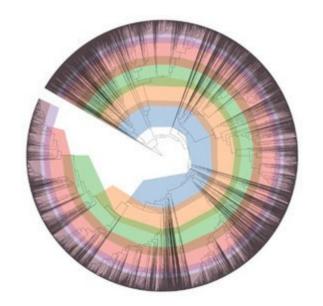
ENVIRONMENTAL METAGENOMICS

Physalia course, online, 13-17 October 2025

Metagenome de-novo assembly and quality control

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NB: original course material courtesy: Dr. Antti Karkman, University of Helsinki Dr. Igor Pessi, Finnish Environment Institute (SYKE)

Typical analysis methods used in metagenomics

1) Alignment:







2) Classification:

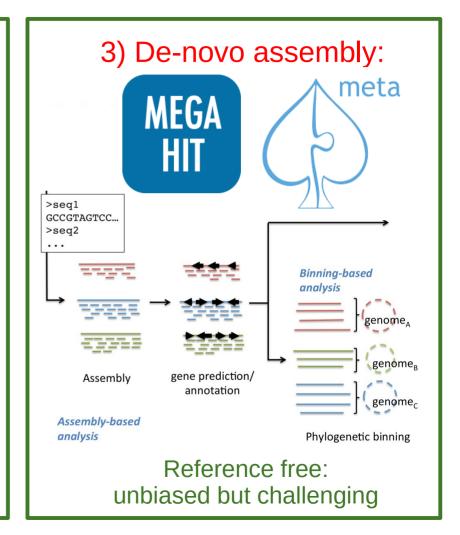


Centrifuge

MetaPhlan

Clark

Reference based: assume similarity to reference



Strenghts and weaknesses of read-based metagenomics

Comprehensiveness

Can provide an aggregate picture of community function or structure, but is based only on the fraction of reads that map effectively to reference dbs

Community complexity

Can deal with communities of arbitrary complexity given sufficient sequencing depth and satisfactory reference database coverage

Novelty

Cannot resolve organisms for which genomes of close relatives are unknown

Computational burden

Can be performed efficiently, enabling large meta-analyses

Genome-resolved metabolism

Can typically resolve only the aggregate metabolism of the community, and links with phylogeny are only possible in the context of known reference genomes

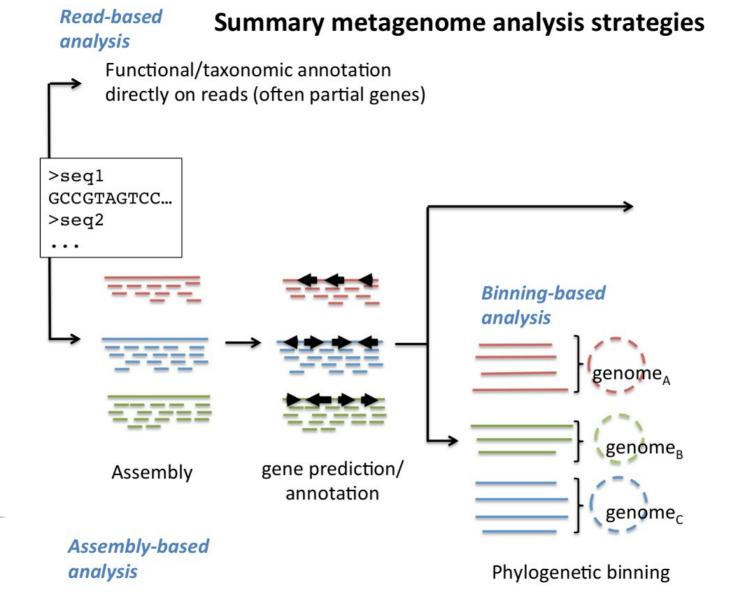
Expert manual supervision

Usually does not require manual curation, but selection of reference genomes to use could involve human supervision

Integration with microbial genomics

Obtained profiles cannot be directly put into the context of genomes derived from pure cultured isolates





Physalia

Courses

Strengths and weaknesses of assembly-based metagenomics

Comprehensiveness Can construct multiple whole genomes, but only for organisms with enough coverage to be assembled and binned

Community In complex communities, only a fraction of the genomes can be resolved by assembly

Novelty Can resolve genomes of entirely novel organisms with no sequenced relatives

Computational Requires computationally costly assembly, mapping and binning burden

Genome-resolved Can link metabolism to phylogeny through completely assembled genomes, even for novel diversity

Expert manualManual curation required for accurate binning and scaffolding and for misassembly detection

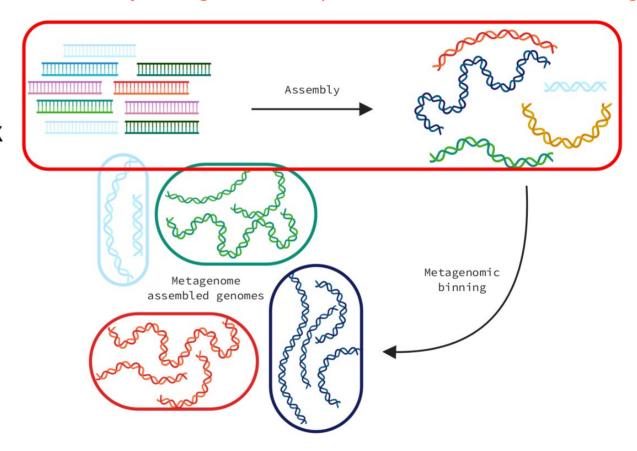
Integration with Assemblies can be fed into microbial genomic pipelines designed for analysis of genomes from pure cultured isolates



De novo assembly

Assemble short nucleotide sequences into longer sequences by finding their overlap / consensus without reference genome

- No reference available
- Uneven and complex communities





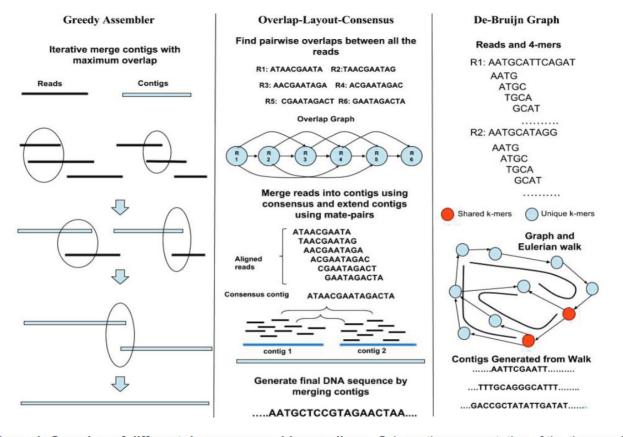


Figure 1: Overview of different de novo assembly paradigms. Schematic representation of the three main paradigms for genome assembly – Greedy, Overlap-Layout-Consensus, and de Bruijn. In Greedy assembler, reads with maximum overlaps are iteratively merged into contigs. In Overlap-Layout-Consensus approach, a graph is constructed by finding overlaps between all pairs of reads. This graph is further simplified and contigs are constructed by finding branch-less paths in the graph, and taking the consensus sequence of the overlapping reads implied by the corresponding paths. Contigs are further organized and extended using mate pair information. In de Bruijn graph assemblers, reads are chopped into short overlapping segments (k-mers) which are organized in a de Bruijn graph structure based on their co-occurrence across reads. The graph is simplified to remove artifacts due to sequencing errors, and branch-less paths are reported as contigs.



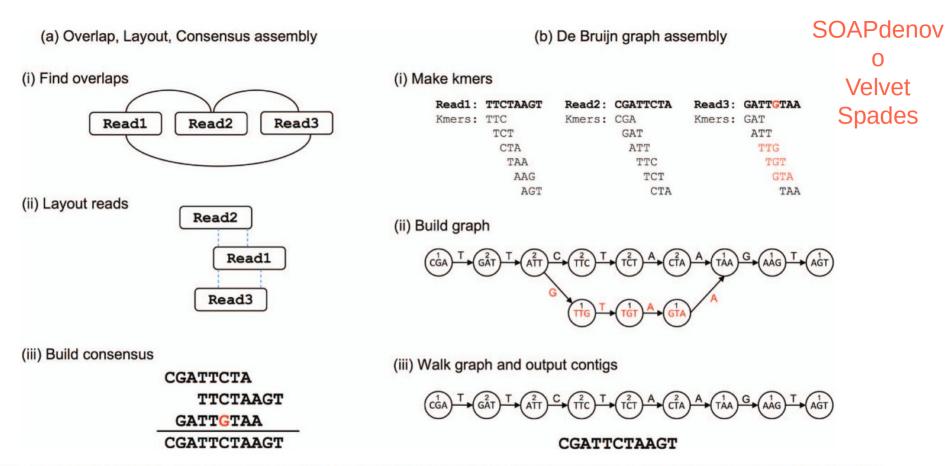


Figure 1. Two different approaches to genome assembly: (a) in Overlap, Layout, Consensus assembly, (i) overlaps are found between reads and an overlap graph constructed (edges indicate overlapping reads). (ii) Reads are laid out into contigs based on the overlaps (dashed lines indicate overlapping portions). (iii) The most likely sequence is chosen to construct consensus sequence. (b) In dBg assembly, (i) reads are decomposed into kmers by sliding a window of size k across the reads. (ii) The kmers become vertices in the dBg, with edges connecting overlapping kmers. Polymorphisms (red) form branches in the graph. A count is kept of how many times a kmer is seen, shown here as numbers above kmers. (iii) Contigs are built by walking the graph from edge nodes. A variety of heuristics handle branches in the graphs—for example, low coverage paths, as shown here, may be ignored.

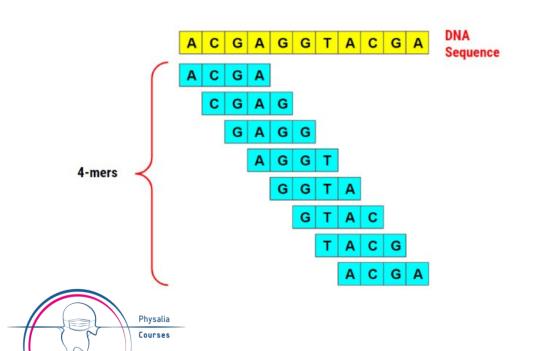
Popular de Bruijn graph *de-novo* metagenomic assemblers for short Illumina reads



We are going to use Megahit in the exercises

De novo assembly using MEGAHIT

MEGAHIT: de Bruijn-graph assembler using a distribution of different k-mer lengths inferred from the length of the sequencing data



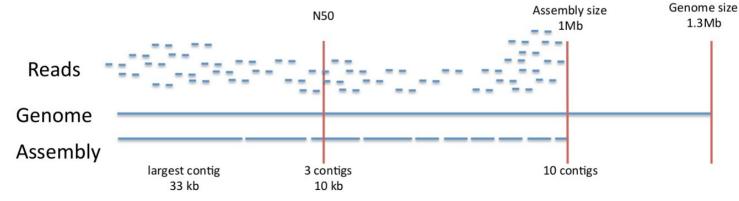
reasons for using MEGAHIT:

- low-memory footprint
- has little issues with the presence of ancient DNA damage
- works with single-end data

BUT: lower assembly quality than other assemblers for modern sequencing data (see CAMI II challenge; DOI: 10.1038/s41592-022-01431-4)

Assembly metrics

- assembly size
- number of contigs, largest contig
- N50

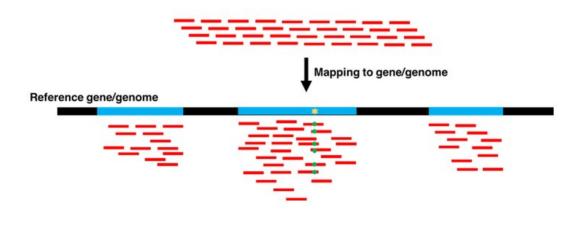




Alignment against the contigs

Many of the following steps require the alignment of the short-read data against the de novo assembled contigs, e.g.

- correction of the contig sequences
- binning of the contigs into MAGs (coverage along the contigs)
- quantification of the presence of ancient DNA damage





Taxonomic classification - on contig level

The likely taxonomic origin of contigs can be determined by aligning them against a

reference database.

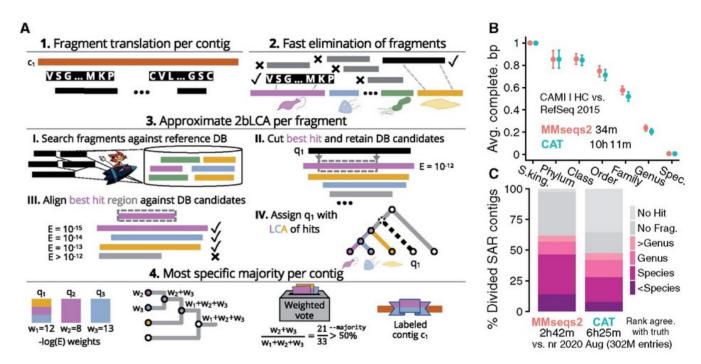
available aligners:

- BLAST/DIAMOND
- Kraken2
- Centrifuge
- MMSeqs2

available databases:

- NCBI NT/RefSeq
- GTDB





Mirdita et al. (Bioinformatics, 2021; doi: bioinformatics/btab184) Fig. 1