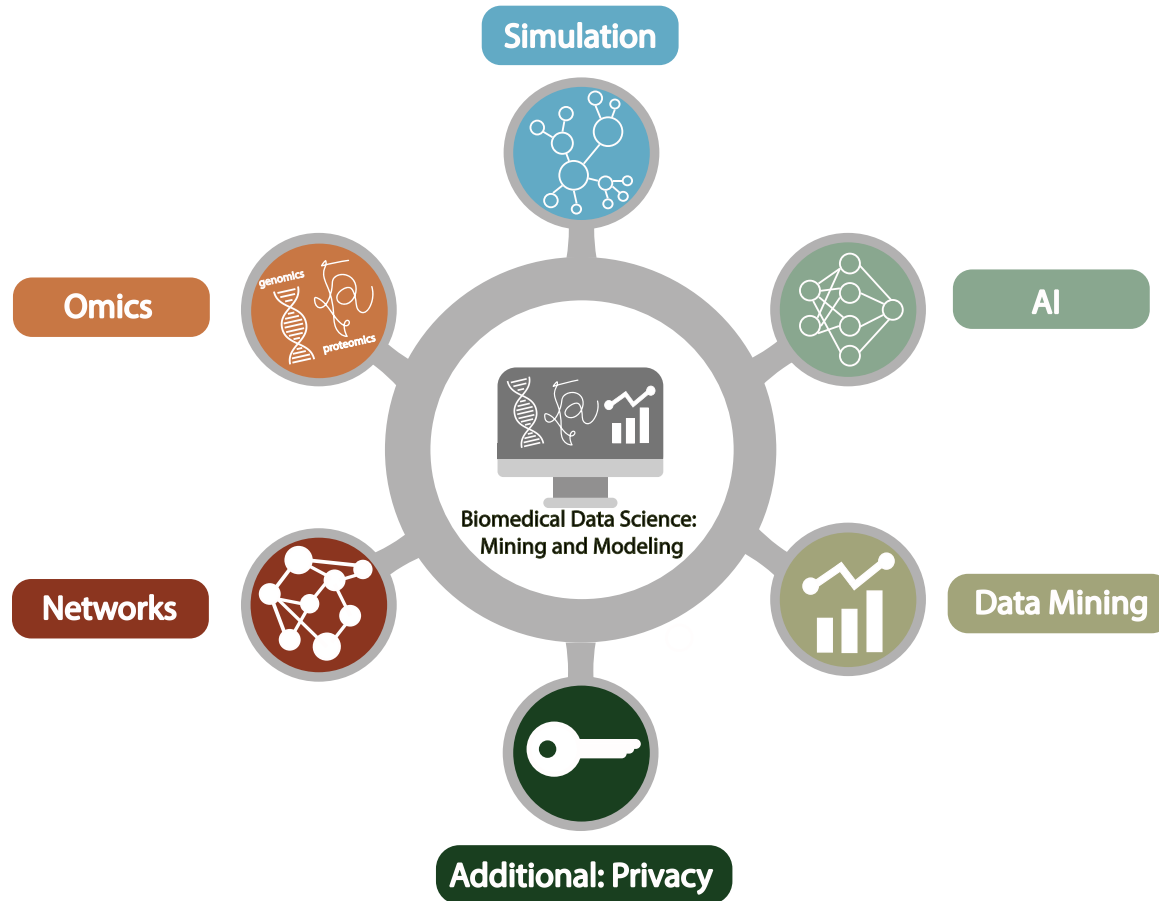


Biomedical Data Science (GersteinLab.org/courses/452)

Introduction (25i1+25i2a)



Last edit in spring '25.
Combines & integrates i1 [which has
a video] & i2a from previous years.
Takes ~50' with rest of class going
over website syllabus

**Please Fill Out Course Web Forms –
Right now, if you haven't already!**

Course Web Form
Due Today (1/13)

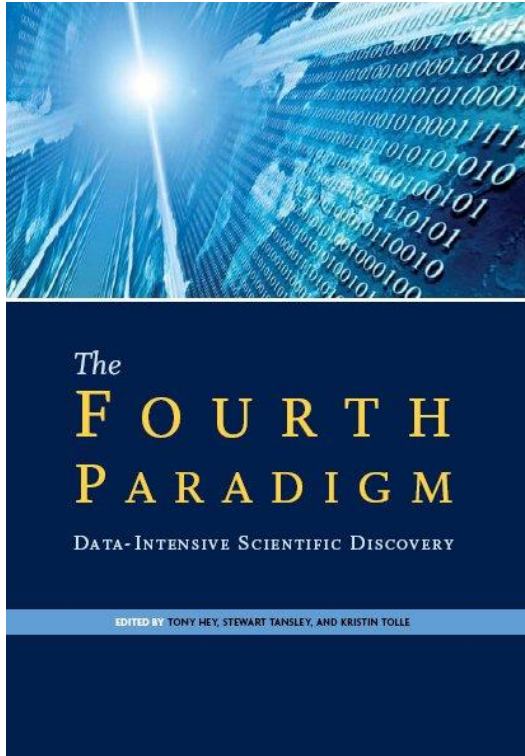


Link is also available from class website:
GersteinLab.org/courses/452

**Overview: what is
Biomed. Data science?**

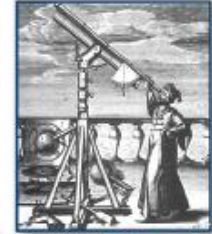
**(in the context of Data
Science, in general)**

Jim Gray's 4th Paradigm

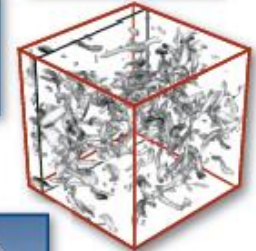


Science Paradigms

- Thousand years ago: science was **empirical**
describing natural phenomena
- Last few hundred years: **theoretical** branch
using models, generalizations
- Last few decades: a **computational** branch
simulating complex phenomena
- Today: **data exploration** (eScience)
unify theory, experiment, and simulation
 - Data captured by instruments or generated by simulator
 - Processed by software
 - Information/knowledge stored in computer
 - Scientist analyzes database/files using data management and statistics



$$\left(\frac{\dot{a}}{a}\right)^2 = \frac{4\pi G\rho}{3} - K\frac{c^2}{a^2}$$



Jim Gray's 4th Paradigm

#3 - Simulation

Prediction based on physical principles (eg Exact Determination of Rocket Trajectory)

Emphasis on:
Supercomputers

#4 - Data Mining

Classifying information & discovering unexpected relationships

Emphasis: networks,
"federated" DBs

Science Paradigms

- Thousand years ago: science was **empirical** describing natural phenomena
- Last few hundred years: **theoretical** branch using models, generalizations
- Last few decades: a **computational** branch simulating complex phenomena

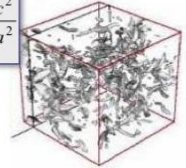
Today:

data exploration (eScience)

- unify theory, experiment, and simulation
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Or generated by simulator
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$$\left(\frac{\dot{a}}{a}\right)^2 = \frac{4\pi G\rho}{3} - K\frac{c^2}{a^2}$$



Gray died in '07.

Book about his ideas came out in '09.....

What is Data Science? An overall, bland definition...

- Data Science encompasses the study of the entire **lifecycle of data**
 - Understanding of how data are **gathered** & the issues that arise in its collection
 - Knowledge of what data sources are available & how they may be synthesized to solve problems
 - The **storage**, access, annotation, management, & transformation of data
- Data Science encompasses many aspects of **data analysis**
 - Statistical inference, machine learning, & the design of algorithms and computing systems that enable **data mining**
 - Connecting this mining where possible with **physical modeling**
 - The presentation and **visualization** of data analysis
 - The use of data analysis to make **practical decisions** & policy
- Secondary aspects of data, not its intended use – eg the **data exhaust**
 - The appropriate protection of **privacy**
 - Creative **secondary uses** of data – eg for Science of science
 - The elimination of inappropriate bias in the entire process

- Ads, media, product placement, supply optimization,
- Integral to success of GOOG, FB, AMZN, WMT...

Data Science in the wider world: a buzz-word for successful Ads



Harvard Business Review

Data Scientist: The Sexiest Job of the 21st Century

by Thomas H. Davenport and D.J. Patil



Artwork: Tamar Cohen, Andrew J Buboltz, 2011, silk screen on a page from a high

When Jonathan Goldman arrived for work in June 2006 at LinkedIn, the business ne up. The company had just under 8 million accounts, and the number was growing qu friends and colleagues to join. But users weren't seeking out connections with the pe rate executives had expected. Something was apparently missing in the social expe

Forbes

New Posts
+30 posts this hour

Most Popular
16-Year-Old Innovator

Lists
Promising Companies

CIO Network
INSIGHTS AND IDEAS FOR TECHNOLOGY LEADERS.
+ Follow (49)

TECH | 12/12/2012 @ 1:57AM | 3,289 views

Why Big Data Is All Retailers Want for Christmas

Eric Savitz, Forbes Staff
+ Comment Now + Follow Comments

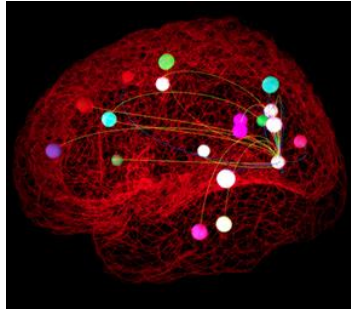
Guest post written by Quentin Gallivan
 Quentin Gallivan is CEO of Pentaho Corp., an Orlando, Florida-based provider of business analytics software.

Data Science in Traditional Science

- Pre-dated commercial mining
- Instrument generated
- Large data sets often created by large teams not to answer one Q but to be mined broadly
- Often coupled to a physical/biological model
- Interplay w/ experiments



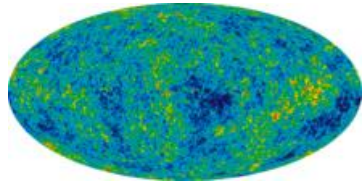
High energy physics - Large Hadron Collider



Neuroscience - The Human Connectome Project



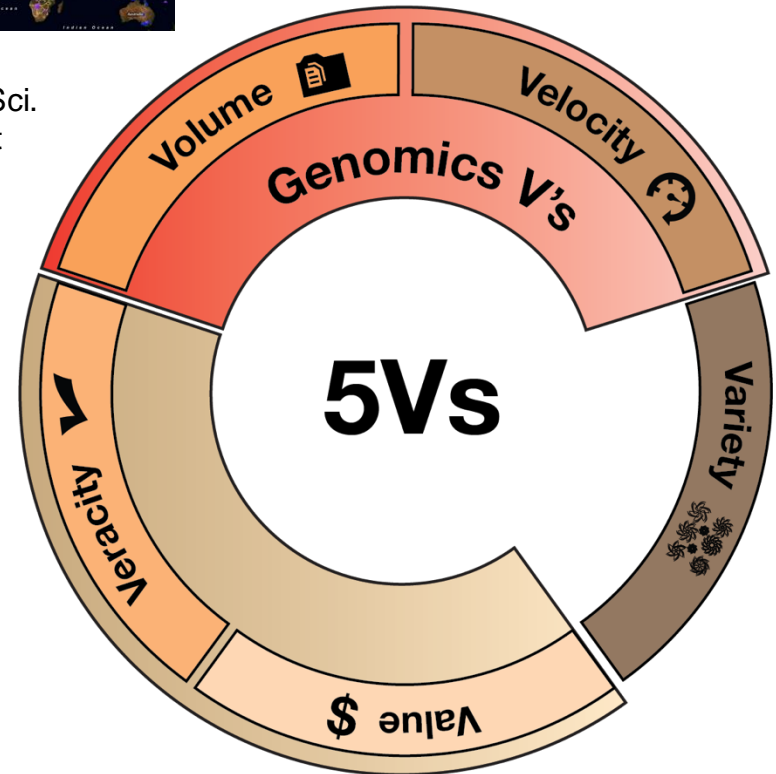
Ecology & Earth Sci. - Fluxnet



Astronomy - Sloan Digital Sky survey

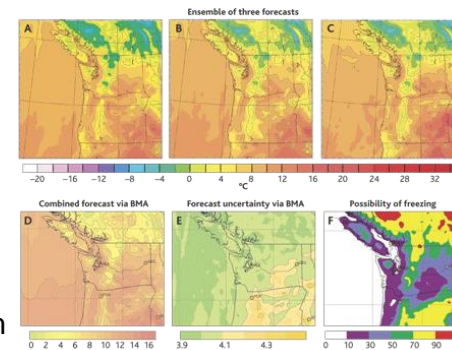
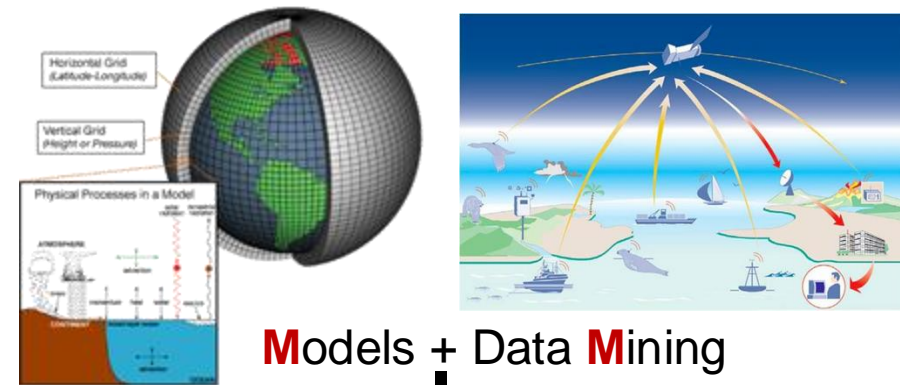
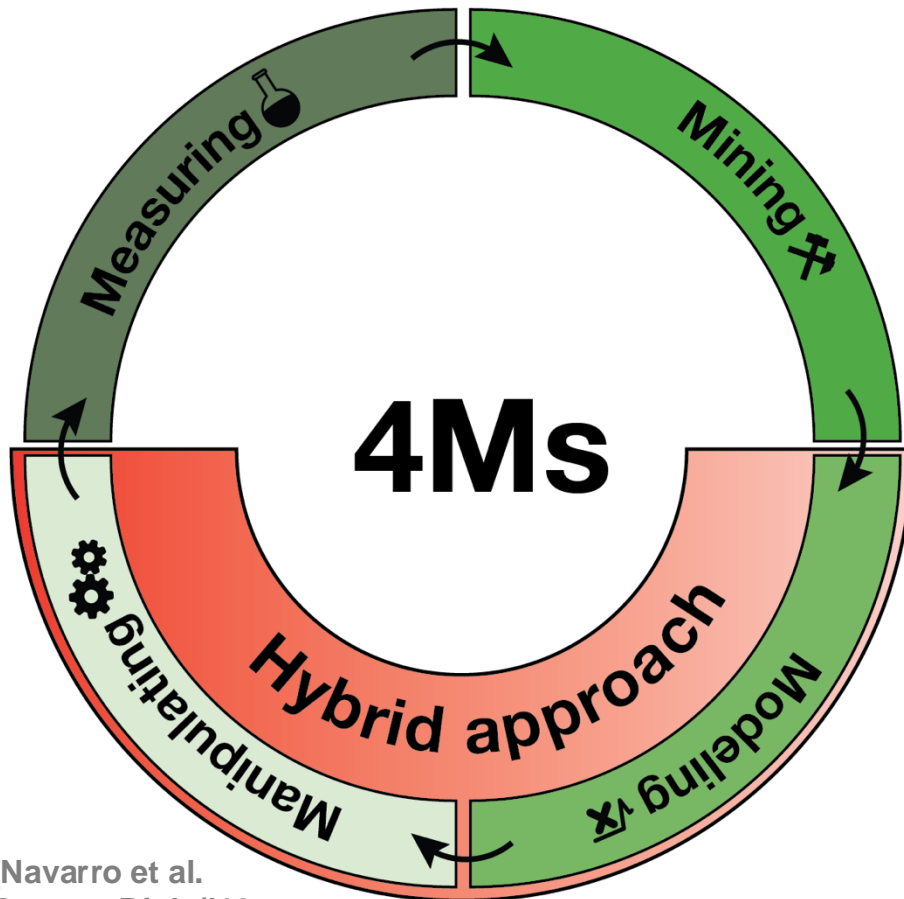


Genomics DNA sequencer



Coupling of Scientific Data to Models & Experiments

- Scientific data often coupled to a physical/biological model
- Lauffenburger's Sys. Biol. **4Ms**:
Measurement, **M**ining, **M**odeling & **M**anipulation
(Ideker et al.'06. Annals of Biomed. Eng.)
- Weather forecasting as an exemplar
 - Physical models & simulation useful but not sufficient ("butterfly" effect)
 - Success via coupling to large-scale sensor data collection



NOAA

[Navarro et al. GenomeBiol. ('19, in press)]

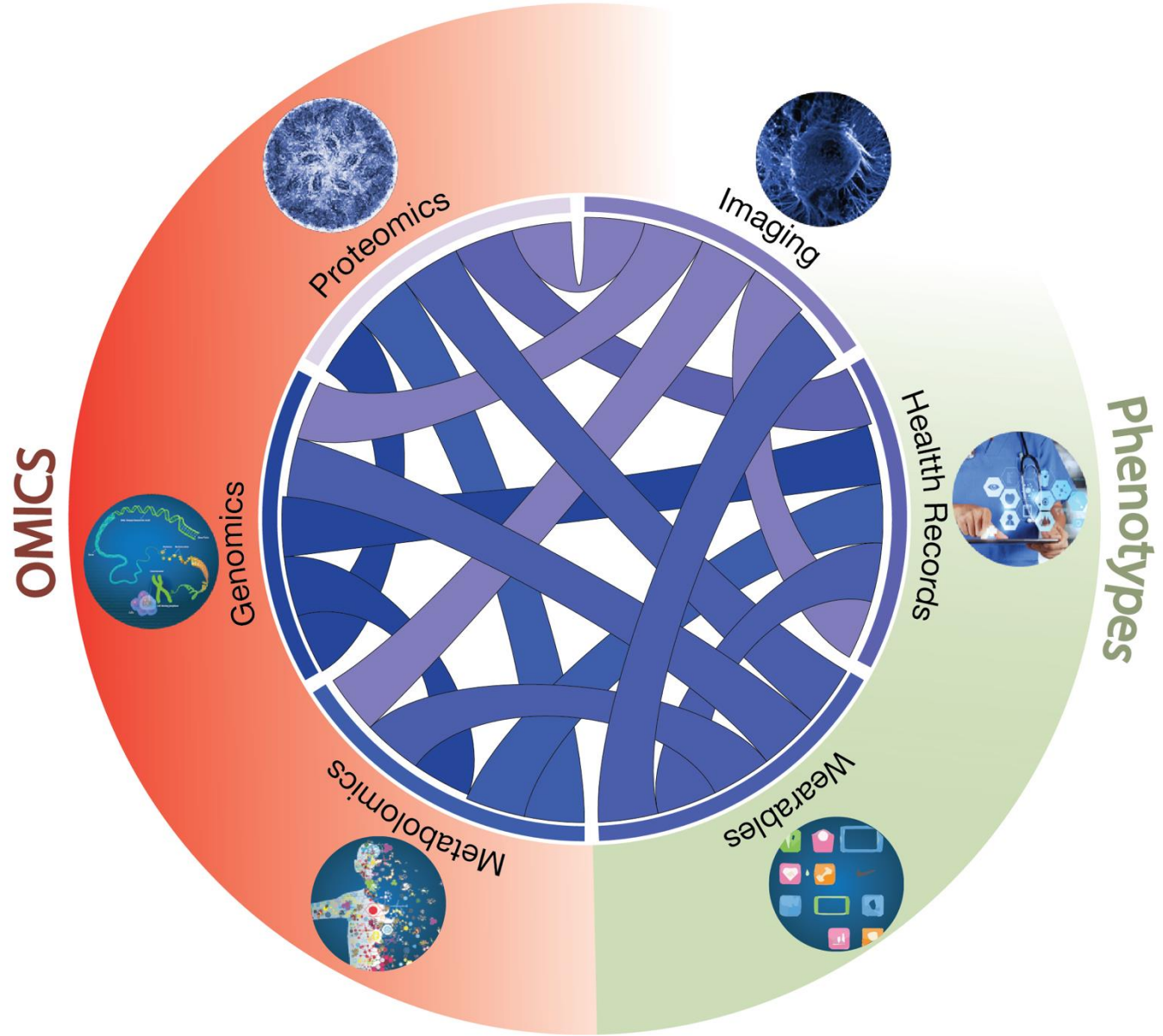
Image from <http://web.aibn.uq.edu.au/cssb/ResearchProjects.htm>

Biomed. Data science:

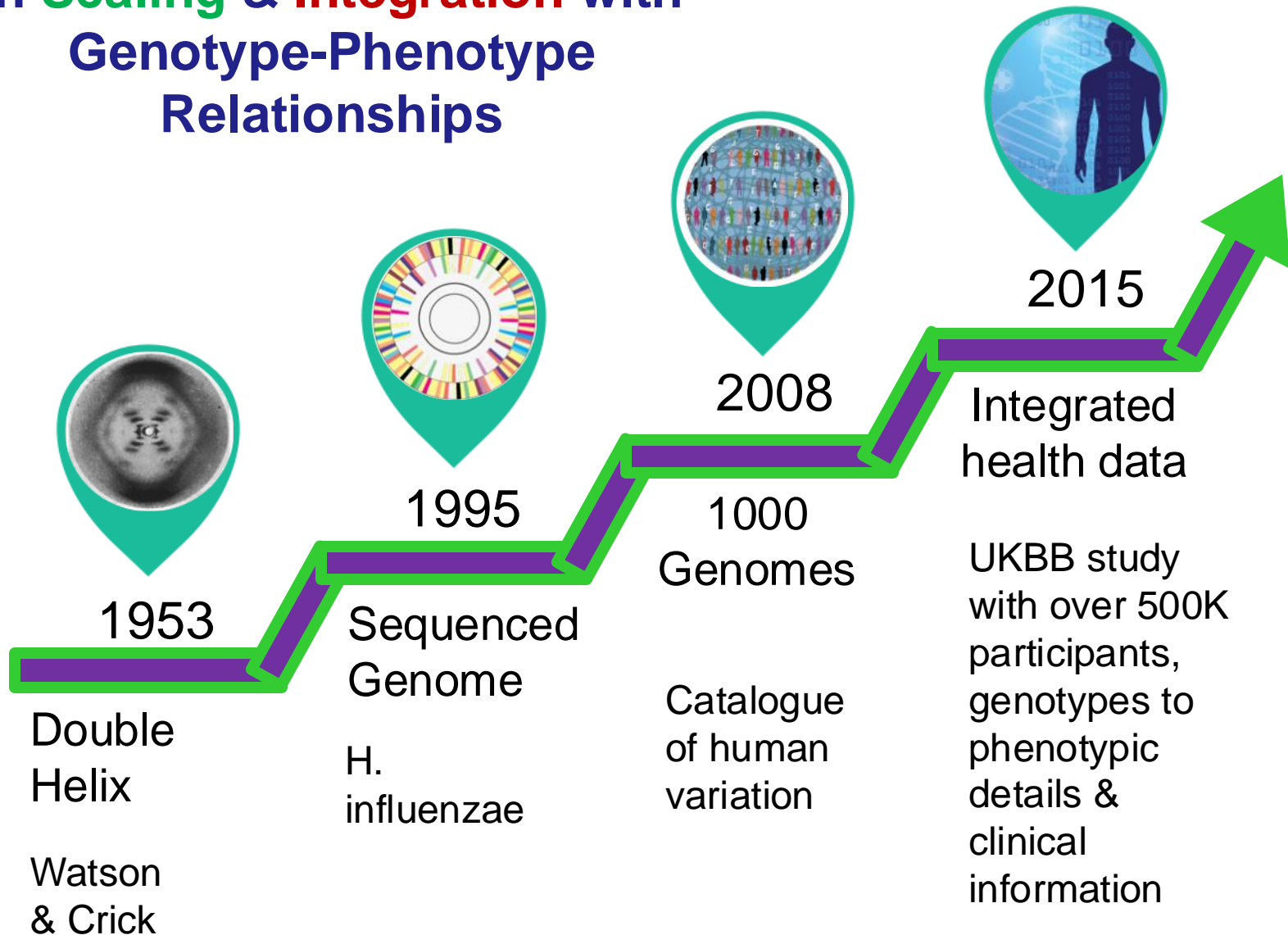
Scaling & Integration

Drivers of Biomedical Data Science

- **Integration** across data types
- **Scaling** of individual data types



Case Study: Amazing Progress in **Scaling & Integration** with Genotype-Phenotype Relationships

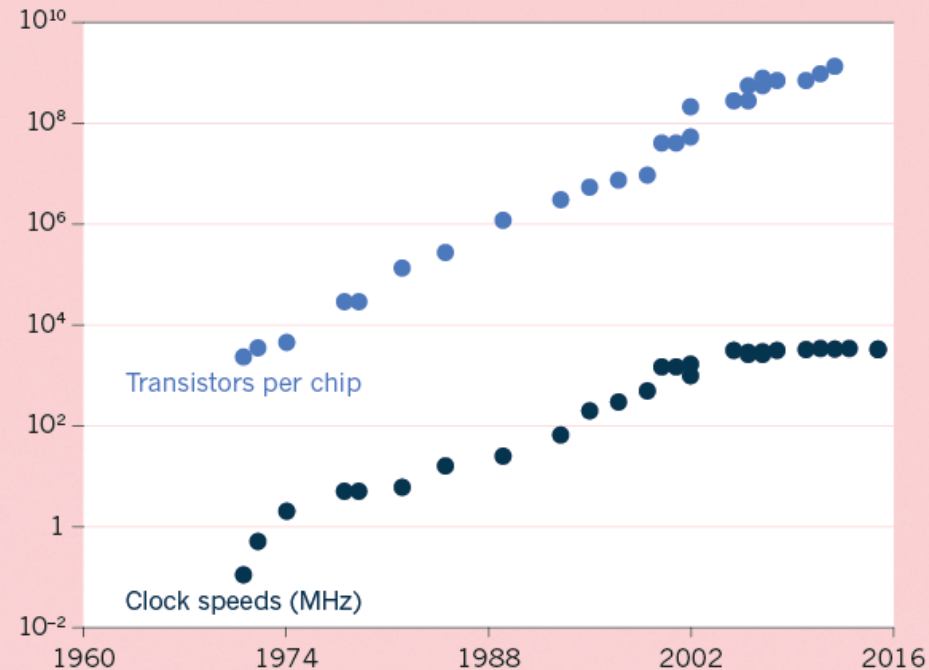
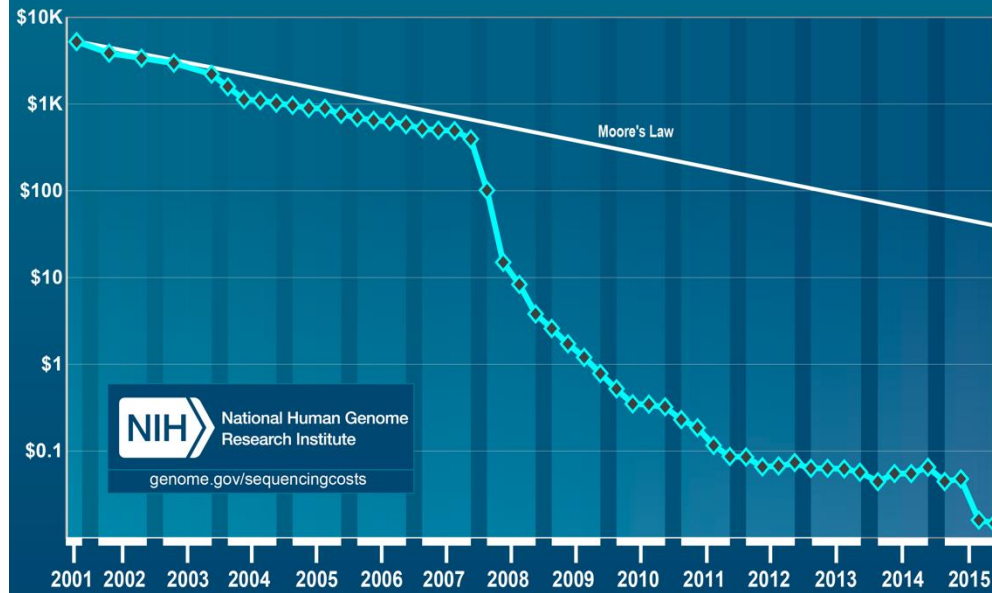


The **Scaling** of
Genomic Data
Science:

Powered by
exponential
increases in
data & computing

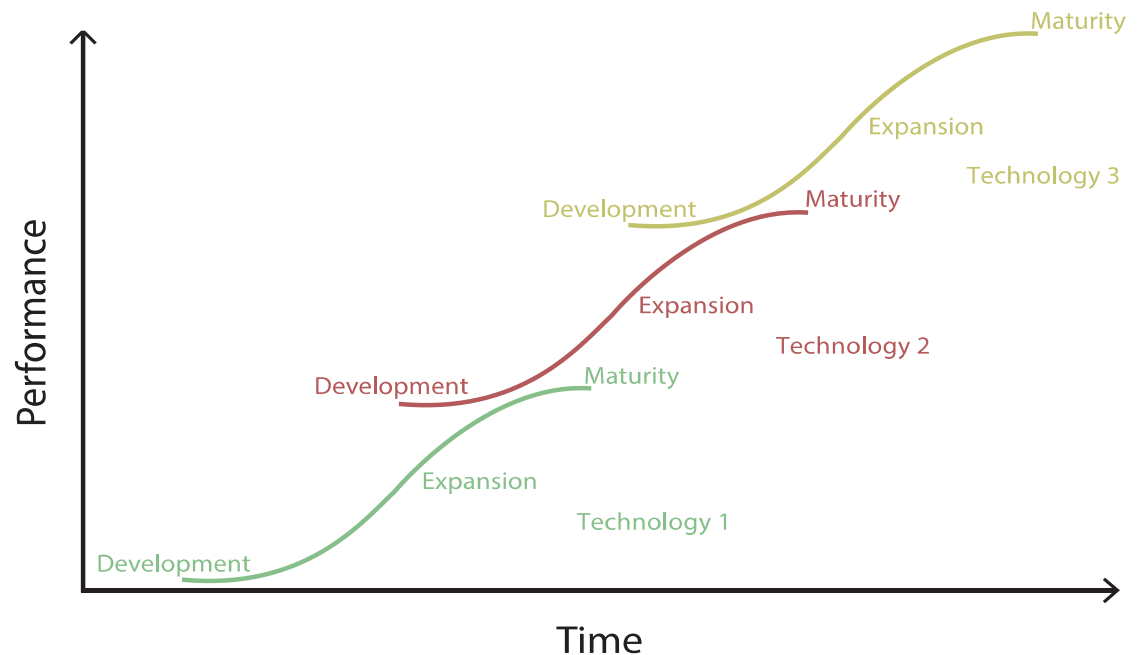
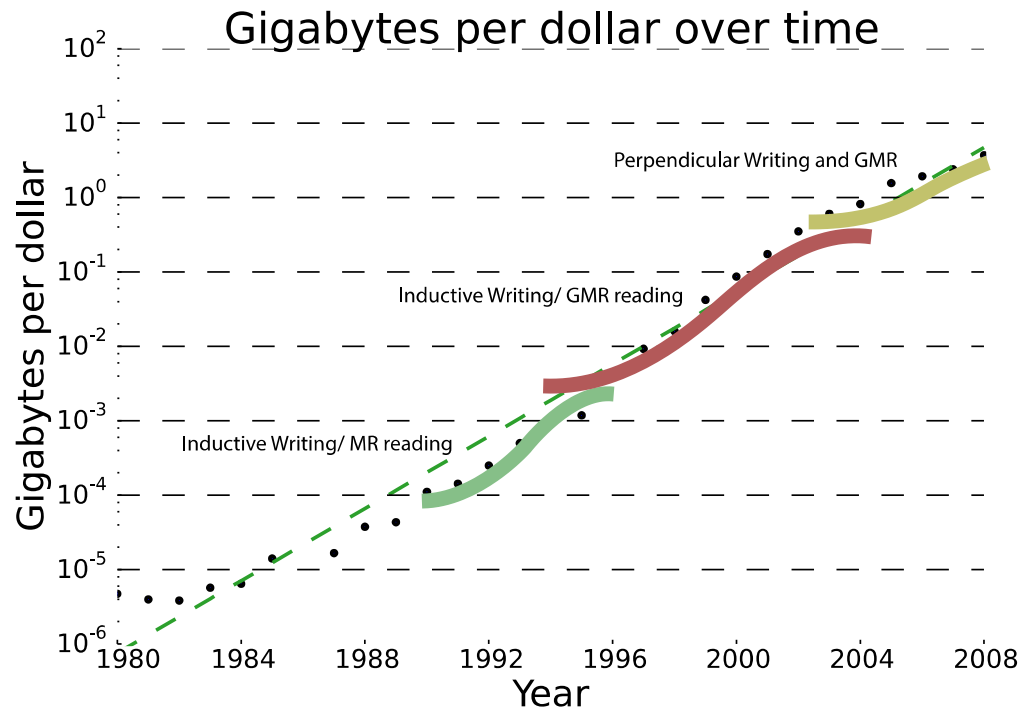
(Moore's Law)

Cost per Raw Megabase of DNA Sequence

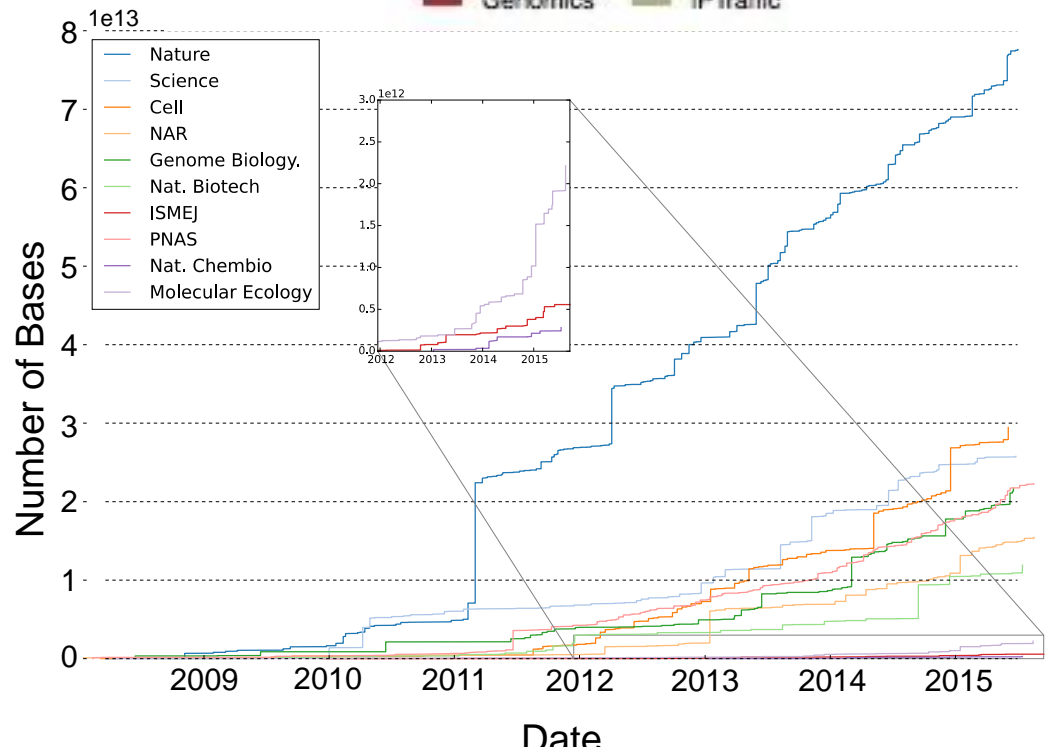
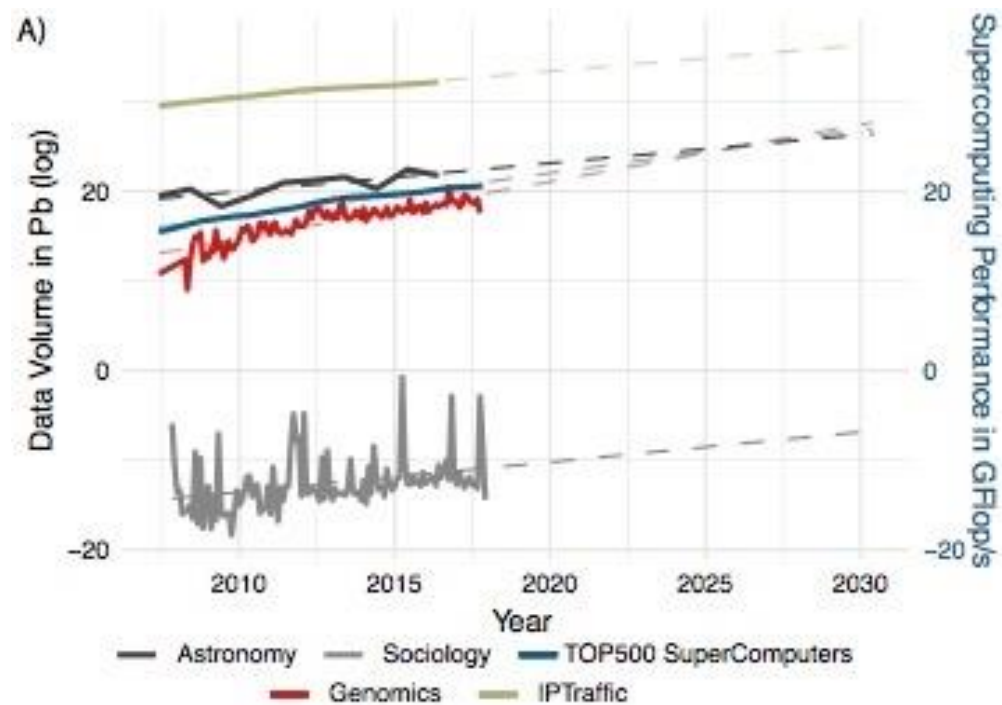


Kryder's Law and S-curves underlying exponential growth

- Moore's & Kryder's Laws
 - As important as the increase in computer speed has been, the ability to store large amounts of information on computers is even more crucial
- Exponential increase seen in Kryder's law is a superposition of S-curves (sigmoids) for different technologies

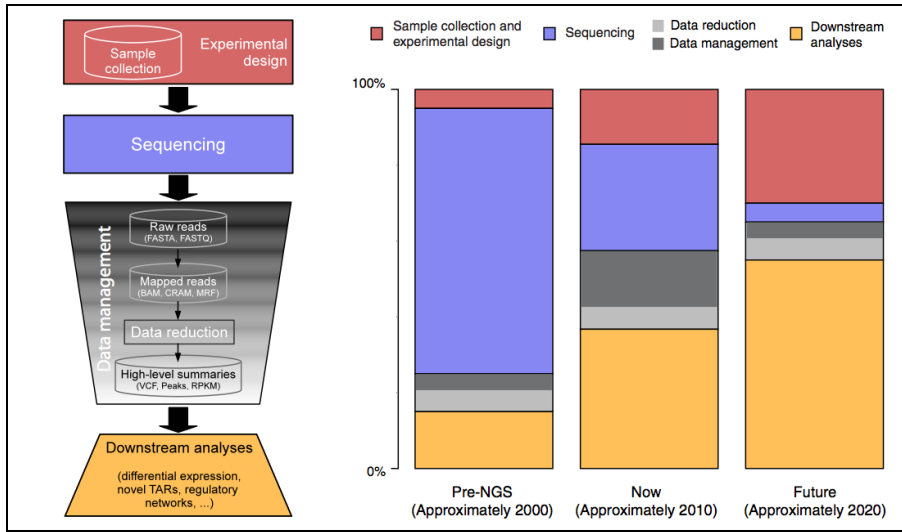


Sequencing cost reductions have resulted in an explosion of data



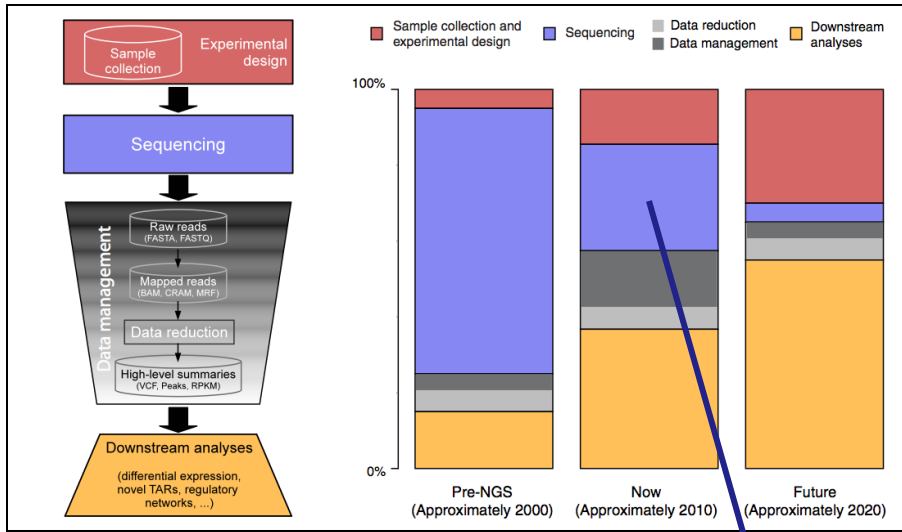
- The type of sequence data deposited has changed as well.

The changing costs of a sequencing pipeline

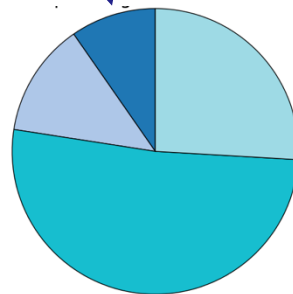
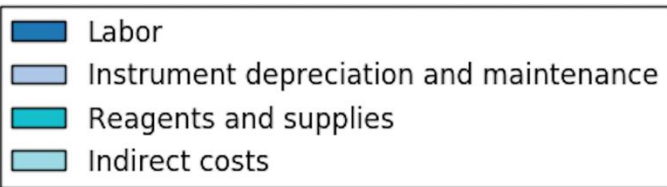


From '00 to ~' 20,
cost of DNA sequencing expt. shifts from
the actual seq. to sample
collection & analysis

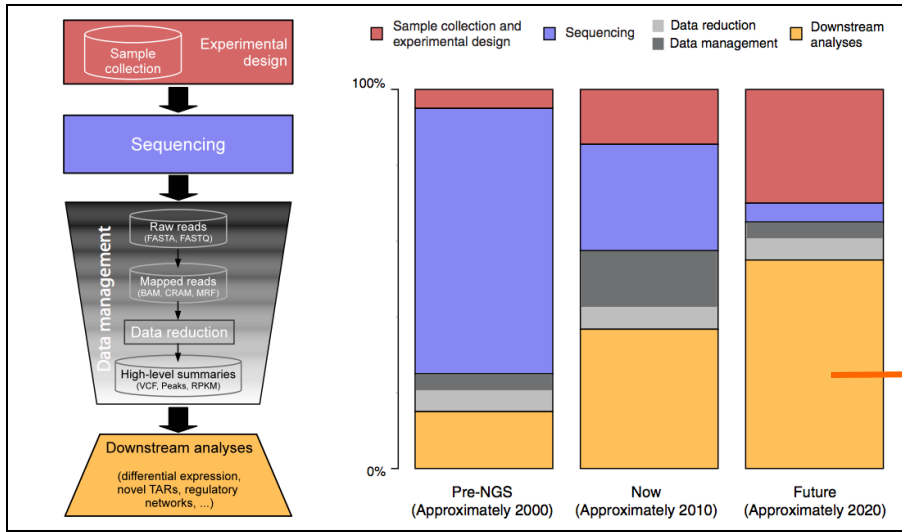
The changing costs of a sequencing pipeline



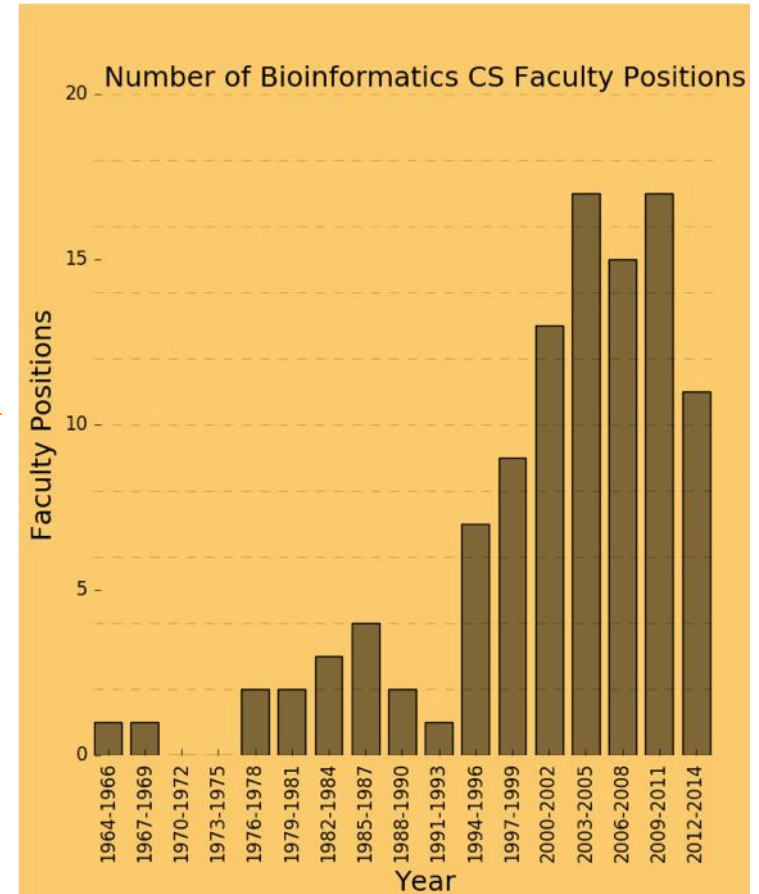
From '00 to ~' 20, cost of DNA sequencing expt. shifts from the actual seq. to sample collection & analysis



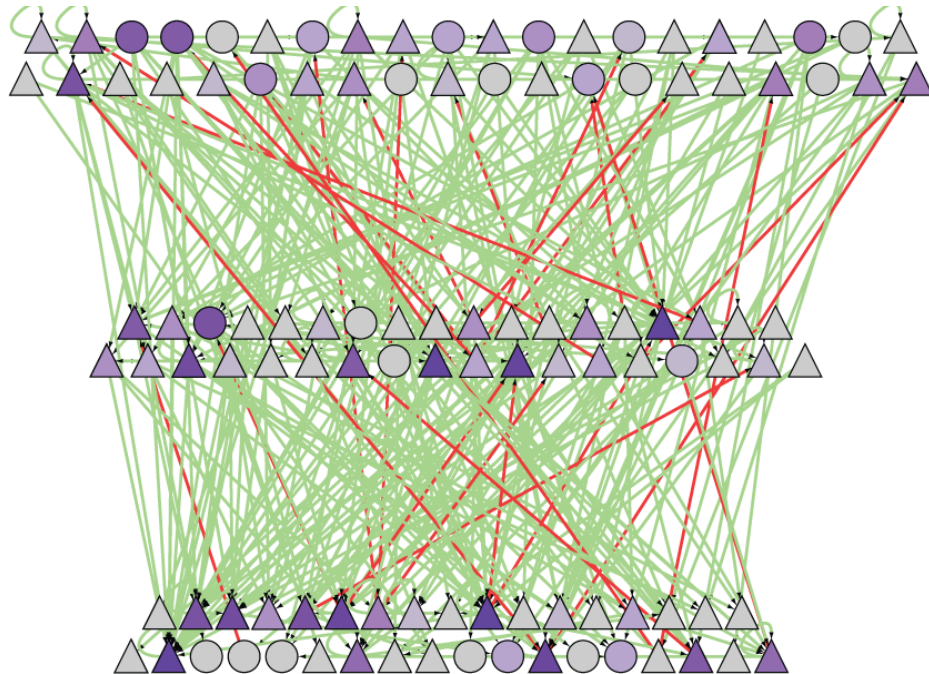
The changing costs of a sequencing pipeline



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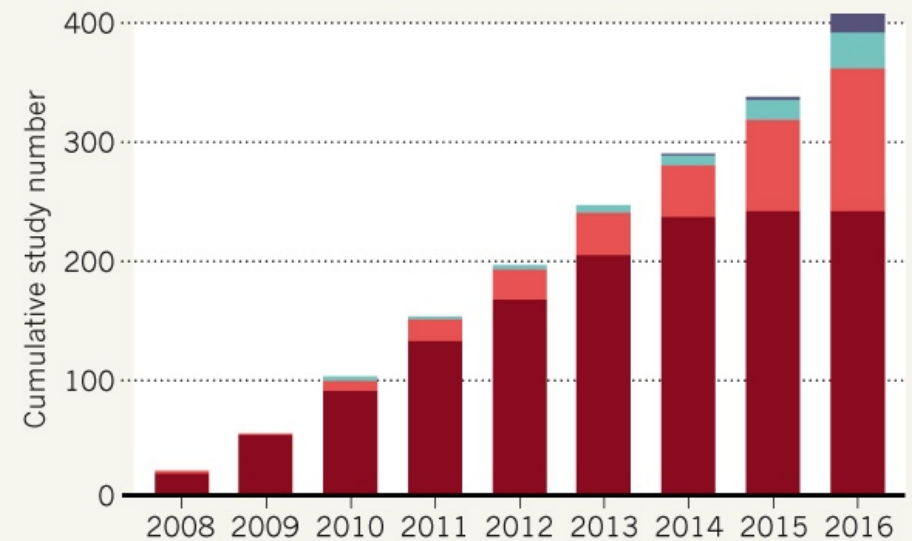
**A Success of
Scale & Integration:
Many GWAS
variants found,
most not in genes,
but affecting
regulatory network**



THE GENOME-WIDE TIDE

Large genome-wide association studies that involve more than 10,000 people are growing in number every year — and their sample sizes are increasing.

Sample sizes: ■ More than 200,000 ■ 100,000–199,999
■ 50,000–99,999 ■ 10,000–49,999

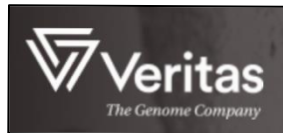


©nature

- A 1st GWAS done at Yale, for AMD: (Klein et al. 05, Science)
- Many since then
- Most SNVs fall into non-coding regulatory regions (major contributions by Yale groups to this ENCODE annotation effort)

Basic Science to Medicine

INITIATIVES



STARTUPS

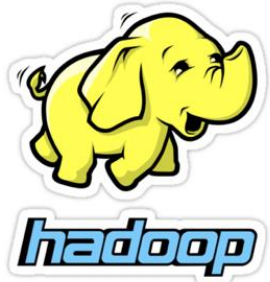
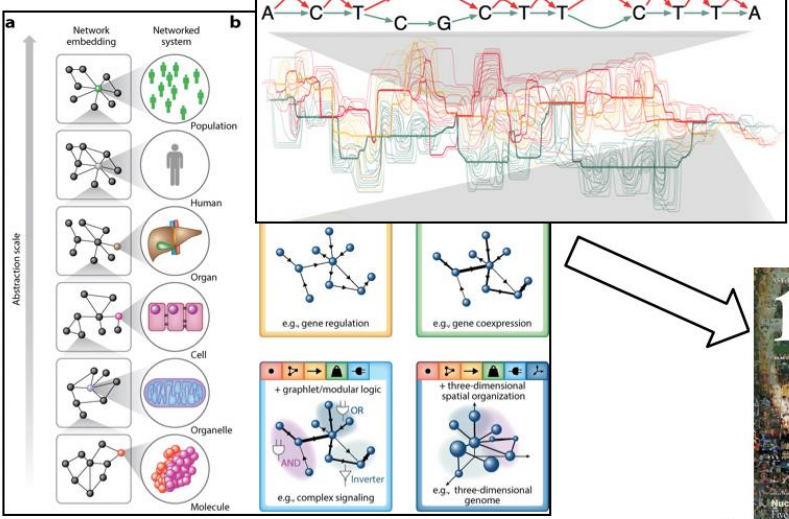
- Large-scale 'omics data as an anchor to organize phenotypic data – EMRs, wearables...
- 1st ['05-]: Exomes & chips of disease-focused cohorts – init. GWAS, TCGA, PGC
- 2nd ['15-]: Integration of full WGS with rich & diverse phenotypes - UKBiobank, TopMed, Genomics England, PCAWG, All of Us

Examples of Imports & Exports to/from Genomics & Other Data

Science Application Areas

Technical Imports

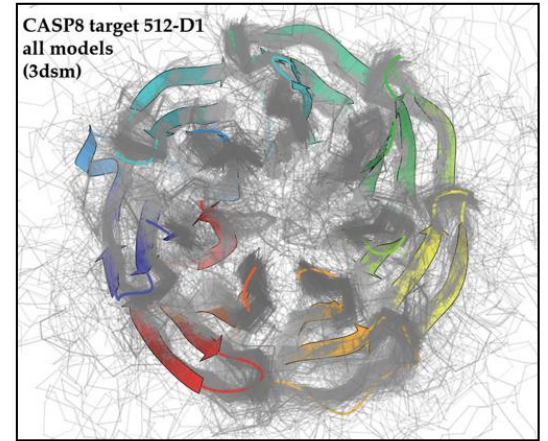
Networks and graphs



Importing tech. developed in other big data disciplines

Cultural Imports

CASP

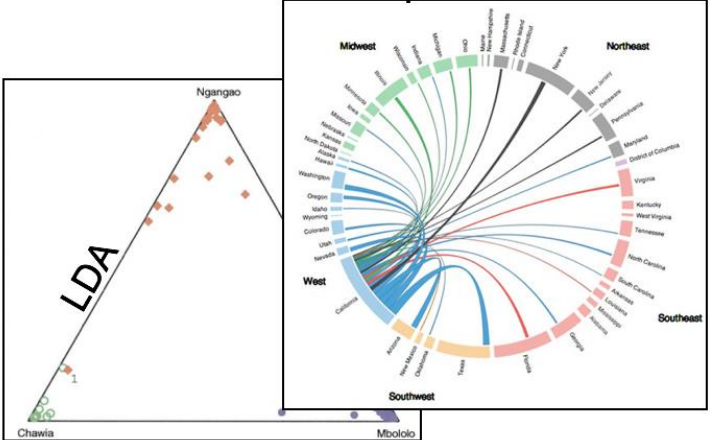


Cultural Exports



Technical Exports

Circos plot

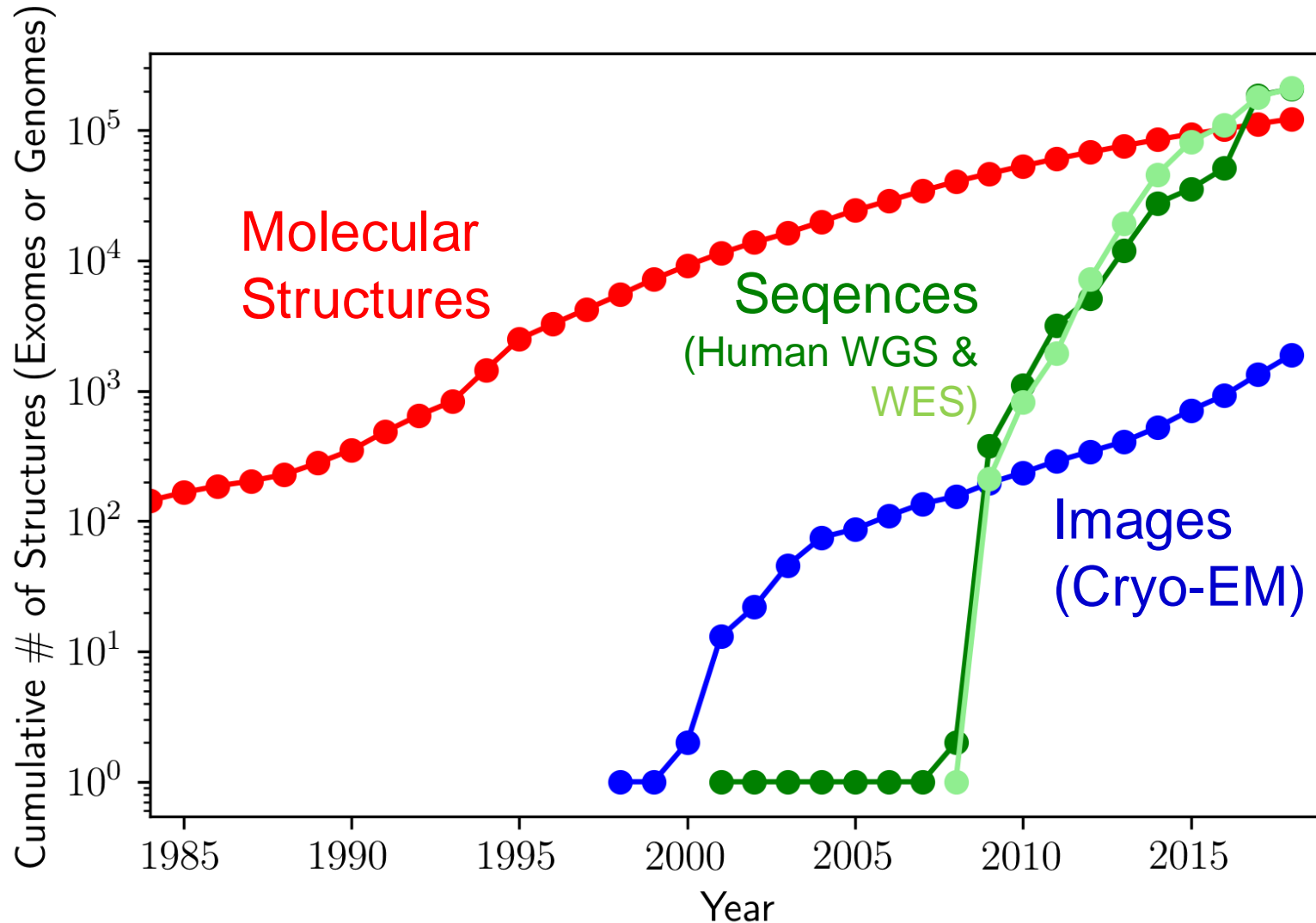


Open Science



[Navarro et al. GenomeBiol. ('19, in press)]

How will the Data **Scaling** Continue? The Past, Present & Future Ecosystem of Large-scale Biomolecular Data

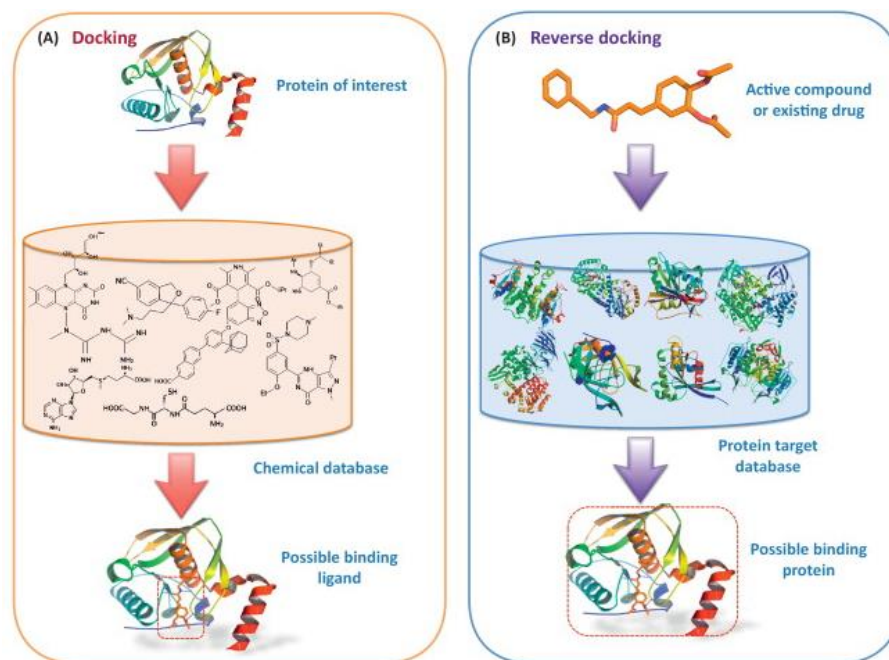
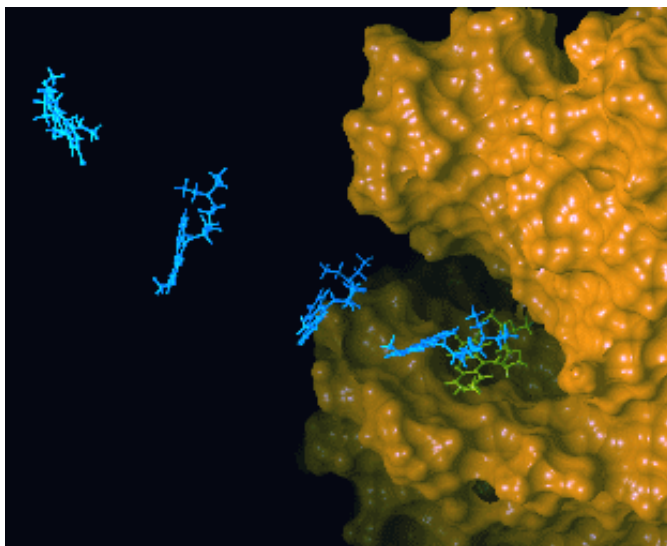


Biomed. Data science:

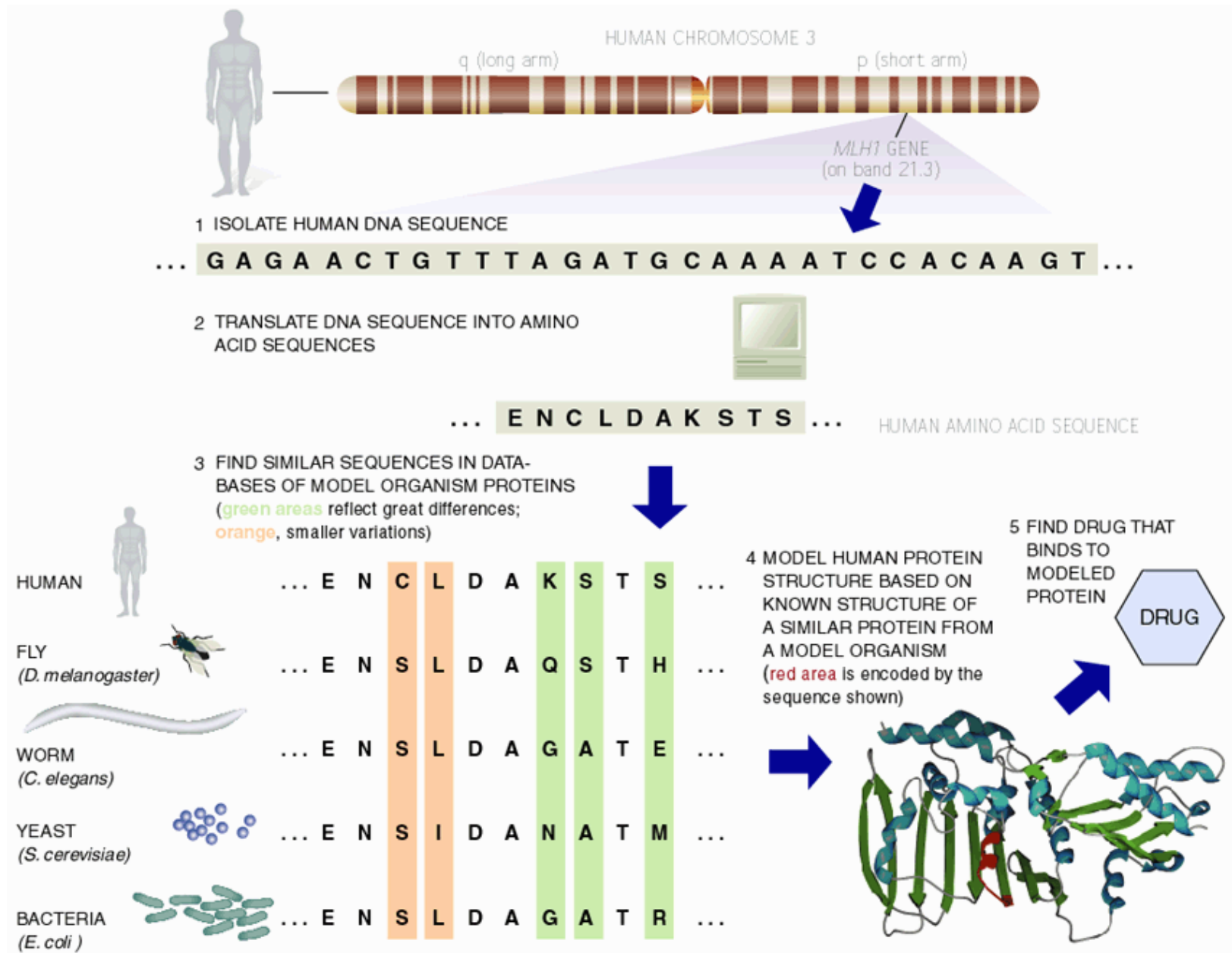
Applications

Major Application I: Designing Drugs from Structural Targets

- Understanding how structures bind other molecules
- Designing inhibitors using docking, structure modeling
- *In silico* screens of chemical and protein databases

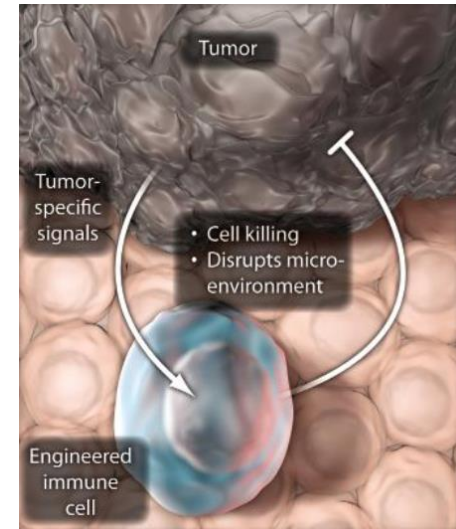
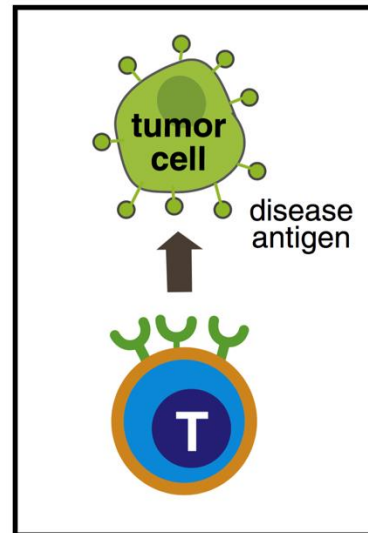
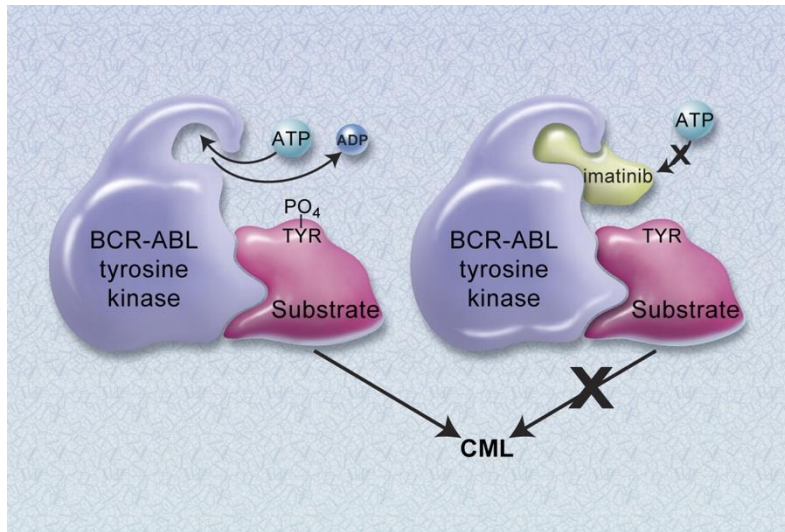


Major Application II: Finding Homologs, to Find Experimentally Tractable Gene Targets



Major Application III: Customizing treatment in oncology

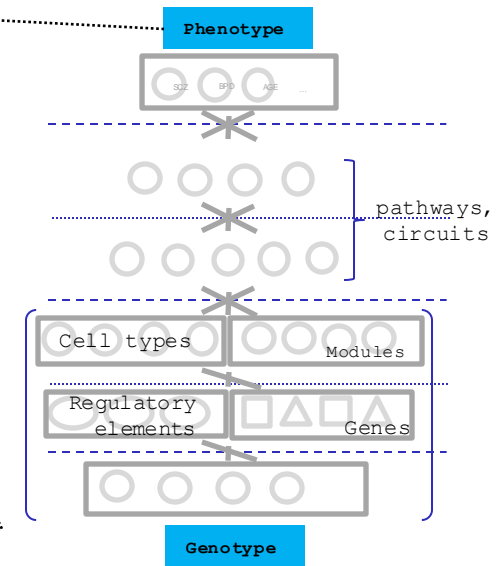
- Identifying disease causing mutations in individual patients
- Designing targeted therapeutics
 - e.g. BCR-abl and Gleevec
 - Cancer immunotherapies targeting neoantigens



(From left to right, figures adapted from Druker BJ. Blood 2008 and the Lim Lab at UCSF)

Major Application IV: Finding molecular mechanisms & drug targets for diseases we know little about (Neuro-psychiatric Diseases)

Disease	Heritability*	Molecular Mechanisms
Schizophrenia	81%	-
Bipolar disorder	70%	-
Alzheimer's disease	58 - 79%	Apolipoprotein E (APOE), Tau
Hypertension	30%	Renin–angiotensin–aldosterone
Heart disease	34-53%	Atherosclerosis, VCAM-1
Stroke	32%	Reactive oxygen species (ROS), Ischemia
Type-2 diabetes	26%	Insulin resistance
Breast Cancer	25-56%	BRCA, PTEN



Many psychiatric conditions are highly heritable

Schizophrenia: up to 80%

But we don't understand basic molecular mechanisms underpinning this association
(in contrast to many other diseases such as cancer & heart disease)

Moreover, current models substantially underestimate heritability using genetic data

Schizophrenia : ~25%

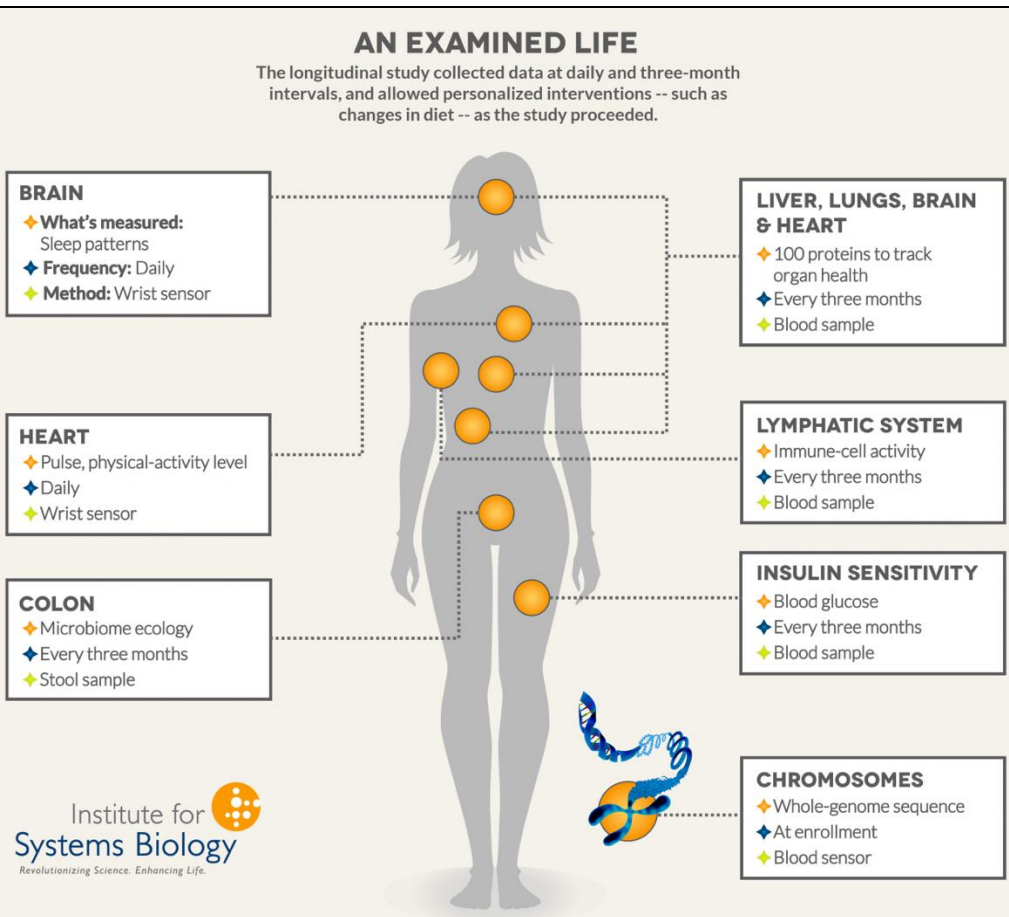
Thus, interested in developing predictive models of psychiatric traits which:

Use observations at intermediate (molecular levels) levels to inform latent structure.

Use the predictive features of these “molecular endo phenotypes” to begin to suggest actors involved in mechanism

Major Application V: Holistic Personal Genome Characterization, in Normal Individuals

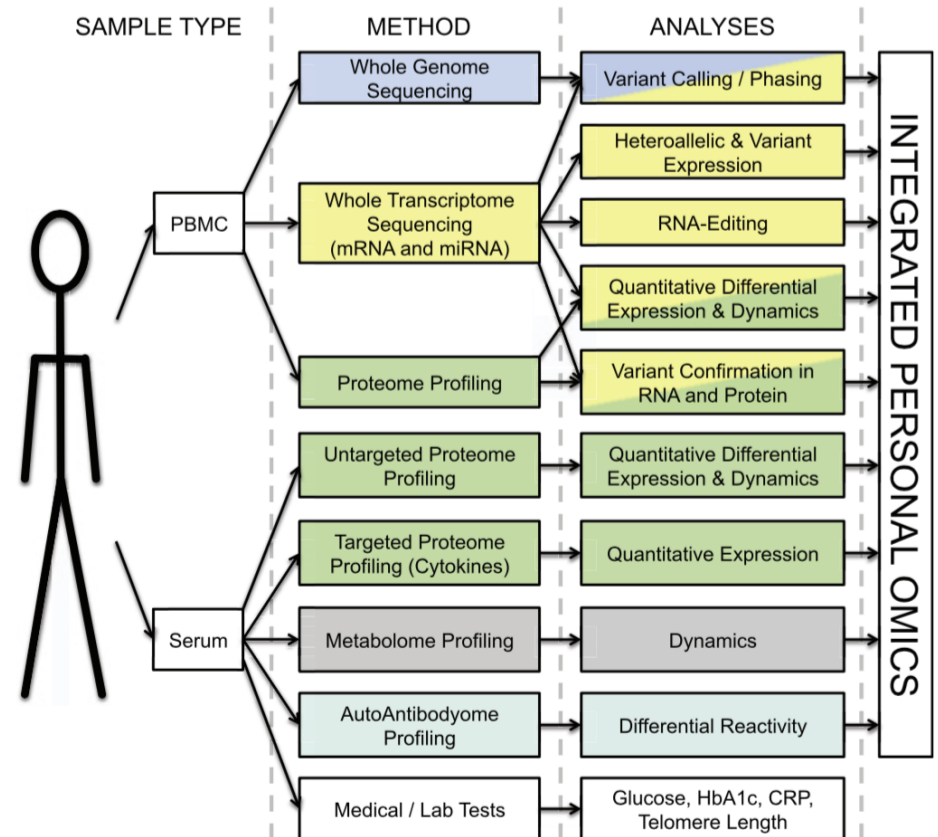
- Mental disease & cancer are two extremes with respect to genomics (CEN, 92: 26)
 - Many other conditions in between, often involving interaction with the environment
- Pers. Genome Characterization
 - Identify mutations in personal genomes (SNPs, SVs, &c)
 - Estimate phenotypic (deleterious or protective) impact of variants.
 - Compare one person to wider population.
- Track changes over time & consider interaction w/ environment
 - Transcriptome studies
 - Longitudinal health studies (e.g. 100K wellness project, Framingham Heart Study)



(Figure from Institute for Systems Biology)

Integrated personal omics profile (iPOP)

- Numerous types of data were collected, primarily from blood samples. The datasets include:
 - Transcriptomic
 - Proteomic
 - Metabolomic
 - Cytokine profiling
 - Autoantibody profiling
 - Medical exams



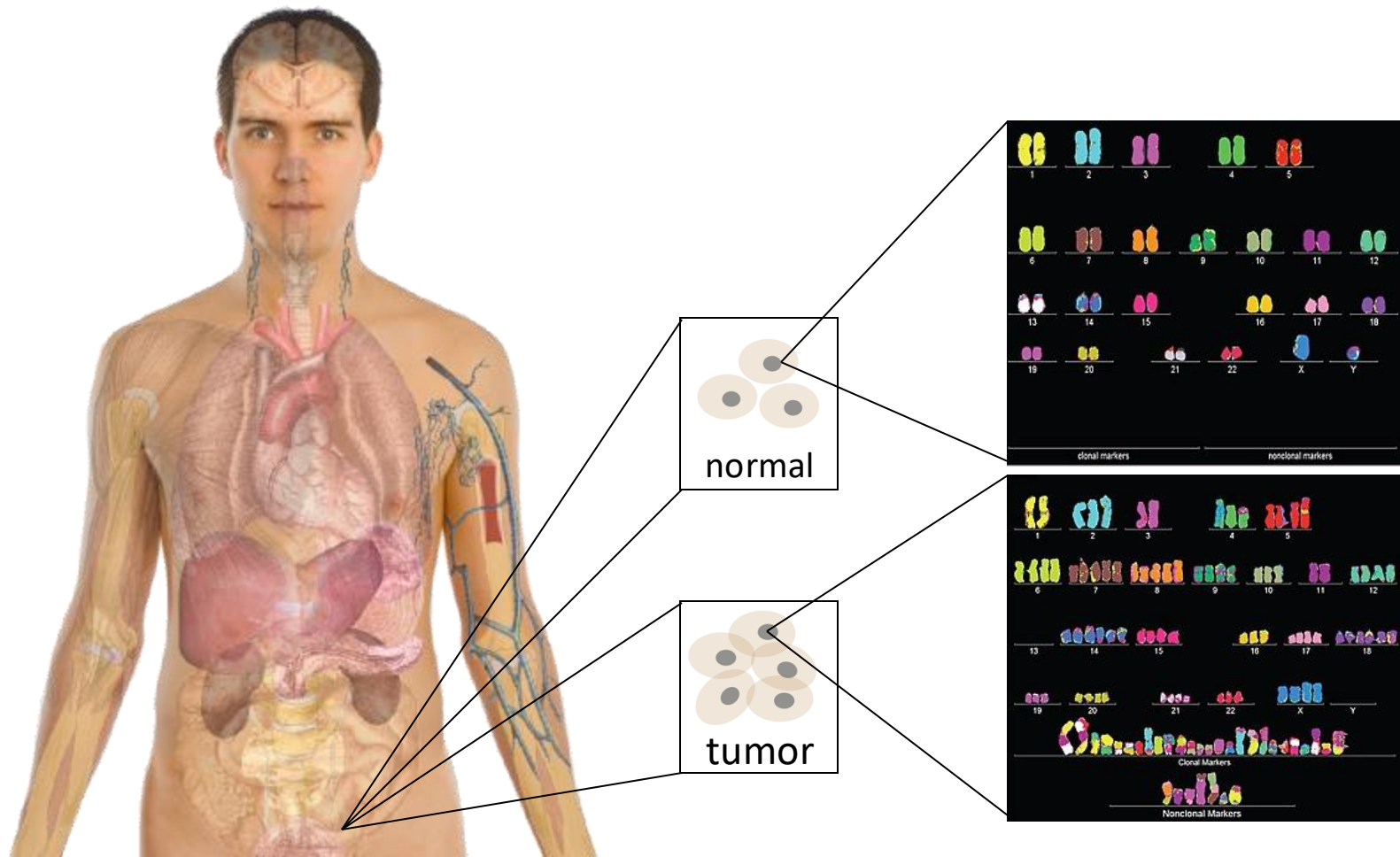
Expanding personalized medicine beyond the genome.

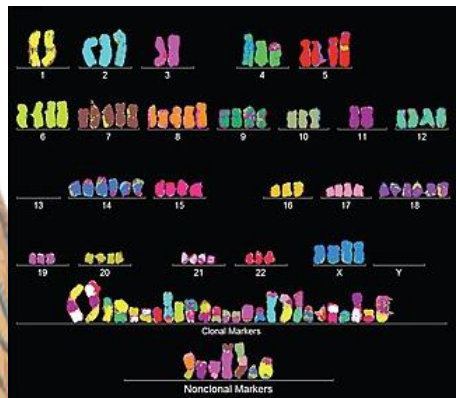
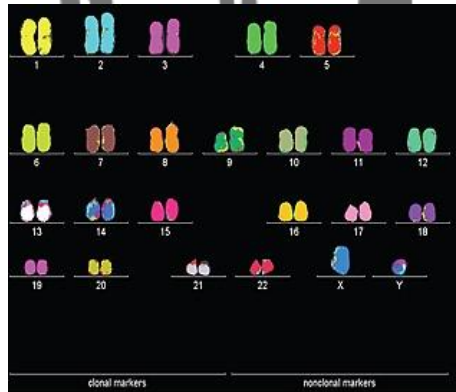
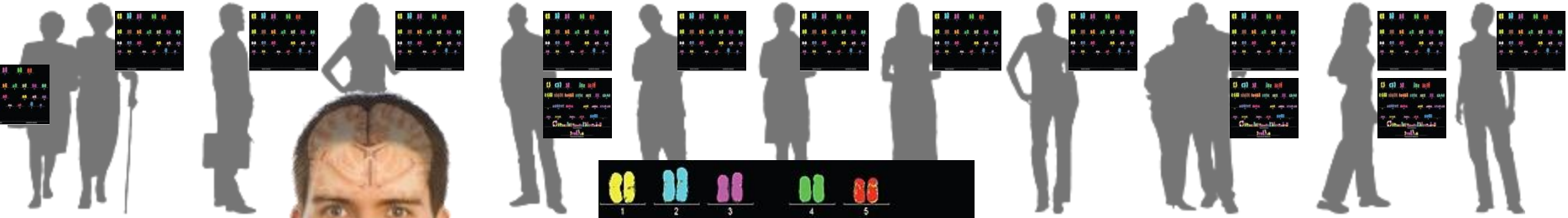
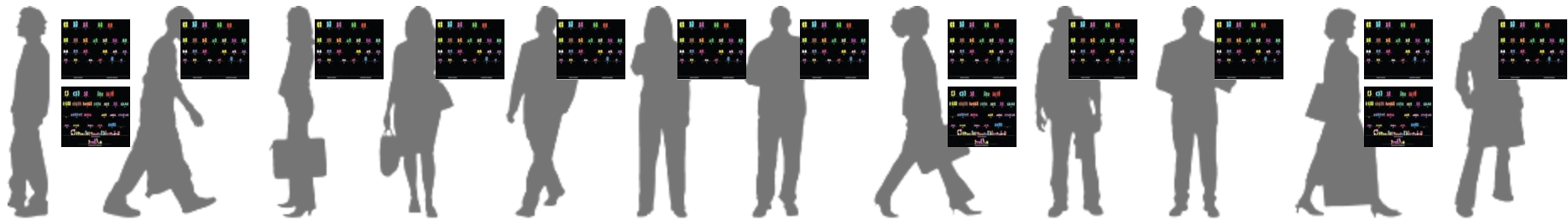
- An integrated personal omics profile (iPOP) is an example of a more comprehensive version of personalized medicine.
- Michael Snyder had his genome sequenced and collected many other large scale datasets over an extended period of time.



Our field as future Gateway – Personal Genomics as a Gateway into Biology

Personal genomes soon will become a commonplace part of medical research & eventually treatment (esp. for cancer). They will provide a primary connection for biological science to the general public.





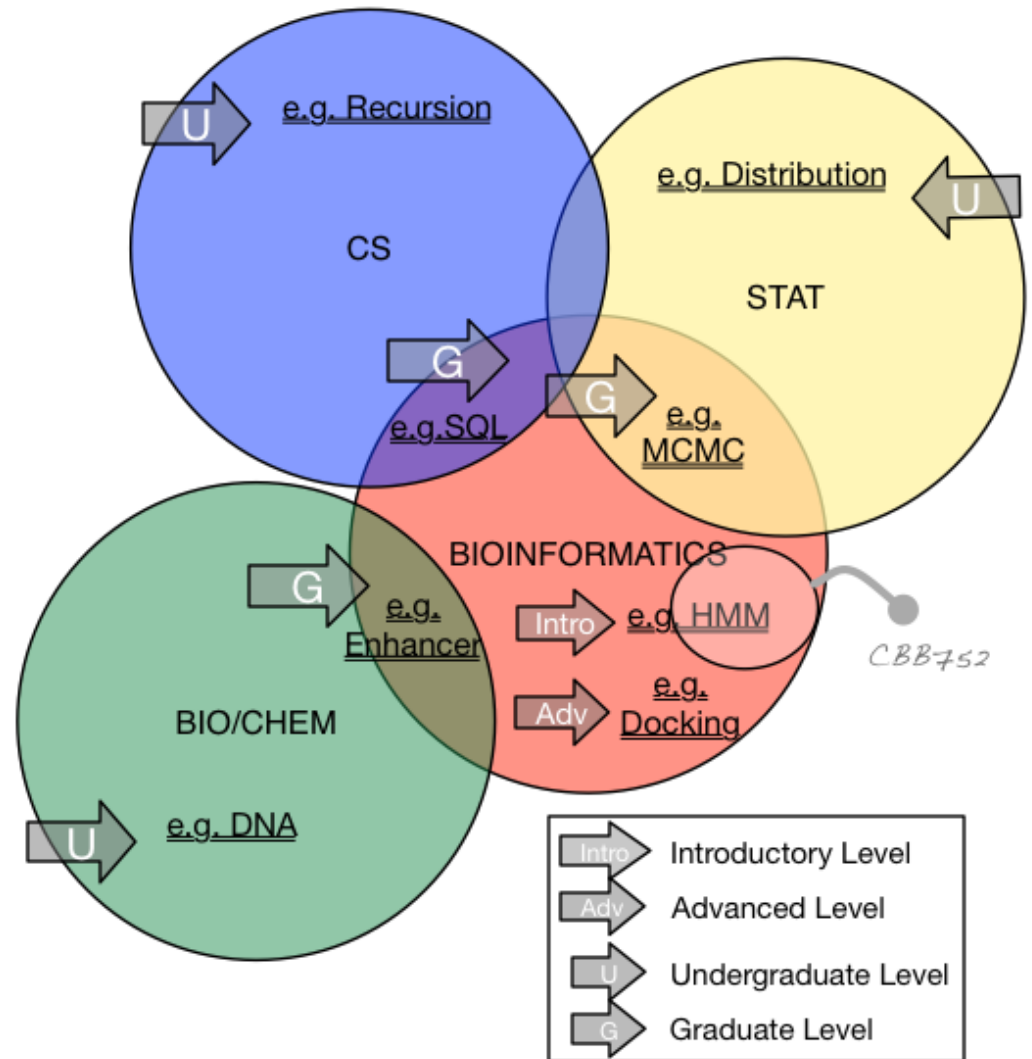
Placing the individual into the context of the population & using the population to build a interpretative model

Biomed. Data science:

The Course

Defining the field – by crowd-sourced judgement

- Bioinformatics
 - Related terms
 - Biological Data Science
 - Bioinformatics & / or / vs Computational Biology
 - Bio-computing
 - Systems Biology
 - “Qbio”
- What are its boundaries
 - Determining the “Support Vectors”



Overview of Topics Surveyed

Introduction

& Overview of the Data

- Genomics & Sequencing
- Proteomics & Structure
- Databases

Data Mining & Machine Learning

- "Classic" Supervised & Unsupervised Approaches
 - Decision Tree & SVMs
 - Clustering & SVD
- Application to 'Omics Data
 - Comparing sequences
 - Processing single cell & epigenomic data

Network Analysis

- Topology & Connectivity
- Gene Networks

Deep Learning

- Basic Theory & Applications

Physical Modeling

- Macromolecular Simulation
- Markov Models
- Molecular Packing

Additional Topics

- Privacy
- Personal Genome Analysis
- Image Analysis

What is Bioinformatics?

- (*Molecular*) **Bio - informatics**

- One idea for a definition?

Bioinformatics is conceptualizing **biology in terms of molecules** (in the sense of physical-chemistry) and then applying **“informatics” techniques** (derived from disciplines such as applied math, CS, and statistics) to **organize, mine, model & understand the information associated** with these molecules, **on a large-scale.**

- Bioinformatics is a practical discipline with many **applications.**

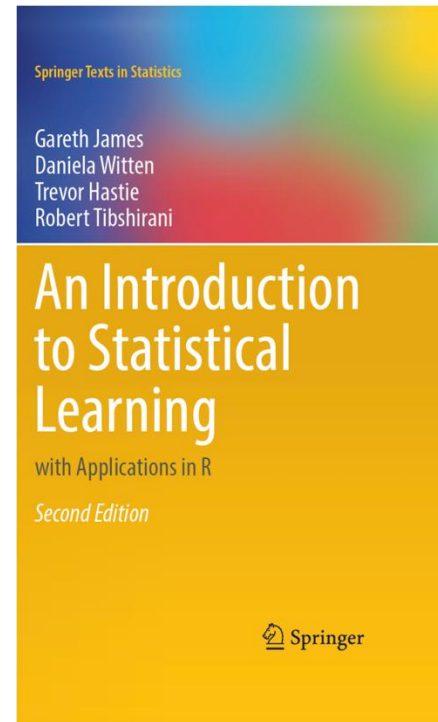
Thoughts on the Class

GersteinLab.org/courses/452 (Class Web Page)

- Broad overview with a few deep dives
 - Fundamentally interdisciplinary field
 - Here, focusing on molecular bioinformatics
 - Some deep dives into sequence comparison, Bayesian approaches, low-dimensional representations
 - Steering away from material in related Yale classes
- Goal is good intuition on approaches & the application area
 - Apply to related problems
- Lectures provide structure of knowledge to be assimilated
 - Varied backgrounds
 - Variety of learning approaches
- Sections for interaction & more hands-on treatment
- Quizzes & homework for individual command of basic knowledge
- Final Project for teamwork
- cbb752@gersteinlab.org for issues

Lectures (& Readings)

- Lectures form the backbone of what you need to know
 - We will post final pptx & pdf AFTER the lecture
 - Also, will have current, lecture-hall recorded videos put up quickly on canvas
 - Class-produced lecture summaries about a week after each lecture (see course website)
- No book
 - Key readings for each lecture listed in the slides
 - ISLR as close as we can get to a text
 - Section papers
- Past Year's As a Guide
 - Convention for numbering lectures:
YYMN = (**Y**)ear, (**M**)odule, (**N**)umber
e.g. **23m3**, **22m3**, (21)**M3**
 - If you want to look ahead, we will mostly follow the flow in **2021-2023** (See the notations at the top of each slide pack for key differences.)
 - Mostly 2021 has well-produced videos, with a few from following years



Key References for i1+i2a

(ranked from most #1 to least important)

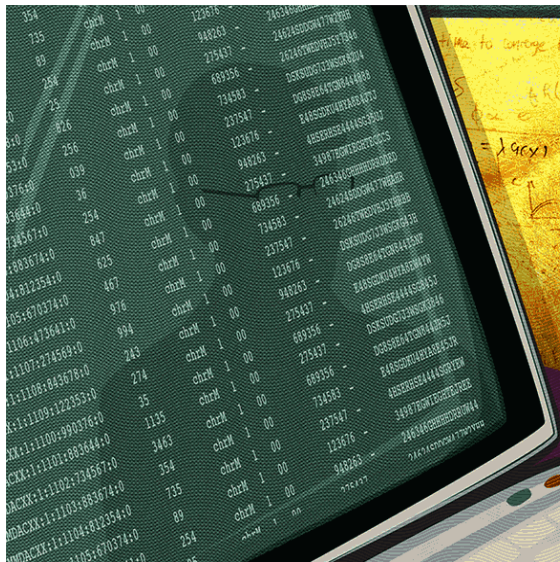
1. Navarro et al (2019) Genome Biology
<https://genomebiology.biomedcentral.com/articles/10.1186/s13059-019-1724-1>
(Read Abstract & Introduction)
2. Muir et al (2016) Genome Biology
<https://genomebiology.biomedcentral.com/articles/10.1186/s13059-016-0917-0>
(Read first 3 sections)
3. Zimmer (2023). STAT
<https://www.statnews.com/feature/game-of-genomes/season-one>
(Just look at the first season & read more if you want.)
4. Luscombe et al (2001) Methods Inform Med
<http://archive.gersteinlab.org/papers/e-print/whatis-mim/text.pdf>
(Read Introduction)
5. Babu et al. (2023). Annual Review of Medicine
<https://doi.org/10.1146/annurev-med-052422-020437>
(Just Skim)

Biomed. Data science:

The Final Project

Analyzing Carl Zimmer's genome

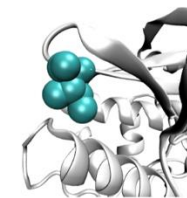
CARL ZIMMER'S GAME OF GENOMES SEASON 1



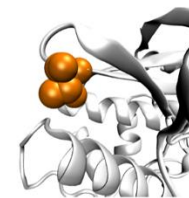
SNV

AAGCT → ACGCT

Protein
Structure



Wild-type



Mutated

Ancestry



History of the Analysis of the “Zimmerome” in the Class

2017

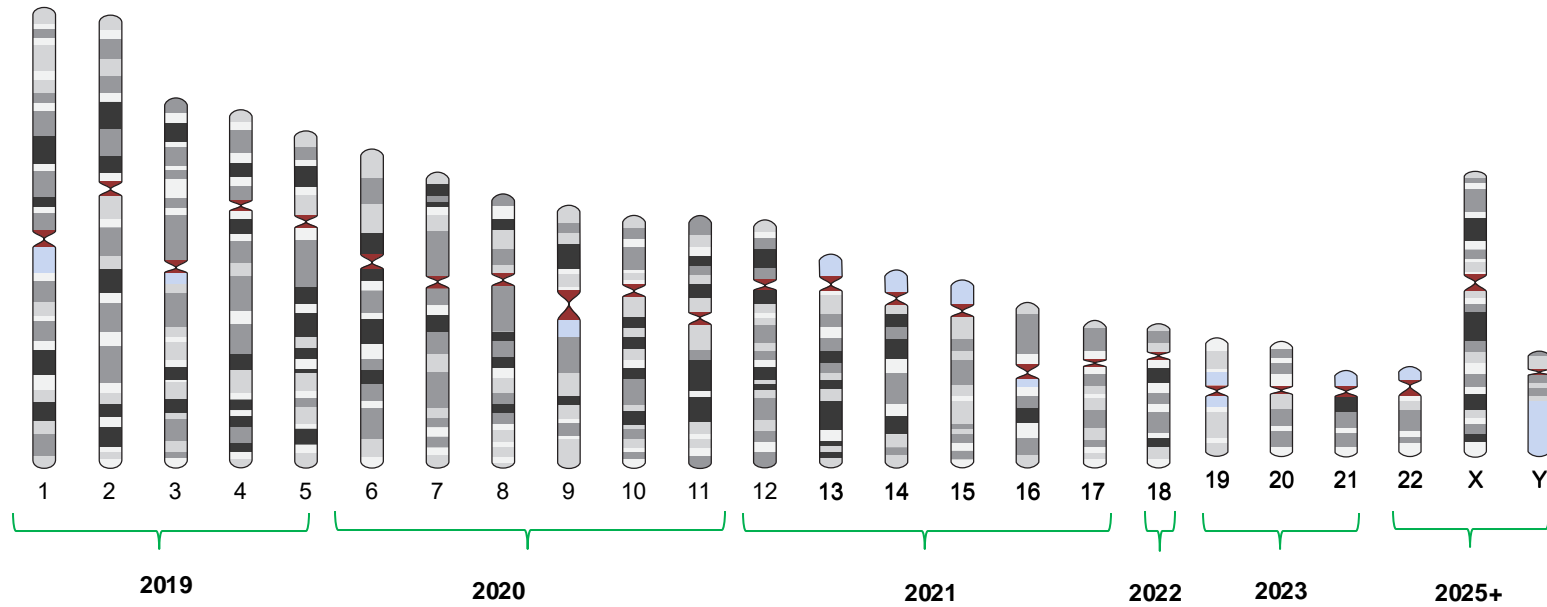
- Each group created a GitHub page detailing the work of each team
 - Additionally, each group has a power point presentation:
- Topics of projects include:
 - Comparative analysis of personal genomes
 - Personal genomes and personalized medicine (CRISPR)
 - Network analysis of personal genomes
 - Structure analysis

2018

- Each group had a power point presentation and a writeup
- Topics of projects include:
 - Finding how much of your genetic material comes from the Neanderthals
 - Using Carl's genome to predict differences in gene expression from the average human and infer possible changes in physiology from these differences (GTEx analysis)
 - Predicting gene expression values from Carl's SNP information
 - Finding a common variant associated with inflammatory response in Carl
 - Calculating Zimmer's risk for Alzheimer's disease
 - Identifying significant protein-coding mutations in Carl's genome
 - polygenic risk score prediction in coronary artery disease, type II diabetes, and schizophrenia for Carl

2019 – 2023

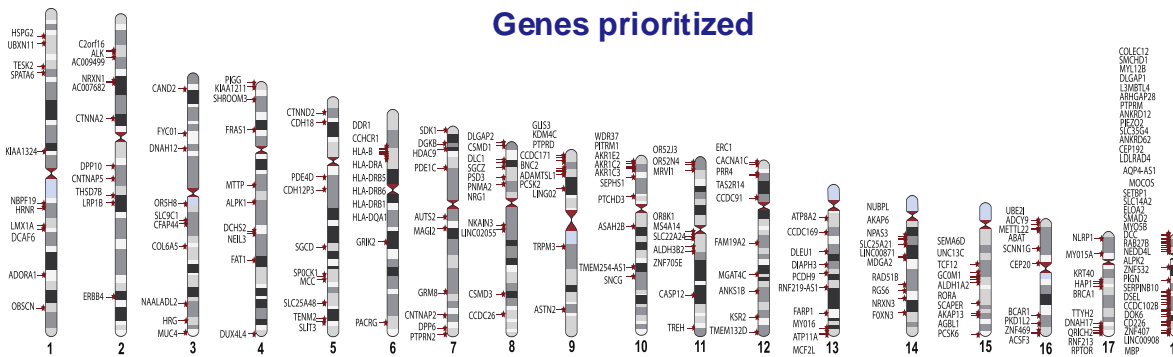
- Each group had a power point presentation and a write-up
- Started analyzing Carl's gene chromosome by chromosome



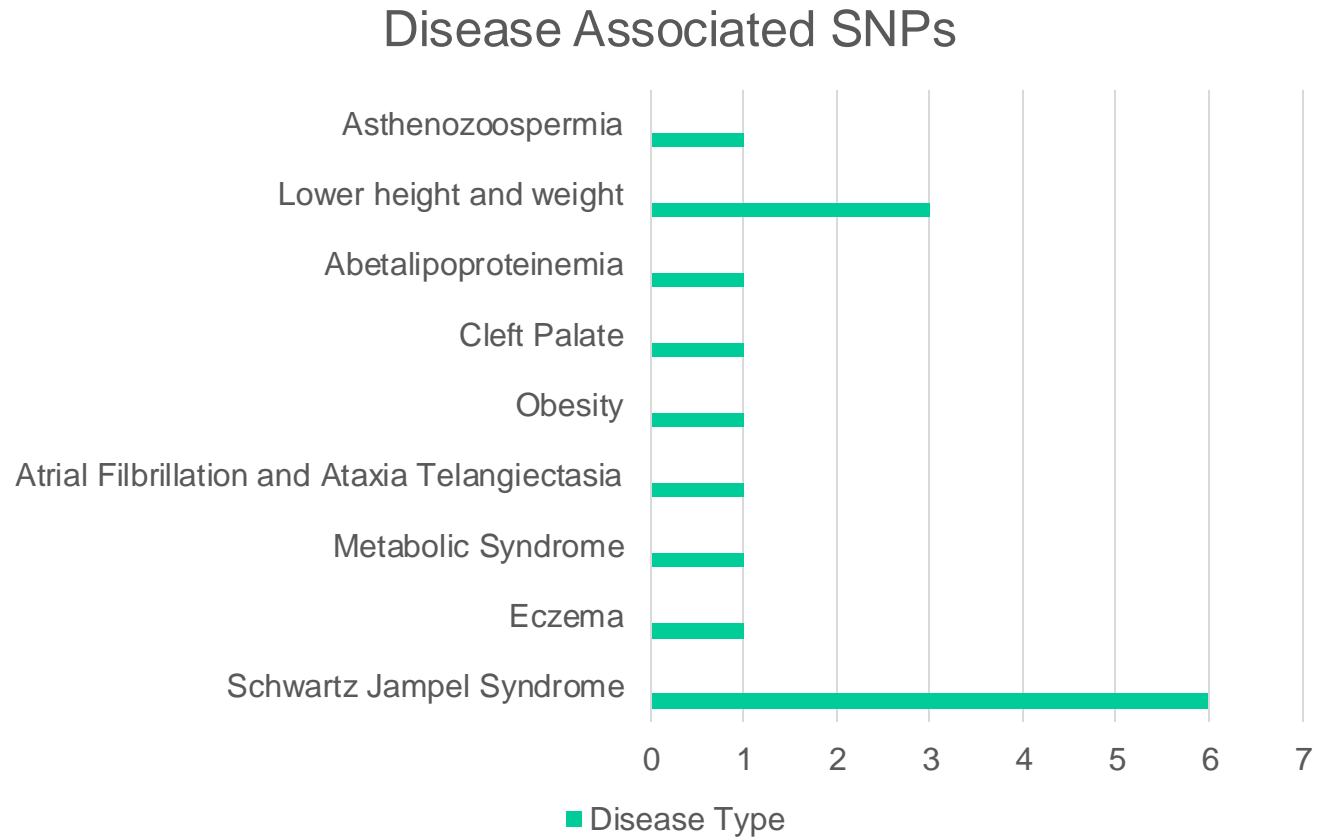
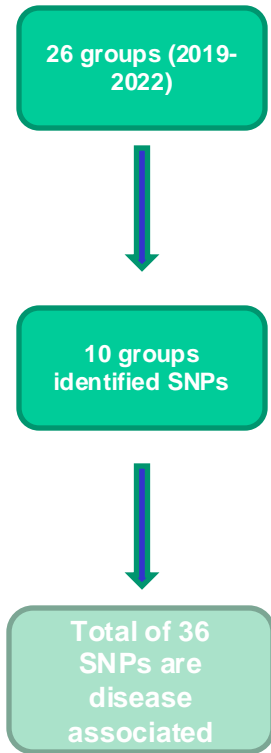
- Part 1: Prioritization of 10 genes
- Part 2: In-depth Analysis of prioritized genes:

- Gene expression analysis
- Network analysis
- Protein structure analysis
- Text mining analysis

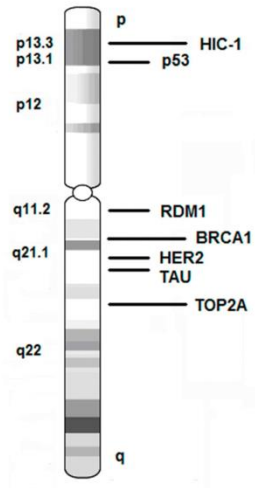
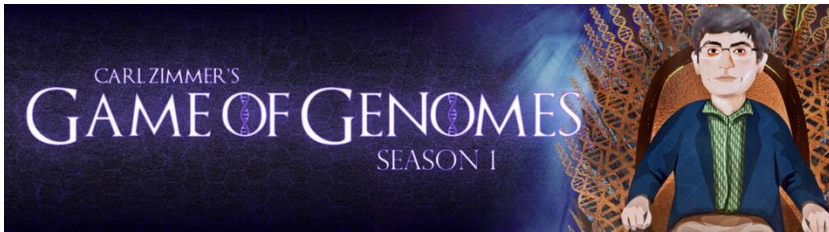
History of Analyzing the “Zimmerome” in Class



History of the Analysis of the “Zimmerome” in the Class



This year's Zimmerome Assignment: Investigate and Analyze a Personal Genome Using Bioinformatic/Biomedical Tools



Team based approach

- Assigned Teams (4-5 people in your section, assigned by TFs)
- Each team focuses on a single chromosome
- Cross-disciplinary

1. Computational

- Leveraging tools to prioritize genes or variants
- Pipeline Development

2. Biological/Biomedical

- Interpretation of prioritized genes or loci

3. Written and Oral

- Communication of project and results through written report

1. Computational Pipeline Development

1

VCF to BED

Converted Zimmer SNV VCF file for ease of use; filtered for Ch17 (*BEDOPS*)

2

GENCODE

Took GTF file for Gencode (GRCh37) and converted to BED (*BEDOPS*)

3

Filtering

Extracted CDS regions only; eliminated repeat entries; kept position/category/gene info

7

Future Direction

Weight variants with other variant prioritization tools or databases

Noncoding analysis

4

Intersect Files

Intersected annotation file with variant file (*BEDTools*), created gene-SNV barcode

5

Removing Duplicates

Eliminated repeat position entries from gene isoforms using barcodes

6

Compile Data

Sum mutations by gene, sort high to low, extract top 10; convert file to VCF

→ GTEx

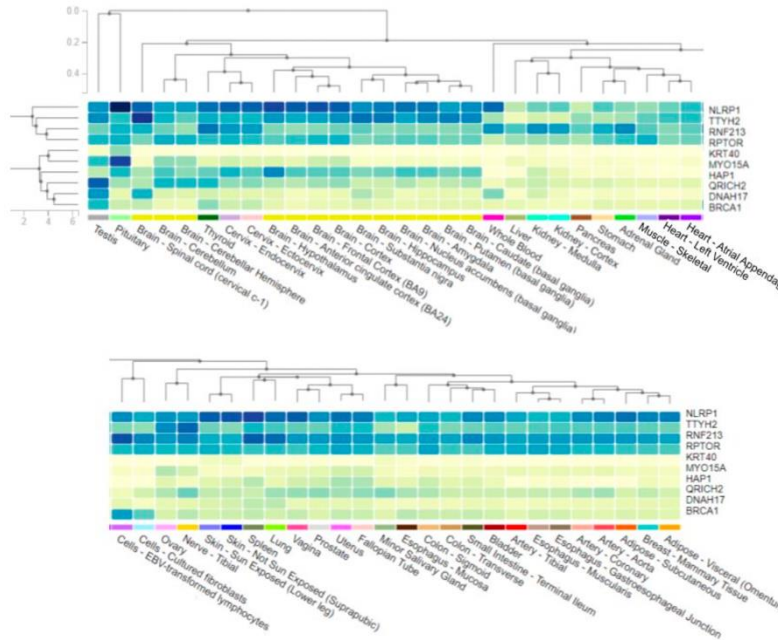
Computational Pipeline

- Full code/software/script package
- GitHub
- Data files
- readme

2. Biological/Biomedical Interpretation

Tissue Specific Expression
Extracted from
GTEx

TPM 0.0 1.8 7.0 22 64 1.8e+2



Interpretation of Results

- Biological interpretation of prioritized genes or loci
- Leveraging public omics or biomedical data
- Further discussion of results

3. Oral Presentation and Written Report

I. Introduction

In 2016, journalist and author Carl Zimmer released an analysis of his personal genome to the public, conducted by the Gerstein Laboratory at Yale. Using standard computational genomics techniques, the scientists were able to confirm an absence of pathogenic variants in Zimmer's genome,¹ and, although Zimmer was not impacted health-wise, such an analysis was key for demonstrating the benefit of personalized genomics for healthcare.

The purpose of this report is to further expand on the work done by Gerstein and re-analyze the ten genes with the most mutational burden contained on chromosome 17 of Carl Zimmer's genome.

Chromosome 17 is characterized by approximately 1,100 protein-coding genes, having the second-highest gene density in the human genome.² It is known for containing the HoxB gene cluster, which is involved in morphogenesis³, as well as oncogenes and tumor suppressor genes that can influence breast cancer risk (i.e. BRCA1, TAU, HER2).⁴ Through in-depth computational analysis of genes affected by SNVs, the genes with a high mutational burden were identified. Their tissue-specific expression was then studied using the GTEx database. These steps provided a broad perspective on the impact of SNVs with regards to gene function and pathogenicity.

II. Methods

The data was pre-processed by the Gerstein Lab into a VCF file format for interpretation by the students. Zimmer's genome was sequenced by Illumina and a BAM file was generated using the Isaac aligner. This was re-aligned to the reference genome GRCh37 using the BWA-mem algorithm. Standard aligners, like GATK, were used to call SNVs, and these were compiled into a VCF File.⁵

One of the goals of the project was to determine the relationship between variants and genes. Custom code as well as existing packages were used to achieve this. All analysis, data, and code was designed to be used on hg19 (GRCh37.p13).

First, the VCF file was converted to a BED file for ease of use in downstream analysis. This was performed using vcf2bed, which is part of the BEDOPS tool suite. Position and annotation information for the variants were retained. A simple awk statement was used to filter for only variants on chr17, the focus of our analysis.

In addition to processing the variants, we aimed to collect and process gene data in order to determine the location of all protein-coding genes. Specifically, we used the GENCODE comprehensive gene annotation file, a GTF file. We converted this to a BED file and filtered for protein-coding regions categorized as CDS to encapsulate the entire transcribed area in our analysis. To do so, we made use of gtf2bed (BEDOPS) as well as additional awk statements for filtering, keeping the position, category, gene type, and gene name. Only unique entries were kept. As a side note, this file contained protein-coding regions as well as their isoforms separately.

In order to prioritize genes based on their mutation burden, we intersected the gene annotation BED file with the variant BED file. This was done using bedtools intersect (v2.29.0) from the BEDTools toolset. To eliminate SNVs double-counted across isoforms, a barcode was created containing position-gene information without isoform demarcation. Only uniquely-barcodeed SNVs were kept.

The resulting data was then summed for the total number of unique mutations per gene and sorted from highest to lowest mutational burden.

The expression profiles documented for these ten genes across individual tissue types were extracted from the Genotype-Tissue-Expression Database (GTEx). Literature searches were run to further characterize the nature of these genes and connect them to tissue-specific expression.

III. Results

SNVs were found from protein-coding genes on Chromosome 17. The top ten genes with the greatest aggregation of SNVs are shown below.

Gene Name	SNV Count	Description
DNAH17	24	DNAH17 codes for an outer dynein arm used as a specific axoneme motor for sperm motility - it is highly expressed in the testis.
NLRP1	19	NLRP1 is a NACHT, leucine-rich repeat and pyrin domain containing 1 protein that senses stress to induce inflammation.
QRICH2	14	The GTEx analysis shows increased expression of QRICH2 in the testis and brain. This protein is important for flagellar structure development of sperm.
RNF213	12	RNF213 gene encodes for RNF213 protein, whose function is not fully understood. In studies, it has been shown to affect vascularity and is thought to induce capillary dilation.
KRT40	11	KRT40 gene encodes for type-I keratin structural proteins. These intermediate filament proteins compose cytoskeleton of epithelial cells.
HAP1	10	HAP1 gene encodes for a huntingtin-associated protein that binds tightly to huntingtin with expanded glutamine repeat. This is believed to be linked to protection from Huntington's Disease pathology in humans.
BRCA1	9	BRCA1 encodes for a protein which in complex promotes S phase or G2 arrest. It is involved in DNA repair by

Oral Presentation

- April 23
 - 2 to 3 minute mp4 recording per group (nominate 1 person to make the recording)
 - We will play these recordings in class on 4/23
- in your Discussion Section of Week April 23
 - Approximately 10 minute presentation by other members of the group

Written Report

- Due: May 5, 2025
- At least 1000 words

Summary Slide

- 1 summary slide giving an overview of your project

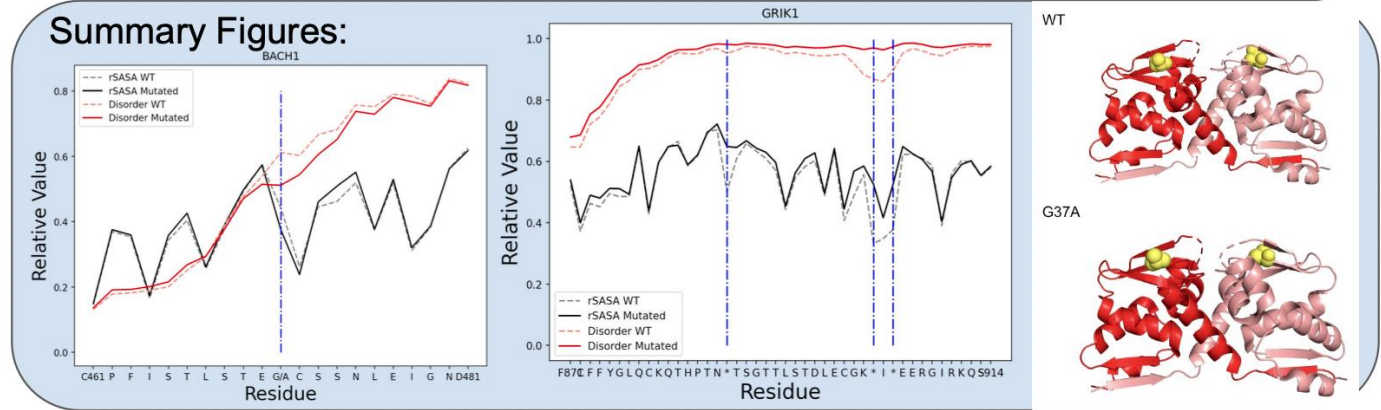
Summary Metadata File

- A single text file containing relevant information
- More description in assignment file

2023 group 3 (chr 21)

Top 10 Prioritized Genes

1. DSCAM
2. RUNX1
3. NCAM2
4. KCNJ6
5. TSPEAR
6. GRIK1
7. ERG
8. APP
9. CHODL
10. BACH1



Summary:

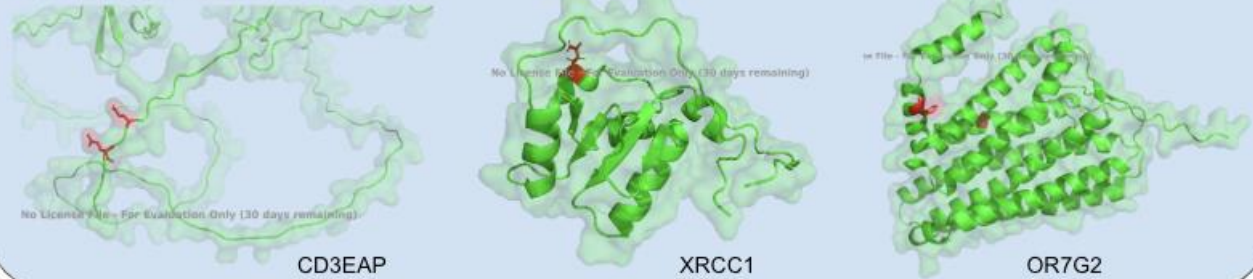
1. Prioritization approach: protein coding genes with highest mutational burden
2. Downstream analysis: protein structure (rSASA) analysis with NetSurfP
3. Findings:
 - a. APP causes protein aggregates that are well-linked to Alzheimer's: found no protein coding variants (good news!)
 - b. GRIK1 L902S has a correlation with ADHD
 - it is a cationic channel in the Cerebellum and hypothalamus; binds to excitatory neurotransmitter L-glutamate

2023 Group 1 Section 3 (chr 19)

Top 10 Prioritized Genes

1. CD3EAP
2. XRCC1
3. OR7G2
4. OR10H5
5. LILRB4
6. KIR2DL3
7. KIR2DL1
8. KIR3DL2
9. ZFP28
10. GP6

Summary Figure:



Summary:

1. Resistance to Cisplatin-based cancer treatment
2. Dysregulation of certain immune cell subtypes ability to distinguish host and tumor cells
3. Dysregulation of collagen-based platelet adhesion

Notes on the Course



- Surveys: Please make sure these are done quickly
 - will count in overall grade
 - Available from GersteinLab.org/courses/452
- Sections:
 - Discussion section assignments will be sent out shortly
 - Will start next week
 - Lecture summaries will start on Wed.
- For issues, please discuss with TFs right after class or email cbb752@gersteinlab.org
 - e.g. for students registered as “guest student” on canvas