# **Introduction to Next-generation sequencing**

10.11.2021

Melanie Lang & Guillem Salazar

1953: Discovery of the structure of DNA Ο





Francis Crick





**Rosalind Franklin** 



Maurice Wilkins





- O 1953: Discovery of the structure of DNA
- 1965: "Sequencing" of the first tRNA

→ use of ribonucleases with cleaving sites at specific nucleotides → reconstruction of the original nucleotide sequence by determining the order in which small fragments occurred in the tRNA molecule



Robert W. Holley

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https://the-dna-universe.com/2020/11/02/a-journey-through-the-history-of-dna-sequencing/

**Frederick Sanger** 

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 $\rightarrow$  Main sequencing technology for next 25 years

→ Key innovations mainly in automation of wet-lab and data analysis pipelines

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  - $\rightarrow$  Pyrosequencing



nucleotides



 $\rightarrow$  Pyrosequencing



nucleotides

https://www.ebi.ac.uk/training/online/courses/functional-genomics-ii-common-technologies-and-dataanalysis-methods/next-generation-sequencing/454-sequencing/

#### 1996: Beginning of NEXT-GENERATION SEQUENCING Ο

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nucleotides

analysis-methods/next-generation-sequencing/454-sequencing/

wash

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analysis-methods/next-generation-sequencing/454-sequencing/

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  - $\rightarrow$  454 sequencing platform



Roche 454 Sequencing System

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  - $\rightarrow$  Pyrosequencing
- 2005: Implementation of pyrosequencing in automated system Ο
  - $\rightarrow$  454 sequencing platform
- 2007: Illumina acquires Solexa Ο
  - $\rightarrow$  Advanced sequencing technology
  - $\rightarrow$  Improved throughput



#### Illumina MiSeq Sequencing platform

- $\rightarrow$  In each cycle, one dNTP is incorporated into the reaction and it's fluorescent signal captured in an image
- $\rightarrow$  Process is repeated until a full "read" is assembled



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https://www.ebi.ac.uk/training/online/courses/functional-genomics-ii-common-technologies-and-data-analysis-methods/next-generation-sequencing/454-sequencing/



Improvements in DNA sequencing: Some numbers...



\*Moore's law is an observation and projection of a historical trend. Rather than a law of physics, it is an empirical relationship linked to gains from experience in production

https://www.genome.gov/about-genomics/fact-sheets/DNA-Sequencing-Costs-Data

○ 2010: Beginning of THIRD-GENERATION SEQUENCING
 → PacBio sequencing (Pacific Biosciences, Inc.)



PacBio RSII sequencer



→ polymerase immobilized at the bottom of a "well" (zero-mode waveguide ZMW) in a SMRTcell



 $\rightarrow$  Incorporation of fluorescent dNTPs produces a base-specific light pulse  $\rightarrow$  Replication process in all ZMWs is recorded as a "movie" in real-time

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PacBio RSII sequencer

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- → Nanopore sequencing (Oxford Nanopore Technologies)





Nanopore MinION

- $\rightarrow$  single-stranded DNA/RNA molecules pass through protein nanopore
- ightarrow Each nucleotide that passes the pore leads to a different change in electrical current across pore
- $\rightarrow$  Resulting signal is decoded to provide sequence information

https://the-dna-universe.com/2020/11/02/a-journey-through-the-history-of-dna-sequencing/ https://www.sciencedirect.com/topics/neuroscience/nanopore-sequencing https://nanoporetech.com/applications/dna-nanopore-sequencing

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SOLiD 5500×1	2nd	$2 \times 60$	5	$8 \times 10^8$	6 days	0.11	[14,24]
PacBio RS II: P6-C4	3rd	$1.0-1.5 \times 10^4$ on average	13	$3.5 - 7.5 \times 10^4$	0.5–4 h	0.40-0.80	[5,12,15]
Oxford Nanopore MinION	3rd	$2-5 \times 10^3$ on average	38	$1.1 - 4.7  imes 10^4$	50 h	6.44-17.90	[22,23]

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→ Numbers outdated, main features still remain!

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- $\rightarrow$  Platforms of all generations still in use today...

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#### Brainstorm: (NGS) sequencing platform applications



Brainstorm: (NGS) sequencing platform applications

# Different data types for different applications/questions!



# Break...



Given a community of bacteria in any given habitat (soil, gut, ocean, ...) we want to know:





- **Taxonomic precision**
- Resolution



#### Meta-barcoding (metaB)

Seq approach Seq material Target Taxonomic precision Resolution Targeted Amplicon DNA Bacterial genomes Genus/Species Higher

#### Meta-genomics (metaG) Meta-transcriptomics (metaT)

Non-targeted Whole genomic DNA All genomes Strain/Genome Lower Non-targeted Transcribed RNA All active genomes Strain/Genome Lower



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Goal:Identify the members of a bacterial community and its compositionMethod:...





Goal: Identify the members of a bacterial community and its composition

Method: PCR amplification of (part of) bacterial universal marker gene

#### The 16S rRNA gene (part of prokaryotic ribosome)



Fukuda et al. (2016) Molecular approaches to studying microbial communities: Targeting the 16S ribosomal RNA gene *Journal of UOEH* 38(3): 223-232 Yarza et al. (2014) Uniting the classification of cultured and uncultured bacteria and arachae using 16S rRNA gene sequences *Nature Reviews Microbiology* 12: 635-645



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#### The 16S rRNA gene (part of prokaryotic ribosome) $SCIENTIFIC DATA^{(1)}$ Ribosome **OPEN** Data Descriptor: The effect of 16S 30S subunit rRNA region choice on bacterial 16S ribosomal RNA 50S subunit community metabarcoding results Sambo et al. BMC Bioinformatics (2018) 19:343 **BMC Bioinformatics** https://doi.org/10.1186/s12859-018-2360-6 16S 23S Bacterial genome 5S rRNA gene 16S rRNA gene 23S rRNA gene METHODOLOGY ARTICLE **Open Access** ( CrossMark Optimizing PCR primers targeting the V2 V3 V4 V5 V6 V7 V8 bacterial 16S ribosomal RNA gene 100 200 300 400 500 600 700 800 900 1000 1100 1200 1300 1400 base Francesco Sambo<sup>1</sup>, Francesca Finotello<sup>2</sup>. Enrico Lavezzo<sup>3</sup>. Giacomo Baruzzo<sup>1</sup>. Giulia Masi<sup>3</sup>. Elektra Peta<sup>3</sup>. Marco Falda<sup>3</sup>, Stefanc Conserved region $\rightarrow$ ideal as primer binding sites! frontiers **ORIGINAL RESEARCH** published: 04 August 2015 in Microbiology doi: 10.3389/fmicb.2015.00771 Hypervariable region\* $\rightarrow$ ideal to resolve sequence variation in bacterial population Primer and platform effects on 16S rRNA tag sequencing Julien Tremblay<sup>1,2</sup>, Kanwar Singh<sup>1</sup>, Alison Fern<sup>1</sup>, Edward S. Kirton<sup>1</sup>, Shaomei He<sup>1</sup>, Tanja Woyke<sup>1</sup>, Janey Lee<sup>1</sup>, Feng Chen<sup>3</sup>, Jeffery L. Dangl<sup>4</sup> and Susannah G. Tringe<sup>1\*</sup> <sup>1</sup> Department of Energy Joint Genome Institute, Walnut Creek, CA, USA, <sup>2</sup> National Research Council Canada, Montreal, QC, \*Form helical structures, which allow for considerable Canada, 3 Illumina, Inc., San Francisco, CA, USA, 4 Department of Biology and Howard Hughes Medical Institute, Curriculum in Genetics and Molecular Biology, Department of Microbiology and Immunology, Carolina Center for Genome Sciences,

#### sequence variation

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University of North Carolina, Chapel Hill, NC, USA

Goal:Identify the members of a bacterial community and its compositionMethod:PCR amplification of (part of) bacterial universal marker gene




#### Data analysis pipeline





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#### Generation of operational taxonomic units (OTUs)





#### Data analysis pipeline





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#### Popular 16S rRNA gene analysis tools



Mothur, University of Michigan https://www.mothur.org/



Robert Edgar http://www.drive5.com/usearch/



University of Colorado http://qiime.org/

#### Data analysis pipeline





Amplicon Sequencing. Exactly. Version 1.18

A2A A2C A2G A2T 1e+00 1e-01 1e-02 1e-03 · 1e-04 C2A C2C C2G C2T 1e+00 1e-01 frequency (log10) 1e-02 1e-03 1e-04 G2A G2C G2G G2T 1e+00 1e-01 Error 1e-02 1e-03 1e-04 T2A T2C T2G T2T 1e+00 1e-01 1e-02 1e-03 1e-04 20 30 40 10 20 30 40 0 10 20 30 40 10 20 30 Consensus quality score

#### Learning the error model from the sequencing data:

- Infer error rates for all possible nucleotide transitions per consensus quality score
- black line represents the estimated error rates after convergence of the machine-learning algorithm
- Inferred error model is used to correct individual reads (separately for forward and reverse read)
- Merging of forward and reverse reads
- Only identical consensus reads are grouped into
  Amplicon Sequence variants (ASVs)





OTUs vs ASVs



Taxonomic annotation



#### Popular 16S rRNA gene databases

Taxonomy: Kingdom Phylum Class Order Family Genus Species



University of Michigan https://rdp.cme.msu.edu/

green genes silva

LBNL Berkeley, now second genomes http://greengenes.lbl.gov

MPI Bremen https://www.arb-silva.de/









Caveat of multiple 16S rRNA gene copies



#### NGS short-read sequencing: Different data types



#### **Meta-barcoding (metaB)**

Seq approach Seq material Target **Taxonomic precision** Resolution

Targeted Amplicon DNA **Bacterial genomes** Genus/Species Higher

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Meta-genomics (metaG) Meta-transcriptomics (metaT)

Non-targeted **Transcribed RNA** All active genomes Strain/Genome Lower



Goal: Identify the genomic content of a community, its composition and function Method: ...





Goal: Identify the genomic content of a community, its composition and function Method: Shotgun sequencing





Goal: Identify the genomic content of a community, its composition and function

Method: Shotgun sequencing







https://international.neb.com/-/media/nebus/files/manuals/manuale7103-e7645.pdf?rev=339d6c65a9314c9e988851a9d671fd9a&hash=2AF765847CD54F1B7464205F7920A50Ffiles/manuals/manuals/manuale7103-e7645.pdf?rev=339d6c65a9314c9e988851a9d671fd9a&hash=2AF765847CD54F1B7464205F7920A50Ffiles/manuals/manuals/manuale7103-e7645.pdf?rev=339d6c65a9314c9e988851a9d671fd9a&hash=2AF765847CD54F1B7464205F7920A50Ffiles/manuals/manuals/manuale7103-e7645.pdf?rev=339d6c65a9314c9e988851a9d671fd9a&hash=2AF765847CD54F1B7464205F7920A50Ffiles/manuals/manuals/manuals/manuale7103-e7645.pdf?rev=339d6c65a9314c9e988851a9d671fd9a&hash=2AF765847CD54F1B7464205F7920A50Ffiles/manuals/manu





https://international.neb.com/-/media/nebus/files/manuals/manuale7103-e7645.pdf?rev=339d6c65a9314c9e988851a9d671fd9a&hash=2AF765847CD54F1B7464205F7920A50Ffiles/manuals/manuals/manuale7103-e7645.pdf?rev=339d6c65a9314c9e988851a9d671fd9a&hash=2AF765847CD54F1B7464205F7920A50Ffiles/manuals/manuals/manuale7103-e7645.pdf?rev=339d6c65a9314c9e988851a9d671fd9a&hash=2AF765847CD54F1B7464205F7920A50Ffiles/manuals/manuals/manuale7103-e7645.pdf?rev=339d6c65a9314c9e988851a9d671fd9a&hash=2AF765847CD54F1B7464205F7920A50Ffiles/manuals/manuals/manuals/manuale7103-e7645.pdf?rev=339d6c65a9314c9e988851a9d671fd9a&hash=2AF765847CD54F1B7464205F7920A50Ffiles/manuals/manu



**Assembled reads** 



#### Individual reads





- 1. Remove sequencing adaptors
- 2. Quality trimming of reads
- 3. Remove unwanted reads (human, mouse, etc.)

# Assembly Gene calling

MAGs\*

\*Metagenomeassembled genomes

→ More this afternoon from Lucas



**Binning** 







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#### Data analysis pipeline



Data applications





Data applications

- 1. Accurate microbial abundance estimation using marker genes
- 2. Increased taxonomic resolution
- 3. Linking function to phenotype



1. Accurate microbial abundance estimation using marker genes

Common problems when using metaB data:

- Variation in 16S copy number
- Taxonomic annotation is database-dependent



Further:

- Genomes from different species can be up to 95% identical<sup>1</sup>
  → hard to map reads of length 100-150 to the original genome
- Genomes have different length



1. Accurate microbial abundance estimation using marker genes

Solution: Single-copy universal marker genes → Present in almost all known organisms

 $\rightarrow$  Only one copy within each genome







Uses 10 universal singlecopy marker genes (here 3 are represented)



a) Reference genomes

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Map metagenomic reads to marker genes using

- a) Reference genomes
- b) Assembled and linked contigs

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Map metagenomic reads to marker genes using

- a) Reference genomes
- b) Assembled and linked contigs
- c) MAGs

Sunagawa et al. Nature methods (2013); Milanese et al. Nature comm (2019)

2. Increased taxonomic resolution

Genome- wide ANI	Taxonomic rank	
	Domain	
	Phylum	
	Class	
	Order	
	Family	
<<85%	Genus	
95%	Species	
97%	Subspecies	
>99.9%	Strain	$\phi \widehat{} \phi \widehat{} \phi \widehat{} \phi$
>99.99999%	Subclonal	



2. Increased taxonomic resolution



2. Increased taxonomic resolution



3. Linking function to phenotype

**Systems**°

AMERICAN SOCIETY FOR MICROBIOLOGY



Check for updates

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FIG 1 Protein family richness associates with disease. Density plots of the distribution of protein family richness across case and control populations for seven diseases. Asterisks beside plot titles indicate significance from Student's t test (\*, P0.05; \*\*, P0.01; \*\*\*, P0.001)





- Shown are MDS plots based on Bray-Curtis dissimilarity between all samples based on their KO abundances
- functional composition of the gut microbiome differs between case and control populations for 6 out of 7 diseases



FIG 2 Changes in functional composition associate with disease. NMDS plots of Bray-Curtis dissimilarity between cases and controls across diseases; ellipses represent 95% confidence level. Asterisks in NMDS plot titles indicate significance from PERMANOVA (\*\*\*, P0.001; Table S6). Box plots represent dispersion in beta-diversity within groups. Asterisks in box plots denote significance from P test and ANOVA (\*, P 0.05).

MDS2

Armour, R., Nayfach, S., Pollard, K.S., Sharpton, T.J. (2019) mSystems 4(4) e00332





#### 3. Linking function to phenotype



Random Forest by Disease						
Level	Disease	Color	OOB error	AUC		
Module	Crohn's Disease	Yellow	5.56%	0.954		
Module	Liver cirrhosis	Orange	17.09%	0.902		
Module	Obesity	Green	22.57%	0.803		
Module	Ulcerative colitis	Brown	25.26%	0.783		
Module	Type II diabetes	Blue	31.58%	0.708		
Module	Rheumatoid arthritis	Purple	35.58%	0.664		
Module	Colorectal carcinoma	Red	36.36%	0.596		
Module	Carcinoma (without adenoma)	Grey	35.21%	0.715		

"These results suggest that the potential for use of the functional composition of the gut microbiome in disease diagnosis varies by the type and severity of disease"

FIG 4 Classifying disease status based on the functional composition of the microbiome. ROC curves from random forest classifiers for cases and controls in each disease. The table shows OOB error and AUC values.

#### NGS short-read sequencing: Different data types



#### Meta-barcoding (metaB)

Seq approach Seq material Target Taxonomic precision Resolution Who is there? At what proportions? What are they doing? Targeted Amplicon DNA Bacterial genomes Genus/Species Higher

#### Meta-genomics (metaG) Meta-transcriptomics (metaT)

Non-targeted Whole genomic DNA All genomes Strain/Genome Lower Non-targeted Transcribed RNA All active genomes Strain/Genome Lower

#### NGS short-read sequencing: Different data types



#### Meta-barcoding (metaB)

Seq approach Seq material Target Taxonomic precision Resolution Who is there? At what proportions? What are they doing? Targeted Amplicon DNA Bacterial genomes Genus/Species Higher Yes Yes (with limitations) No

#### Meta-genomics (metaG) Meta-transcriptomics (metaT)

Non-targetedNon-targetedWhole genomic DNATranscribed RNAAll genomesAll active genomesStrain/GenomeStrain/GenomeLowerLowerYesYes, if activeYes (metabolic potential)Yes



Different DNA sequencing technology have been developed over the last 30 years

Different sequencing technologies still in use today for specific applications/questions

Usually there is a trade-off between throughput and accuracy (but still improving)  $\rightarrow$  needs to be tailored to research question

Different technologies generate different data types with individual characteristics (Pros and Cons)  $\rightarrow$  needs to be tailored to research question

Meta-barcoding: Cheap, abundance-independent, limited taxonomic resolution, no functional information

Meta-genomics: expensive, abundance-dependent, high taxonomic resolution, functional information

## Break...



#### Block-course study data: The gut microbiome in acute myeloid leukemia (AML)

#### AML = Acute myeloid leukemia

- → Cancer of the blood and bone marrow that progresses quickly and always ends in death if untreated
- $\rightarrow$  Increased incidence with age
- → Different genetic variants known to affect treatment outcome
- → Current best treatment approach: Intensive chemotherapy



Block-course study data: Impact of intestinal microbiota on systemic infections, response to chemotherapy and overall outcomes in patients with acute myeloid leukemia – a prospective, non-interventional, single-center study

#### Intensive chemotherapy

- highly toxic (Gastrointestinal mucositis with enterocolitis extremely common)
- high risk of life-threatening infections during neutropenia
- ➤ Gut is main source of bacteria causing infections → use of antibiotics/gut decontamination
- Overall benefit of gut decontamination unknown
- Dysbiosis of the gut microbiome caused by gut decontamination might aggravate patient susceptibility to infection

Bottom line: "The impact of intensive chemotherapy with/without prophylactic gut decontamination on the microbiota, systemic infections and leukemia response in AML patients has not been clarified" Block-course study data: Impact of intestinal microbiota on systemic infections, response to chemotherapy and overall outcomes in patients with acute myeloid leukemia – a prospective, non-interventional, single-center study

Study design



3-4 months
## NGS long-read sequencing: MetaB <u>and</u> MetaG

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