



VEuPathDB

Eukaryotic Pathogen, Vector & Host Informatics Resources

Crash Course in Omics Terminology, Concepts & Data Types

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KAYAK Round-trip Atlanta X + Tunis X + Wed 11/29 - Wed 12/6 1 adult, Economy

Our Advice
We're still gathering data for this route
Track prices Off

224 of 633 flights

Stops
☐ Nonstop
☒ 1 stop \$1,117
☒ 2+ stops \$894

Fee Assistant
Carry-on bag 0 +
Checked bag 0 +

Book on KAYAK
Show offers instantly bookable on KAYAK

Times
Take-off Landing
Take-off from ATL

Cheapest \$894 • 18h 37m

Best \$1,121 • 13h 07m

Quickest \$1,121 • 13h 07m

Other sort

priceline Land a great deal for less. Book your flight with confidence. Go To Your Happy Price. Book now travel anytime.

ITA Airways 10:10 am - 10:35 am⁺¹ 2 stops 18h 25m IAD, FCO ATL-TUN \$904 Economy Priceline View Deal

ITA Airways 11:25 am - 12:14 am⁺¹ 2 stops 18h 49m FCO, JFK TUN-ATL

Operated by Delta Air Lines Ad

Best

Delta 3:40 pm - 9:50 am⁺¹ 1 stop 12h 10m CDG ATL-TUN \$1,121 Basic Economy Delta View Deal

Delta 5:30 am - 1:35 pm 1 stop 14h 05m CDG TUN-ATL

Operated by Air France Main Cabin \$1,301

Cheapest

ITA Airways 10:10 am - 10:35 am⁺¹ 2 stops 18h 25m IAD, FCO ATL-TUN \$894 Economy ScholarTrip View Deal

ITA Airways 11:25 am - 12:14 am⁺¹ 2 stops 18h 49m FCO, JFK TUN-ATL

2

The Travel Site has Very Useful Data Filters!

OUR ADVICE
We're still gathering data for this route
Track Prices ☐ OFF

Stops

- ☐ Nonstop
- ☒ 1 stop \$1553
- ☒ 2+ stops \$2821

Times

Take-Off Landing

Take-Off from ATL
Sun 5:30 PM ~ 11:30 PM

Take-Off from TUN
Thu 8:00 AM ~ 8:00 PM

Airlines

- ☒ Alitalia \$3265
- ☒ Delta \$3260
- ☒ Frontier
- ☒ Qatar Airways
- ☒ Tunisair
- ☒ Multiple airlines

Show 8 more airlines

Duration

Flight Leg
13h 45m ~ 41h 17m

Layover
0h 55m ~ 22h 55m

Price

\$1553 ~ \$15484

Cabin

- ☒ Economy \$1553
- ☒ Prem Econ \$4956
- ☒ Business \$10933
- ☒ Mixed \$6037

Alliance

- ☐ oneworld
- ☐ SkyTeam \$2821
- ☐ Star Alliance \$1779

Layover Airports

- Algeria
- ☒ Algiers (ALG)
- Canada
- ☒ Toronto (YYZ)
- France
- ☒ Paris (CDG)
- Germany
- ☒ Frankfurt am Main (FRA)
- ☒ Stuttgart (STR)

Flight Quality

- ☐ Show Wi-Fi Flights Only
- ☒ Show Hacker Fares¹
- ☒ Show Red-Eyes
- ☐ Show 65 Longer Flights

Aircraft

- ☒ Narrow-Body Jet
- ☒ Wide-body jet

Booking Sites

- ☐ Airlines Only
- ☒ Air France \$6863
- ☒ Alitalia \$3265
- ☒ Delta \$3260
- ☒ Expedia
- ☒ FlightHub \$1779

Show 6 more sites

3

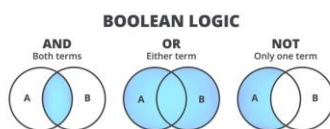
Filters vs Boolean operators

Filters - are very useful, but...

- Can only narrow down the original search
- They only return a subset of the original data
- Examples:
 - All genes on chromosome 4
 - All genes with "kinase in their name"
 - All genes from *Trypanosoma cruzi*

Boolean operators (and, or & not)

- Intersect, union, subtract
- They can operate on two different searches!
- They can narrow down, or, expand the original search
- Examples:
 - All genes on Chr 4 that have kinase in their name
 - All genes on chr 4 or chr 8
 - All genes in *T. cruzi* that also have a signal peptide



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The Biological Equivalent of Travel Search Engine with Filters and Boolean Logic

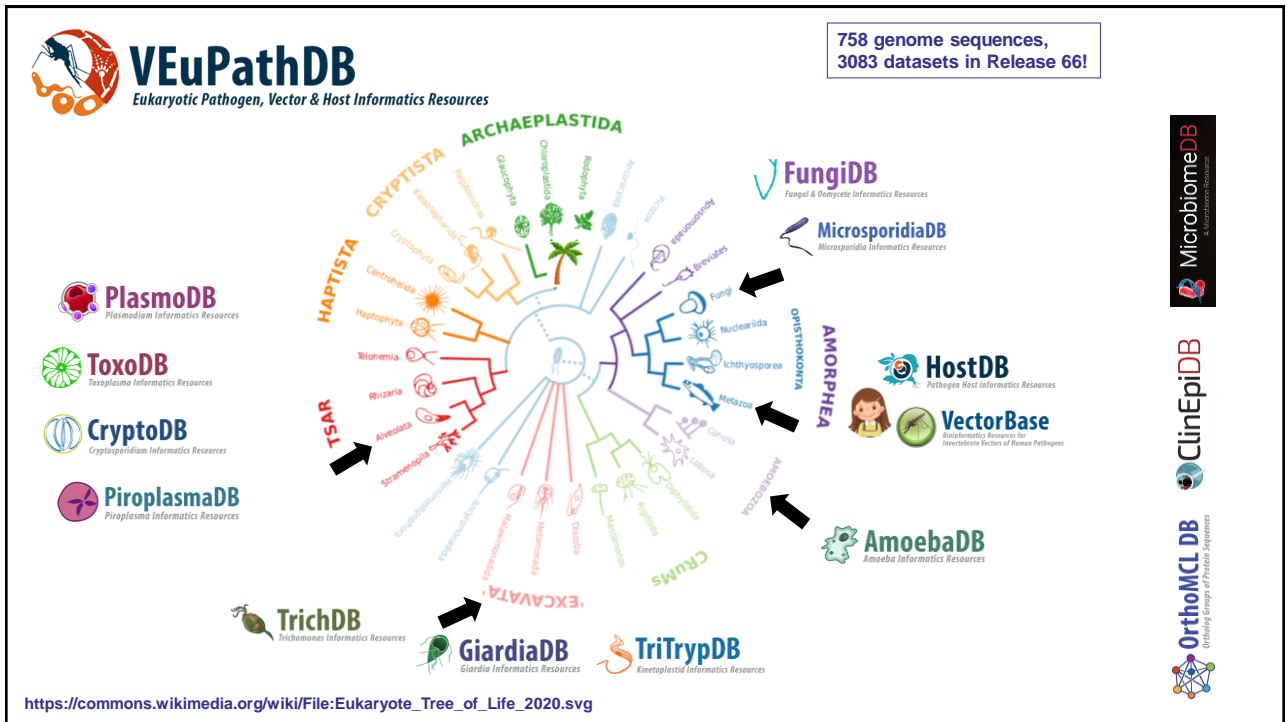
- Find all genes that....
 - That are near centromeres
 - That encode a predicted signal protein
 - That encode the amino acid motif CC..CC
- Which have evidence of expression ...
 - In developmental stage X
 - After treatment with drug Y
- That are phosphorylated in proteomic studies
- That show evidence of diversifying selection in population studies

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Searching biological data is difficult because there are so many different technologies!

- Each technology e.g. genomics, transcriptomics, proteomics, metabolomics, etc.. has its own vocabulary that is more complicated than selecting a window or aisle seat.
- So,...to use the databases efficiently, you do not need to be a bioinformatician, rather you need to be an expert on the technologies related to the data you will mine so you can use the filters and Boolean operators well and interpret your results.
- Since nobody can keep up with all of the technologies and terminologies, and because we come from so many different backgrounds, we have created this crash course in omics

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Most Genomic terminology in VEuPathDB refers to the following biological concepts:

Genome assembly: Reads, contigs, scaffolds, chromosomes, genome sequences, gaps, indels rearrangements, sequence

Genome annotation: Genes, sequence, coding and non-coding, intergenic regions, untranslated regions, introns, Promoters

Evolution: Sequence differences, SNPs, SNV, InDels, synonymous, non-synonymous, orthologs, paralogs, homology

Chromatin status: Epigenetics, Methylation, open chromatin, closed chromatin

Gene expression: Transcripts, splicing, alternative splicing, differential expression, expression levels (relative or absolute), transcript modifications. Analyses can bulk on a tissue or population of cells/organisms or can be single-cell

Proteins: sequence, protein features (motifs, signal peptides, TM domains: chemical properties, chemical modifications (phosphorylation, glycosylation), expression, processing, localization

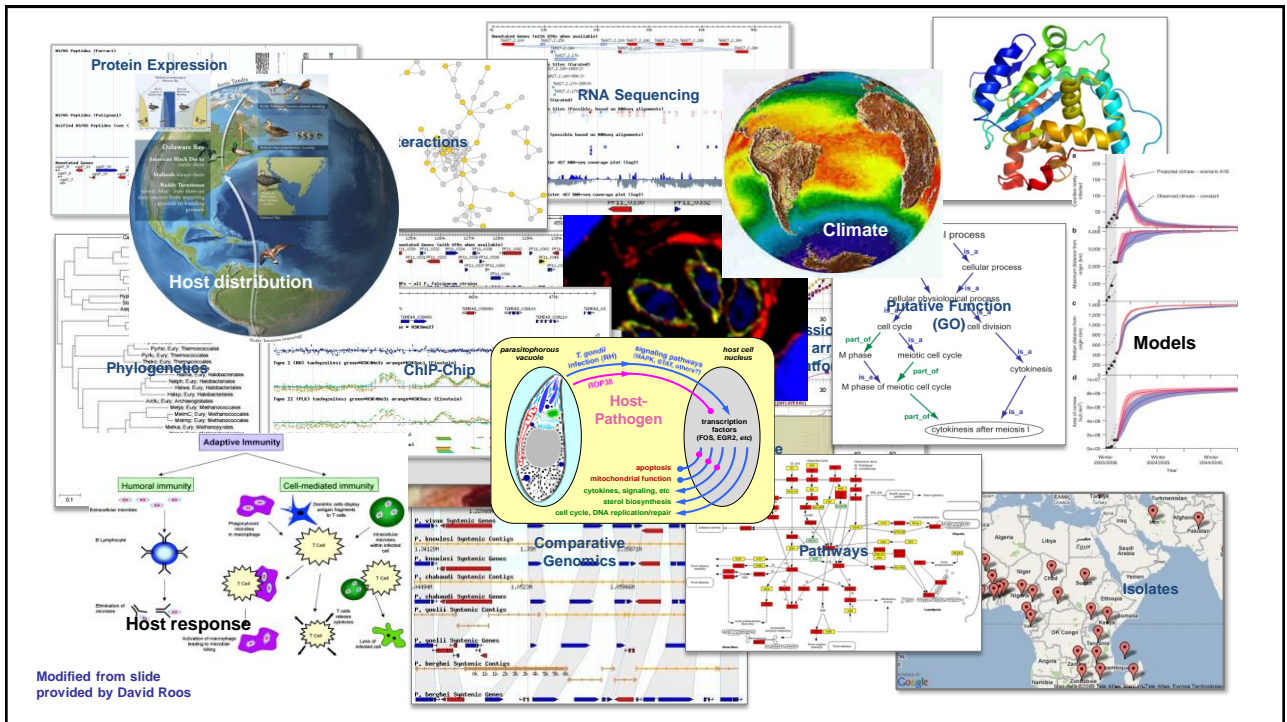
Metabolites: chemical compounds, enzymes, pathways, flux

Host(s): Host response, immune responses, gene regulation responses, metabolic responses

Mutant analysis: phenotypic response to gene knock-down or knock out, e.g. via CRISPR or other approach, or specific mutations

Metadata: data about the data, e.g. the patient, source, environment or experimental condition

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Genome Assembly 30,000 ft View

FASTQ format for reads

The diagram shows a sequence alignment with four components labeled with blue arrows:

- Label:** @FORJUSP02AJWD1
- Sequence:** CCGTCAATT CATTTAAGTTTAACTTGCGGCCGTACTCCCAGCGCGT +
AAAAAAAAAAAA::99@:::??@:::FFAAAAACCAA:::BB@@?A?
- Base:** Base = T, Q = A = 25 (pointing to the first 'A' in the second line)
- Q Scores (as ASCII charts):** (pointing to the second line of the alignment)

Figure 2 – Flowchart of an NGS workflow

$$Q = -10 \log_{10} P$$

Phred Quality Score	Probability of Incorrect Base Call	Base Call Accuracy
10	1 in 10	90%
20	1 in 100	99%
30	1 in 1000	99.9%
40	1 in 10,000	99.99%
50	1 in 100,000	99.999%
60	1 in 1,000,000	99.9999%

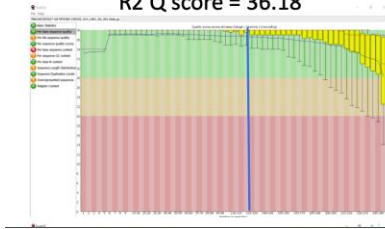
Figure 3 – Phred quality score chart

https://www.abmgood.com/marketing/knowledge_base/next_generation_sequencing_data_analysis.php

FastQC Analysis – Passing Q Scores

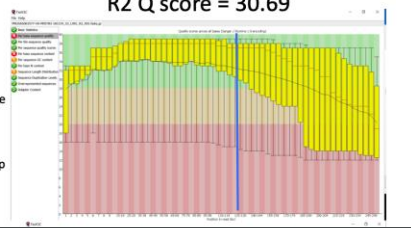
Per Base Sequence Quality & Per Sequence Quality Scores

R2 Q score = 36.18



- Horizontal red line: median Q score
- Horizontal blue line: mean Q score
- Yellow boxes: 50% of the reads
- Whiskers: 80% of the reads
- Vertical blue line: 125 bp of the read

R2 Q score = 30.69



FastQC Analysis – Suboptimal Q Scores (pass with extra coverage)

Per Base Sequence Quality & Per Sequence Quality Scores

R2 Q score = 29.56



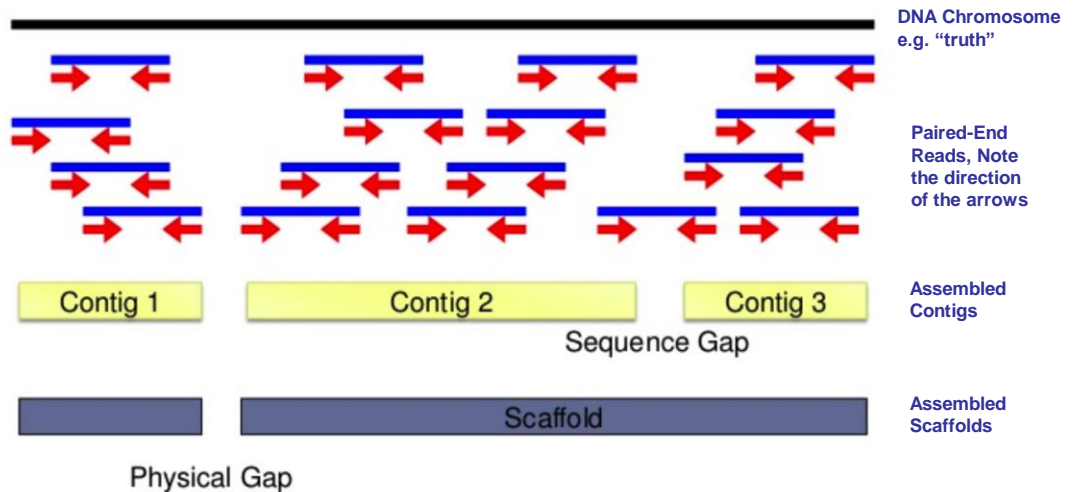
R2 Q score = 28.56



https://www.aphl.org/conferences/proceedings/Documents/2018/4_Eija%20Trees.pdf

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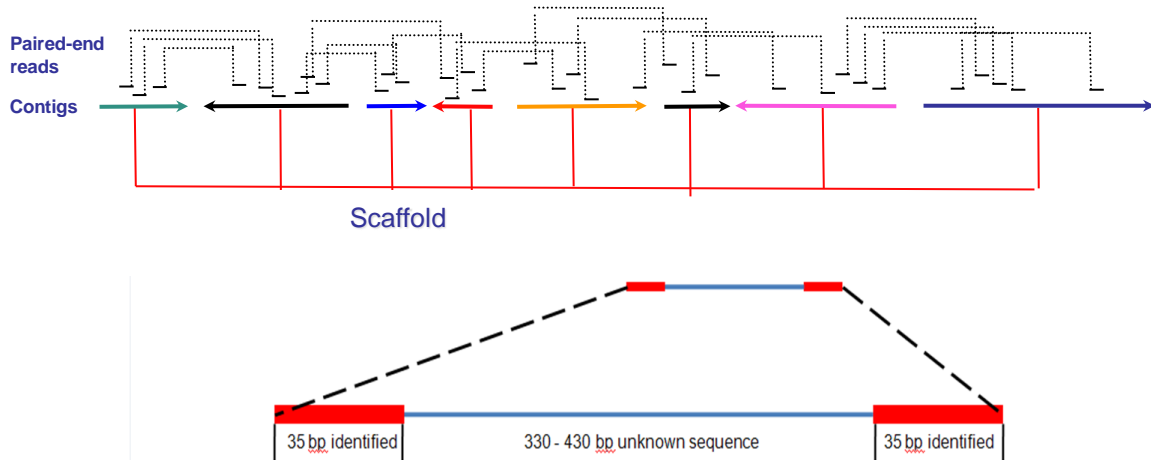
A de novo Short-Read Paired-End Genome Assembly



<https://github.com/Ecological-and-Evolutionary-Genomics/eeg2016/wiki/Mar-21-Exercise-7----SPAdes-assembler>

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Paired-End Reads can Yield Order & Orientation of Contigs

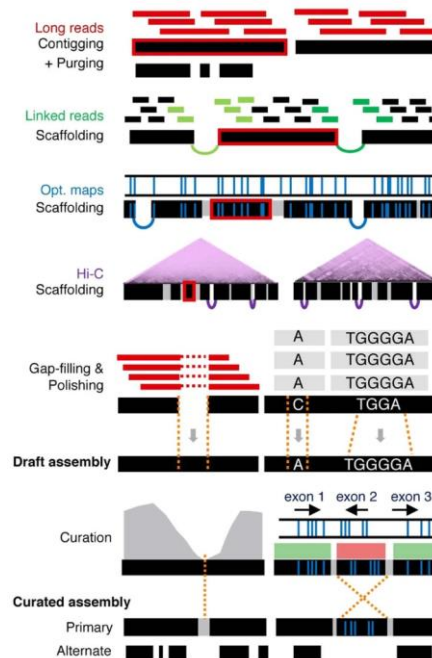


<https://www.biostars.org/p/104218/>

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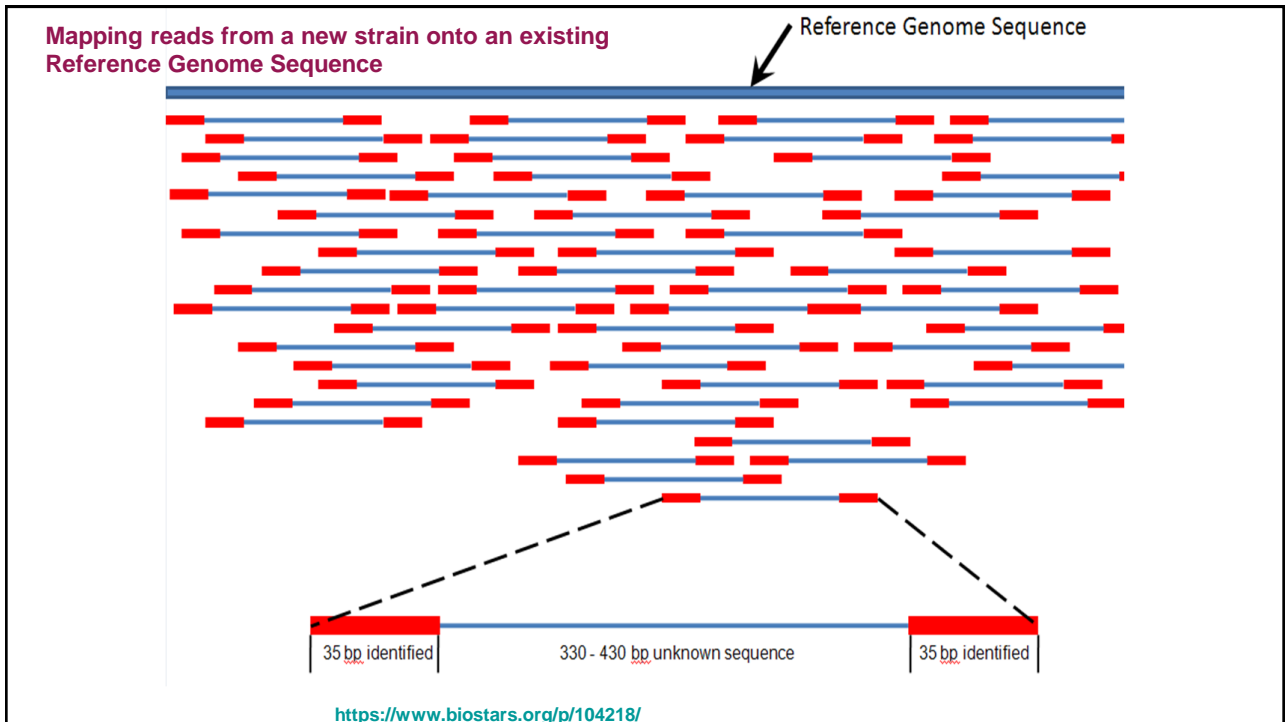
De novo assembly of a complex genome sequence from scratch requires many technologies:

- Deep long reads or Long reads and Illumina short-reads
- Some form of physical mapping, can be genetic or optical mapping for chromosome interactions captured with Hi-C
- All assemblies have gaps and these need to be filled and/or corrected this phase is called polishing.
- Assemblies should be curated by a human to catch errors of mis-assembly (often apparent when read coverage is low as in the example

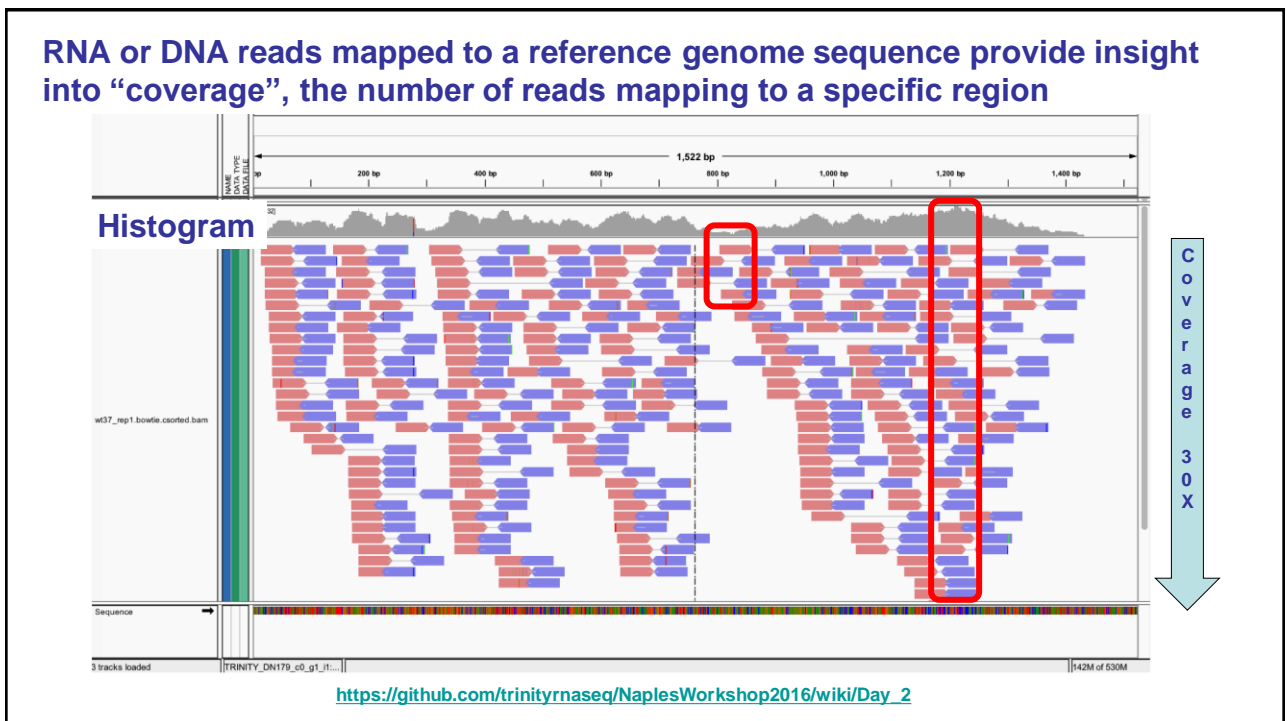


Rhie et al 2021 Nature

14



15

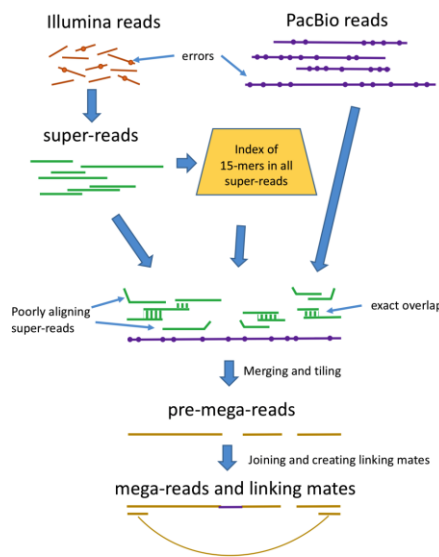


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Hybrid Assembly = short + long reads from differing technologies

It is a VERY useful
approach for "correcting"
and completing telomere to
telomere (T2T) genome
assemblies

<https://genome.cshlp.org/content/early/2017/01/27/gr.213405.116.full.pdf>



Long reads can
be PacBio or
Oxford
Nanopore, ONT

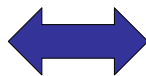
Figure 1. Overview of the mega-reads algorithm. Low-error rate Illumina reads (top left) are used to build longer super-reads (green lines), which in turn are used to construct a database of all 15-mers in those reads. PacBio reads (purple lines) and super-reads are then aligned, using the 15-mer index. Inconsistent super-reads are shown as kinked lines; these are discarded and the remaining super-reads are merged, using the PacBio read as a template, to produce pre-mega-reads (yellow). These are further merged to produce the final mega-reads and to generate linking mates across gaps.

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Genomes: Important Considerations for Assembly and Interpretation

Biological

- Size
 - Mb
 - Gb
- Ploidy
 - Haploid
 - Diploid
 - Tetraploid
- Repeat content
 - Retrotransposons
 - Big gene families
 - AT content
- Clone vs population



Technical

- Read length
 - Short
 - Long
- Coverage
 - 5X
 - 100X
- Read Quality
 - 20
 - 30
 - 40
 - Bias?

DNA sequencing technologies: 2006–2016 Elaine R Mardis NATURE PROTOCOLS | VOL.12 NO.2 | 2017 | 213 [Seq types chart download \(11 MB\)](#)

<https://www.dropbox.com/s/kfkkft5qlmxd68z/ForAllYouSeqMethods.pdf?dl=0> (PDF figures for next two slides)

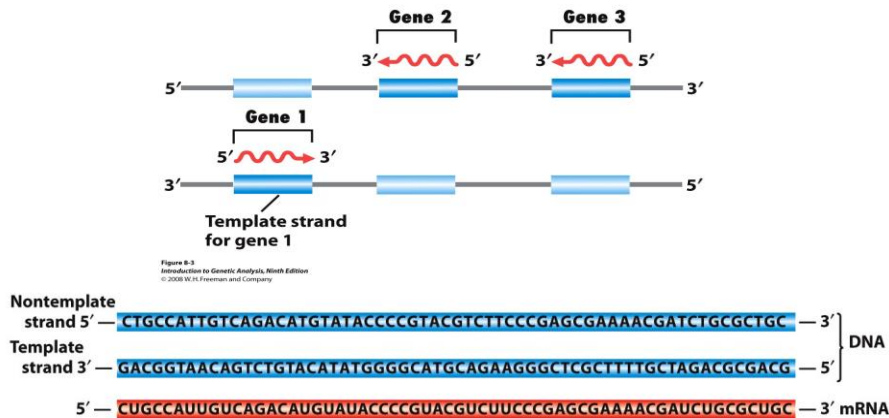
18

[illegible]

The Genome Sequence

[illegible]

Genes can be located on either DNA strand Convention -
Gene location = non-template strand, i.e. the sequence of the
gene is the same as the mRNA (except U = T in DNA)



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Six Frame Translation Looking for Open Reading Frames, ORFs

```

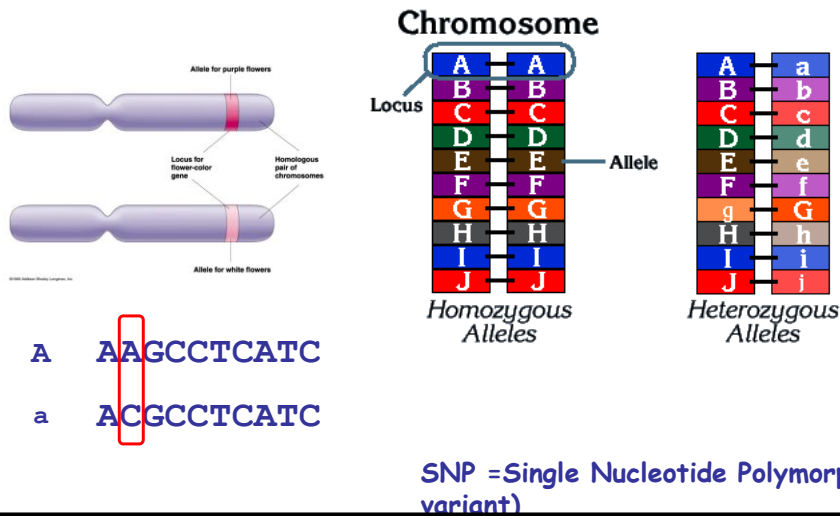
1/1          31/11          61/21
M Y A L L I L Y Y I I I R H * S H H A C R G V Y Y I Y
H V R F T D S I L Y Y Y * T L V T S C M * G G L L Y L
A C T L Y * F Y I I L L L D T S H I M H V G G S T I S
GCA TGT ACG CTT TAC TGA TTC TAT ATT ATA TTA TTA TTA GAC ACT AGT CAC ATC ATG CAT GTA GGG GGG TCT ACT ATA TCT
CGT ACA TGC GAA ATG ACT AAG ATA TAA TAT AAT AAT AAT CTG TGA TCA GTG TAG TAC GTA CAT CCC CCC AGA TGA TAT AGA
C T R K V S E I N Y * * * V S T V D H M Y P P R S Y R
M Y A K S I R Y * I I I L C * D C * A H L P T * * I *
H V S * Q N * I I N N N S V L * M M C T P P D V I D I
121/41          151/51          181/61
* L E L E R I D L A * L Y N F S D I Y I P A S R G K W
L A R A R T H R L S M T I * F Q R H I Y S R L A G K M
A S S * N A S T * H D Y I I S A T Y I F P P R G E N
GCT AGC TCG AGC TAG AAC GCA TCG ACT TAG CAT GAC TAT ATA ATT TCA GCG ACA TAT ATA TTC CCG CCT CGC GGG GAA AAT
CGA TCG AGC TCG ATC TTG CGT AGC TGA ATC GTA CTG ATA TAT TAA AGT CGC TGT ATA TAT AAG GGC GGA GCG CCC CTT TTA
S A R A L V C R S L M V I Y N * R C I Y E R R A P F I
* S S S R M S K A H S Y L K L S M Y I G A E R P F H
L E L * F A D V * C S * I I E A V Y I N G G R P S F P

```

ORFs ≠ Genes – but they can be part of a gene

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Evolution Homologous chromosomes (in a diploid)



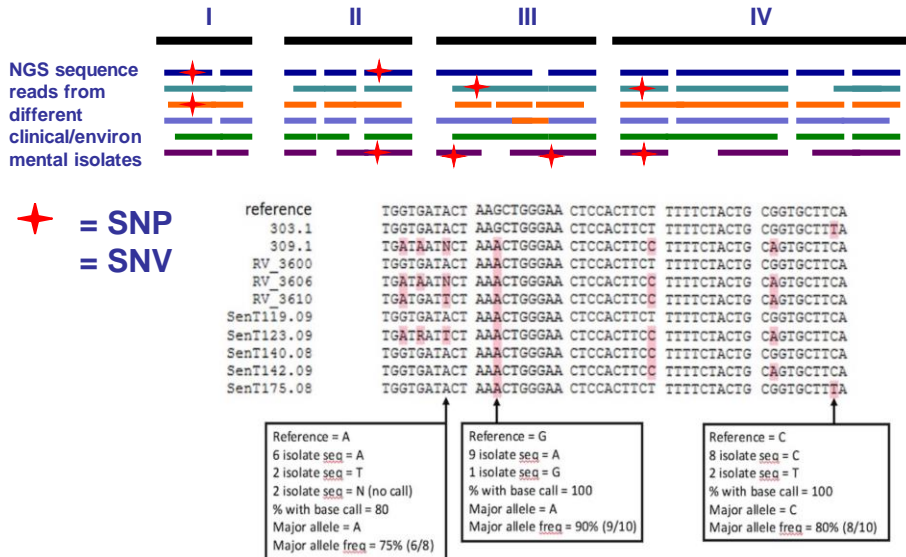
25

Alleles and Phenotype

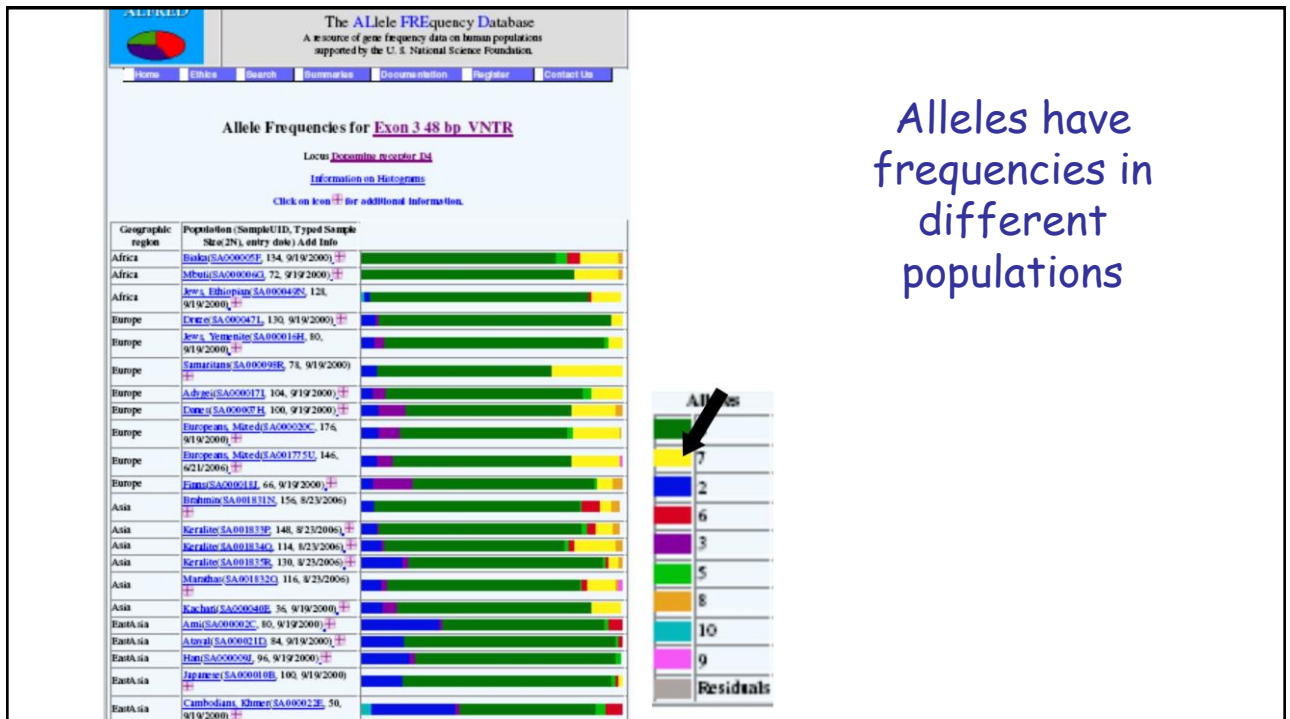
- Some phenotypes are caused by a single locus in the genome and a single allele at that locus (e.g. some flower colors, or *Drosophila* eye color)
- Other phenotypes (Type-I diabetes, heart disease) are multi-locus or “complex” (i.e. many genes are involved, each potentially with many alleles)

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30,000 ft View- NGS SNPs



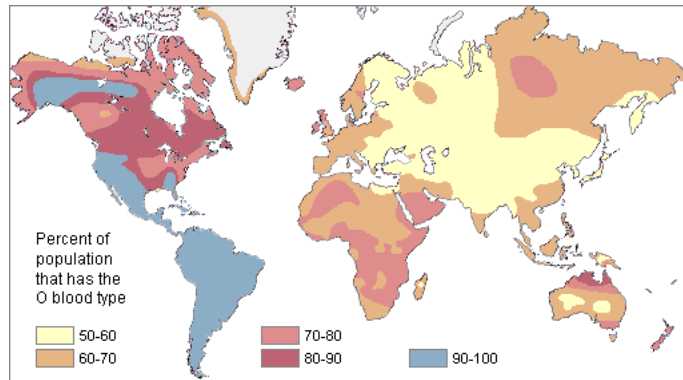
27



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Populations and alleles can have geographic boundaries

A parasite isolate comes from a particular population, a particular location and will have a specific haplotype (e.g. representation of alleles) often characterized via SNPs



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Population variation data

Data

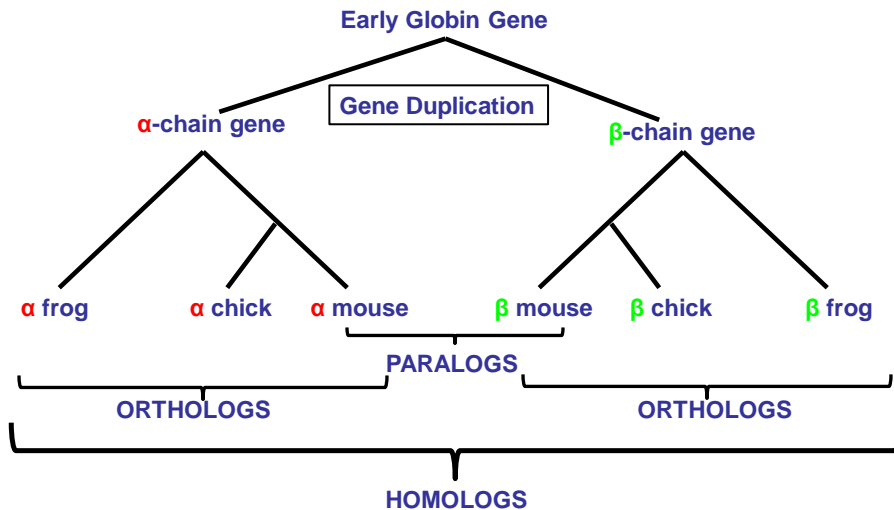
- Single Nucleotide Polymorphisms, SNPs, SNVs
- Rearrangements
- Alleles
- Allele frequency
- Haplotypes (an organism's collection of variants)

Technology

- Next Generation Sequencing, NGS
- Synteny (conserved positions on chromosomes)

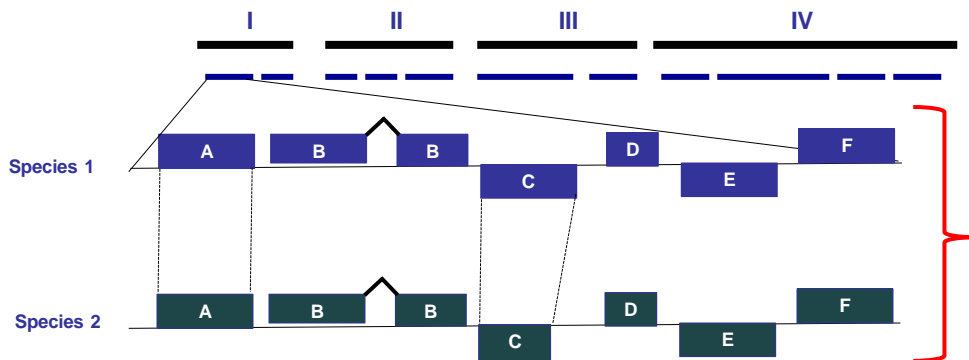
30

Homology - a vocabulary for different types of evolutionary relationships



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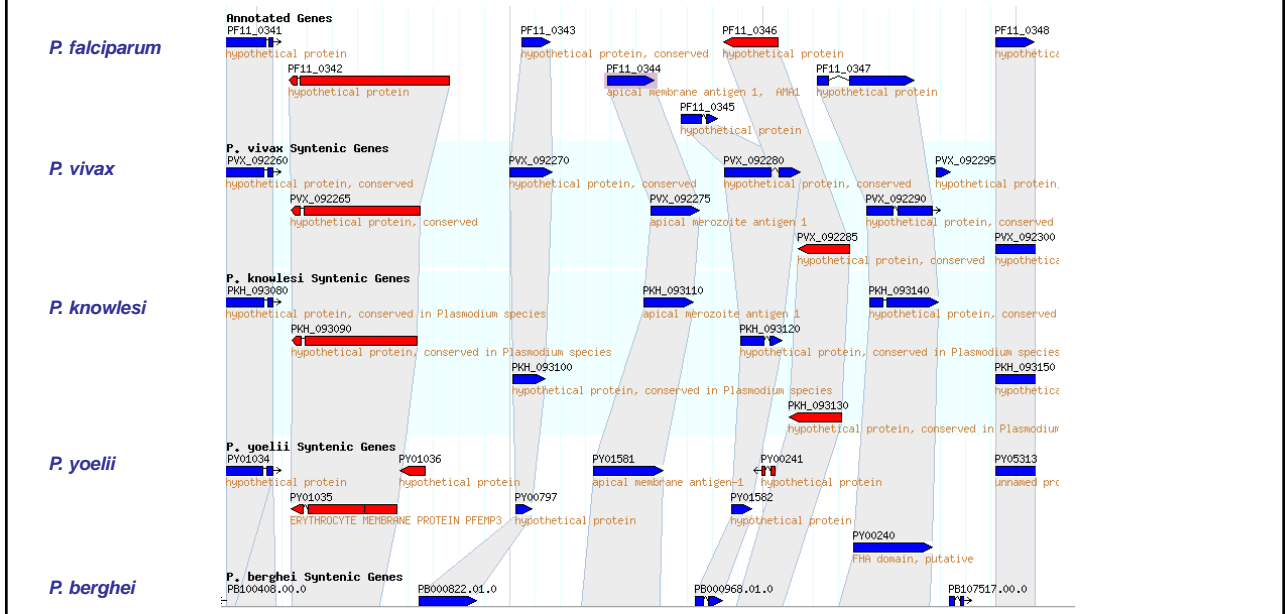
30,000 ft View - Synteny



Synteny = the majority of the same genes are present in the same order and orientation in another species. The chromosomal regions are evolutionarily related

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Synteny among *Plasmodium* species



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Synteny shows relationships in positioning: Ontologies show relationships in meaning

- The Gene Ontology - GO provides terms to link genes with similar functions and/or locations in the cell.
- An ontology was needed because the cultural traditions in different organisms led to different gene naming schemes that made it difficult to identify orthologous genes with the same function.

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For Example:

D. melanogaster gene CG3340 annotated as: "Kruppel"
and *P. falciparum* gene PF3D7_1209300 annotated as a
"putative KROX1"

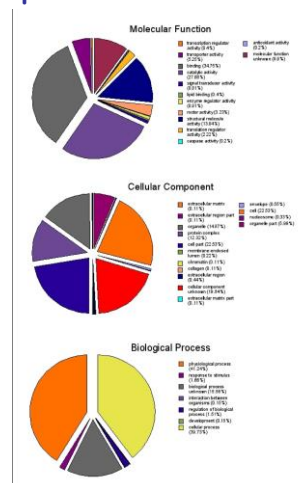
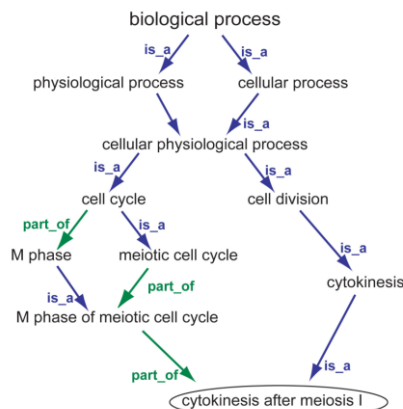
Both can be annotated with GO term:

GO:0003705 (RNA polymerase II distal enhancer
sequence-specific DNA binding transcription factor
activity)

Both proteins, functionally, are Zinc Fingers despite
their different names

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Note that the Gene Ontologies themselves
contain only information about terms in the
ontology and their relationships to other terms



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Gene expression

Expression Profiles (RNA and Protein)

- The pattern of expression of one or more genes over time or a set of experimental conditions, e.g. during development or a drug treatment or in a genetic mutant such as a gene knock-out.
- Always... has a time and location component, much like a photograph

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RNA expression

Bulk sequencing from many cells

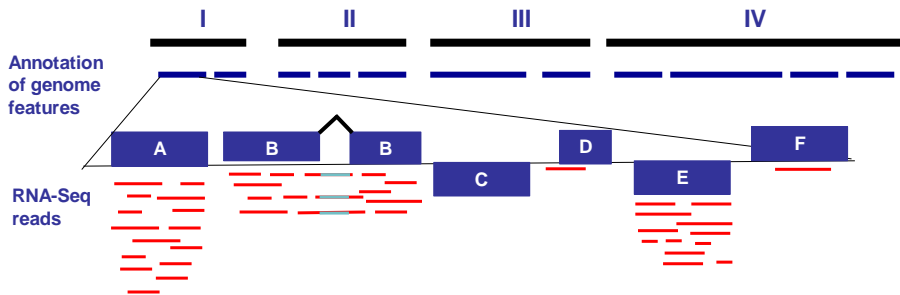
- RNA-Seq (NGS)
 - Little sequence bias
 - Quantitative
 - Usually are strand-specific
- PacBio ISO-seq
 - Full-length transcripts from single molecules
- ONT Direct seq
 - Single-molecule, direct sequencing of RNA (or can sequence cDNA)
- All of these methods can be used to identify UTR's and exon splice junctions

Single-Cell Sequencing

- Examines the transcriptome inside each cell analyzed
- Excellent for detecting cellular heterogeneity or differentiation
- Often only detects a fraction of the transcripts within a cell
- Often analyzed with tSNE plots to categorize cells that have similar transcriptional profiles.

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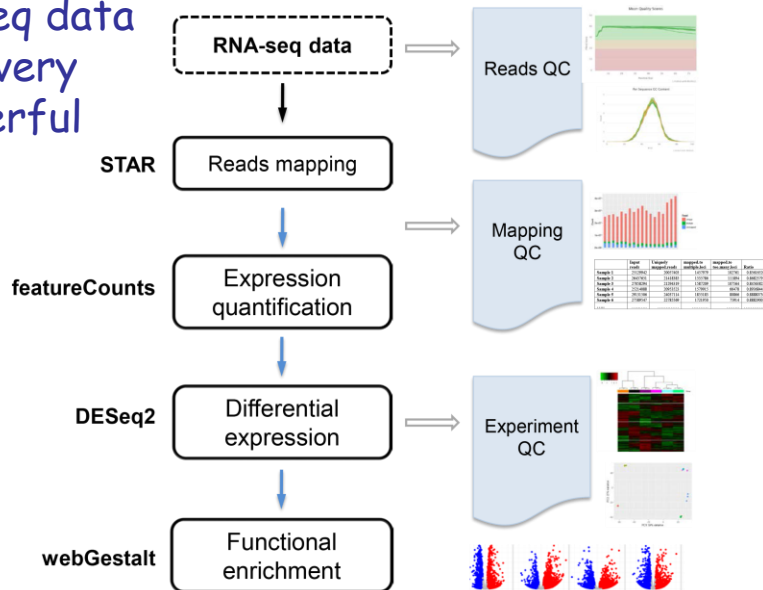
30,000 ft View - RNA-Seq



FPKM = Fragments per kilobase of exon per million fragments mapped (old calculation)
 TPM = Transcripts per kilobase million (counts per length of transcript (kb) per million reads mapped)

39

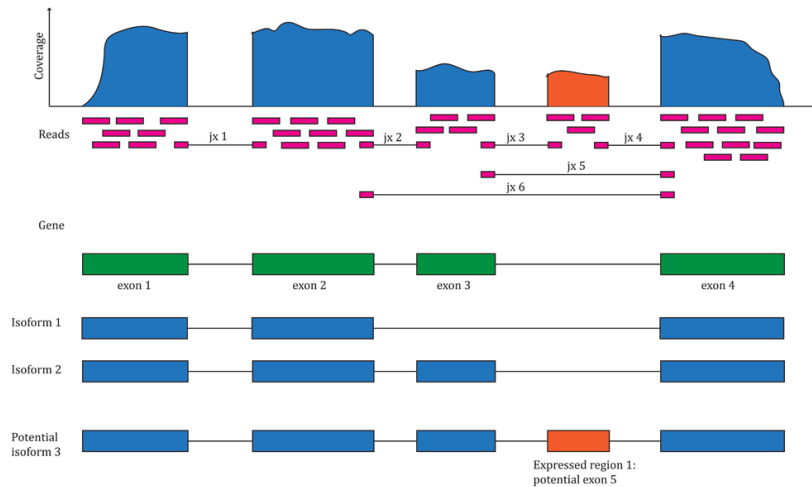
RNA-seq data
are very
powerful



<http://bioinfo.vanderbilt.edu/vangard/services-rnaseq.html>

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RNA-seq identifies splice junctions if present (remember context dependent)



<https://bioconductor.org/packages/devel/workflows/vignettes/recountWorkflow/inst/doc/recount-workflow.html>

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Complex patterns of eukaryotic mRNA splicing: What is a Gene?

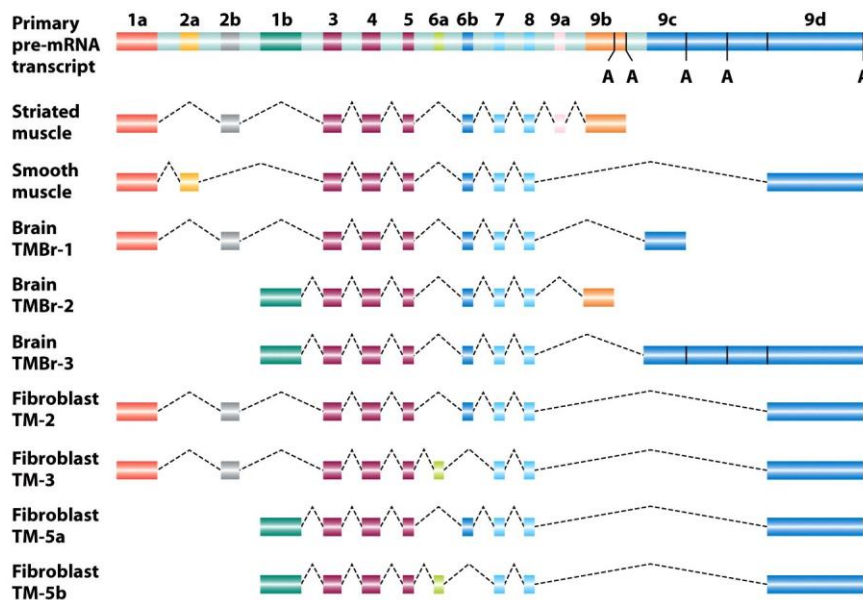
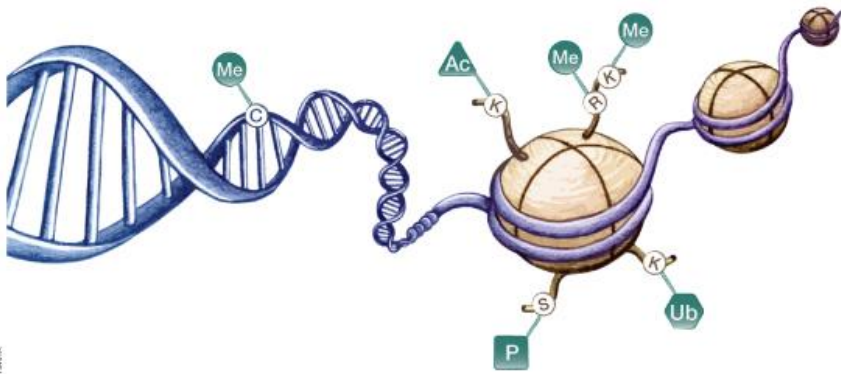


Figure 8-14
Introduction to Genetic Analysis, Ninth Edition
© 2008 W. H. Freeman and Company

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Chromatin Status and Epigenetic Gene Regulation



<https://www.promega.com/resources/guides/nucleic-acid-analysis/introduction-to-epigenetics/>

- DNA methylation at CpG islands
- Bisulfite sequencing is a common assay
- H3K4me3 = transcriptionally active chromatin
- H3K27me3 = compact chromatin
- There are MANY other histone modifications
- ChIP-Seq (Chromatin Immunoprecipitation) is a common assay for histone markers

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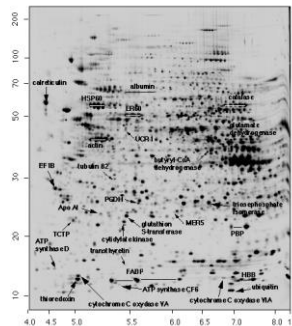
Protein Expression/Sequence

Data

- MW-Isoelectric point
- MW
- Sequence/spans

Technology

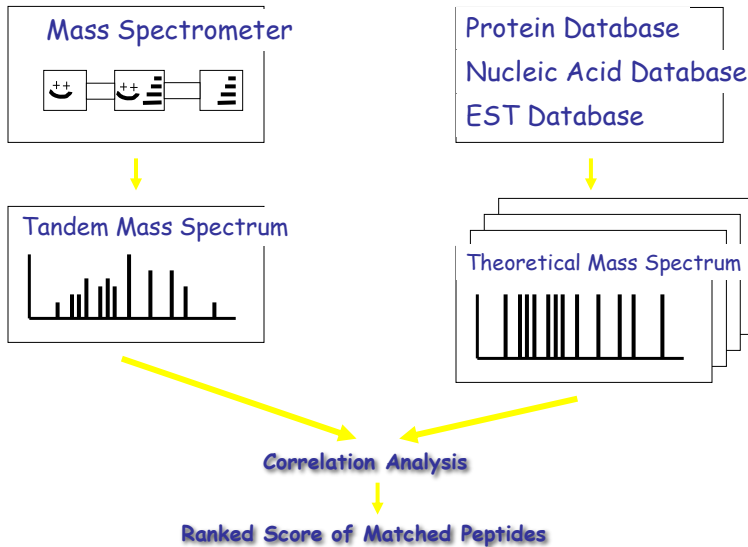
- 2D gel electrophoresis
- Mass spectrometry
- Tandem MS (MS-MS, LC MS-MS etc)



Typical 2 D gel

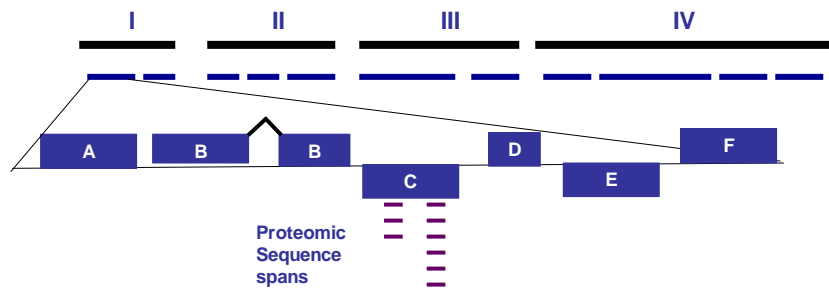
44

Sequest Database Search



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30,000 ft View - Proteomics



When looking at protein mass-spec sequences it is common to only detect parts of proteins. Some regions are refractory to detection, so don't be alarmed.

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Overview

PubChem Compound ID: [CID:93072](#)

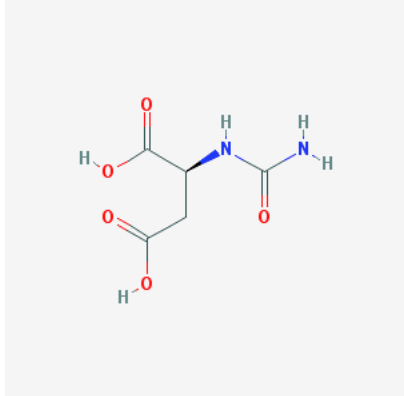
PubChem Substance ID(s): 3727

Synonyms: N-Carbamoyl-L-aspartate

Molecular Weight: 176.12742

Molecular Formula: $C_5H_8N_2O_5$

2D Structure

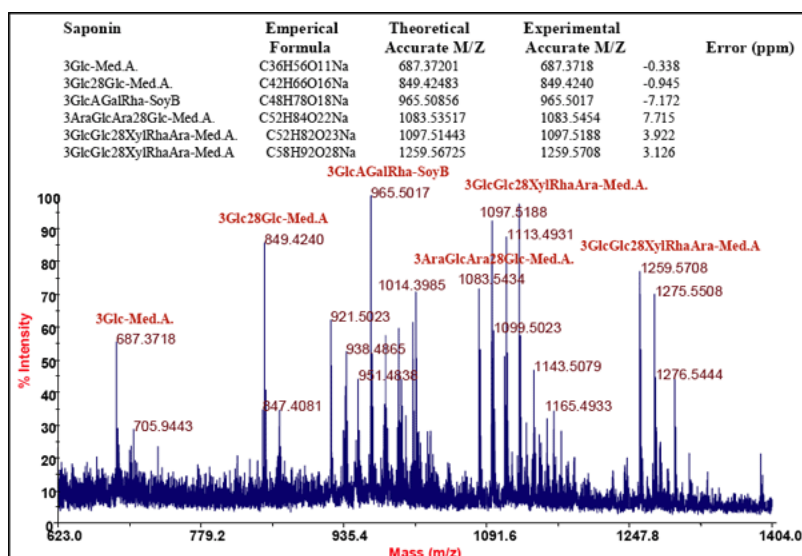


Metabolites

Mass Spectrometry
can be used to
measure metabolic and
other chemical
compounds

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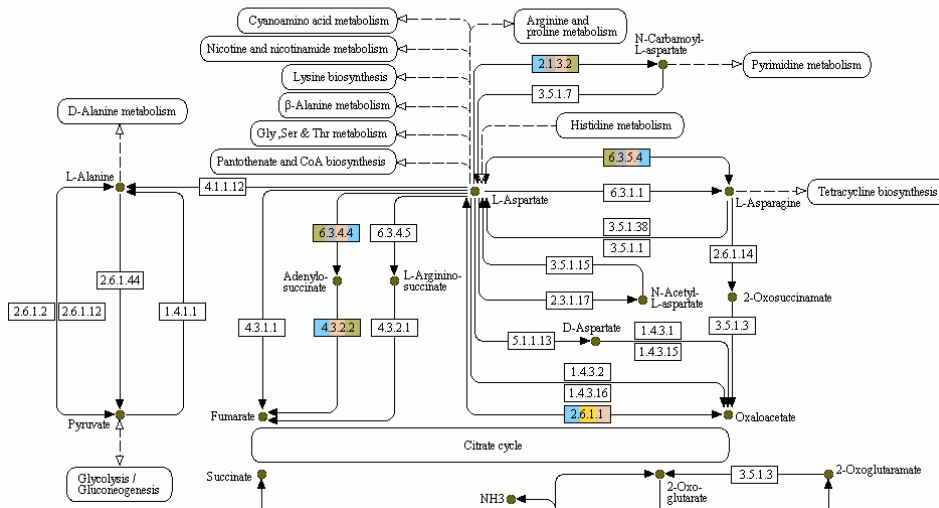
Complex mixtures can be
analyzed and interpreted



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Metabolites can be linked to metabolic pathways and enzymes

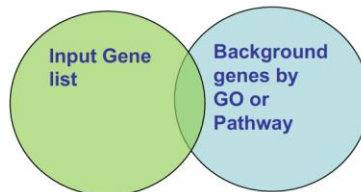
ALANINE, ASPARTATE AND GLUTAMATE METABOLISM



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Gene & Pathway Enrichment

Gene list:
Up/Down-regulated
based on some
experiment, e.g.
RNA-Seq



Background-Pathway
information: All genes
known to be involved in
some process, e.g.
glycolysis or cell
signaling. ALL pathways
are examined

Result: GO:ID or Pathway ID that is enriched

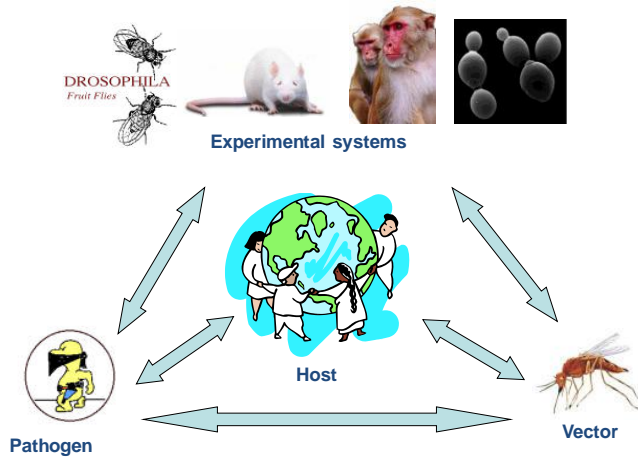
Statistics: Are more genes observed than expected (P-value)
Multiple hypothesis testing (Bonferroni, Benjamini-Hochberg)

Atul Butte Review: <http://journals.plos.org/ploscompbiol/article?id=10.1371/journal.pcbi.1002375>

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Host(s)

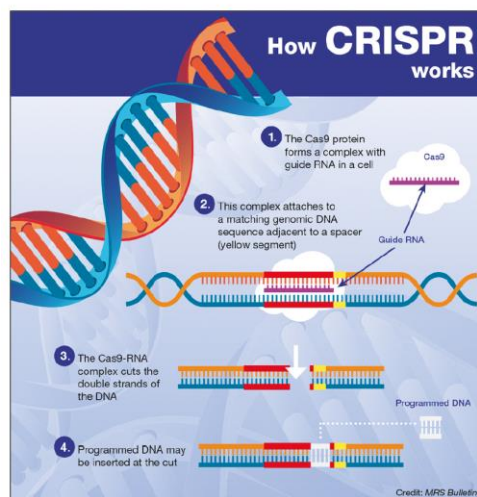
Infectious Disease Paradigm of Host-Pathogen Interactions



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Mutant analysis

CRISPR-CAS



- Need to provide both the enzyme and the guide RNA to the cell
- Need to design the guide RNA to the gene of interest, ideally at multiple target locations per gene

Ball et al., MRS Bulletin November 2016

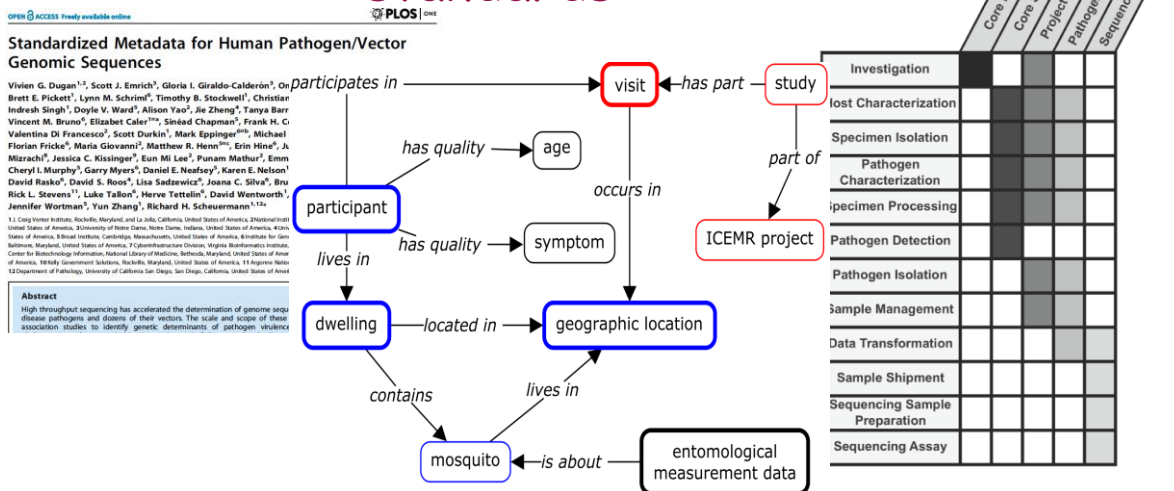
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Metadata - The next Frontier

- Data about the data are critical
- What makes a data set valuable? (The reason it was generated...but often this is missing)
- Introducing the "data set"
- How can you find the data set you need? Pull down Menu? A search of data set properties?
 - Person and technology that generated the data
 - Clinical outcome
 - Geographic location
 - Phenotype

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Data sharing standards



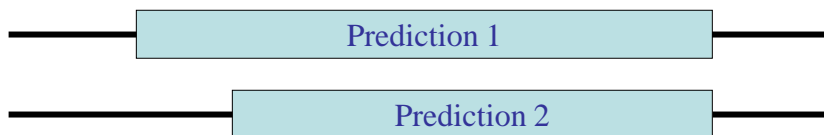
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Bioinformatics uses algorithms

- Algorithms are sets of rules for solving problems or identifying patterns
- Algorithms can be general or case specific and often need to be trained
- Computational analysis, like wet-bench analyses are only as good as the tools, techniques and material allow, and all interpretations come with caveats (like the experimental conditions, often call parameters in bioinformatics).

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Different algorithms often generate different results



We provide lots evidence so that you can decide or design an experiment to confirm!

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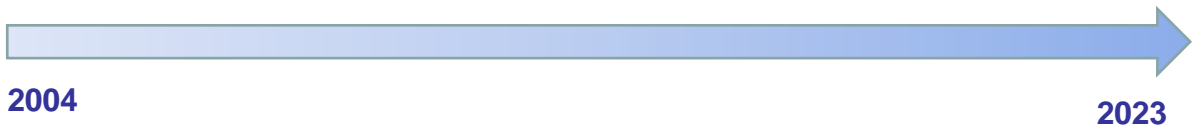
Garbage in Garbage out!

- The algorithms will almost always return a result, it is up to you, the scientist to evaluate if it has made a mistake. Much of the data in the archival databases have errors. Not intentional errors but errors
- If you can't find the gene or answer it does NOT mean that it does not exist. It may be in a gap, or never have been annotated, or discovered after the annotation e.g. lncRNAs. Interpret carefully

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Bioinformatics Resource Center Community Evolution

Browsing ➡ Mining ➡ Integrating ➡ Facilitating



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The End

- If you have questions, I and the other instructors will be around and we are happy to talk to you.
- These slides are available to you as a PDF on the workshop web site.

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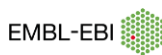
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Jessie Kissinger – UGA
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George Christophides - Imperial

Thank you to the data providers, participants
and community for their feedback



Our goal: enabling end users in the lab, field & clinic
to make effective and appropriate use of large-scale datasets, expediting
discovery research and translational application by making data FAIR



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