## Background

Working with mathematical concepts is always a bit out of the comfort zone for most biologists. Unfortunately, with technical improvements and big data encroaching in our field, and statistical methodology being an essential part in data analysis, ignoring mathematics is just not an option. One concept that became increasingly more important in sequencing data analysis is the concept of “compositional data”. Several papers (Greenacre et al. 2021b; Gloor et al. 2017; Quinn et al. 2018) made it abundantly clear that sequencing data is of compositional nature, which means it has different mathematical characteristics than other data types. Furthermore, as machine learning concepts become more widespread and useful, their performance in combination with compositional data and its necessary transformations have not been fully analyzed.

The goal of this master thesis is an attempt in making the information around compositional data more approachable, summarizing the achieved solutions, and in a practical part, trying to assess if these achievements are also applicable when combining compositional data and machine learning concepts.

As this master thesis uses microbiome sequencing data and was created in a microbiome research group, this text will mostly focus on this field and its papers. However, all results are applicable to other high-throughput sequencing data, as well as any data that is in some way confined by an arbitrary sum. Such data is found for example in geochemistry, ecology, sociology, political sciences, etc., and therefore ultimately spans the problematic into various different fields (Greenacre et al. 2021a).

### CHARACTERISTICS OF COMPOSITIONAL DATA

In order to define and illustrate the concept (and problems) of compositional data, let’s assume a classical biological example. The following Figure (1A) shows two different ecological fields: A and B. In field A, four rabbits, seven birds, eight bees and one wolf have been counted, whereas field B contains two rabbits, four birds, four bees and one wolf. It becomes clear that, as similar as the diversity may be, the fact that field B seems to have only half of the population of field A, is already valuable information in itself. The total counts per field can be preserved in our data collection and therefore, the absolute count of each organism in this field matters.

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Figure 1: Information Loss of Normalized Data

(A) Illustration of the number of animals found in two different samples. Field A contains four rabbits, eight bees, seven birds and one wolf, whereas field B contains two rabbits, four bees, four birds and one wolf. In (B) the absolute counts have been plotted as a stacked bar plot, with each animal in a different color. (C) shows the stacked bar plot as normalized counts, e.g., percentages.

When using absolute counts, the difference between both fields is easily visible (1B). However, when we really want to compare both fields, we need to transform the samples to a common scale. This is called normalization and we can see the effect in (1C). As soon as the data is normalized, the particular information of absolute counts gets lost. When collecting ecological data ourselves, we can preserve the fact that field B only contained 11 individuals and field A contained 20, by saving that number somewhere on our Excel sheet. However, the problem with sequencing data is: we get the data in the form of 1C.

To demonstrate how the method of using a sequencing machine cannot preserve absolute counts, imagine the following situation: We want to sample field A multiple times a day, but in order to be more efficient, we buy a machine to do the counting for us. Three times a day this machine transmits the number of all the different animals coming to this field. However, this machine has one flaw: it can only count to 20. As soon as the 21st animal on this day comes to the field, it is just simply not counted.

This ultimately means, that the overall number of 20 carries no meaning. Every sample has this exact total number, so it carries no valuable information. Of course, a limit of 20 is weird for us to understand, but sequencing machines do the exact same thing. They are limited in their capacity on the flow cells and even the biggest sequencing machines could never fully sequence the entirety of the organisms RNA contents. And not only the sequencing machines, but the whole RNA-Seq procedure limits the total number of sequences measured. The total number of sequences measured by sequencing machines ultimately depends on the *chemistry of the assay*, not the input material (Quinn et al. 2018).

~~Sequencing data is achieved by taking a population of (total or fractionated) RNA, converting them to a library of cDNA fragments, optionally amplifying the fragments, and then sequencing those fragments in a ‘high-throughput manner’ (Quinn et al. 2018). This methodology is known as next generation sequencing. The result of NGS is a virtual library of many short sequence fragments that are converted to a numeric dataset through alignment (most often to a previously established reference genome or transcriptome) and quantification (Griffith et al. 2015). In essence, the total number of sequences measured by sequencing machines ultimately depends on the~~ *~~chemistry of the assay~~*~~, not the input material (Quinn et al. 2018).~~

The consequence of this sampling problem is, that we have to accept the fact that the sum of counts in sequencing data are irrelevant. This leads us to the concept of “Compositional Data”, first introduced by John Aitchison (Aitchison 1982), roughly 40 years ago. Because thankfully, we can still use sequencing data. We just have to adjust for the fact that the absolute counts are non-informative (Quinn et al. 2018; Greenacre et al. 2021b). We can instead use relative abundances, or the proportions between features in a sample.

### THE SIMPLEX SPACE

As mentioned, absolute counts in compositional data are irrelevant and only relative abundances are of interest. This puts the data in the so-called “simplex space”, instead of the for us more common Euclidean space. The following Figure 2 shows how the data from field A would look like A picture containing diagram

Description automatically generatedin the simplex space:

Figure 2: Biological Example in the Simplex Space

Assuming the collected ecological data from Figure 1 is compositional, puts it in a S3-Simplex space. Geometrically, a tetrahedron is created with all different components (here animals) placed on the four corners of the polytope. A composition is one possible combination of components confined in the simplex space.

We stick with our ecological example and place all our animals as one corner in a geometrical space. With four features, we are able to create a 3-Simplex and a geometric figure called tetrahedron (otherwise called a pyramid). ~~What I want to demonstrate here is one of the main problems with compositional data: the samples can influence each other directly, which makes them mutually dependent!~~

We use our flawed machine, and one day, we sample 20 rabbits in field A. This would lead to a point in the simplex space that sits directly in the left corner, with the coordinates (0,20,0,0), because we only have rabbits, no other animal. Another day, we sample only 20 bees, and no other animals, then we would find our data point where the bee is, very at the top. Marked in red is a sample where the machine counted 12 bees, 12 wolves and no bees and no rabbits. Every sample round produces one “composition” and the examples show, that the distance between any two variables is sensitive to the presence or absence of other components (Quinn et al. 2018). If a composition is moved from one corner of the animal-simplex, it directly influences the other values in the composition. Consequently, that makes all variables *mutually dependent* on one another and leads, amongst other things, to problems in our assumptions about statistical testing. In statistical literature this data is also called “spurious” because it appears as if the data points have a causal relationship. When a composition is moved from bees in the direction of wolves it seems like there is a causal relationship because the increase in the number of wolves, directly decreases the number of bees.

~~It is commonly assumed - and all experiments are created to accommodate these assumptions – that data is collected IID: independent and identically distributed. The IID assumption is important for e.g., the central limit theorem, Markov sequence, hypothesis testing in general and of course machine learning. Having such an obvious violation in compositional data can have serious consequences on the reproducibility of results. In life sciences, count data are usually modelled using the Poisson distribution or negative binomial, because using anything else would imply that negative and non-integer counts would exist, which is biologically not feasible (Quinn et al. 2018).~~

To describe this a bit more mathematically, the problem described above is formally known as “the negative bias problem” (other names are also the constant-sum problem, the closure problem, or the null correlation difficulty) (Aitchison 2003), which is the main reason why we have a dependency problem. When the sum of a component is constant, then it can be mathematically proven that the covariance between any two compositions equals 0. This has the consequence that some variances would be negative, which is problematic, as variances are always positive. Therefore, negative covariances are presupposed by the limitation of the sum, instead of produced by stochastic factors (Pawlowsky-Glahn and Egozcue 2016; Aitchison 2003).

Using any form of statistical test or machine learning tool seems redundant, as a type two error is almost preconditioned, and we easily would make false assumptions about the correlation of the data. Thus, a correct handling of compositional data and the simplex space is not optional (Gloor et al. 2017).

### MAPPING THE SIMPLEX SPACE INTO EUCLIDEAN SPACE

The difficulty of confined data points has already been commented on by Pearson (1897) in the context of spurious correlations and has been taken up by Aitchison 1982 in an attempt to overcome the “bounded sum problem”.

In our ecology sampling, we could easily overcome the simplex by e.g., normalizing to a field size from the start, to preserve indirectly an information about the total number of animals.

Similarly, it has been tried for sequencing data to calculate an “effective library size” and to recover this way the original scale of data. For that, normalization methods like trimmed mean of M-values (TMM) have been introduced, as well as RPKM and TPM (Quinn et al. 2018). However, all of those methods involve rescaling counts by the library size and these normalizations come with the drawback that some of these methods are sensitive to the removal of low abundant counts, as well as to data symmetry (Quinn et al. 2018).

Furthermore, Aitchison already criticized very early that there is no “magic to open up closed data” (Aitchison 2003), which is what normalization tries to do. Moreover, since information provided in compositional data is essentially about ratios of the components, it seems logical to also think in terms of ratios. Thus, the only way forward is to transform the data in a way that allows us to use it with Euclidean space rules, first by Aitchison 1982 with several logistic transformations proposed to produce “transformed-normal” models, and later with the definition of the Aitchison geometry (Pawlowsky-Glahn and Egozcue 2001). The general idea is, that the simplex space is endowed with a Euclidean space structure, which has several mathematical advantages: if one can map the simplex space into Euclidean space, then all advantages of the Euclidean space can be accessed, i.e., orthogonal projections are possible, the concepts of linear combination, linear dependence, Euclidean distances, as well as all the typical geometrical elements are available (Pawlowsky-Glahn and Egozcue 2016).

Building on top of the Aitchison geometry, methods of analyzing compositional data were proposed by Mateu-Figueras et al., (2011) with the “staying-in-the-simplex” approach or Greenacres (2017) “pragmatic approach”. In this master thesis, mentioning these methods is as far as I will go here, because they require a technical understanding of the algebraic-geometric structure of the simplex. Here, I will focus more on log-ratio transformations, as they have been more heavily favored in the last decades due to their practicability (Greenacre et al. 2022).

### LOG-RATIO TRANSFORMATIONS

There are several types of log-ratios, which were proposed of the last 40 years, and I want to take the time and introduce them. Some more in detail than others, as not every log-ratio transforms the data perfectly and it is important to point out here, that there are still ongoing discussions about which log-ratio transformation is preferrable over the other in terms of accuracy, complexity, and interpretability (Greenacre et al. 2022; Quinn and Erb 2020; Rivera-Pinto et al. 2018).

In general, all log-ratio transformations capture the relationship between the features in the data set and taking the logarithm of these ratios makes the data symmetric and linearly related. It moves the simplex into real space and imparts key properties on the data set: scale invariance (compositions do not change with e.g., sequencing depth), perturbation invariance (i.e., converting a composition between equivalent units will not change the results), and permutation invariance (i.e., changing the order of the components within a composition will not change the results).

Two more important properties exist that are transformation-specific: sub-compositional coherence (i.e., scientists A and B get identical results for components when these components are included in compositions) and sub-compositional dominance (i.e., using a subset of a complete composition carries less information than using the whole) (Quinn et al. 2018; Greenacre et al. 2021a; Greenacre et al. 2022). From a scientific standpoint, it seems to be a no-brainer to try to adhere to both of these properties, as they are the gold standard of reproducibility. Not following sub-compositional coherence would mean that two sequencing runs from the same patient (and the same bioinformatics pipeline) couldn’t be compared and ignoring sub-compositional dominance would mean we couldn’t filter data before using.

The log-ratio transformation that imparts all those properties is called isometric log-ratio (ILR). ILRs are considered the “gold standard” of log-ratio transformations, as they engender exactly the same multivariate geometric structure of the sample points as that of the formerly mentioned Aitchison geometry (Greenacre et al. 2021b). The ILR maps a composition in the D-part Aitchison-simplex isometrically to a D-1 dimensional Euclidian vector, which is not just confusing to understand but makes it also difficult to interpret (Greenacre et al. 2021a; Greenacre et al. 2022). Additionally, they are also particularly problematic when the numbers of components are high (Greenacre et al. 2021b), which is a quality worth considering as sequencing data is usually very high-dimensional.

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Description automatically generatedThankfully, we have more types of log-ratio transformation, that are easier to use and interpret. They do not fully impart sub-compositional coherence, but interestingly, it has been shown recently that quasi-coherence is sufficient in practice, as well as quasi-isometry (Greenacre et al. 2022), especially in high-dimensional data sets. As a result of this, it was decided to use two types of log-ratio transformation in this master thesis: ALR (additive log-ratio) and CLR (centered log-ratio).

Figure 3: Equation for CLR

The equation describes the calculation of CLR, with xj as vector of sample features, Dj the total number of features, and g(x) the geometric mean of sample vector x. Log-ratio transformations are applied within a sample (i.e., row-wise).

The CLR uses the geometric mean of the whole composition as the reference feature (Gloor et al. 2017). It has the advantage that it is computationally easy to do, which becomes more important with high-dimensional data sets. Furthermore, it reproduces the log-ratio geometry perfectly, but is not sub-compositionally coherent, because the whole composition (i.e., sample) is used to calculate the geometric mean and every sample will therefore use a different geometric mean. Unfortunately, it is not very easy to interpret and it is not very useful in sparse data containing a lot of 0s (Gloor et al. 2017).

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Description automatically generatedThe second log-ratio transformation is ALR. Here, the log-ratio is taken of each measurement within a composition and divided by a chosen reference feature.

Figure 5: Equation ALR

The equation describes the calculation of ALR, with xj as vector of sample features, D the total number of features, and xref the reference feature. Log-ratio transformations are applied within a feature (i.e., column-wise).

Thus, the interpretation of ALR log-ratios is very straight-forward and it is also sub-compositional coherent, which is traded for a small loss of isometry. The biggest problem with ALR has always been the choice of reference. When choosing a reference, Greenacre et al. 2021 proposed to use three criteria to find a good reference: (i) the reference component should maximize the Procrustes correlation between the additive log-ratio geometry and the exact log-ratio geometry, (ii) the reference should minimize the variance the relative abundances of log-transformed components, and (iii) it should be a well populated component. Using these guidelines produces additive log-ratios close to being isometric, which would make them a favorable log-transformation. The obvious drawback is the computational complexity (if a Procrustes analysis is used beforehand), which increases especially in higher-dimensional data.

In general, log-ratio transformation do not normalize the data (does not “open it”), but makes the interpretation of the transformed data dependent on the reference used and aim for a straight-forward interpretation of the data (Quinn et al. 2018). For machine learning purposes, it is still unclear if any log-ratio transformation improves the performance in a prediction task. This will be one of the core goals of this benchmarking project and previous studies and results will be described in the next section.