Bioinformatics: A perspective

Dr. Matthew L. Settles

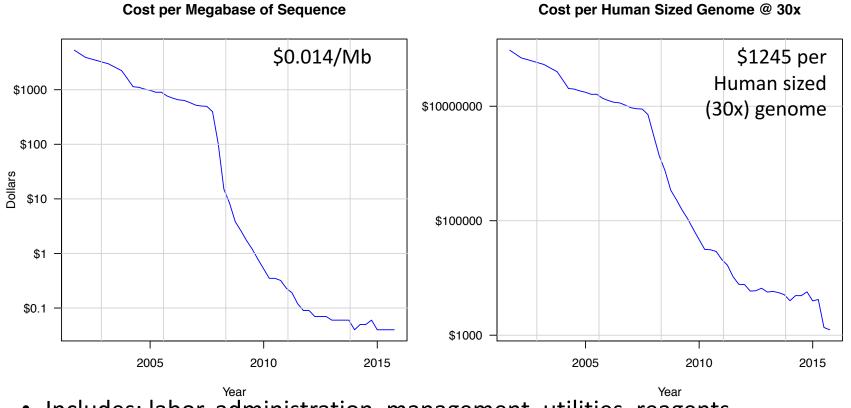
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Outline

- The World we are presented with
- Advances in DNA Sequencing
- Bioinformatics as Data Science
- Viewport into bioinformatics
- Training
- The Bottom Line

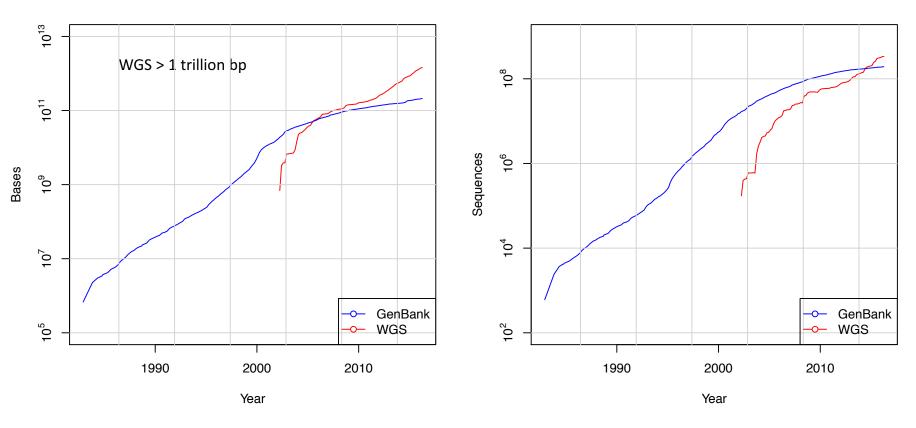
Sequencing Costs

October 2016



- Includes: labor, administration, management, utilities, reagents, consumables, instruments (amortized over 3 years), informatics related to sequence productions, submission, indirect costs.
- http://www.genome.gov/sequencingcosts/

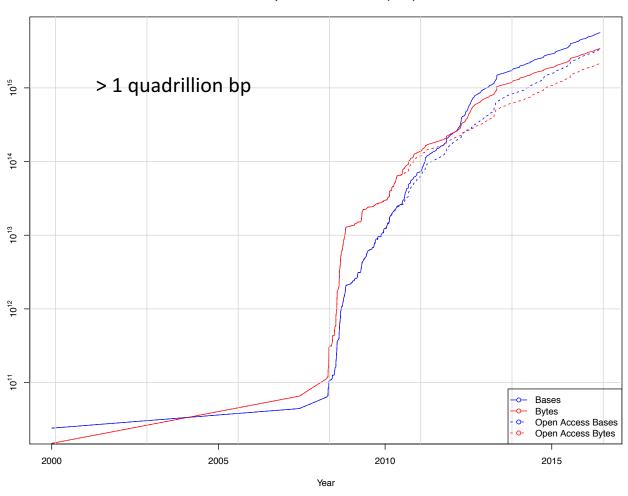
Growth in Public Sequence Database



http://www.ncbi.nlm.nih.gov/genbank/statistics

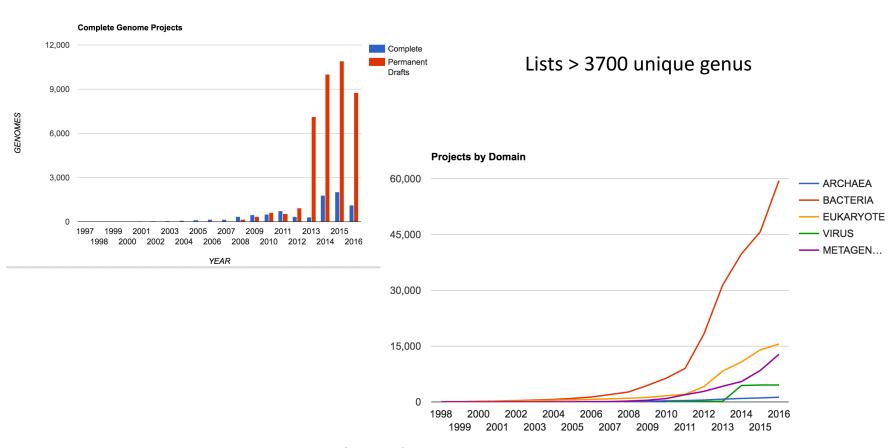
Short Read Archive (SRA)

Growth of the Sequence Read Archive (SRA) over time



http://www.ncbi.nlm.nih.gov/Traces/sra/

Increase in Genome Sequencing Projects

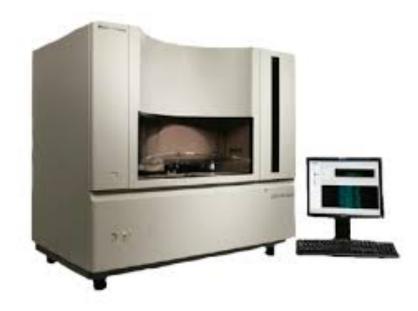


- JGI Genomes Online Database (GOLD)
- 67,822 genome sequencing projects

Brief History

Sequencing Platforms

 1986 - Dye terminator Sanger sequencing, technology dominated until 2005 until "next generation sequencers", peaking at about 900kb/day



'Next' Generation

 2005 – 'Next Generation Sequencing' as Massively parallel sequencing, both throughput and speed advances. The first was the Genome Sequencer (GS) instrument developed by 454 life Sciences (later acquired by Roche), Pyrosequencing 1.5Gb/day



Illumina

• 2006 – The second 'Next Generation Sequencing' platform was Solexa (later acquired by Illumina). Now the dominant platform with 75% market share of sequencer and and estimated >90% of all bases sequenced are from an Illumina machine, Sequencing by Synthesis > 200Gb/day.



Complete Genomics

 2006 – Using DNA nanoball sequencing, has been a leader in Human genome resequencing, having sequenced over 20,000 genomes to date. In 2013 purchased by BGI and is now set to release their first commercial sequencer, the Revolocity. Throughput on par with HiSeq

NOW DEFUNCT

Human genome/exomes only.

10,000 Human Genomes per year



Bench top Sequencers

Roche 454 Junior

- Life Technologies
- Ion Torrent
- Ion Proton

Illumina MiSeq



The 'Next Next' Generation

• 2009 – Single Molecule Read Time sequencing by Pacific Biosystems, most successful third generation sequencing platforms, ~2Gb/day, New Pac Bio Sequal ~14Gb/day.



Oxford Nanopore

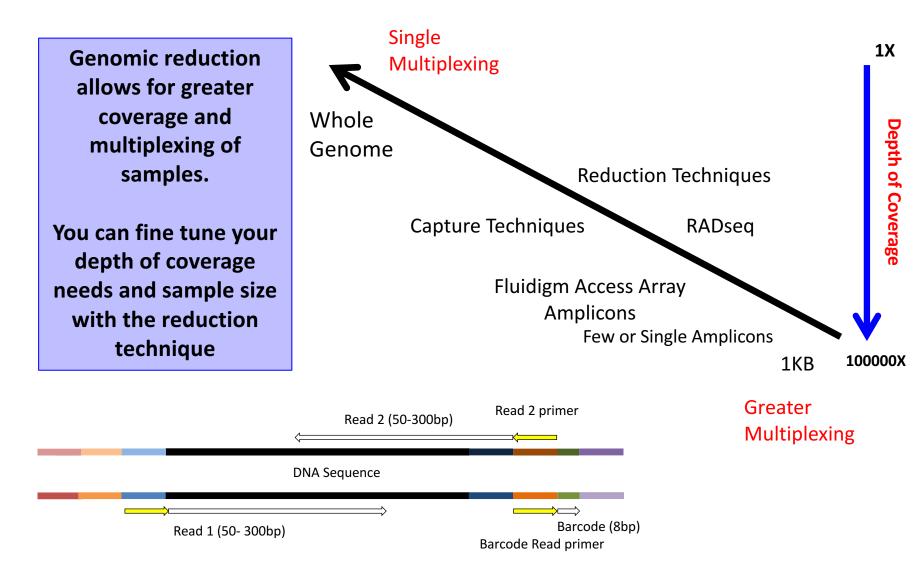
• 2015 – Another 3rd generation sequencer, founded in 2005 and currently in beta testing. The sequencer uses nanopore technology developed in the 90's to sequence single molecules. Throughput is about 500Mb per flowcell.

Fun to play with but results are highly variable



FYI: 4th generation sequencing is being described as In-situ sequencing

Flexibility



Sequencing Libraries

DNA-seq	DNase-seq	tagRNA-seq
•		•

RNA-seq	ATAC-seq	PAT-seq
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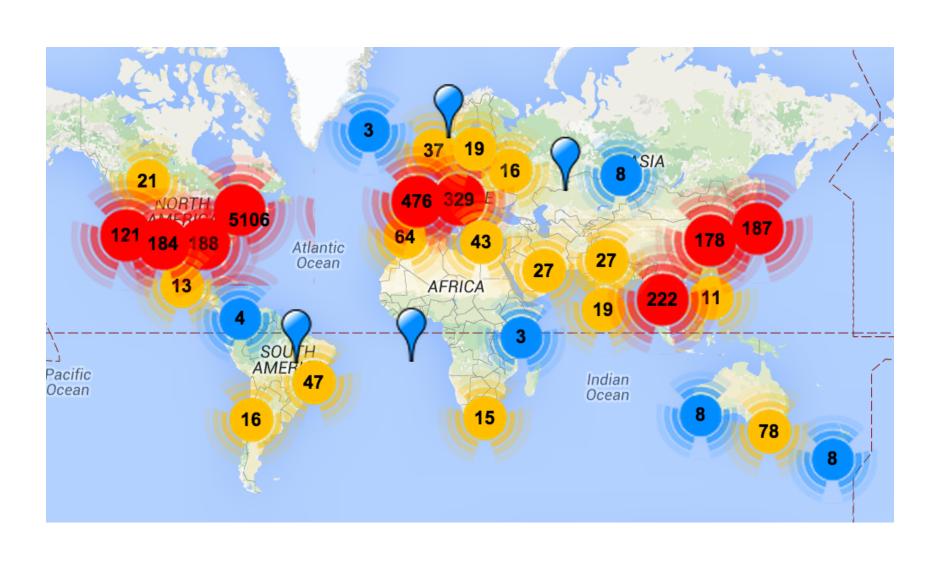
 Amplicons 	MNase-seq	Structure-seq
	14114436 364	

Medif-seq		
	Pihaca caa	$STARR_{-SDA}$

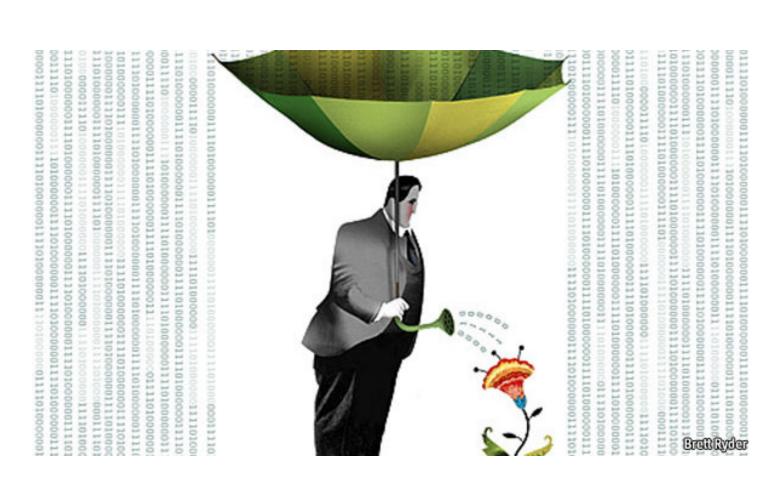
	Ribose-seg	3 IANN-SEY
• RAD-sea		•

QTL-seq G&T-seq

omicsmaps.com



The data deluge



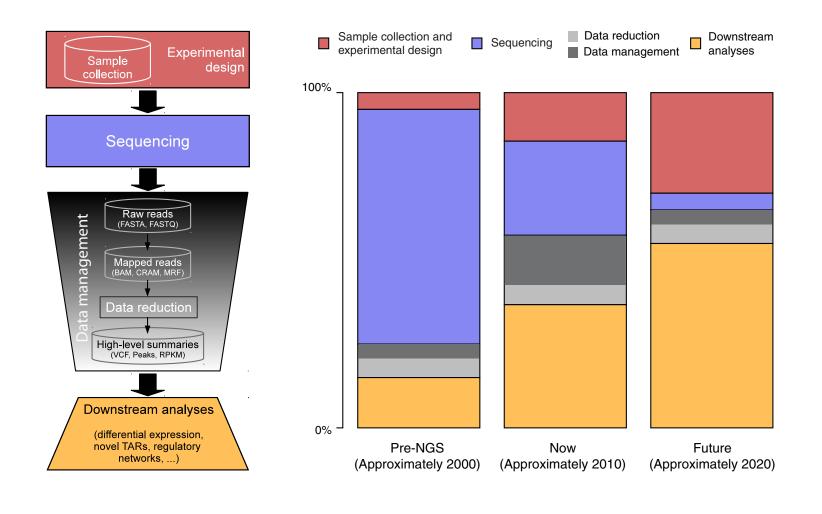
Plucking the biology from the Noise

Reality

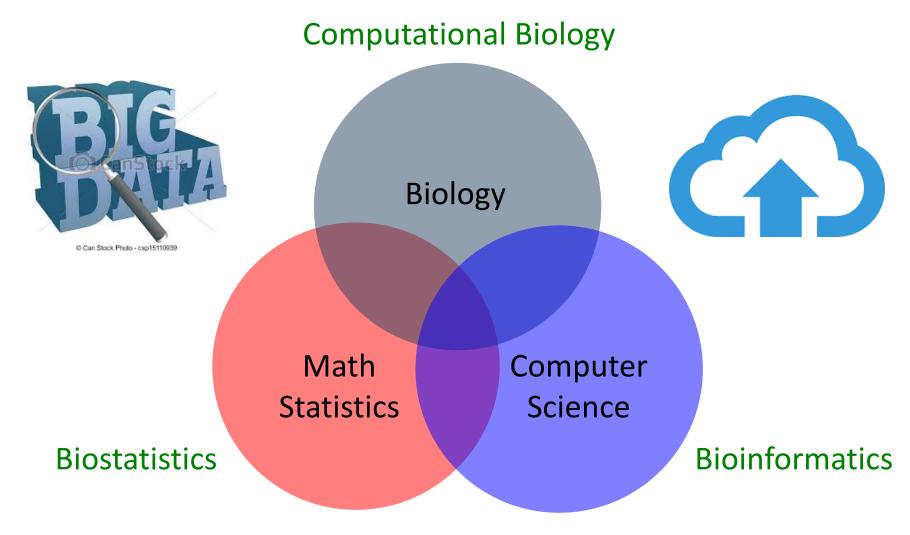


• Its much more difficult than we may first think

The real cost of sequencing



Bioinformatics is Data Science



'The data scientist role has been described as "part analyst, part artist."'
Anjul Bhambhri, vice president of big data products at IBM

Data Science

Data science is the process of formulating a quantitative question that can be answered with data, collecting and cleaning the data, analyzing the data, and communicating the answer to the question to a relevant audience.

7 Stages to Data Science

- 1. Define the question of interest
- 2. Get the data
- 3. Clean the data
- 4. Explore the data
- 5. Fit statistical models
- 6. Communicate the results
- 7. Make your analysis reproducible

1. Define the question of interest

Begin with the end in mind!

what is the question how are we to know we are successful what are our expectations

dictates

the data that should be collected the features being analyzed which algorithms should be use

- 2. Get the data
- 3. Clean the data
- 4. Explore the data

Know your data!

know what the source was technical processing in producing data (bias, artifacts, etc.) "Data Profiling"



Data are never perfect but love your data anyway!

the collection of massive data sets often leads to unusual, surprising, unexpected and even outrageous.

5. Fit statistical models

Over fitting is a sin against data science!

Model's should not be over-complicated

 If the data scientist has done their job correctly the statistical models don't need to be incredibly complicated to identify important relationships

 In fact, if a complicated statistical model seems necessary, it often means that you don't have the right data to answer the question you really want to answer.

- 6. Communicate the results
- 7. Make your analysis reproducible

Remember that this is 'science'!

We are experimenting with data selections, processing, algorithms, ensembles of algorithms, measurements, models. At some point these *must all be tested for validity and applicability* to the problem you are trying to solve.



Data science done well looks easy – and that's a big problem for data scientists

simplystatistics.org
March 3, 2015 by Jeff Leek

Training: Data Science Bias

Data Science (data analysis, bioinformatics) is most often taught through an apprentice model

Different disciplines/regions develop their own subcultures, and decisions are based on cultural conventions rather than empirical evidence.

- Programming languages
- Statistical models (Bayes vs. Frequentist)
- Multiple testing correction
- Application choice, etc.

These (and others) decisions matter **a lot** in data analysis "I saw it in a widely-cited paper in journal XX from my field"

The Data Science in Bioinformatics

Bioinformatics is not something you are taught, it's a way of life

"The best bioinformaticians I know are **problem solvers** – they start the day not knowing something, and they enjoy finding out (themselves) how to do it. It's a great skill to have, but for most, it's not even a skill – it's a passion, it's a way of life, it's a thrill. It's what these people would do at the weekend (if their families let them)."

Mick Watson – Rosland Institute

Models

- Workshops
 - Often enrolled too late
- Collaborations
 - More experience persons
- Apprenticeships
 - Previous lab personnel to young personnel
- Formal Education
 - Most programs are graduate level
 - Few Undergraduate



MAKING DATA SCIENCE MORE EFFICIENT

Bioinformatics

- Know and Understand the experiment
 - "The Question of Interest"
 - Build a set of assumptions/expectations
 - Mix of technical and biological
 - Spend your time testing your assumptions/expectations
 - Don't spend your time finding the "best" software
 - Don't under-estimate the time Bioinformatics may take
 - Be prepared to accept 'failed' experiments

Bottom Line

The Bottom Line:

Spend the time (and money) planning and producing **good quality, accurate and sufficient data** for your experiment.

Get to know to your data, develop and test expectations

Result, you'll **spend much less time** (and less money) extracting biological significance and results during analysis.

Substrate

Cloud Computing



Cluster Computing





BASTM



Laptop & Desktop





Environment

"Command Line" and "Programming Languages"











VS



Bioinformatics Software Suite





Prerequisites

- Access to a multi-core (24 cpu or greater), 'high' memory 64Gb or greater Linux server.
- Familiarity with the 'command line' and at least one programming language.
- Basic knowledge of how to install software
- Basic knowledge of R (or equivalent) and statistical programming
- Basic knowledge of Statistics and model building