Compositional analysis: a valid approach to analyze microbiome

high throughput sequencing data

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**Abstract**

A workshop held at the annual meeting of the Canadian Society of Microbiologists highlighted compositional data analysis methods, and the importance of exploratory data analysis, for the analysis of microbiome datasets generated by high throughput sequencing. A summary of the content of that workshop, a review of new methods of analysis, and information on the importance of careful analyses are presented herein. The workshop focussed on explaining the rationale behind the use of compositional data analysis, and a demonstration of these methods for the examination of microbiome datasets using published datasests as examples. A clear understanding of bioinformatics methodologies and the type of data being analyzed is essential given the growing number of studies uncovering the critical role of clusters of microbes in health and disease, and the need to understand alterations to their composition and function following intervention with fecal transplant, probiotics, diet and pharmaceutical agents.

**Key Words:** microbiome, compositional data, correlation, multiple test correction

**Introduction**

Human microbiome studies have shown a major link between microbial composition and health and disease and dysbiosis (Fremont et al. 2013; Lourenço et al. 2014; Urbaniak et al. 2014). High throughput sequencing methodologies have made this possible, along with breakthroughs in culture techniques. The former has used approaches such as 16S rRNA gene sequencing, metagenomics, transcriptomics and meta-transcriptomics, leading to vast datasets that must be simplified and analyzed (Di Bella et al. 2013). Indeed, each sample may have tens of thousands to millions of sequence reads associated with it, and the entire dataset across all samples can easily have hundreds of millions to billions of reads. Such has been the rapidity of these developments that some studies appear to have been published using methods that are at worst flawed and at best not sufficiently well utilized. The result can be papers that journals and the lay media publicize as major advances or breakthroughs, when in some cases the data are far from sufficient for such claims (Hsiao et al. 2013; Mazmanian 2015).

A Bioinformatics Workshop was held on June 16, 2015 in Regina at the Annual Meeting of the Canadian Society of Microbiologists with the goal of demonstrating how to analyse large microbiome datasets, the importance of individual and group exploratory data analysis, and on how to increase the accuracy and dependability of the analyses. Participants were introduced to the concept and importance of multivariate compositional data and why datasets of this type can give misleading results when analyzed by current methods. Examples were used from the literature that outlined the dangers of improper understanding of data analysis in this area. This manuscript provides an expanded rationale for using compositional data analysis methods, a brief review of methods for compositional data analysis of microbiome datasets and a complete description of the approach. A supplementary document is included that contains all the R code and further explanation for two worked examples.

The goals of analysis: Any analysis of a microbiome dataset usually has three major goals:

1. Does the data show any structure? That is, does the data partition into groups?
2. What is the difference between groups? This can be between groups identified beforehand, or by exploratory analysis of the data.
3. What is the correlation structure of the taxonomic groups? Do any of these taxa correlate with the metadata?

These analyses are usually done using either the mothur (Schloss et al. 2009) or the QIIME (Kuczynski et al. 2012) of aggregated toolsets, containing approaches adapted from ecology. However, the use of an analysis paradigm based on compositional data analysis (Aitchison 1986), or CoDa, offers a number of advantages over these tools, as explained below.

Brief explanation of the data type: Data for microbiome analysis are collected by the following general workflow. The sample (swab, stool, saliva, urine or other type) is collected, and the DNA is isolated and a small amount amplified using the polymerase chain reaction with primers specific to one or more variable regions of the 16S rRNA gene. It is also possible to target other conserved genes such as the *cpn60* gene (Schellenburg et al. 2009). However, analysis problems are the same regardless of the amplification target chosen, and Walker et al. (2015) present a good summary of the effect choices taken upstream of data analysis can affect the results. Following amplification, a random sample of the product is used to make a sequencing library, and it is common to multiplex many samples in the library. A small aliquot of the library is processed on the high throughput-sequencing instrument. This workflow imposes constraints on the resulting data.

It should be recognized that the investigator is sequencing a random sample of the DNA in the library, which is itself a random sample of the DNA in the environment. Thus, it is important to ensure that any analysis takes this random component into account (Fernandes et al. 2013). Perhaps less obvious is that the number of sequencing reads obtained for a sample bears no relationship to the number of molecules of DNA in the environment. This is because the number of reads obtained for a sample is determined by the capacity of the instrument: for example, the same library sequenced on an Illumina MiSeq or HiSeq would return approximately 20 million or 200 million reads. That there is no information in the actual read numbers per sample is implicitly acknowledged by the common use of ‘relative abundance’ values for analysis of microbiome datasets. Such datasets are referred to as compositional and there is a long history of the development of proper analysis techniques in other fields (Pawlowsky-Glahn et al. 2015).

Why worry about compositional data? Data constrained to relative abundances are subject to the constant arbitrary sum constraint that generates significant unanticipated problems for analysis and is the main reason to use a compositional data approach (Aitchison 1986). Compositional data is a term used to describe a dataset in which the parts in each sample have an arbitrary or non-informative sum (Aitchison 1986), such as high throughput sequencing data (Friedman and Alm 2012, Fernandes et al. 2013). These data have long been known to be problematic when analyzed using standard approaches (Pearson 1896).

The essential problem is illustrated in Figure 1 where we count the number of molecules in the environment, and one part (shown in blue) increases 10-fold between samples 1 and 2, while the abundance of 49 other parts (in red) remain unchanged. The proportion panel shows how the data are distorted when we convert it to relative abundances or proportions, or as happens when a constant sum is imposed by the sequencing instrument. The blue part still appears to become more abundant, although it is less than a 10-fold change. However, the 49 red parts appear to become less abundant. This property leads to the *negative correlation bias* observed in compositional data, and renders invalid any type of correlation or covariance based analysis such as correlation networks, principle component analysis, and others (Pearson 1896, Aitchison 1986).

Indeed, the original issue with compositional data identified by Pearson (1896) was that of spurious correlation. That is, two or more variables can appear to be correlated simply because the data are transformed to have a constant sum. Spurious correlation also causes the correlations observed in these data to depend on the membership of the sample. For example, consider the simple case of three samples (a, b and c) with four taxonomic variables measured to have the following absolute counts in three environmental samples (i.e., samples are in rows, taxa are in columns):

abc = , cor(abc)= .

The Pearson correlation for the numerical values is in the upper triangle of the matrix, and we see that taxon 1 and taxon 3 have a near perfect negative correlation of -0.99 (shown in bold), and taxon 2 and taxon 3 have a positive correlation of 0.59. The lower triangle shows the Pearson correlation values that are found when these are converted to relative abundances by dividing by the total sum of counts in each sample. Now, the correlations between the same taxa have changed. The correlation between 1 and 3 is now moderately negative at -0.30, and between 2 and 3 is now -0.37. Thus, the correlation observed in compositional data is not the same as the correlation for the counts, and can even change sign. However, there is a further complication: the correlations observed in compositional data depend on the membership in the sample. So, for example, when the last value is dropped from each sample, the correlations between taxa 1 and 2 is positive (0.43), and the correlation between 2 and 3 is even more strongly negative at -0.79. Thus, correlation determined from proportional or compositional data has the potential to be wildly wrong, and normal approaches to determine correlation cannot be used (Lovell et al. 2015). It is also worth noting that any method of determining correlation (including Spearman, Kendall, etc) will suffer from the same problems.

Thus the current tools used to examine the analysis goals give results that may be inconsistent, difficult to interpret and in many cases completely wrong (Filmoser et al. 2009, Friedman and Alm 2012, Fernandes et al 2013, Fernandes et al. 2014, Lovell et al. 2015, Kurtz et al. 2015).

The essential first step of proper compositional data analysis is to convert the relative abundances of each part, or the values in the table of counts for each part, to ratios between all parts. This can be accomplished in several ways (Aitchison 1986, Aitchison and Greenacre 2002), but the most widely used and most convenient for our purposes is to convert the data using the centred log-ratio (clr) transformation. So if we have a vector of numbers *X* that contains *D* parts:

X = [x1,x2, … xD],

the centered log-ratio of *X* can be computed as:

Xclr = [log[x1/gX], log[x2/ gX], … log[xD/ gX],

where *gX* is the geometric mean of all values in vector *X* (Aichison 1986). This simple transformation renders valid all standard multivariate analysis techniques (Aitchison 1986, van den Boogaart 2013), and as shown in Figure 1 Ratios, reconstitutes the shape of the data so that univariate analyses are also more likely to be valid. This transformation is also the starting point for correlation-based assessments of the datasets.

This approach would be ideal if microbiome datasets did not contain any 0 values, however a frequent criticism is that the geometric mean cannot be computed if any of the values in the vector are 0. It is here we reiterate that our data represent the counts per taxa through the process of random sampling (Fernandes et al. 2013, 2014). Thus, some 0 values could arise simply by random chance, while others arise because of true absence in the environment. Fortunately, we can couple Bayesian approaches to estimate the likelihood of 0 values with the compositional analysis approach (Fernandes et al. 2013, 2014). With this paradigm we dispose of taxa with very 0 counts in all or most samples (Palarea-Albaladejo and Martin-Fernandez 2015), and assign an estimate of the likelihood of the 0 being a sampling artifact to the remainder. When performing univariate tests or correlation analyses, it is often convenient to keep many such estimates of 0 and to determine the expected value of test statistics to reduce false positive inferences (Friedman and Alm 2012, Fernandes et al. 2013, Fernandes et al, 2014).

**Microbiome analysis tools that account for compositional data**

Fortunately, the compositional data analysis problem of microbiome datasets is starting to be examined by several groups and there are now an increasing number of tools available.

1: is there structure in the dataset? This is generally handled by beta-diversity analysis in the microbiome field. Beta-diversity as currently used requires a distance or dissimilarity measure, and popular ones include the unweighted or weighted Unifrac distance metrics or the Bray-Curtis dissimilarity metric. These methods are included in both the mothur and QIIME toolkits. The distance metrics from these tools can be used to generate Principle Co-ordinate (PCoA) plots that can be used to assess similarities and differences between samples and groups. Unfortunately, distance-based tools can confuse location (difference) and dispersion (variance) effects (Warton et al. 2012), and so additional approaches based on a compositional paradigm should be used for exploratory data analysis.

The compositional data analysis analog to PCoA is a principle component analysis of center-log ratio transformed data that has been modified to either remove taxa with 0 observed counts, or to adjust 0 values to an estimated value (Palarea-Albaladejo and Martin-Fernandez 2015). PCA has the advantage of being a more interpretable metric than PCoA, since it directly assesses the variance in the data and because both the locations of the samples and the contribution of each taxon to the total variance can be shown on the so-called compositional biplot (Aitchison and Greenacre 2002). The ability to examine variation of both the samples and the taxa on the same plot provides powerful insights into which taxa are compositionally associated and which taxa are driving (or not) the location of particular samples. Thus, the biplot can serve as a summary of the entire dataset, and it is up to the investigator to attach numerical significance to the qualitative results observed.

2: What is the difference between groups? Several methods are in widespread use to assess the difference in abundance of taxa between groups. These include microbiome specific methods, and more general t-tests or nonparametric tests. However, all use as input a table of proportional abundances. As shown in Figure 1, examination of proportions can result in a gross distortion of the data, such that some taxa can appear to change in abundance when measured by proportion, when in fact, their true abundance in the environment is unchanged. This effect can be ameliorated by the center-log ratio transformation.

There are two approaches that assess differential abundance in a compositional data analysis framework. The simplest approach is the ANCOM tool (Mandal et al. 2015), which assesses statistical significance on log-ratio transformed data. This is more robust than both traditional t-tests and more sophisticated approaches such as zero-inflated Gaussian methods. It should be noted that the software is not deposited into a public repository, and that the 0-replacement value used is fixed in the software.

A slightly more complex approach is used by the ALDEx2 package, available from Bioconductor (Fernandes et al 2013, Fernandes et al 2014). Like ANCOM, ALDEx2 centre log-ratio transforms the data prior to the assessment of statistical significance, however ALDEx2 differs greatly in how values of 0 are handled. ALDEx2 estimates a large number of possible values for 0 (and any other count for a taxon in a sample), conducts significance tests on all estimated values, and takes the average significance test value as the most representative for that taxon. In essence, ALDEx2 determines which taxa are significant after accounting for the random sampling that occurs when the DNA is extracted and loaded onto the sequencing instrument. In either case, both ANCOM and ALDEx2 explicitly acknowledge the multivariate compositional nature of the data, and control for false positive identifications much better than do the usual approaches.

3: What is the correlation structure of the taxonomic groups? As noted above, spurious correlation is a very large problem in microbiome datasets, and any analysis that reports correlations using traditional methods, such as Pearson’s or Spearman’s correlations, Kendall’s Tau or Partial correlations is likely to be wrong (Friedman and Alm 2012, Lovell et al. 2015, Kurtz et al 2015). However, there are a number of approaches that use a compositional data analytic approach to correlation. In a compositional approach, the variance between ratios of two taxa should be 0 or nearly so for two taxa to be counted as correlated (Aitchison 1986, Lovell et al. 2015). The difficulty comes when placing this approach into a familiar null hypothesis test framework, or when applying a consistent scale to the measure. The simplest approach is to calculate the phi statistic for two taxa X and Y, which is the var(log(X/Y)/var(log(X) (Lovell et al, 2015), where log() is meant to imply the clr values of X or Y. This measure has the advantage of being easily calculated and strictly enforcing the compositional data analysis approach. The SparCC method (Friedman and Alm, 2012) uses Bayesian estimates of the value of X and Y but calculates a mean value of a measure similar to the concordance correlation coefficient. The SPIEC-EASI approach (Kurtz et al. 2015) uses clr-transformed values and infers a graphical model under the assumption of a sparse correlation network. Both of the latter approaches are less rigorous for estimating correlations in compositional data than is the calculation of phi, and make strong assumptions about the scarcity of the data. However, they bot offer the advantage of using a full or partial Bayesian approach, which is generally more powerful than point-estimate based approaches.

**Results and Use Cases**

Having introduced the issue of compositional data analysis, we now present the results of two worked examples illustrating how these approaches can be applied to two different 16S rRNA gene sequencing datasets from the recent literature. A full description of the methodology, the datasets and the code used to generate the figures is given in the Supplementary file **workshop.Rnw**. Downloading and running this file in R or RStudio will generate the associated workshop.pdf. The .Rnw document contains both the code and annotation for the code, and the .pdf document contains the code and the resulting figures.

First worked example (a vaginal microbiome dataset): We first use a dataset from an experiment that examined the effect of treating women suffering from bacterial vaginosis (BV) with antibiotics and placebo or antibiotics plus a probiotic supplement (Macklaim et.al, 2015). For this example, we extracted only the ‘before’ (samples BXXX) and ‘after’ (AXXX) treatment samples, which were further identified by their Nugent status, a Gram stain scoring system that acts as a rough indicator of whether the subject had BV or was healthy (normal, n), or whose status was indeterminate (labeled as ‘ i’ for intermediate). In addition, individual taxa were aggregated to genus level using QIIME (Kuczynski et al. 2012), except for *Lactobacillus iners* and *Lactobacillus crispatus*, which remain as separate species in the tables.

The **compositional biplot** is the essential initial tool for exploratory compositional data analysis and replaces ordinations based on Unifrac or Bray-Curtis metrics. They are principle component plots of the singular value decomposition of the data that seek to display the major axes of variance (or change) in the dataset (Aitchison and Greenacre 2002). Properly made and interpreted, they summarize all the essential results of an experiment. However, their weakness is that they are descriptive and exploratory, not quantitative. Note that quantitative tools can be applied later to support the conclusions derived from the biplot.

For simplicity, we filtered the dataset to include only those taxa that were at least 0.1% abundant in any sample. It should be noted that one of the desirable properties of compositional data analysis is that subsets of the dataset should give essentially the same answer as the entire dataset *for the taxa in common* between the whole and the subset dataset (Aitchison 1986).

Figure 2 shows the compositional biplot for this dataset along with the associated scree plot showing the percentage of variance explained by each sample or component. The sample names (labeled in red for BV, blue for Normal or cyan for Intermediate) illustrate the variance between the samples, and the taxa values (represented by the black rays) illustrate the variance between the taxa. There are many interpretation rules for biplots of compositional data (Aitchison and Greenacre 2002), but these boil down to remembering that only the *ratios* between taxa can be examined. Thus, the links between the tips of the rays, or between samples contains the most information. Keeping this in mind, we can see the following:

First, the proportion of variance explained in the first component is very good, being 47%, then falling to 13% on component 2, and decreasing rapidly thereafter. This indicates that the major difference between samples can be captured in essentially one direction along component 1.

Second, the longest link from the center to a taxon is the one to *L. iners*. This indicates that the ratio of this taxon to all others is the most variable across all samples. Likewise, the shortest link is to *Gardnerella*, implying that the ratio of this taxon to all others is the least variable.

Third, the longest link is between *L. iners* and *Leptotrichia*. This means we can infer that these two taxa likely have the strongest reciprocal ratio relationship. That is, when one becomes more abundant relative to everything else, the other becomes less abundant relative to everything else.

Fourth, the shortest link is between *Megasphaera* and BVAB2. From this we conclude that the ratio of these two taxa is relatively constant across all samples. That is, their ratio abundance is highly correlated. These two taxa should be seen to have a low value of phi.

Fifth, the link between *Prevotella* and *L. crispatus* passes directly through *Atopobium*. This indicates that these three taxa are linearly related. In this case, it is clear when *L. crispatus* increases, the other two will decrease.  Likewise, this property can be extended to any linear relationships containing three or more links.

Sixth, the link between *L. iners* and *Megasphaera*, and the link between *Leptotrichia* and *Lactobacillus* cross at approximately 90°. The cosine of the angle approximates the correlation between the connected log ratios. Thus, we can conclude that the abundance relationship between the former pair of taxa is poorly correlated with that of the latter two taxa. In other words, these two pairs vary independently in the dataset.

Some samples (A312\_bv, B312\_bv, A282\_n at the bottom), are tightly grouped, indicating that they contain similar sets of taxa at similar ratio abundances. We would expect that these samples contain an abundance of *Lactobacillus* and be depleted in *Leptotrichia*. Furthermore, we can see that the samples divide into two fairly clear groups, with most of the before or “B” samples on the left, and most of the after or “A” samples on the right, and that the majority of the B samples are colored red indicating a diagnosis of BV, and the majority of the A samples are colored blue indicating a diagnosis of non-BV.

The result of the biplot suggested that there were two main groups that could be defined with this set of data. With a few exceptions, there appears to be a fairly strong separation between the samples containing a majority of *Lactobacillus* sp., and those lacking them. We can explore this by performing an **unsupervised cluster analysis** on the log-ratio transformed data. In traditional microbiome evaluation methodologies, clustering is based on the weighted or unweighted unifrac distances or on the Bray-Curtis dissimilarity metric, for example see the standard workflow in QIIME (Kuczynski et al. 2012). These metrics are much more sensitive to the abundance of community members than is the Aitchison distance used in compositional data analysis (Martin Fernandez 1998). Thus, here we used the Aitchison distance metric that fulfills the criteria required for compositional data. In particular, by using a compositional approach, it is appropriate to examine a defined sub-composition of the data (i.e., a subset of the taxa).

The results of unsupervised clustering of the dataset are shown in Figure 3. Again, it is important to remember that all distances are calculated from the ratios between taxa, and not on the taxa abundances themselves. For this figure, we used the ward.D2 method which clusters groups together by their squared distance from the geometric mean distance of the group. There are many other options, and the user should choose one that best represents the data, although Ward.D and Ward.D2 are usually the most appropriate (Martin-Fernandez 1998).

The cluster analysis supports the results of the biplot and shows the split between two types of samples rather clearly. Samples containing an abundance of *Lactobacillus* sp. are grouped together on the right, and samples with an abundance of other taxa are grouped together on the left. The cluster analysis helps explain and clarify the compositional biplot. For example, the four samples in the middle lower part of the biplot in Figure 2 labelled A/B312 and A/B282, group together in both the biplot and the cluster plot. These samples are atypical for both the N and BV groups., containing substantially more of the *Lactobacillus* taxon, and somewhat more of the taxa normally found in BV than in the other N samples. Based on these two results it would be appropriate to exclude these four samples from further analysis because of their atypical makeup.

Next, a **univariate** comparison between the B and A groups was performed. For simplicity of coding, we kept the four outlier samples, but the reader is encouraged to remove them and see how the results change. For this, we used the ALDEx2 tool (Fernandes et al. 2013, 2014) that incorporates a Bayesian estimate of taxon abundance into a compositional framework, with the results shown in Table 1 and the effect plot (Gloor et al. 2016) shown in Figure 4. Of note, ALDEx2 examines differential abundance by estimating the measurement error inherent in high throughput sequencing experiments, including the measurement error associated with 0 count taxa, and uses the assumptions of compositional data analysis to normalize the data for sequencing effort.

When interpreting these results, it is important to remember that we are actually examining ratios between values, rather than abundances. Thus, we are examining the the change in abundance of a taxon *relative to all others* in the dataset. The user should also remember that all values reported are the means over the number of Dirichlet instances as given by the mc.samples variable in the aldex.clr function and explained more fully in the Supplement.

In the examples given in Table 1, we filtered to show only those taxa where the expected Bejamini-Hochberg (1995) adjusted P value was less than 0.05, meaning that the expected likelihood of a false positive identification per taxon is less than 5%, with the actual value per taxon given in the wi.eBH column. Using *L. iners*, we note that the absolute difference between groups can be up to −2.25. Thus, the absolute fold change in the ratio between *L. iners* and all other taxa between groups for this organism is on average 4.76 fold (1/2-2.25): being more abundant in the A samples than in the B samples. However, the difference within the groups (roughly equivalent to the standard deviation) is even larger, giving an effect size of −0.79. Thus, the difference between groups is less than the variability within a group, a result that is typical for microbiome studies.

These quantitative results are largely congruent with the biplot, which showed that the taxa represented here were the ones that best explained the variation between groups, and that the *Leptotrichia* and *Lactobacillus* taxa were uncorrelated in these samples with the separation of the two large groups.

Table 1: List of significantly different taxa.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Taxon | diff.btw | diff.win | effect | overlap | wi.ep | wi.eBH |
| *Atopobium* | 0.86 | 1.51 | 0.53 | 0.30 | 0.007 | 0.037 |
| *Prevotella* | 1.41 | 1.77 | 0.75 | 0.22 | 0.000 | 0.002 |
| *L. crispatus* | -1.07 | 1.78 | -0.49 | 0.23 | 0.000 | 0.004 |
| *L. iners* | -2.25 | 2.68 | -0.79 | 0.20 | 0.000 | 0.001 |
| *Streptococcus* | -1.14 | 2.38 | -0.37 | 0.30 | 0.008 | 0.041 |
| *Dialister* | 0.89 | 1.38 | 0.59 | 0.25 | 0.001 | 0.009 |
| *Megasphaera* | 1.56 | 2.31 | 0.63 | 0.28 | 0.002 | 0.015 |

The left panel of Figure 4 shows a plot of the within to between condition differences, with the red dots representing those that have a BH adjusted P value of 0.05 or less. Taxa that are more abundant than the mean in the B samples have positive y values, and those that are more abundant than the mean in the A samples have negative y values. These are referred to as ‘effect size’ plots, and they summarize the data in an intuitive way (Gloor et al. 2015). The grey lines represent the line of equivalence for the within and between group values. Black dots are taxa that are less abundant than the mean taxon abundance: here it is clear that the abundance of these taxa, in general, are difficult to estimate with any precision.

The middle plot in Figure 4 shows a plot of the effect size vs. the BH adjusted P value, with a strong correspondence between these two measures. In general, an effect size cutoff is preferred because it is more robust than P values. The right plot in this figure shows a volcano plot for reference.

Finally, we can determine **which taxa are most correlated or compositionally associated**. As noted above, correlation is especially problematic, and the only way to avoid false positive associations is to identify those taxa that have constant or nearly constant ratios in all samples: this is the underlying basis of the phi measure (Lovell et al. 2015). In the example shown in the Supplement, we calculate the mean phi using the same philosophy as outlined above for univariate statistical tests.

When examining compositional data it is important to remember that the ratio between taxa is the only information available. In the context of microbiome datasets, the phi metric (Lovell et al. 2015) seeks to identify those pairs of taxa that have the most constant ratio abundances. Applying this approach to the dataset shows that the two most compositionally associated taxa are *Prevotella* sp. and *Megasphaera* sp. Note, that these taxa do not have the shortest links in the compositional biplot, indicating that the amount of variance explained is not high enough to provide an accurate projection of the dataset.

Second worked example:Examining the Hsiao Dataset using compositional approaches: We include in the workshop.Rnw document a second example based on the data of Hsiao et al. (2013) that examined the effect of *Bacillus fragilus* supplementation on the microbiome composition of a mouse model of autism. Figure 5 shows a compositional biplot of this dataset, and it is obvious that there is little evidence of difference between the control (IC) and *B. fragilus* (Bf) groups when analyzed using this approach. This is in accordance with their conclusions when analyzing the data in a multivariate way.

However, these authors identified a number of univariate differences in taxon abundance between groups. When examining univariate differences with the ALDEx2 tool, we found that none of the univariate differences reported in the original paper were supported by subsequent analysis (Supplementary Table 3). The reason for this discrepancy is that inspection of the original paper reveals that raw, and not Benjamini-Hochberg adjusted P values were reported. Thus it is likely that the majority, if not all, of the taxa different between the control and treatment groups are false positive identifications. While being critical of this paper, we acknowledge that other published papers exhibit many of the same flaws: namely an over-reliance on tools that do not treat the data as compositions, the identification of extremely rare taxa as the most ‘significantly different’ taxa between groups, and inappropriate use or lack of corrections for multiple hypothesis testing.

**Discussion and Summary**

Using a 16S rRNA gene sequencing dataset, we have illustrated that microbiome data are compositional and so best treated as ratios because the total number of reads is uninformative. By treating the data as ratios where the denominator is the geometric mean for a sample, we can accurately recapitulate the shape and the error profile of the input data. Dirichlet Monte-Carlo replicates coupled with the centered log-ratio transformation show that point-estimates of statistical significance in a real dataset can substantially inflate the observed P value because of random partitioning of low count values across datasets.

In essence, we argue that 16S rRNA gene sequencing datasets, RNA-seq datasets, and many other -seq datasets are not special and do not each need their own unique statistical analysis approach. The data generated can be examined by a general multivariate approach after accounting for the compositional nature of the data, and such an analysis is comparable or superior to the domain- specific approaches (such as those used in the Hsieh et al. paper).

With the human body associated with a large number and diversity of bacteria, we need to understand why it evolved like this, how and when programing between microbes and human cells happens, and how and when we can influence it by either probiotic supplementation or nutrient or antimicrobial means. More and more studies are exploring how the microbiome can predict outcomes, including following fecal transplant, probiotic, dietary and drug treatment (David et al. 2014; Kwak et al. 2014; Seekatz et al. 2014; Rajca et al. 2014). This work will require carefully designed studies with high quality clinical documentation, and samples that are processed using some of the methods described herein. As the compositional toolkit for microbiome analysis evolves, these studies will reveal aspects of human life not previously envisaged. In order to have confidence in such findings, datasets must be interrogated with rigour. The public is thirsty for knowledge and the media anxious to attract attention. Reliance on pharmaceutical agents is longer acceptable, and the ability to manipulate the microbiome is not only appealing but actually feasible. Thus, studies that help to understand how such manipulations occur, what communication is taking place between microbes and the host, will allow for more precisely targeted interventions, even to some extent personalized. In particular for the latter, as precise knowledge of microbiome components and activity will be critical.

Interested readers wishing to progress beyond this demonstration should consult the compositional data literature, but in particular the original book by Aitchison (1986) and a comprehensive book that outlines the essential geometric problem of compositional data as it is understood at present by Pawlowsky-Glahn et al. (2015). For a step-by-step guide that goes beyond the introduction given in the Supplement, a book outlining how to use the compositions R package by Van den Boogaart and Tolosana-Delgado (2013) is particularly helpful. For others wishing to understand bioinformatics and data analysis of sequencing data in general terms, hopefully this paper will prove helpful, and encourage people to enroll in specialized courses. The temptation may be to rely on third party systems, even at a cost, but the ‘devil is in the details’ and for thoroughness we recommend developing the highest level of skill possible, especially to continue to create new analytical tools.

We hope that this report will help avoid making claims that are later disproven, and more importantly bring badly needed breakthroughs in prevention, treatment and cure of disease.

**Figure Legends**

**Figure 1:** The difference between counting, proportions and ratios. The ‘Counts’ panel shows a scatter plot of two samples composed of 49 invariant taxa in open circles, and 1 taxon that changes in count 10-fold (black-filled circle). This is the type of data that most current analysis tools in the microbiome filed expect is being analyzed. The ‘Proportions’ panel shows the same samples after they have been sequenced and so constrained to have a constant sum. With such a constraint, there representation is the same whether the sum is 1 (as shown here) or an arbitrarily larger number (such as would be obtained from a sequencing instrument). The distortion in the data is obvious: the black-filled cirle still appears to be more abundant, but the open circles appear to have become less abundant! It is obvious that we would draw incorrect inferences regarding abundance changes in these data, yet these are the data as used by existing tools. The third panel shows that much of this distortion can be removed using the a ratio transformation where each count (or proportion) is divided by the geometric mean of the 50 taxa in the sample a. Examination of the data after this transformation can thus provide more robust inferences.

**Figure 2:** The left figure shows a covariance biplot of the abundance- filtered dataset, the right figure shows a scree plot of the same data. This exploratory analysis is encouraging because the amount of variance explained is rather substantial with 0.469 of the variance being explained by component 1, and 0.139 being explained by component 2. The numbers on the left and right indicated unit-scaled variance of the taxa, the numbers on the top and right indicate unit scaled variances of the samples. The scree plot also shows that the majority of the variability is on component 1. We can interpret this biplot with some confidence, although it is likely that any associations will be found to have large variation.

**Figure 3:** Unsupervised clustering of the reduced dataset. The top figure shows a dendrogram of relatedness generated by unsupervised clustering of the Aitchison distances, which is a distance that is robust to perturbations and sub-compositions of the data (Aitchison 1986). The bottom figure shows a stacked bar plot of the samples in the same order. The legend indicating the colour scheme for the taxa is on the right side.

**Figure 4:**  An effect plot showing the univariate differences between groups. The left plot shows a plot of the maximum variance within the B or A group vs. the difference between groups. Red points indicate those that have a mean Benjamini-Hochberg adjusted P-value of 0.05 or less using P values calculated with the Wilcoxon rank test. The middle plot shows a plot of the effect size vs. the adjusted P value. In general, effect size measures are more robust than are P values and are preferred. For a large sample size such as this one, an effect size of 0.5 or greater will likely correspond to biological relevance. The right plot shows a volcano plot where the difference between groups is plotted vs the adjusted P value.

**Figure 5:**  A biplot of the Hsiao dataset. Here we can see that the control and experimental samples are intermingled and that the proportion of variance explained in the first component is not as compared to the other components is not as obvious as in the biplot in Figure 2.

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