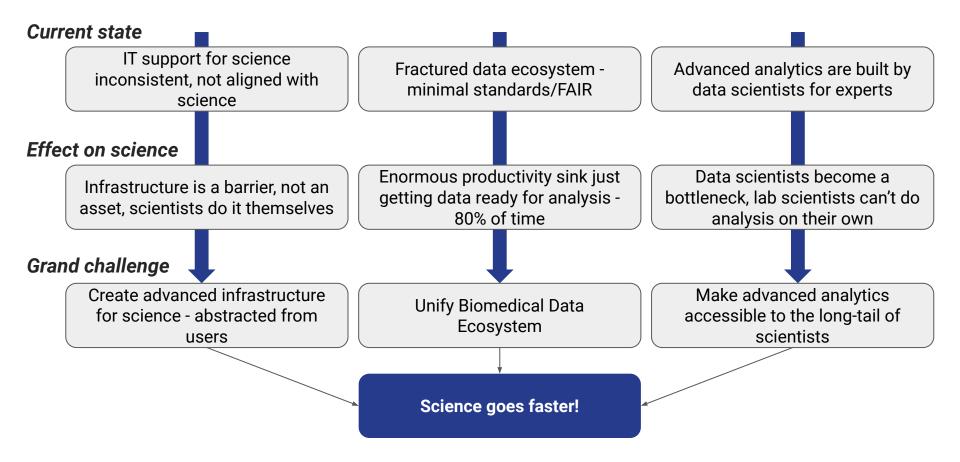


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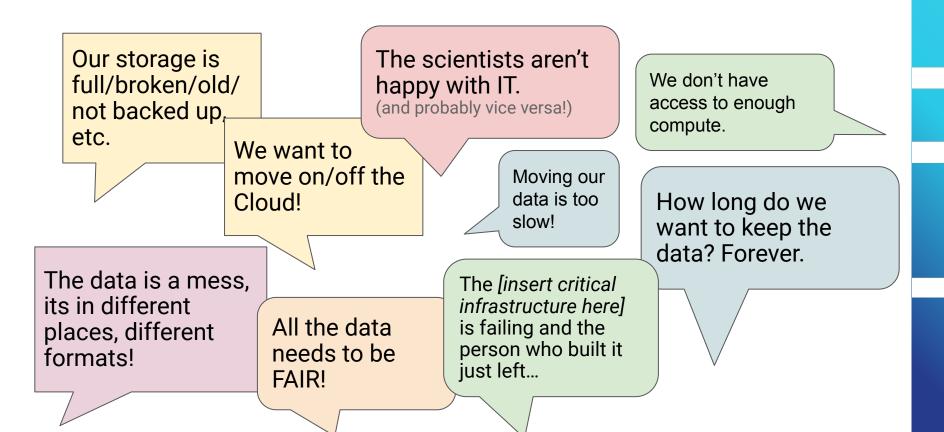
Practical Tools and Approaches

aka 'unleashing the possibilities'

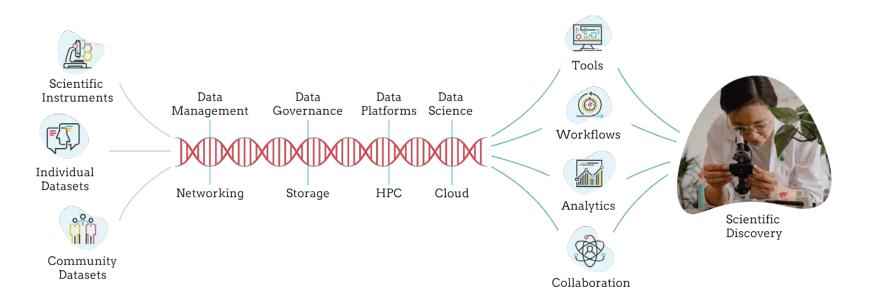
Grand Challenges



To address the challenges, something needs to change!



It gets quite complicated...



There are a lot of interconnected pieces, each of which is complex in its own right, all of which are created, managed, and used by people...

Given the complexities of tech, people, etc.

How do you:

- Find out about common goals?
- Identify common ground?
- Understand the complexities?
- Help people work together?
- Communicate effectively?
- Figure out what's really going on?
- Know what to change?



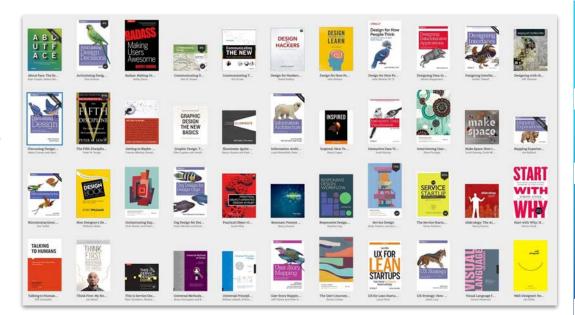
Design

Milwaukee Art Museum, Santiago Calatrava "Everyone designs who devises courses of action aimed at changing existing situations into desired ones."

> Herbert A. Simon Nobel prize winner for economics, 1978

What sort of 'design' is needed in BioIT?

- Software design
 - Interface design for web sites and tools
 - Responsive design for web sites and tools
 - **Object-oriented design** for software
- Information design (Information architecture)
 documents, websites, etc.
- **Graphic design** for ppts, documents, posters, graphics, etc.
- System design networks, compute, storage, etc.
- **Organizational design** hiring, org charts, reporting structures
- Service design for ourselves, for our clients
- Learning design for training, educating
- Human-centered design as an overall theme
 - User experience, UX
- Articulating/communicating design to explain why this rather than that...?

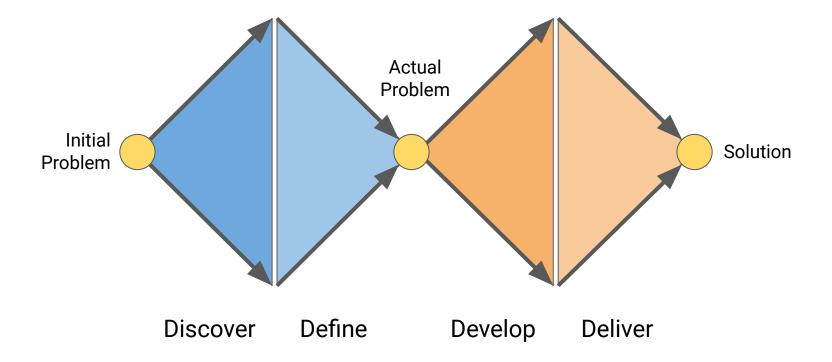


How can design help us?

Design has a rich body of knowledge, established tools to help us understand what is going on, and established processes that we can follow to figure out how to solve the problems we find.

Given that we're going to have to create all these things anyway, we might as well design them intentionally and leverage the tools and approaches that the design community has created.

Specific phases, specific activities



Double Diamond design process - popularized by the British Design Council in 2005

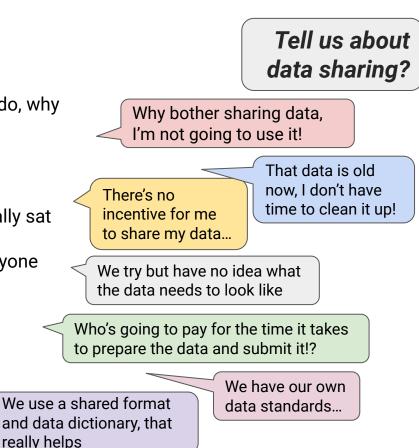
What happens at each stage?

| | Discover | Define | Develop | Deliver |
|------------|---|---|---|--|
| Goal | Expand options, gather as much information about the problem and situation | Group, aggregate, narrow down to a solid definition of the key problem at hand | Explore and expand the potential approaches to the problem | Implement the most effective option |
| Activities | Interviews, reading and research, workshops and group discussions, use cases, personas, user journeys | Synthesize information, create systems maps, identify potential intervention points | Whiteboarding, discussions with stakeholders, prototypes, mockups, etc. | Creation and delivery of the selected solution |

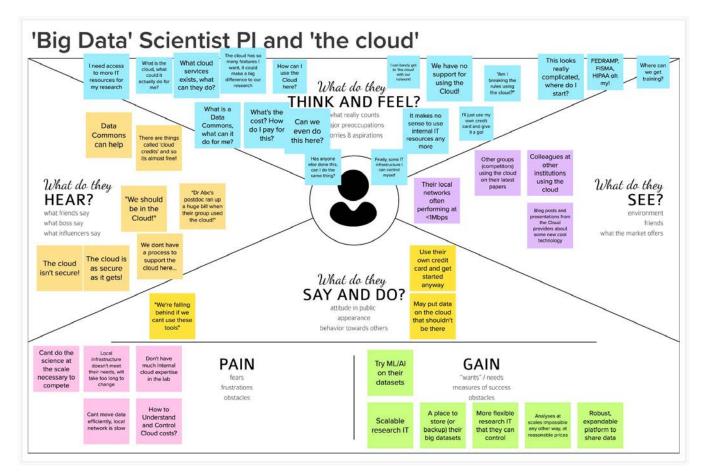
Interviews (discussions, chats, etc)

Never underestimate the power of talking to people!

- Do your research who are they, what do they do, why are they relevant to the problem at hand
- Have a plan for what you want to ask
- Be prepared!
 - It may be the first time anyone has actually sat down and listened to them...
- Take good notes, record the discussion if everyone agrees.
- Afterwards, review your notes for
 - Things that are working
 - Things that are not working
 - Existing workarounds
 - $\circ \quad \text{Suggestions and ideas}$



Get inside their head with Empathy Maps



Document key Use Cases

Staff Researcher

Support to use the cloud effectively



As a PI, I want training and guidance to move to the cloud in order to be able to effectively utilize the cloud to support my research.

Core Motivations

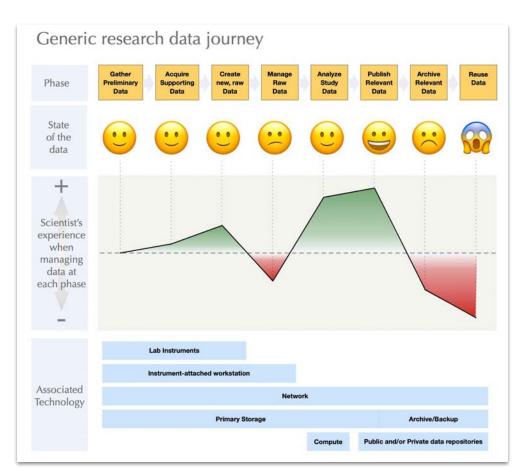
- Many PIs are interested in using the cloud in their work
- However, there are many unknowns: how to design a cloud system, how to move existing workflows, the budgetary implications, how to move data to and from the cloud, how the Org can help, etc.
- These are all barriers to more widespread adoption of the cloud

Potential Data Sources

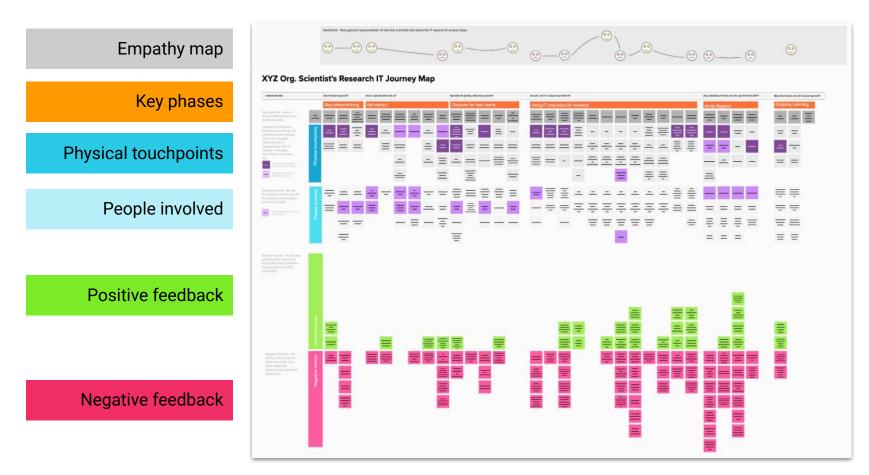
- Amazon Web Services
- Microsoft Azure
- Google Cloud Platform
- Internal cloud team

Create Journey Maps of processes

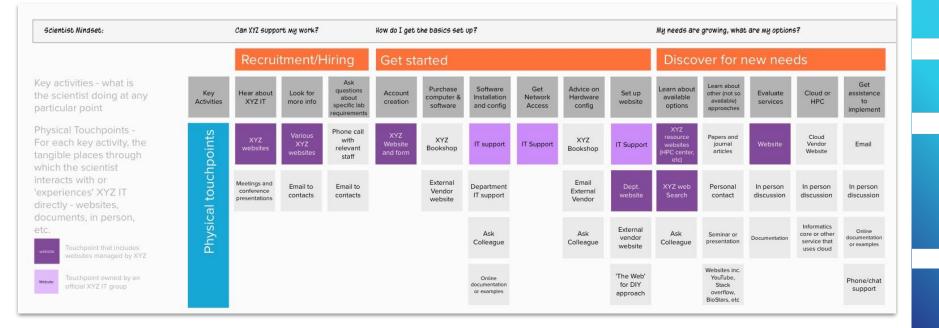
- Map out key processes
- Identify pain points
- Communicate to stakeholders



In-depth journey / service maps

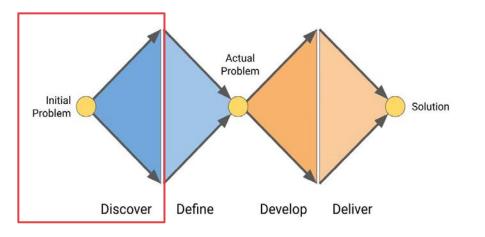


In-depth journey maps



Design methods help us collect and communicate information





We now know about

- The People
- Their Use Cases
- Their Processes
- Their pain points

But what's really going on?

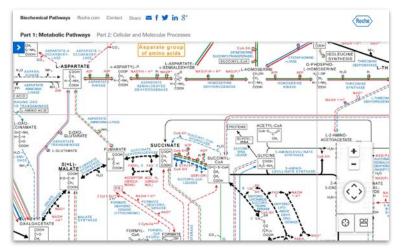


Systems

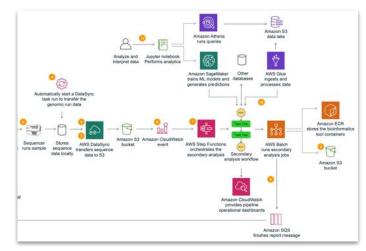
COVID19 systems map by Alex Vipond https://kumu.kumu.io/covid-19

What do we mean by a system?

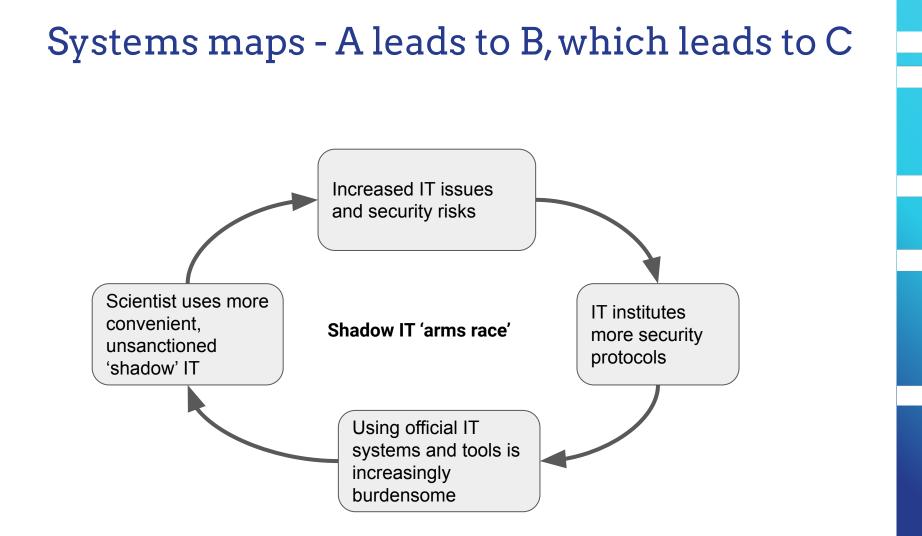
Below are examples of systems familiar to the Bio and Bio-IT community: they have components, relationships, dependencies, feedback loops, but we're focusing on ones where people are in the mix...



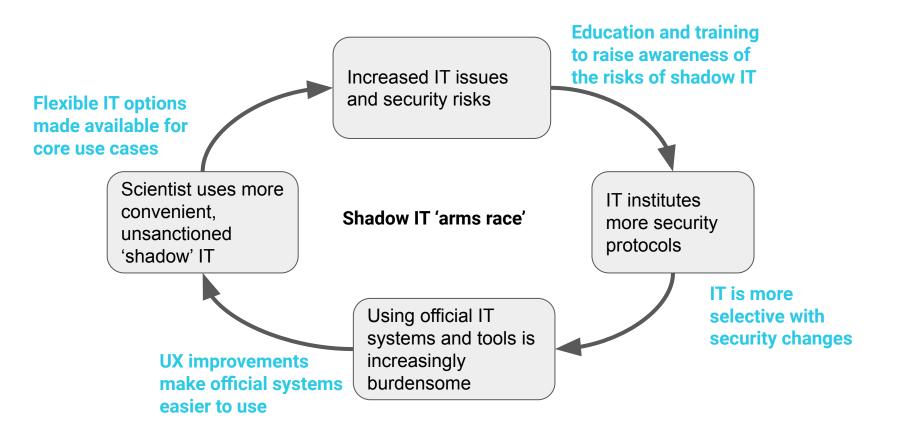
Roche Metabolic Pathways (biochemical-pathways.com)



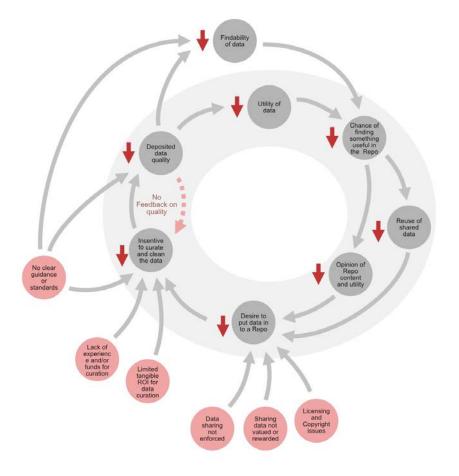
AWS Genomics Reporting Architecture



Identification of intervention points

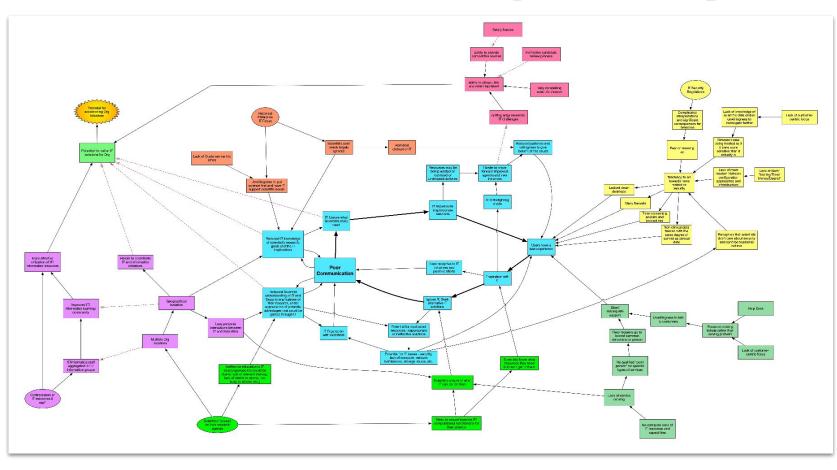


Generic FAIR Data Systems Map

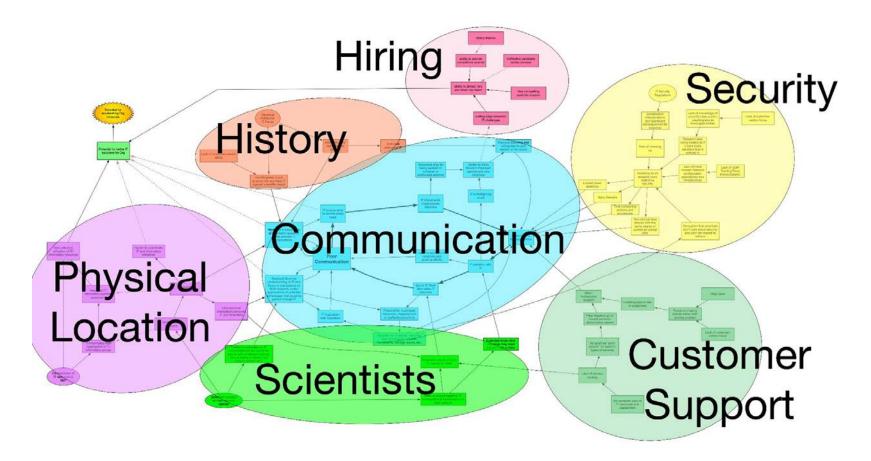


- Making data FAIR is a common desire expressed by labs, organizations, and the scientific community as a whole
- However the system often has various factors that get in the way of these initiatives
- A systems map can help identify some of these factors and how they relate to each other.
- These relationships often form loops that can progressively help (or hinder) the system.
- Identifying these loops can be vital in changing the behavior of the system.

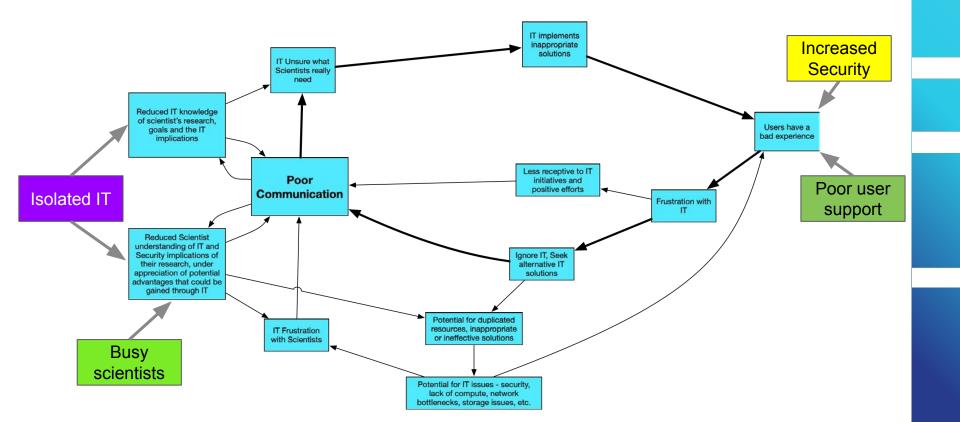
Large Bio organization IT systems map



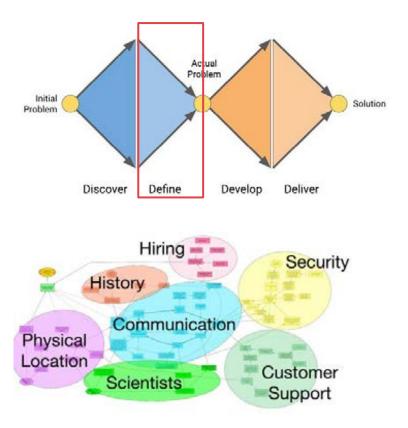
Large organization Bio-IT systems map



Core loop - communication



Systems maps help us put the information in context



We now know about

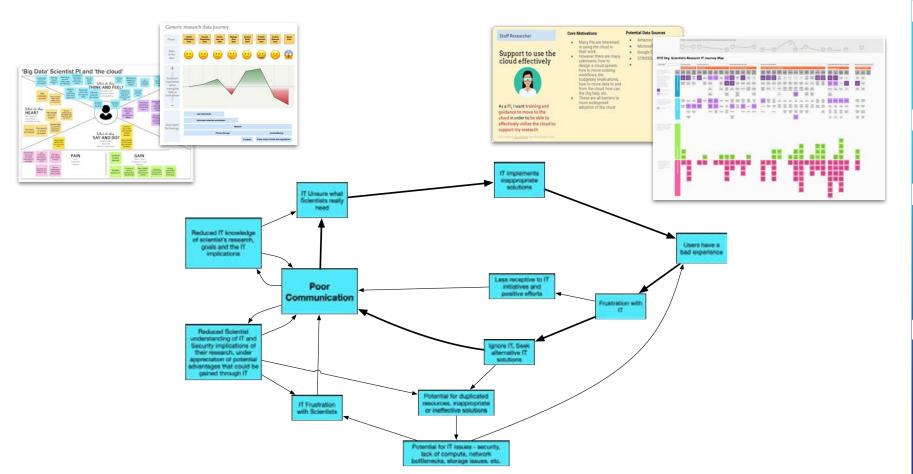
- The components
- The relationships
- The feedback and regulatory systems
- The actual problem

But how to change it?



Change

We now have a lot of information



Identify other places for change



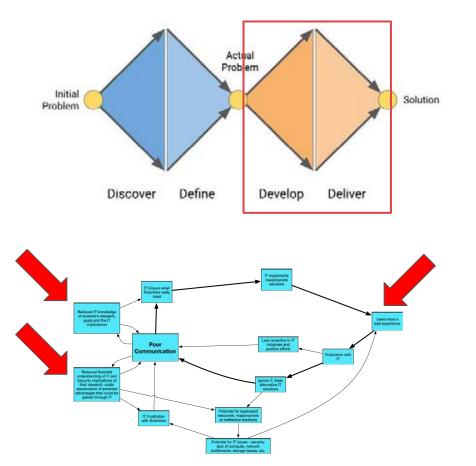
In this example, various factors in the organization are contributing to poor communication and this is impacting IT's ability to support and enable the research organization fixing this and establishing common ground are key:

How would you do that?

Potential Ideas might include:

- Town Hall meetings to discuss the issues more widely
- Collaborative projects to get IT and researchers working together, aligned around a common goal
- IT office hours in the lab space to make IT more accessible
- Lunch and Learn on Data Management, using the tiered storage, getting the most out of the network, large-scale data transfer methods, getting started on the cloud, etc.

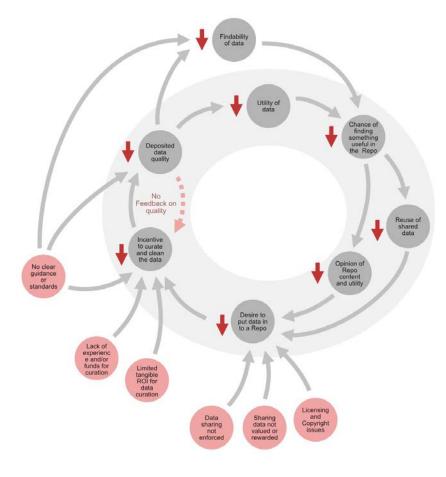
Systems maps help identify how to change

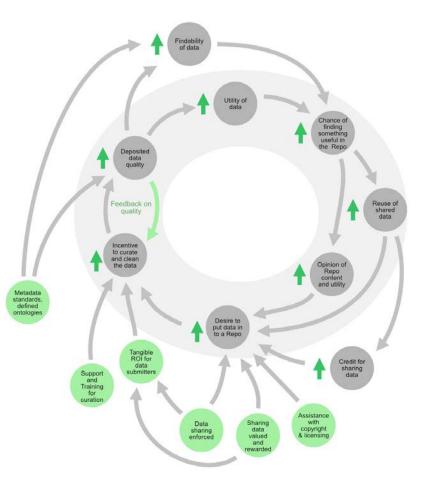


We have a model to help:

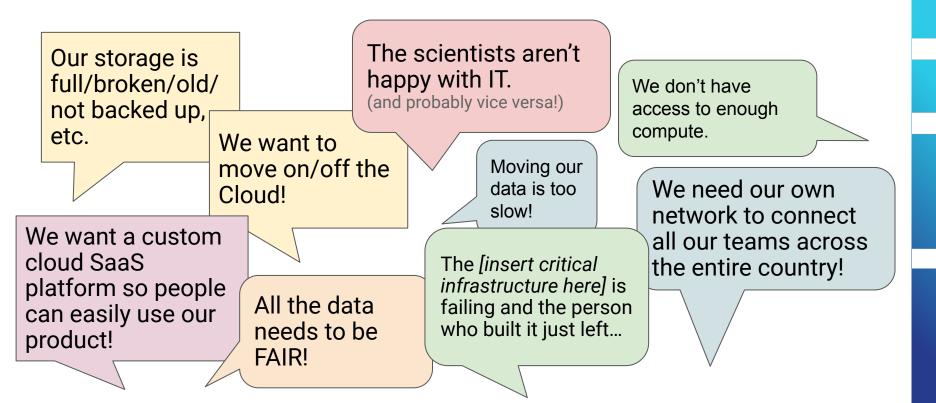
- Flag areas to intervene
- Identify possible solutions
- Identify potential unintended consequences
- Suggest small proof of concept activities

Generic FAIR Data System - Ways to improve



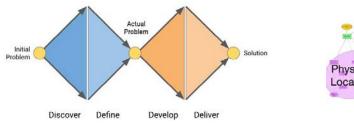


Something (always) needs to change - now we have some new tools to make it happen





"Everyone designs who devises courses of action aimed at changing existing situations into desired ones."

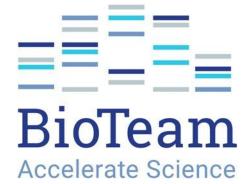


Design tools and processes



Systems Maps

Opportunities for Change







Useful links

Design Thinking

- <u>interaction-design.org/literature/article/what-is-design-thinking-and-why-is-it-so-popular</u>
- **Mapping Experiences**, Jim Kalbach, O'Reilly publishing, Journey mapping and other visualizations
- **Double Diamond** <u>fulcrum.rocks/blog/double-diamond-design</u>

Systems Thinking, Systems Mapping

- "Thinking in Systems" Donella Meadows
- Systems Mapping Training
 - acumenacademy.org/course/systems-practice/

Systems thinking and Design, Systemic Design

https://medium.com/@miekevanderbijl/systems-thinking-design-72209d534c4c