

Microbiome

Normalization and microbial differential abundance strategies depend upon data characteristics

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1.Effect of normalization method and uneven library size on beta diversity

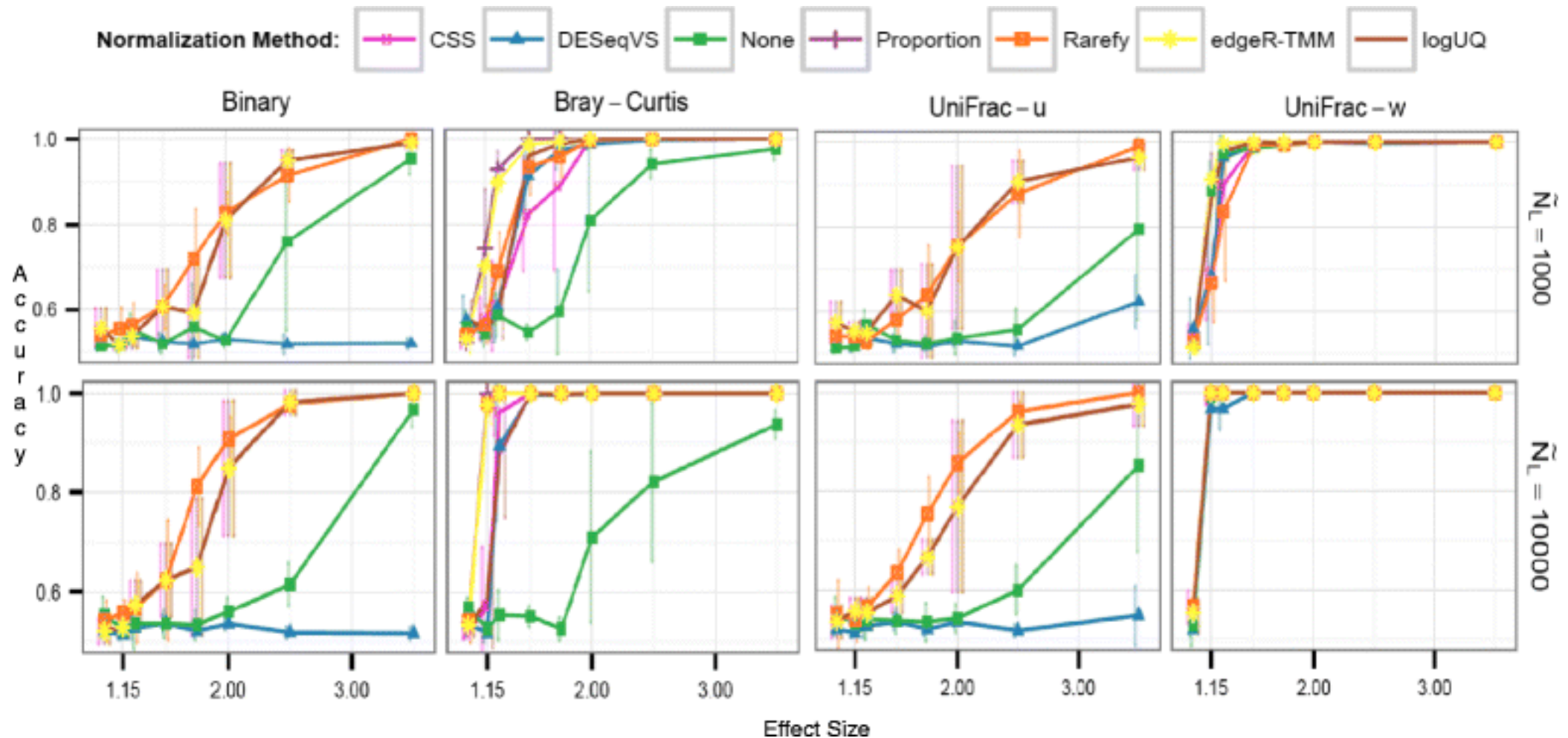
2.Effect of normalization, uneven library size, and differential abundance test on differential abundance results

tl;dr: if your library sizes are super uneven, you should probably do something about it.

Weighted Unifrac is good no matter what you do.

Differential abundance methods are all not that great?

Weighted Unifrac is the best beta diversity metric.
For unweighted metrics, DESeqVS and “No normalization” are not great.

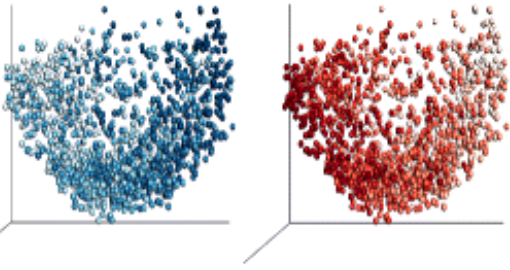


High Microbial Dysbiosis Index
Low Microbial Dysbiosis Index

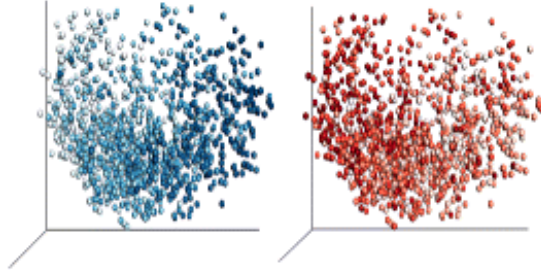
High Library Size
Low Library Size

*** $p < 0.001$

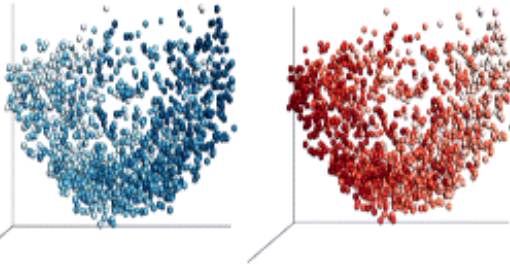
a None: PERMANOVA R^2
Library_Size: 0.039***
Microbial Dysbiosis Index: 0.040***



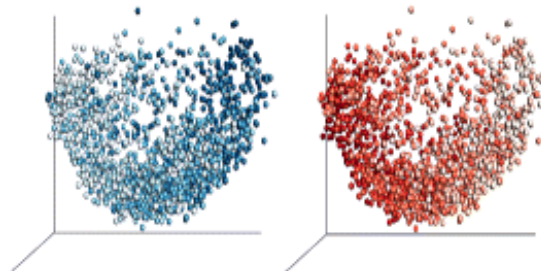
b Rarefy: PERMANOVA R^2
Library_Size: 0.0086***
Microbial Dysbiosis Index: 0.047***



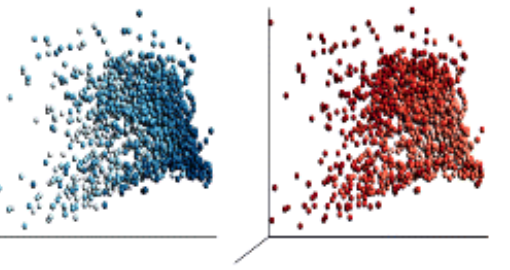
c Proportions: PERMANOVA R^2
Library_Size: 0.039***
Microbial Dysbiosis Index: 0.040***



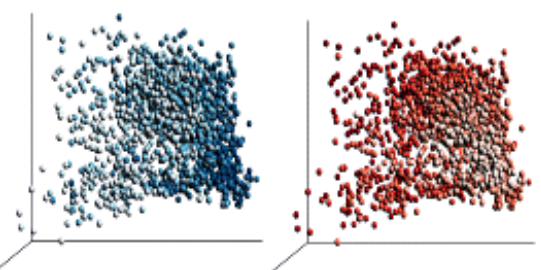
d CSS: PERMANOVA R^2
Library_Size: 0.037***
Microbial Dysbiosis Index: 0.041***



e DESeq: PERMANOVA R^2
Library_Size: 0.18***
Microbial Dysbiosis Index: 0.11***



f edgeR-TMM: PERMANOVA R^2
Library_Size: 0.096***
Microbial Dysbiosis Index: 0.13***



Rarefying reduces the effect of library size best.

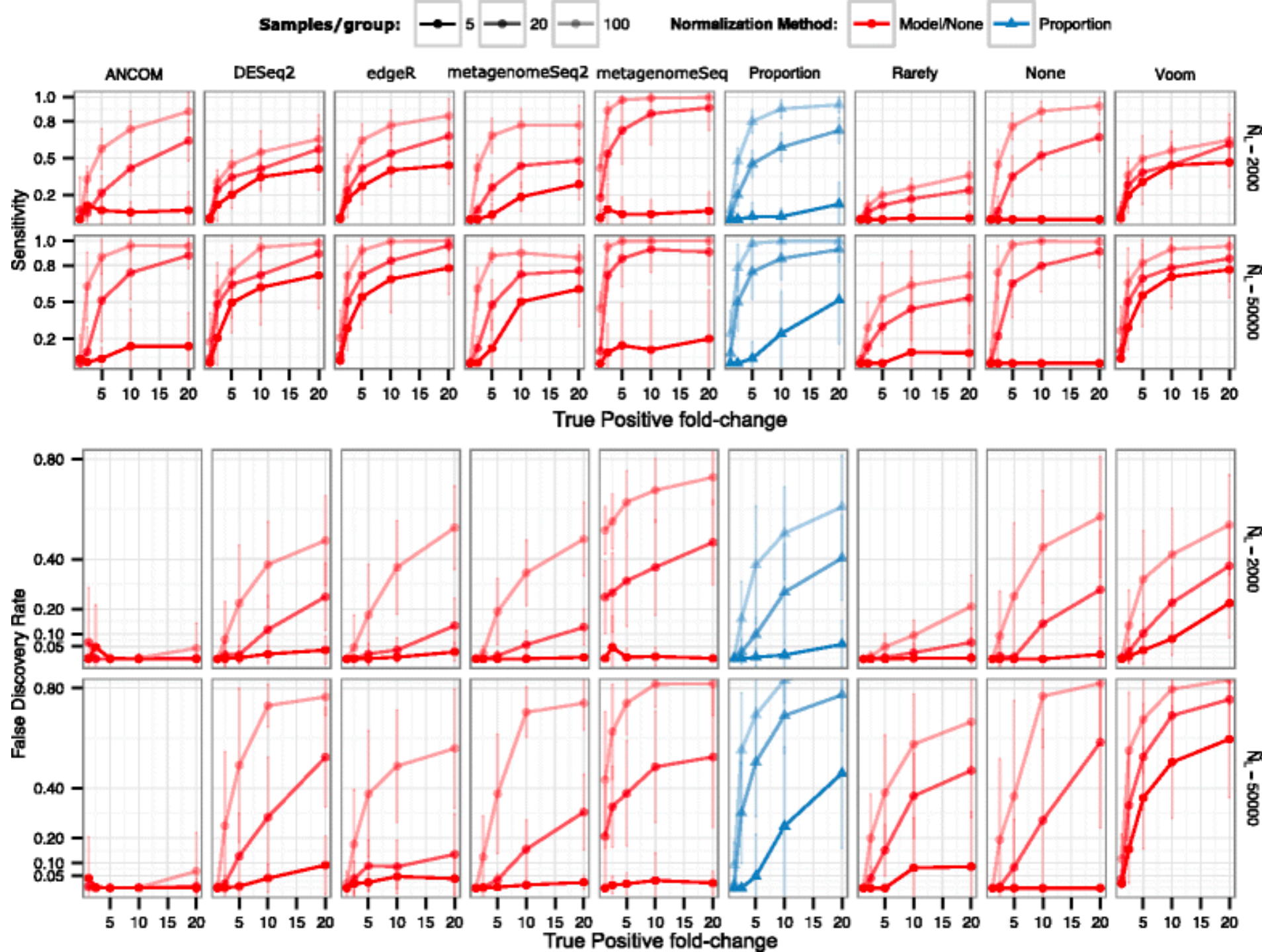
a-d are unweighted metrics
e-f are weighted unifracs

Word before "PERMANOVA R^2 " is the normalization

There are trade-offs in sensitivity (top) and FDR (bottom).

Some methods are better at small sample sizes.

Other than ANCOM they all kind of look the same



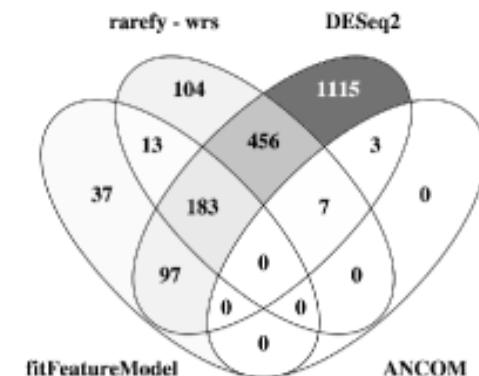
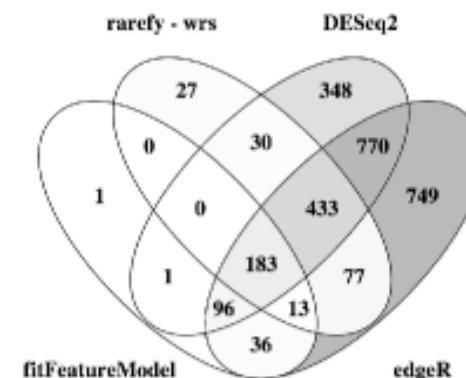
Differential abundance methods don't find the same things.

DESeq2 and edgeR give a lot of hits

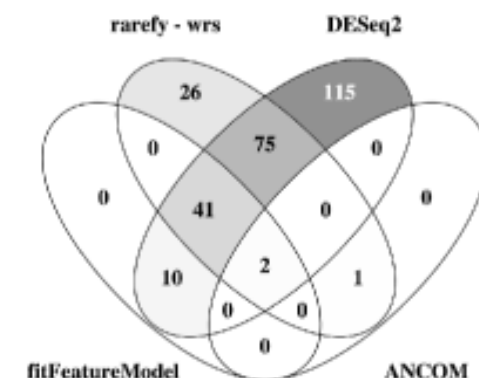
Venn diagrams with more than 3 circles are really hard to interpret

We really need gold-standard datasets to know what is true

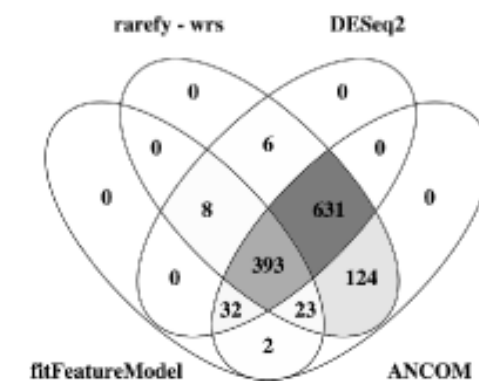
a Caporaso *et al.* Ultra-high-throughput microbial community analysis on the Illumina HiSeq and MiSeq platforms *ISME* (2012).
~ 6 skin samples, 8 soil samples
mean sequences per sample: 1.3 million



b Piombino *et al.* Saliva from Obese Individuals Suppresses the Release of Aroma Compounds from Wine. *PLoS One* (2014).
~28 samples per category (lean vs. obese)
mean sequences per sample: 75,580



c Caporaso *et al.* Moving Pictures of the Human Microbiome. *Genome Biology* (2011).
~500 samples per category (tongue vs. left palm)
mean sequences per sample: 25,600



`skbio.stats.composition.ancom()`

Performs a differential abundance test using ANCOM.

This is done by calculating pairwise log ratios between all features and performing a significance test to determine if there is a significant difference in feature ratios with respect to the variable of interest.

In an experiment with only two treatments, this test tests the following hypothesis for feature i

$$H_{0i} : \mathbb{E}[\ln(u_i^{(1)})] = \mathbb{E}[\ln(u_i^{(2)})]$$

where $u_i^{(1)}$ is the mean abundance for feature i in the first group and $u_i^{(2)}$ is the mean abundance for feature i in the second group.