Análisis de datos ómicos: metagenómica, metatranscrictómica y RNA seq con GAIA y AIR

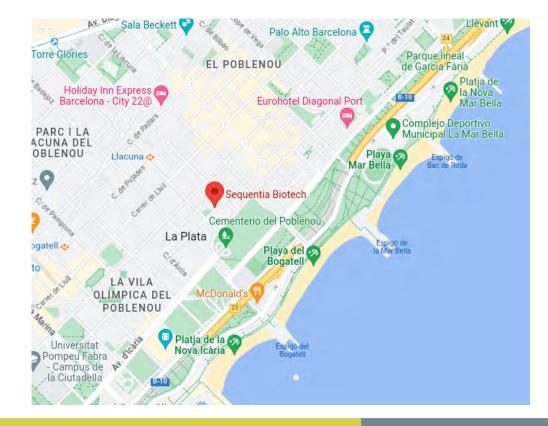
Data-Science para biociencias - 5 Julio 2023 Daniel Julián djulian@sequentiabiotech.com



Who are we?













1. First part: omic data, metagenomics, metatranscriptomics and GAIA

- 1. Om ic data
- 2. A little bit of history
- 3. Applications
- 4. Strategies: amplicon-based and shotgun
- 5. Bioinformatic approaches and limitations
- 6. GAIA
- 7. Future insights

1. Second part: RNA -seq and AIR

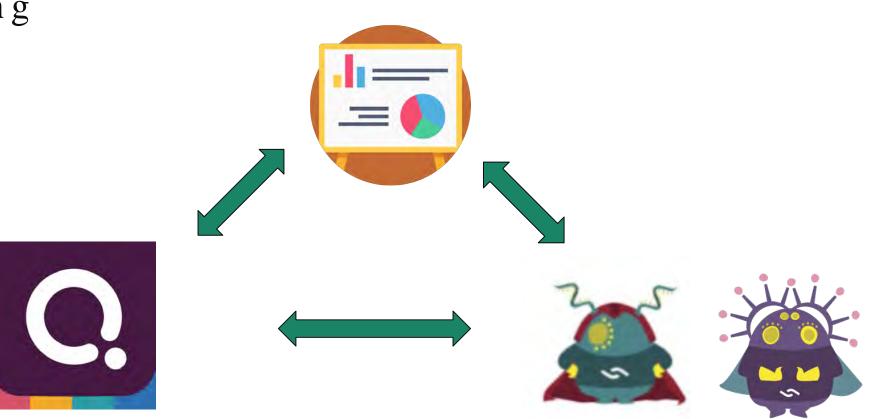
- 1. RNA-seq introduction
- 2. Workflow
- 3. Differential expression analysis
- 4. AIR

How are we going to do it?



Active learning

- questions
- ideas







Ru le s

- 1. People are free to participate, it is not mandatory.
- 2. 45 seconds to answer each question
- 3. Answering well and quickly gives more points Think carefully your answer

Question 1





https://quizizz.com/?lng=es-ES



FIRST PART: omic data, metagenomics, m et atranscriptom ics and GAIA



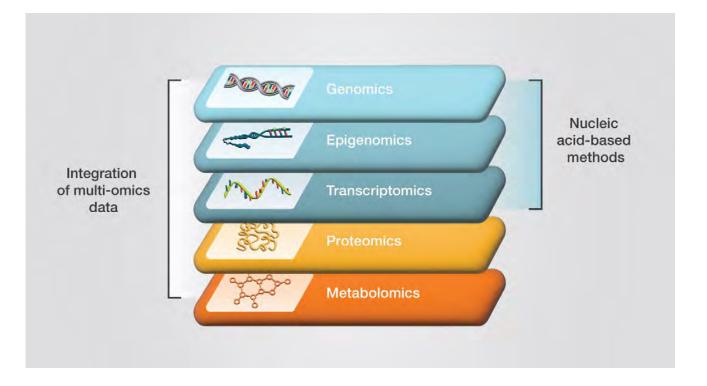


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Omic data





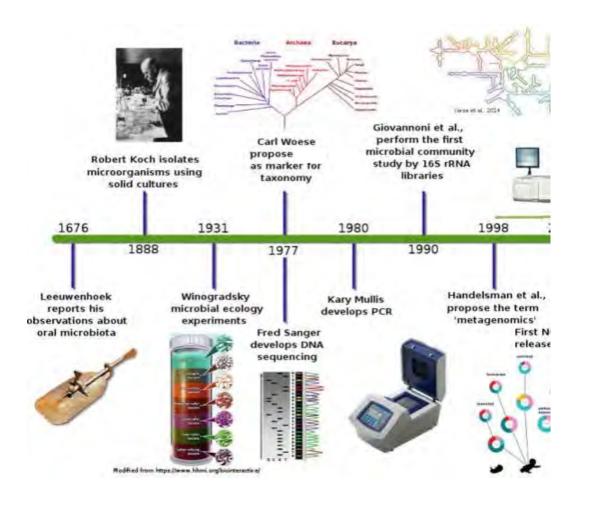
Metagenomics: Intro





A little bit of history...





Metagenomics : application of genomics techniques without the need to do cell cultures in order to study a microbial community .

Genetic diversity in Sargasso Sea bacterioplankton

Stephen J. Giovannoni, Theresa B. Britschgi, Craig L. Moyer & Katharine G. Field

Department of Microbiology, Oregon State University, Corvailis, Oregon 97331, USA

BACTERIOPLANKTON are recognized as important agents of biogeochemical change in marine ecosystems, yet relatively little is known about the species that make up these communities.

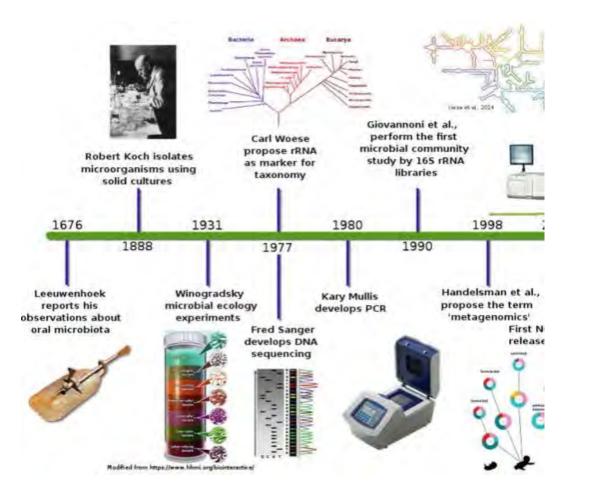
Question 2



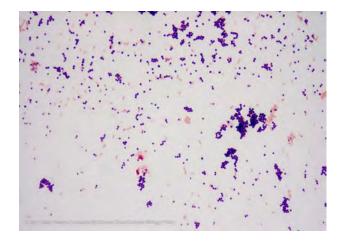


Un poco de historia...





Microscope and staining (e.g. Gram)



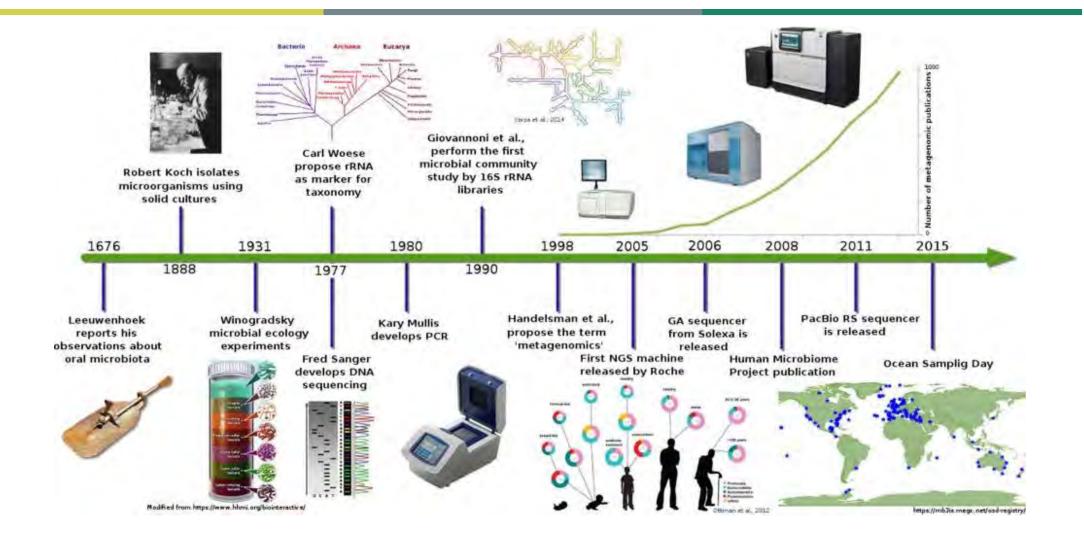
Cell cultures





Un poco de historia...

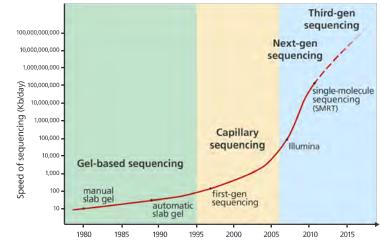




What is Next -Generation Sequencing?

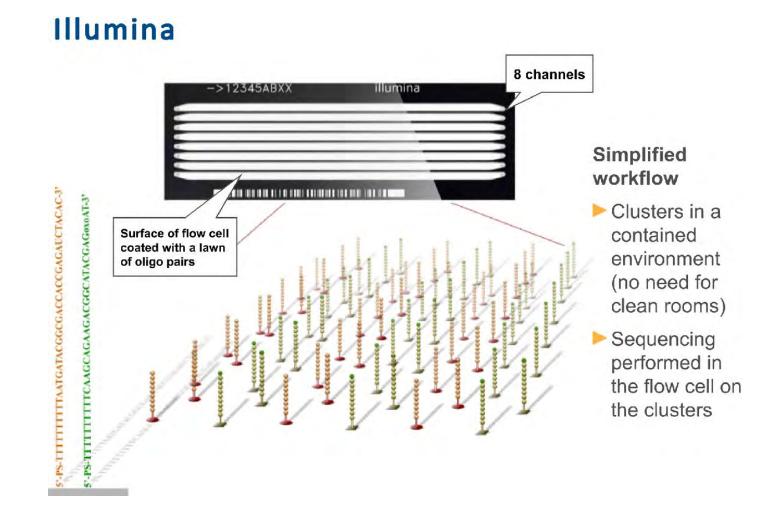


- The high demand for low-cost sequencing has driven the development of high-throughput sequencing (or next-generation sequencing) technologies that parallelize the sequencing process, producing thousands or millions of sequences concurrently.
- High-throughput sequencing technologies are intended to lower the cost of DNA sequencing beyond what is possible with standard dye-terminator methods.



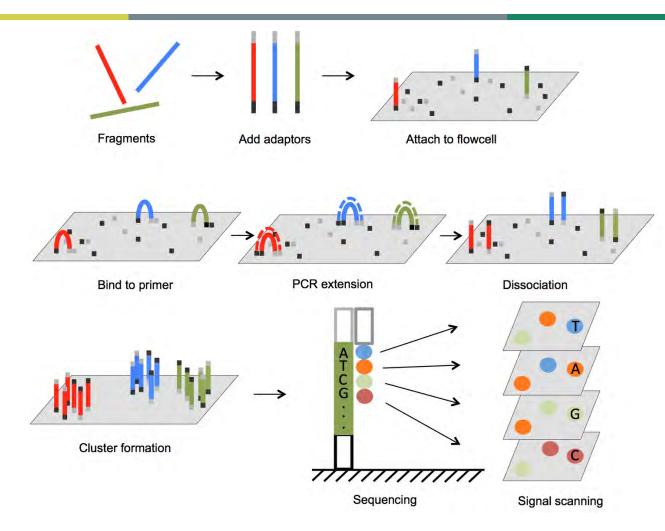
Illumina sequencing





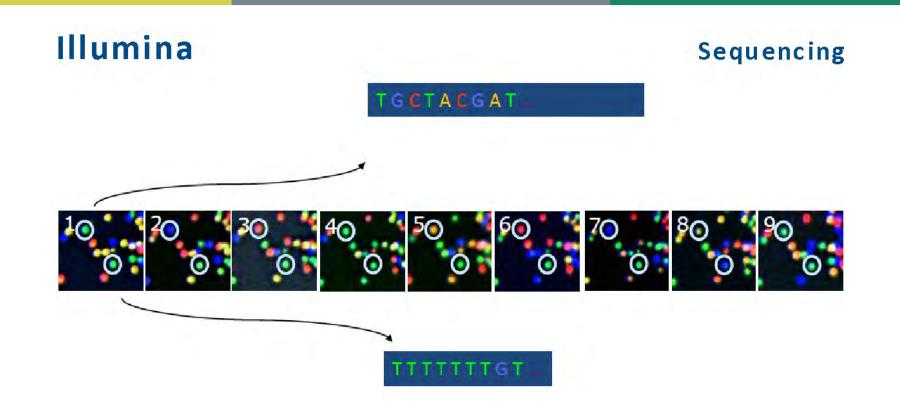
Illumina sequencing





Illumina sequencing





The identity of each base of a cluster is read off from sequential images.

Fastq format



Reads. What do they look like? *FASTQ*

- 1 @SOLEXA2_0414:3:1:19459:1418#0/1
- 2 NTGCGATCTCATGGACAAACCAGACCTTACAACTGTTACTCTGAAT...
- 3 +SOLEXA2 0414:3:1:19459:1418#0/1
- 4 BGGIFMRPOO_____P_T_YYYRYYYM[[[[[__Y__...

Repeated blocks, four lines each:

- 1 ... header, starting with "@"
- 2 ... sequence
- **3** ... header, starting with "+" (often left blank)
- 4 ... base qualities (same length as sequence)

Fastq format



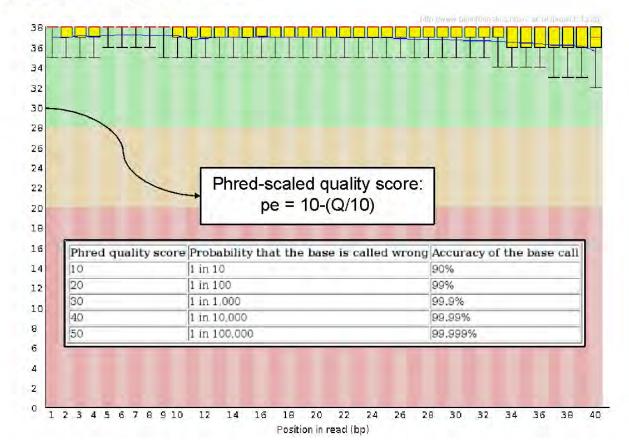
Quality Score

- Each base position in a sequence comes with a "quality score".
- This measures the probability that a base is called incorrectly, by a phred-like algorithm similar to that originally developed for Sanger sequencing experiments.
- The quality score of a given base, Q, is defined by Q = -10*log₁₀(e) where e is the estimated probability of the base call being wrong.
- A quality score of 20 represents an error rate of 1 in 100, with a corresponding call accuracy of 99%.

Fastq format



Basecall Qualities







https://metagenomics.sequentiabiotech.com/gaia/

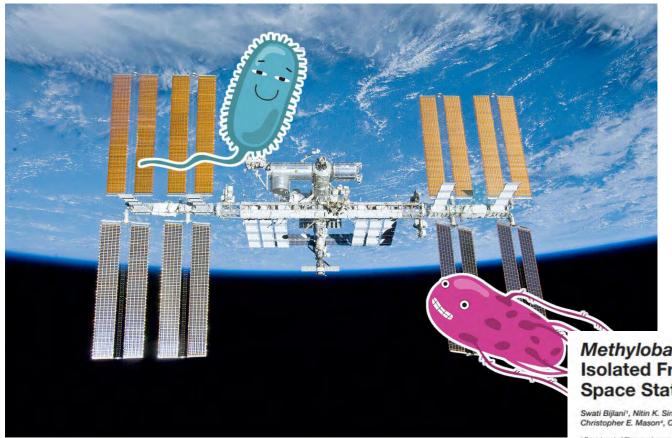
Applications





Applications





Methylobacterium ajmalii sp. nov., Isolated From the International Space Station

Swati Bijlani¹, Nitin K. Singh², V. V. Ramprasad Eedara³, Appa Rao Podile³, Christopher E. Mason⁴, Clay C. C. Wang¹⁺ and Kasthuri Venkateswaran²⁺

¹ Department of Pharmacology and Pharmaceutical Sciences, School of Pharmacy, University of Southern California, Los Angeles, CA, United States, ² Jel Phopulsion Laboratory, California Institute of Technology, Pasadena, CA, United States, ³ Department of Plant Science, School of LiB Sciences, University of Hyderabad, Hyderabad, India, ⁴ WorldQuant Initiative for Quantitative Prediction, Well Correll Medicine, New York, NY, United States;

Question 3

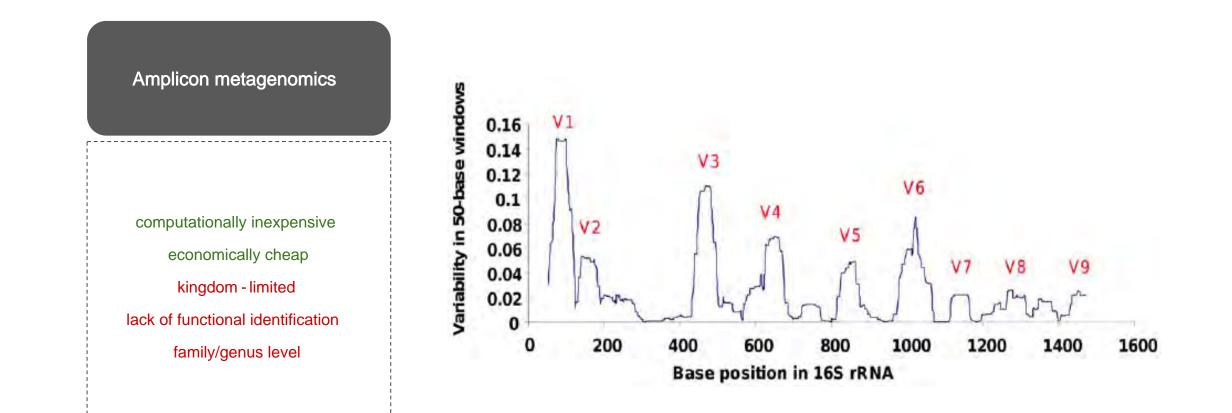




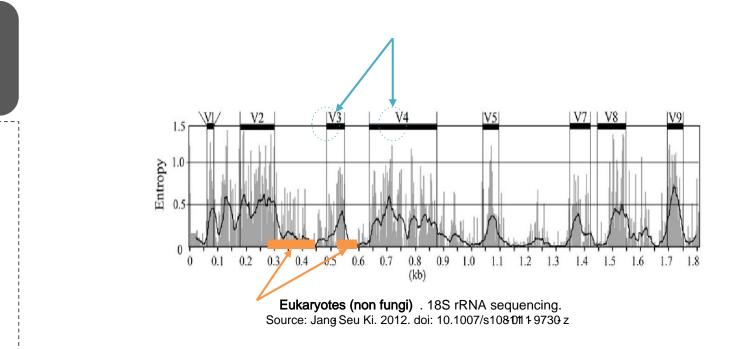


Amplicon metagenomics	
computationally inexpensive	
economically cheap	
kingdom - limited	
lack of functional identification	
family/genus level	

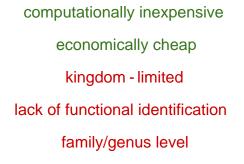




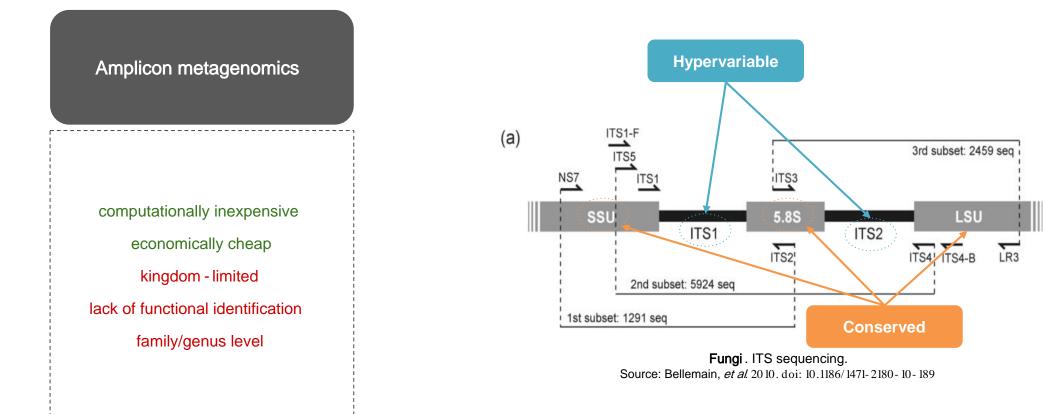




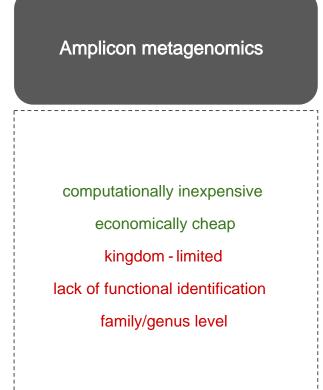
Amplicon metagenomics











Sequencing platforms commonly used Roche $454 \rightarrow 400\ 700\ bp\ (obsolete)$ Illumina MiSeq v3 \rightarrow 2 x 300 bp Ion PGM \rightarrow 400 bp



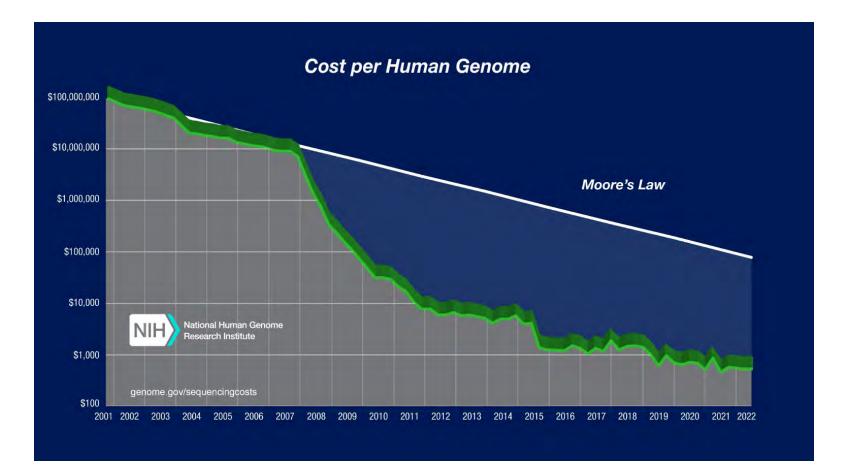
Question 4





Moore's Law





Strategy: shotgun

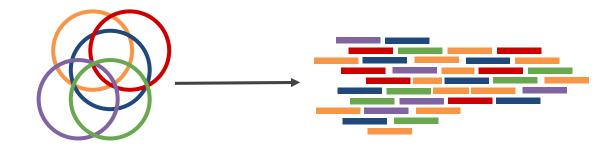
1 - - -



	Shotgun me	Shotgun metagenomics	
Amplicon metagenomics	Whole Genome Sequencing (WGS) metagenomics	Metatranscriptomics	
omputationally inexpensive economically cheap kingdom - limited ck of functional identification family/genus level	strain level functional identification unable to know the gene expression abundance computationally expensive economically expensive (+)	strain level functional identification of expressing genes differential expression between conditions computationally expensive economically expensive (++)	

Strategy: shotgun





Sequencing platforms commonly used Illumina MiSeq v3 \rightarrow 2 x 300 bp Illumina NextSeq 500 \rightarrow 2 x 150 bp Illumina HiSeq 3000 \rightarrow 2 x 150 bp







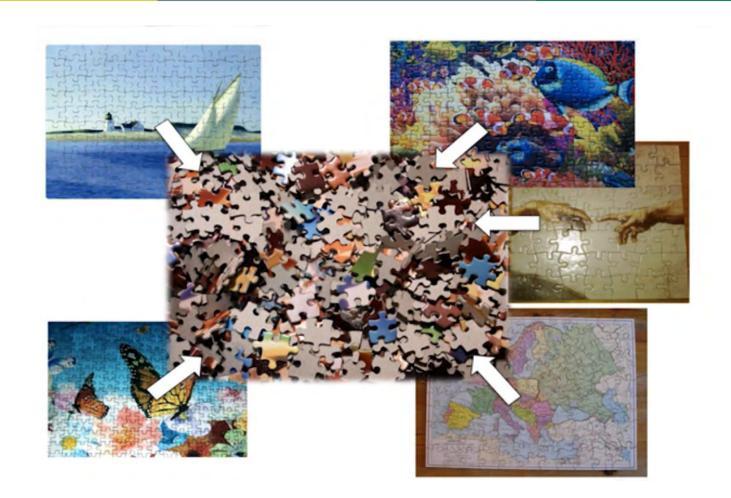
Question 5





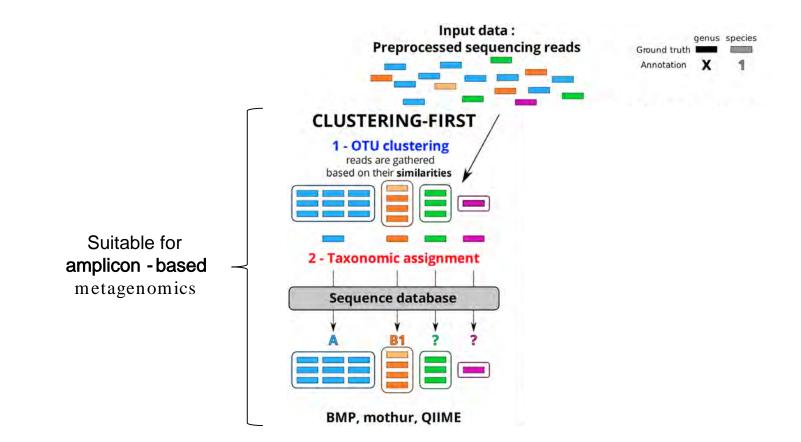
Strategy: shotgun





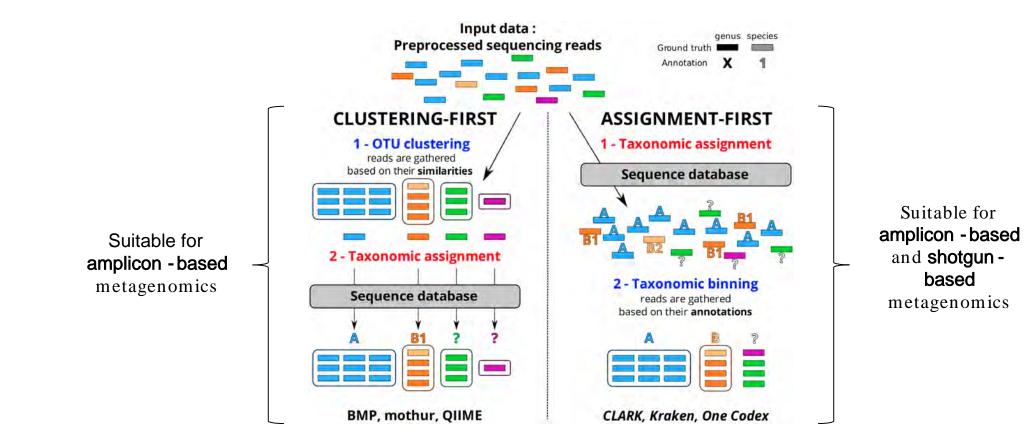
Bioinformatic approaches





Bioinformatic approaches





Question 6

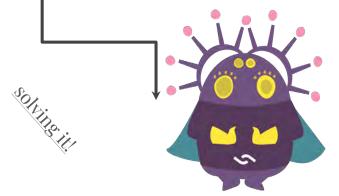




Bioinformatic limitations

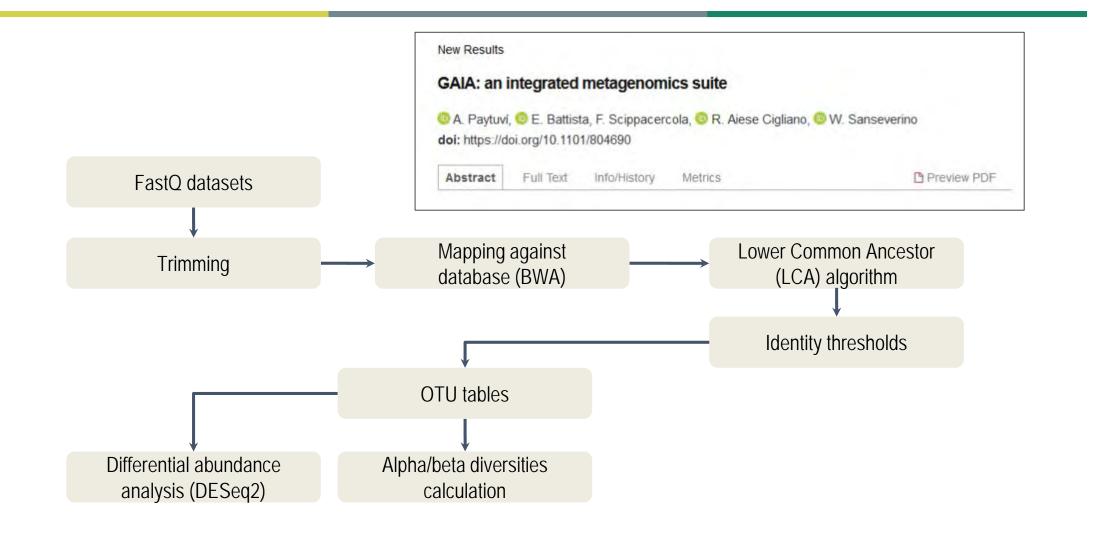


- 1. There is still room for improvement in terms of accuracy
- 2. The vast majority of tools only work on **prokaryotes**
- 3. Lack of true **user-friendly** interfaces for the vast majority of the pipelines
- 4. Computational power and data storage required
- 5. High processing time



GAIA: pipeline





GAIA: OTU table



	A	В	С	D	E	F	G	H	1	1	K	E.	M	N	0	P	Q	R	S	T	U
	otu				-													1000			
1	1.	X10n	X10p	X11n	X11p	X120n	X120p	X121n	X121p	X122n	X122p	X125n	X125p	X126n	X126p	X127n	X13n	X13p	X140n	X140p	X141r
2	Otu001	13679	6292	42	2500	18850	5	43	7138	9432	10541	9	9772	1388	7	31538	38	2338	23	9	135
3	Otu002	18	7134	38	9830	45	61420	182	23751	36	11	4535	3502	11018	5473	26	14411	38	19018	12	308
4	Otu003	9939	8983	31	13	24620	19	19	16	12502	3831	4621	2240	9924	4052	9292	18	0	37	7	368
5	Otu004	3675	4234	24	22	11	16	32967	35	6	18	6908	5	16	8702	24	11	37717	0	25	419
6	Otu005	0	5	0	7	0	8	0	16	20166	0	0	2	5	8	2	16	0	13	0	1
7	Otu006	0	8	0	0	0	8	0	0	5	3	3	0	0	9	0	5	4	0	0	1
8	Otu007	4587	518	4	386	8775	5	6	1102	14336	0	0	3626	51	0	6	12	0	10	0	39
9	Otu008	1	8	2	4408	3	29	6	12355	0	0	0	0	0	9	3	1588	0	6	3	
10	Otu009	115	914	3	325	0	629	1	834	5	0	1354	2108	1117	67	0	2010	1897	11227	1	
11	Otu010	780	8	23810	12	3279	0	12	7	3027	0	2	4156	0	0	18	0	0	0	0	1
12	Otu011	0	3	2	2	0	13	5	5	4	7	3081	11	4	6804	0	3	11	0	5	
13	Otu012	0	0	0	6	0	0	0	16	3	0	0	0	0	0	0	17	0	6	0	1
14	Otu013	6321	2471	2	0	12	3	0	0	4	20272	0	15	9	0	5	0	11	0	14	1
15	Otu014	0	82	4	3304	1	1667	4	9233	13	3	0	2707	0	0	3	4806	9	3	5	
16	Otu015	0	12	0	3	7	25	1	6	10	0	4	2772	1	3	0	2	0	10	13	805
17	Otu016	1	0	0	9	5	0	0	14	0	0	0	0	2654	0	0	6	1	1	0	1
18	Otu017	0	0	0	0	0	0	0	0	17	8	0	0	0	0	0	17	24	48	35210	1
19	Otu018	1	0	9	911	0	0	15	2702	6	4	342	2217	606	0	13	3846	4	6	8513	
20	Otu019	0	0	13	0	0	0	29	0	0	0	0	0	0	0	11	0	0	5	4	
21	Otu020	425	0	1	0	1706	0	8447	1	0	0	0	0	0	26	0	0	3490	0	2620	
22	Otu021	0	4	0	0	0	10	0	0	0	0	2	0	0	4	0	0	0	0	0	1
23	Otu022	0	0	0	4987	0	0	0	6	90	1	1	524	0	467	0	4	8	6198	0	4 3
24	Otu023	4	0	1	0	0	3	0	0	0	0	0	0	3351	3	0	3910	1	2	3	
25	Otu024	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	2	1	
26	Otu025	69	0	0	0	290	0	0	0	21	0	118	2	9	513	2	0	0	2	0	1
27	Otu026	0	2	0	0	0	3	0	0	0	1	0	0	0	0	0	0	0	0	0	1
28	Otu027	6	2304	0	0	5	0	0	0	57	4	0	14529	9597	2	6	0	0	0	0	1

GAIA: benchamrk



Assessment of Common and Emerging Bioinformatics Pipelines for Targeted Metagenomics Léa Siegwald, Hélène Touzet, Yves Lemoine, David Hot, Christophe Audebert 🖬, Ségolène Caboche 🖬 🖬

Published: January 4, 2017 • https://doi.org/10.1371/journal.pone.0169563



precision = # classified reads correctly /

classified reads

6,535

View

10

Share

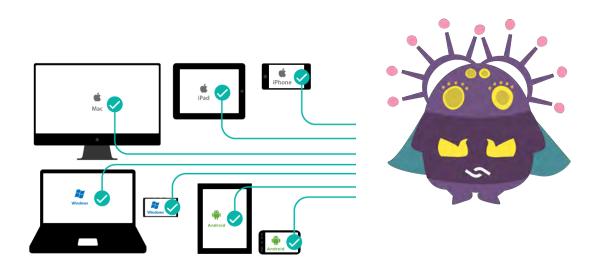
recall = # classified reads correctly / # total number of reads

F-measure = harmonic mean of

precision and recall







gaia.sequentiabiotech.com

Question 7









- 1. There is still room for improvement in terms of accuracy \checkmark
- 2. The vast majority of tools only work on **prokaryotes**
- 3. Lack of true **user-friendly** interfaces for the vast majority of the pipelines
- 4. Computational power and data storage required
- 5. High processing time 🗸

Future





- Portable everywhere
- 10 min library preparation
- Reads of up to tens of kbp

Drawbacks of Oxford Nanopore

- High error rate (~15% for R9 release)
- Low-coverage
- ~ ~ 250bp/s (0.9 Mbp/h)



~1.87 Gbp/h (75 Gbp/40h) for Illumina HiSeq (calculated using Rapid Run Mode with a single flow - cell, 2x150 bp)



Jain, M. *et al.* 2017. doi: 10.12688/f1000research.11354.1

Future

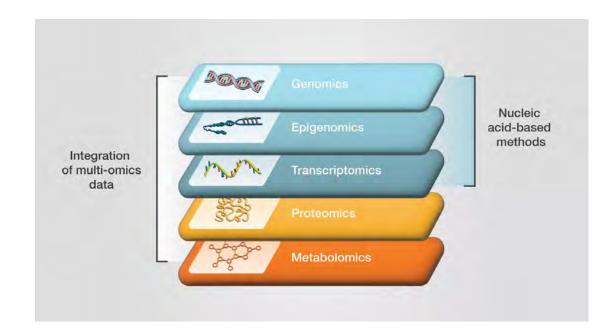




- Portable everywhere
- 10 min library preparation
- Reads of up to tens of kbp



Omics integration



Future

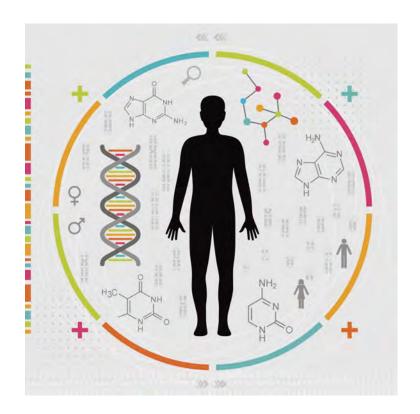




- Portable everywhere
- 10 min library preparation
- Reads of up to tens of kbp



Personalized medicine



Question 8



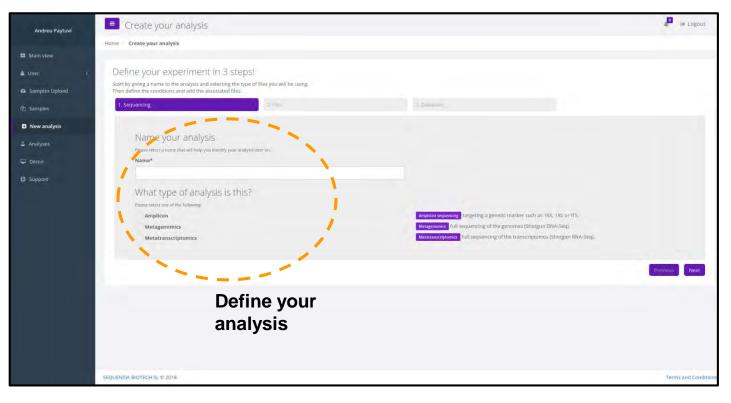


GAIA





Gaia user interface









nalyses			
alyses			Create new Analysis
COMPLETED	Mosaic Training, in-silico Created 2018-02-05 11:56:50	Completion: 100%	Start: 2018-02-05 11:56:49 End: 2018-02-05 13:46:02
COMPLETED	Eukaryotes, in silico analysis Created 2018-02-01 16:00:06	Completion: 100%	Start: 2018-02-01 16:00:06 End: 2018-02-01 18:06:38

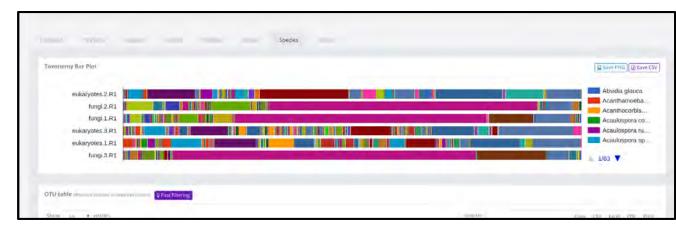




Alpha-diversities

how 10 • entries				Search:	Copy CSV Excel PDF Pri
nowing 1 to 6 of 6 entries					
Samples	11 Observed	Chao1	Shannon	31 Simpson	Fisher
eukaryotes.1.R1	118	118	3.59561	0.95018	8.96918
eukaryotes.2.R1	73	73	2.98961	0.91037	5.33176
eukaryotes.3.R1	158	158	3,78232	0.94305	12,3204
fungi.1.R1	87	.87	2.07557	0.6774	6.43459
fungi.2.R1	84	84	1.99539	0.64321	6.18383
fungi.3.R1	.51	51	1.41224	0.5353	3.61862
Samples Search	Observed Search	Chao1 Search	Shannon Search	Simpson Search	Fisher Search

Taxonomy

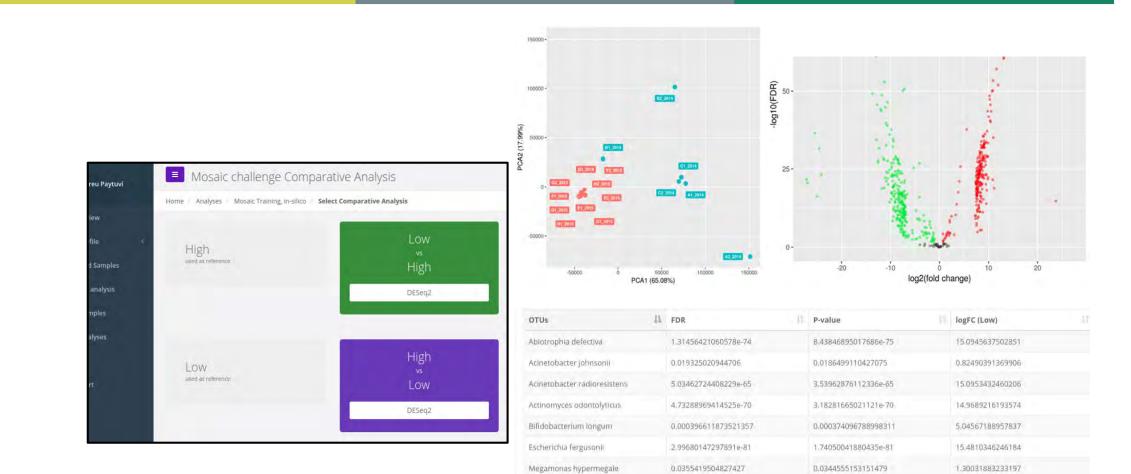




Beta-diversities

GAIA





Parabacteroides johnsonii

2.27290520507079e-73

1.48880253607257e-73

14.7847444643296





ns Paylonn Chose	Tay Ule		
nomy Bar Plot			Save PNG
M8_S8_R1_001			Archaea
M2_S2_R1_001			Bacteria
M12_S12_R1_001			Eukaryota
M3_S3_R1_001			Unknown Viruses
M7_S7_R1_001			Viruses
M9_59_R1_001			

Microorganisms are not only bacteria or archaea... we want to see fungi, algae and other eukaryotes!



FIN DE LA PRIMERA PARTE



SECOND PART: RNA-Seq and AIR





- 1. First part: omic data, metagenomics, metatranscriptomics and GAIA
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1. Second part: RNA -seq and AIR

- 1. RNA-seq introduction
- 2. Workflow
- 3. Differential expression analysis
- 4. AIR

RNA-seq



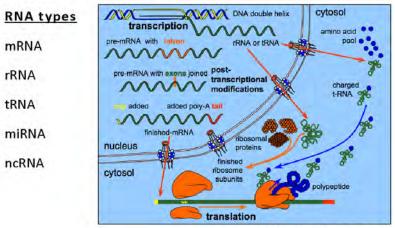
When the NGS technology is applied to RNA molecules we talk about

RNA-seq

Respect to genomic DNA sequencing, RNA-seq requires specific steps:

- Conversion of RNA to cDNA
- Selection of polyA transcripts or removal of rRNA
- Strand-specific libraries

RNA Transcription and Processing



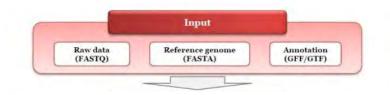
Koning, Plant Physiology Information Website

mRNA -seq: applications

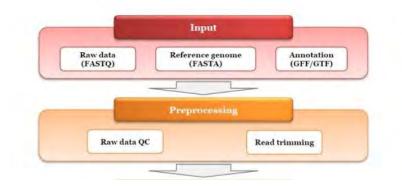


- Differential gene expression analysis
 - Healthy vs. diseased
 - Time course experiments
 - Different genotypes
- Transcriptional profiling
 - Tissue-specific expression
- Novel gene identification/transcriptome assembly
- Identification of splice variants
- SNP finding
- RNA editing







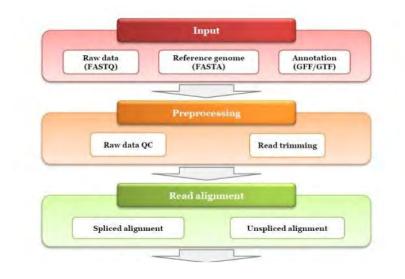


Question 9

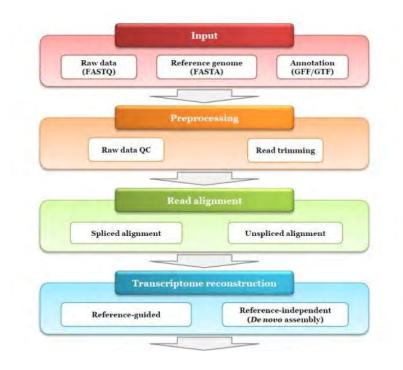




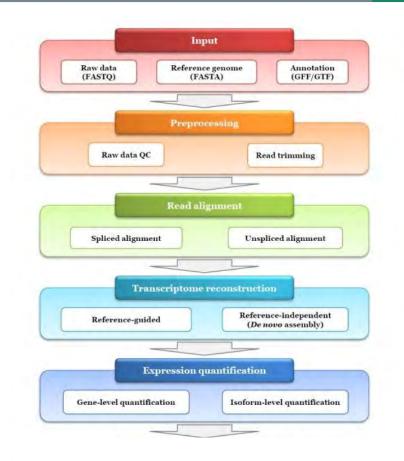




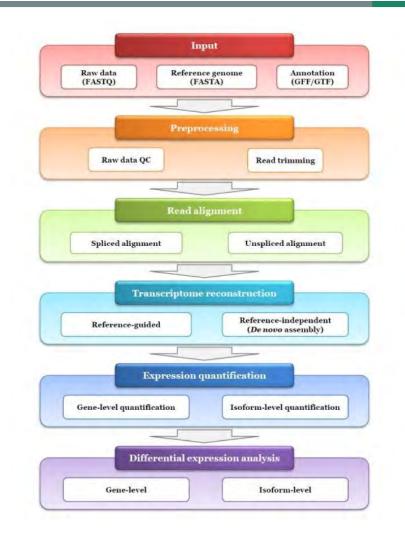




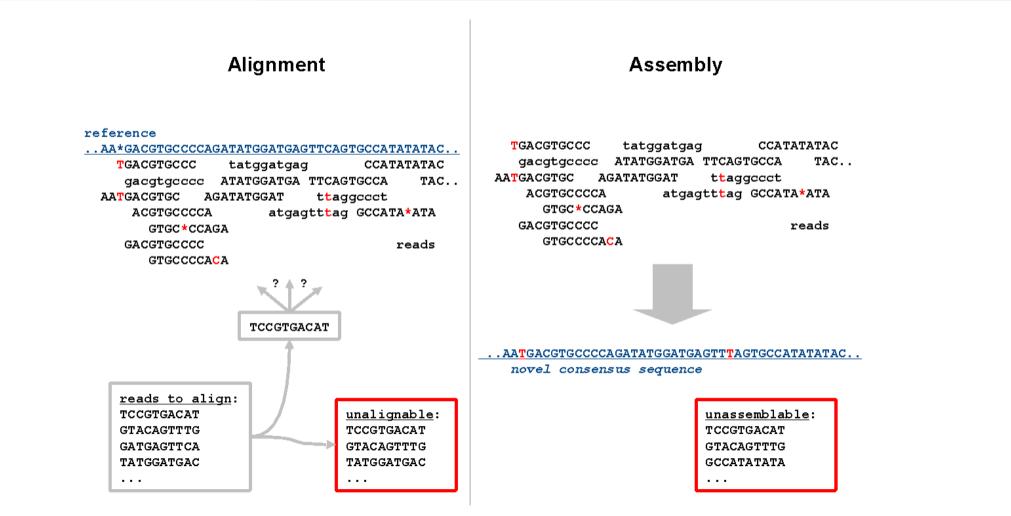








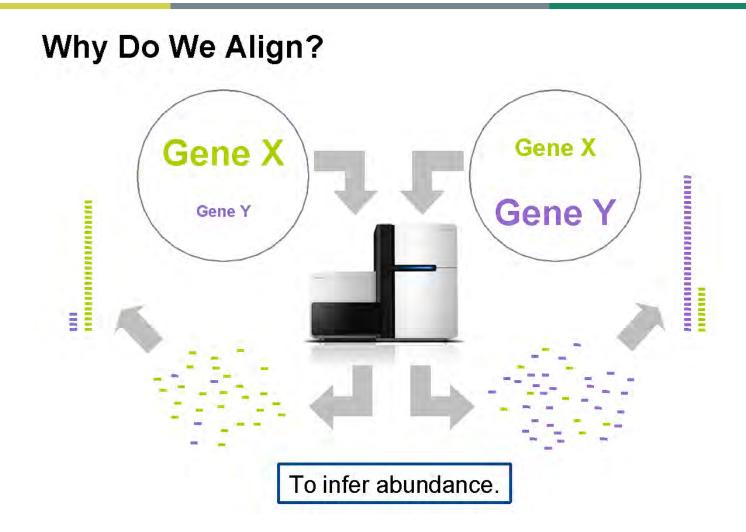
RNA -seq: alignment and assembly





RNA -seq: alignment and assembly





RNA -seq: gene counts



Given a file with aligned sequencing reads and a list of genomic features, a common task is to count how many reads map to each feature. A feature is here an interval (i.e., a range of positions) on a chromosome or a union of such intervals. In the case of RNA-Seq, the features are typically genes, where each gene is considered here as the union of all its exons.

Locus	Sample A	Sample B	Sample C	Sample D
ENSMUSG0000090025	0	0	0	0
ENSMUSG0000064842	0	0	0	0
ENSMUSG00000051951	2637	3201	2180	364
ENSMUSG0000089699	0	0	1	0
ENSMUSG0000088390	0	0	0	0
ENSMUSG0000089420	0	0	0	0
ENSMUSG0000025900	1	1	0	0
ENSMUSG0000025902	0	0	2	0
ENSMUSG0000096126	0	0	0	0
ENSMUSG0000098104	2	7	7	0
ENSMUSG0000088000	0	0	0	0
ENSMUSG0000033845	872	878	952	1875
ENSMUSG0000025903	865	938	927	535
ENSMUSG0000033813	2493	2669	2441	1561
ENSMUSG0000062588	54	98	53	60
ENSMUSG0000002459	144	174	152	70

Question 10





RNA -seq: gene count normalization



Raw read counts correspond to the number of reads associated to each gene in a given sample. In order to compare the expression levels in different samples or between different genes a normalization procedure is required. This is due to:

- Different number of reads in different samples (library size effect)
- Different length of transcripts
- Amplification bias
- %GC content

The most common normalization methods are:

- CPM (Counts Per Million)
- RPKM/FPKM (Reads/Fragment Per Kilobase Per Million)
- TPM (Transcript Per Million)
- TMM (Trimmed Mean Normalization of M-values)

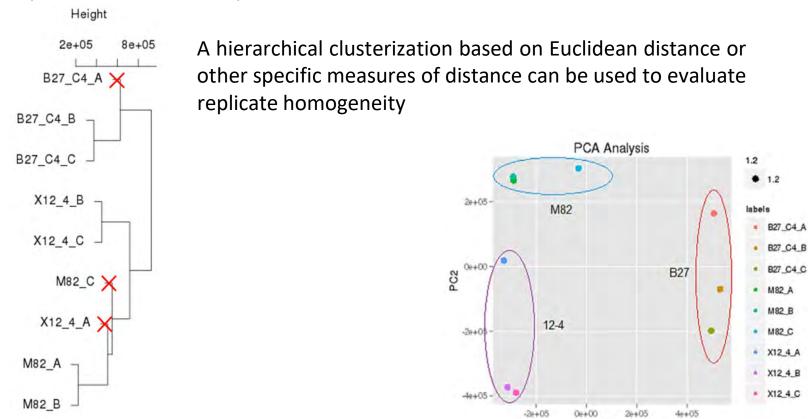
For differential expression analysis TMM was proved to be the most accurate method

RNA - seq: evaluation of similarity



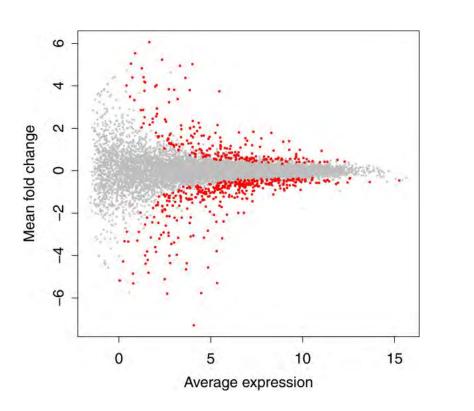
Once data has been normalized, a quality control of the experiment can be performed by evaluating the similarity/distance between replicates

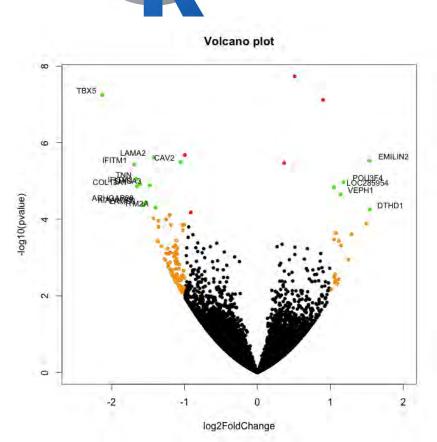
PC1



RNA -seq: differential expression

EdgeR and DESeq2 (parametric) Bayesian (such as EBSeq) or permutation based (such as NOIseq)











- An obvious way to gain biological insight is to assess the differentially expressed genes in terms of their known function(s)
- Required an automated and objective (statistical) approach
- Functional profiling or pathway analysis







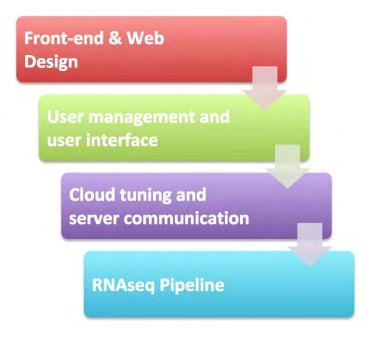
AIR





Artificial Intelligence RNA-seq (AIR)

We started a project to create a system that combining cutting-edge cloud technology together with the most used bioinformatics pipelines would be able to offer a completely user-friendly platform for RNA-seq analysis.



A coordinated effort of informatics engineers, bioinformaticians, web designers and web marketing experts.

Our informatics engineers developed a private cloud configuration system named "Orchestrator" which can use any cloud based computing platform (Google, Amazon, etc.) with an efficient resource management.

On top of this system we mounted our RNA-seq bioinformatics pipeline to perform differential gene expression analysis starting from raw Illumina reads.







http://www.transcriptomics.cloud

THANK YOU



www.sequentiabiotech.com

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