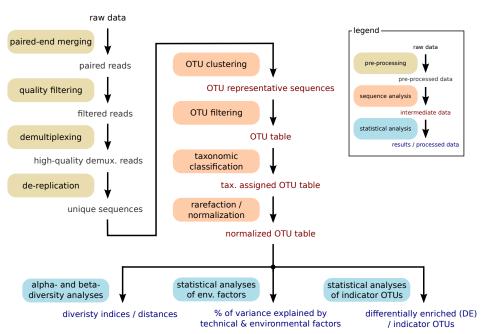
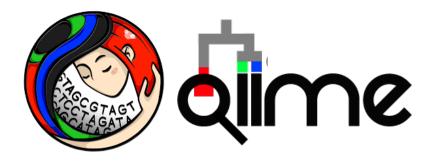


State-of-the-art approaches for amplicon data analysis
Ruben Garrido-Oter

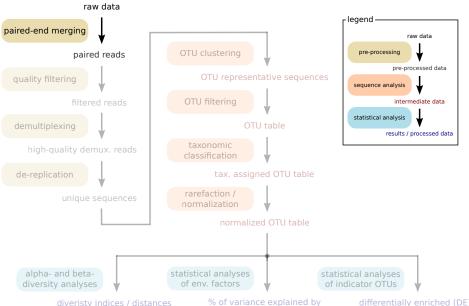


Commonly used toolkits for amplicon sequence analysis



USEARCH

Ultra-fast sequence analysis

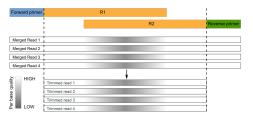


of variance explained by differentially enriched (I cal & environmental factors / indicator OTUs

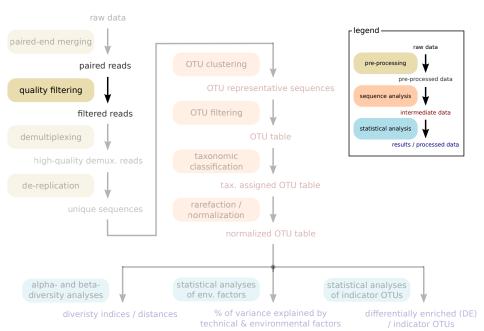
Merging paired-end reads (Illumina)

 Consists on merging (assembling) paired-ed reads into consensus sequences (and consensus quality scores for downstream filtering)



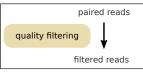


- Poorly overlapping pairs are (generally) discarded for fixed-length markers
- For overlapping pairs quality scores need to be recomputed
- Multiple tools, e.g.:
 - PANDAseg (Masella, et al., 2012)
 - **join_paired_ends** in QIIME (uses the fastq-join tool)
 - fastq mergepairs command in USEARCH



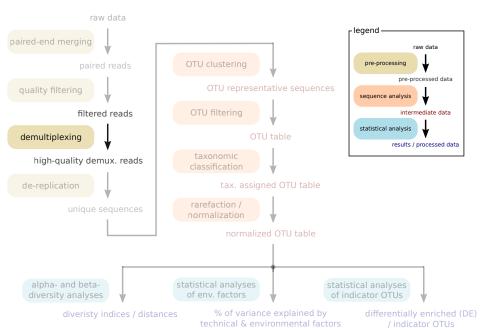
Quality filtering of amplicon reads

 NGS instruments (454, Illumina) indicate the probabilities of sequencing errors using quality (Phred or Q) scores



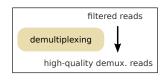
ASCII BASE=33 Illumina, Ion Torrent, PacBio and Sanger											
Q	Perror	ASCII	Q	P_error	ASCII	Q	P_error	ASCII	Q	P_error	ASCII
0	1.00000	33 !	11	0.07943	44 ,	22	0.00631	55 7	33	0.00050	66 B
1	0.79433	34 "	12	0.06310	45 -	23	0.00501	56 8	34	0.00040	67 C
2	0.63096	35 #	13	0.05012	46 .	24	0.00398	57 9	35	0.00032	68 D
3	0.50119	36 \$	14	0.03981	47 /	25	0.00316	58 :	36	0.00025	69 E
4	0.39811	37 %	15	0.03162	48 0	26	0.00251	59 ;	37	0.00020	70 F
5	0.31623	38 €	16	0.02512	49 1	27	0.00200	60 <	38	0.00016	71 G
6	0.25119	39 '	17	0.01995	50 2	28	0.00158	61 =	39	0.00013	72 H
7	0.19953	40 (18	0.01585	51 3	29	0.00126	62 >	40	0.00010	73 I
8	0.15849	41)	19	0.01259	52 4	30	0.00100	63 ?	41	0.00008	74 J
9	0.12589	42 *	20	0.01000	53 5	31	0.00079	64 @	42	0.00006	75 K
10	0.10000	43 +	21	0.00794	54 6	32	0.00063	65 A			

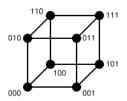
- For amplicon data, it is very difficult to distinguish PRC artifacts (SNP errors / chimeras) from sequencing errors
- Two ways (mainly) to filter sequencing errors:
 - maximum unacceptable Phred quality score in a read e.g. split_libraries_fastq in QIIME
 - expected number of errors in a read (dataset)
 e.g. fastq filter (and fastx learn) command in USEARCH



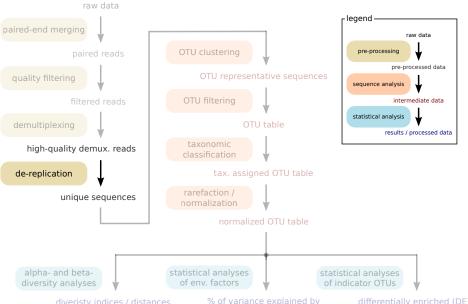
Demultiplexing

 Assign merged reads to samples using (and removing) error-correcting barcode sequences.





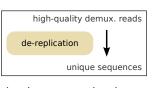
- Barcodes can be added as a tag to the sequence header or as a separate FASTQ file (depending on the instrument)
- Barcodes using Golay codes allow errors (2 for 12 base pair sequences)
- Tools append a sample identifier to the sequence header (and generally use different encodings), e.g.:
 - **split_libraries_fastq** script in QIIME (demultiplex_fasta for 454)
 - derep_fulllength script in USEARCH (with -relabel option)



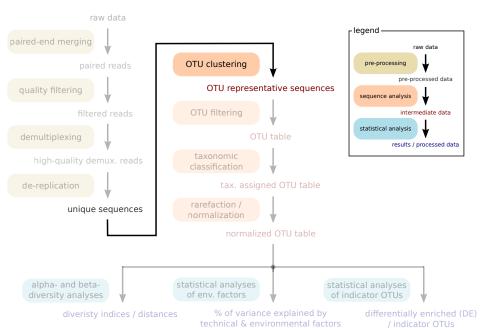
differentially enriched (D s / indicator OTUs

De-replication

 Some steps (e.g. OTU clustering and taxonomic classification of representatives) only need to be done once per set of identical reads

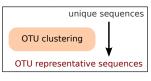


- It is generally advisable to remove singletons. The basic assumption is that these are usually artifacts and that errors seldom occur multiple times on the same template sequence
- Mapping of non-replicated reads onto OTU representatives is necessary to obtain accurate abundances (*usearch_global* script in USEARCH)
- Multiple alternatives implemented for full-length dereplication (paired-end Illumina with overlapping reads), e.g.:
 - **split_libraries_fastq** script in QIIME (demultiplex_fasta for 454)
 - derep_fulllength script in USEARCH (with -relabel option)
- Non-overlapping singleton reads (e.g. ITS) need to be trimmed to equal length *prior* de-replication:
 - fastx_truncate command in USEARCH)
 - truncate_fasta_qual_files script in QIIME (outdated)



OTU (Operational Taxonomic Unit) clustering

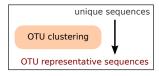
 OTU clustering ('picking') refers to the process of grouping related sequences into constructs that roughly correspond with bacterial species

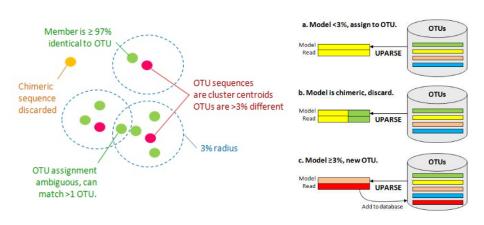


- Arbitrary thresholds of sequence similarly are generally used (97%) that are highly dependent on the marker gene (and region within)
- OTUs are useful data constructs in microbial ecology but suffer from various shortcomings, e.g.:
 - OTUs do not correspond to any meaningul biological entity: isolates from the same OTU often have very different genomes
 - there is a taxonomy bias in sequence variation (some OTUs are more homogeneous than others / have lower conservation in the amplified genetic locus)
 - sequencing and PCR errors impose a resolution limit (tradeoff between resolution and artefactual OTUs)

OTU (Operational Taxonomic Unit) clustering

 OTU clustering ('picking') refers to the process of grouping related sequences into constructs that roughly correspond with bacterial species





Edgar, 2013

OTU (Operational Taxonomic Unit) clustering

There are three main strategies for OTU picking:

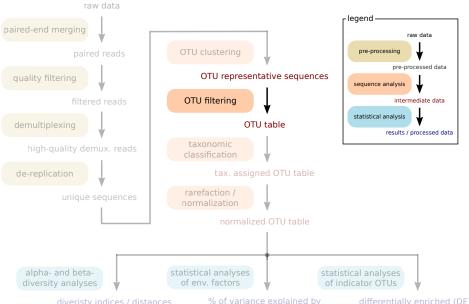


- de novo OTU clustering

 (do not depend on a reference database)

 e.g. UCLUST (Edgar, 2010), UPARSE (Edgar, 2013)

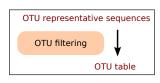
 or Swarm (Mahé et al., 2014)
- closed-reference OTU clustering (take advantage of reference database; SynComs)
- hybrid (open-reference) OTU clustering
 (typically perform a first-pass reference iteration, followed by de novo clustering of left-out sequences)
 e.g. SortMeRNA (Kopylova et al., 2012)
- Multiple implementations of these methods in various toolkits (e.g. cluster_otus command in USEARCH or pick_otus in QIIME)



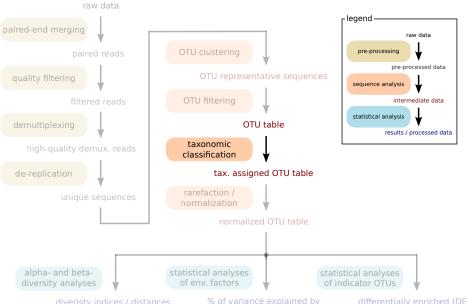
differentially enriched (D / indicator OTUs

OTU filtering

 Filtering of low abundance OTUs assuming these are likely artefacts (depending on the complexity / sequencing depth 1% 0.1% R.A.)



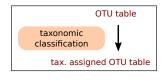
- Chimera detection and removal (artefactual sequences formed from two or more biological sequences joined together e.g. during PCR)
 multiple methods, e.g.: ChimeraSlayer (Haas et al., 2011),
 DECIPHER (Wright et al., 2012), Perseus (Quince et al., 2011)
 or UCHIME (Edgar et al., 2011) (chimera_ref command in USEARCH or identify chimeric segs in OIIME)
- Filtering nonsense OTUs (generated from prevalent sequencing / PCR artefacts that do not align to public databases of bacteria above a certain threshold; e.g. 75% sequence identity)
 - e.g. using the *usearch_global* alignment command in USEARCH



differentially enriched (D / indicator OTUs

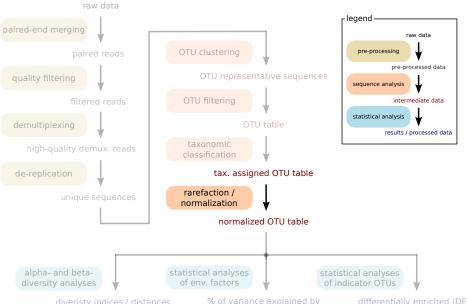
Taxonomic classification

 There are multiple algorithms and tools for classification of marker gene sequences, e.g. RDP, Blast, RTAX, UTAX, mothur-knn, UCLUST, SortMeRNA, etc.



QIIME provies a wrapper for many with the **assign_taxonomy** script USEARCH implements UTAX in the commands **utax** and **cluster_otus_utax**

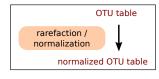
- These methods rely on homology -- results are highly dependent on high similarity with representatives in the database
- Reference databases have poor coverage and are highly biased (e.g. towards culturable bacteria)
- Various types of errors and tradeoffs: type I & II errors and overclassification errors (i.e. tax. assignment for novel sequences)



of variance explained by differentially enriched (I ical & environmental factors / indicator OTUs

Rarefaction / normalization

- Sample depth in amplicon sequencing data (number of reads per sample) is highly variable.
- When studying complex communities deep samples will capture more diversity



- There are two main strategies to address this issue:
 - sub-sampling or rarefaction, which consists on randomly selecting an equal number of sequences from each sample

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 Sub-sampling or rarefaction, which consists on randomly selecting an equal number of sequences from each sample.
 - calculate relative abundances (e.g. by dividing every OTU count by the total sample depth) with or without subsequent transformations
- Both approaches have pitfalls and there is considerable debate as to which strategy is preferable (see e.g. McMurdie et al., 2014 and Weiss et al., 2017)

