

1 **Title:** *A probabilistic model to identify the core microbial community*

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3 **Running header:** *Identifying the probable core microbial community*

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19 **Conflict of Interest statement:** The authors declare no conflict of interest.

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## 27 ***Originality-Significance Statement***

28 More rigorous and less arbitrary statistical methods could increase knowledge  
 29 regarding the role of microorganisms and their interactions. Here, we suggest a  
 30 probabilistic method to identify the microbial core community across systems. Our  
 31 method identifies a large proportion of the rare community that likely belongs to the  
 32 microbial core community, which was not identified by conventional methods. Our  
 33 probabilistic model is a non-arbitrary approach to defining the microbial core  
 34 community, which may help in the next step of the microbial core community studies.

35

## 36 **ABSTRACT**

37 The core microbial community has been hypothesized to have essential functions  
 38 ranging from maintaining health in animals to protection against plant disease.  
 39 However, the identification of the core microbial community is frequently based on  
 40 arbitrary thresholds, selecting only the most abundant microorganisms. Here, we  
 41 developed and tested an approach to identify the core community based on a  
 42 probabilistic model. The Poisson distribution was used to identify OTUs with a  
 43 probable occurrence in every sample of a given dataset. We identified the core  
 44 communities of four extensive microbial datasets, and compared the results with  
 45 conventional, but arbitrary, methods. The datasets were composed of the microbiomes  
 46 of humans (tongue, gut, and skin), mice (gut), plant (grapevine) tissue, and the maize  
 47 rhizosphere. Our proposed method revealed core microbial communities with higher  
 48 richness and diversity than those previously described. This method also includes a  
 49 greater number of rare taxa in the core, which are often neglected by arbitrary threshold  
 50 methods. We demonstrated that our proposed method reveals a probable core microbial  
 51 community for each different habitat, which extend our knowledge about shared  
 52 microbial communities. Our proposed method may help the next steps proving the  
 53 essential functions of core microbial communities.

54

## 55 INTRODUCTION

56 The composition of microbial communities can vary greatly even over fine spatial  
57 and temporal scales, making it difficult to identify the drivers of community dynamics  
58 and the link between composition and function. To overcome the obfuscating effects of  
59 this variation, researchers often limit their focus to the ‘core’ community, which is  
60 defined as organisms that are ubiquitous in a given habitat, despite environmental  
61 fluctuation (Hamady and Knight, 2009). In microbial ecology, the core community  
62 refers to microbial taxa (Shade and Handelsman, 2012), or genes (Turnbaugh *et al.*,  
63 2007), shared across a set of samples in a given ecosystem.

64 There are considerable attempts to identify the core community across different  
65 hosts including corals (Ainsworth *et al.*, 2015), zebrafish (Roeselers *et al.*, 2011), mice  
66 (Pédrón *et al.*, 2012), ruminants (Henderson *et al.*, 2015), *Arabidopsis thaliana*  
67 (Lundberg *et al.*, 2012) and sugarcane plants (Yeoh *et al.*, 2015). It has been suggested  
68 that the core microbial community could play essential roles in ecosystem functioning,  
69 and may also be useful as indicators of system perturbation (Shade and Handelsman,  
70 2012; Saunders *et al.*, 2015). For example, an abundant microbial core was identified  
71 across 210 human adult fecal samples, varying substantially in geographic origin, ethnic  
72 background and diet (Sekelja *et al.*, 2011). The authors suggested that this core has an  
73 important role in gut homeostasis and health. Other studies have suggested roles for the  
74 core in plant growth promotion and the maintenance of plant health (Schlaeppli *et al.*,  
75 2014). However, few studies have been successful in directly linking the core microbial  
76 community to important community or ecosystem functions.

77 The lack of evidences for the importance of the core community may be due to  
78 how the core is identified. Since the core is defined to be ubiquitous in a habitat, it is  
79 assumed that the microbial taxa or genes belonging to the core should be found in every  
80 sample collected from a given habitat. The core microbial community is identified by

81 identifying shared microorganisms or genes across a collection of samples (*discussed by*  
82 Shade and Handelsman, 2012). In this approach, the core is represented by taxa found in  
83 every sample analyzed (100% frequency across samples). However, to date no  
84 methodological approach has fully assessed the microbial diversity of any  
85 environmental sample (Kanagawa, 2003; Feinstein *et al.*, 2009; Prosser, 2015). Current  
86 sequencing methods used to survey complex microbial communities tend to target the  
87 most abundant groups of microorganisms (Caporaso *et al.*, 2011). Consequently, the  
88 rare component of the core microbial community is missed in these studies. The most  
89 commonly used approach to circumvent this problem is the definition of cutoffs for the  
90 frequency of microbes or genes to be classified as a member of the core microbial. For  
91 instance, researchers have used cutoff values ranging from 30% to 99% frequency  
92 across samples (Li *et al.*, 2013; Ainsworth *et al.*, 2015) to define the core community in  
93 environmental samples. However, these cutoffs still do not include rare taxa and also  
94 could result in false assignments to the core, thus influencing inferences about its  
95 function and composition.

96       Given the numerous difficulties associated with sampling and fully sequencing  
97 microbial communities, one solution to identify core community members is to use a  
98 probabilistic model to assign members of the microbial community to the core  
99 community. Here, we develop and test an approach to identifying the core community  
100 based on the Poisson distribution. Given the occurrence distribution of an event, *i.e.* a  
101 microorganism, in a group of samples, this model estimates the probability of this event  
102 in a group of samples (Rao and Rubin, 1964). Among discrete probability models, we  
103 selected the Poisson distribution because it is particularly suitable for large count  
104 datasets, *e.g.* a high number of events, and the occurrence of small or rare probabilities  
105 (Karlis, 2003), situations common when using microbial datasets to estimate a core

community. Unlike other attempts to define the core community (e.g. Turnbaugh *et al.*, 2009) there is no abundance threshold in our proposed method, which allows inclusion of rare taxa as possible members of the core microbial community.

We tested our proposed method using several previously published datasets, and compared our results to those obtained using conventional (i.e. arbitrary threshold) approaches. These datasets included human, mice, plant (grapevine tissue and maize rhizosphere), and soil data, and were obtained from the Earth Microbiome Project (EMP; <http://www.earthmicrobiome.org>). We hypothesized that our approach would lead to the identification of a probable core community that would be a higher proportion of the microbial community, and would also be composed of more microorganisms with low abundances (rare community members), than the core community identified using conventional approaches.

## RESULTS AND DISCUSSION

### *Testing the distribution models and rarefaction effect*

The first step was to select the most appropriate probabilistic method that fitted in OTU distributions. We tested 13 different models (described in Supplementary Material), and in Figure S1, we can observe the fourth best distribution models (Poisson, Chi-squared, Gamma and Beta) fitted on each dataset (Human, Grape, Maize and Mice). The Poisson distribution showed the higher and significant fit on OTU distribution, which is indicated by  $R^2$  and p-value  $< 0.05$  in Table S1. We also observed that the Poisson distribution indicated lesser value of RMSE. Models based on ‘Poissonization’ arguments has also been indicated as good predictor of microbial unknown (Lladser *et al.*, 2011).

The use of rarefaction, normalization method which equalizes the number of sequences (or reads) per sample, is discussed in the literature. According to McMurdie

131 and Holmes (2014), the rarefaction increases the number of false positives species, and  
 132 also with different abundance across sample classes. However, other simulation studies  
 133 indicated that the rarefication is better than other normalization methods, clustering  
 134 samples as biological origin (Weiss *et al.*, 2017). As probability models requires the  
 135 normalization, we evaluated the effect of the rarefaction on our proposed.

136 It can be observed in Figures S2, S3, S4 and S5 that the rarefaction method  
 137 affects the line of Poisson distribution identification. We also observed that the values  
 138 of  $R^2$  decreases with the increase of rarefication levels. However, the number of OTU's  
 139 identified as probable members of the core microbial community did not present a  
 140 significant variation in general (Table S2). In grape dataset only the two highest  
 141 rarefication levels, and in maize and human dataset only the lesser rarefication level  
 142 showed a significant different number of core OTU's identified. As indicated in Figures  
 143 S6, S7, S8 and S9, the taxonomic composition at the phyla level was not significant  
 144 affect by the most of rarefication levels. We verified the similarity of core community  
 145 composition by different rarefication levels using NMDS analyses (Jaccard similarity).  
 146 In Figure S10, we can observe that only the lowest level of rarefaction for the grape  
 147 (Core\_500), maize (Core\_100), and human (core\_100) datasets showed a significant  
 148 difference from the other rarefaction levels. For the mice dataset, we observe the lower  
 149 variation than the other datasets, but with the same pattern (lowest rarefaction level is  
 150 not grouped). Considering this normalization effect, we decided to maintain the same  
 151 method (rarefaction level) used by the authors of each published datasets for the next  
 152 steps.

### 153 ***A probabilistic method to identify the core microbial community***

154 Using this probabilistic model, we identified core microbial communities for each  
 155 dataset selected for analysis with  $R^2$  varying between 0.46 (mice) and 0.91 (grape), and

156 with *p-values* as lower than 0.05. The obtained curves indicated the occurrence of OTUs  
157 with distinct values of frequency occurrence as components of the core microbial  
158 communities, which is not observed when other approaches are used (Figure 1 and  
159 Supplementary Figures S11, S12, and S13). As the results were based on a probabilistic  
160 method, we expected that our proposed method would identify a group closer to the real  
161 core community than the group identified by conventional methods.

162 We observed that our probabilistic method reveals a rich and diverse group of  
163 microorganism which has not been identified by conventional methods, but belong to  
164 the probable core microbial community. For example, the core microbial community  
165 identified in the mice database is composed of 170 OTUs using an arbitrary threshold of  
166 30% detection frequency, and 1,717 OTUs using the method based on the Poisson  
167 distribution (Table 2). In particular, these differences were found for the occurrence of  
168 OTUs with low abundance, much more pronounced in the core community obtained by  
169 the method based on the Poisson distribution (e.g. Figure 1).

170 In the literature, the microorganisms with low abundance are frequently referred  
171 to as the “rare biosphere” (Sogin *et al.*, 2006). The rare biosphere was first described as  
172 microorganisms with low growth rates, which could act as a “seed bank” of species or  
173 genes important in maintaining the functional redundancy of a system (Pedrós-Alió,  
174 2006). These taxa could become dominant (in high abundance) under certain conditions  
175 (Shade *et al.*, 2014). Following this view, members of the rare community can be  
176 classified as conditionally rare taxa (CRT), suggested to be ubiquitous in some systems  
177 (Shade and Gilbert, 2015). As members of a core microbial community, the CRT could  
178 be important to the stability and functional resilience of a system. Using our  
179 methodology, these groups could be properly classified within the core community,  
180 while the arbitrarily defined core rarely included these putative CRTs, likely due to their

181 lower frequency (e.g. Figure 1B). The cut-offs for the core may fail to identify members  
 182 of the core microbial community, *i.e.* this method may produce “false negatives”. By  
 183 failing to include members in the core (*e.g.* low abundance taxa that are ubiquitous),  
 184 researchers may be underestimating the contribution of the core to ecosystem function.  
 185 Data from the mice dataset (Turnbaugh *et al.*, (2009) did not identify a core microbial  
 186 community across 100% of samples, or also using the PSM with abundance threshold.  
 187 The probabilistic method identified the same three phyla as the arbitrary cutoff method  
 188 (*Actinobacteria*, *Bacteroidetes*, and *Firmicutes*), but also recovered an additional eight  
 189 phyla (*Cyanobacteria*, *Fusobacteria*, *Lentisphaerae*, *Proteobacteria*, *Synergistetes*,  
 190 *Tenericutes*, *TM7*, and *Verrucomicrobia*) as members of the core microbial community  
 191 (Figure 2). The authors also indicated the distinct proportions of the *Bacteroidetes* and  
 192 *Actinobacteria* phyla associated to obese and lean mice. Both phyla were also detected  
 193 by our probabilistic method, with OTUs affiliated with these groups as components of  
 194 the core microbial community.

195         Rather than defining a specific, core cutoffs, some researchers have used the  
 196 term ‘persistent’ – referring to taxa with a high (but below 100%) occurrence frequency,  
 197 or ‘transient’ referring to taxa with low occurrence frequency. For example, Caporaso *et*  
 198 *al.*, (2011) have identified a persistent and transient communities, which are classified  
 199 as OTUs occurring in 60% or 20% of samples, respectively. Using this dataset  
 200 (Caporaso *et al.* 2011), we identified a probable core community, also based on OTUs,  
 201 across all of the human site samples made of 8,751 OTUs (Supplementary Figure S10).  
 202 The authors identified classes belonging to the phyla *Firmicutes*, *Proteobacteria*,  
 203 *Bacteroidetes*, and *Tenericutes* in the human gut. Similar results were obtained by our  
 204 approach, with the major affiliation of the OTUs to the phyla *Firmicutes*,  
 205 *Proteobacteria*, and *Bacteroidetes* (Supplementary Figure S14). We believe that our



206 approach better succeeds to identify the core community for two reasons. First, our  
207 method identified core communities across assessments previously identified as not  
208 having a core community (as determined by 100% frequency occurrence). Second, our  
209 method offers a complement to other terms as “persistent” and “transient” communities,  
210 e.g. indicating the rare microorganisms that could be classified in persistent group.

211 Same results were observed applying our proposed method to grapevine (leaves,  
212 flowers, grapes, and roots), and the maize rhizosphere. For example, Zarraonaindia *et*  
213 *al.*, (2015) suggested a bacterial core community identified by three OTUs across 75%  
214 of samples from grape (leaves, flowers, grapes, and roots) and soils, over two growing  
215 seasons. These OTUs belonged to the genera *Bradyrhizobium*, *Steroidobacter* and  
216 *Acidobacteria*. By using our proposed method on the same dataset, 5,039 OTUs were  
217 identified as belonging to the core community (Supplementary Figure S12A and S12B).  
218 In addition, members of the *Cyanobacteria* phylum - which was a dominant group  
219 identified by the arbitrary methods (90% of relative abundance; Supplementary Figure  
220 S15) – comprised only a small component of the core microbial community using the  
221 probabilistic method. This variation in dominance could directly affect the conclusions  
222 about microbial composition across the system and may also affect the correlations with  
223 environmental drivers.

224 Here, we demonstrate the use of a probabilistic model to identify the core microbial  
225 communities. By applying a probabilistic model, our results suggest that the core  
226 microbial community may be higher in richness and diversity than previously  
227 demonstrated using other methods. Our method also allowed us to include rare (low  
228 abundance) members in the core microbial community, which would otherwise be a  
229 challenge using an arbitrary core cutoff. The use of a probabilistic model can extend our  
230 detection of the core microbial community, and could potentially help researchers to

231 better connect the core community to ecosystem functions. An increased understanding  
232 of core microbial functions could support more robust studies in several fields, from  
233 human health (Zaura *et al.*, 2009) to increased crop production. The microbial core  
234 community could also be used as an indicator of system perturbations (Shade and  
235 Handelsman, 2012) such as disease occurrence. This new approach could provide future  
236 studies a more realistic strategy to define calculate the core community, and could help  
237 to investigate the role of core microbial community in ecosystem function, or to  
238 elucidate the drivers of its composition. The probabilistic model is a new tool to step  
239 forward in the microbial community investigation. Only with the use of more rigorous  
240 and less arbitrary statistical methods it will be possible to understand the microbial  
241 ecology and its interactions.

## 242 **EXPERIMENTAL PROCEDURES**

243 We selected four datasets composed of microbiomes from human samples  
244 (tongue, gut, and palms), mice (gut), grapevines (plant organs and bulk soil), and the  
245 maize rhizosphere to study the core microbial community identified using arbitrary  
246 cutoffs and a probabilistic method based on the Poisson distribution (Table 1).

247 The mice dataset was used to evaluate how the gut microbiome influences host  
248 adiposity (Turnbaugh *et al.*, 2009). The data are from fecal samples from 154  
249 individuals (mice) divided into adult females, monozygotic or dizygotic twin pairs, and  
250 their mothers. The core microbial community was identified using the *Phylotype*  
251 *Sampling Model* (PSM), which by Poisson distribution estimates the failures to observe  
252 microbial groups possibly belonging to the core community. The authors established a  
253 threshold value for abundance, considering only the OTUs with more than 0,5% of  
254 relative abundance as members of the core microbial community.

255 The human microbiome database consists of 396 samples, collected along a time

series of two individuals at four body sites, including gut, tongue, and left and right palm (Caporaso *et al.*, 2011). In the original study, the authors aimed to evaluate the temporal variation in the human microbiome. The authors used the terms persistent (microbial taxa with high levels of occurrence across samples), and transient (taxa with low levels of occurrence across samples) community, because it identified a very small temporal core across all samples. The core was defined as the taxa found across 100% of the samples.

In the grapevine database, Zarraonaindia *et al.*, (2015) identify the OTUs shared across grapevine organs (flower, leaves, grapes, root), the root zone, and bulk soil over two growing seasons. The authors reduced the cutoff to 75% occurrence across samples to determine the core community. This decision was justified by the authors due to the lack of OTUs occurring across all samples.

The maize database is the only study included in our dataset that did not attempt to identify the core community. The authors aimed to determine the impact of genetic variation on the composition of bacterial communities inhabiting the maize rhizosphere (Peiffer *et al.*, 2013).

The biological observation matrices (BIOM) derived from these data were obtained from the Earth Microbiome Project (EMP; <http://www.earthmicrobiome.org>), available on the Qiita platform (<https://qiita.ucsd.edu>). We used the BIOM files due to the similar treatment of data by bioinformatics, including quality filters and assignment of OTU taxonomy (Elli *et al.*, 2010; Caporaso *et al.*, 2011; Peiffer *et al.*, 2013; Zarraonaindia *et al.*, 2015). We used the software *QIIME* (Chen and Lifschitz, 1989) to convert the BIOM files into text files, which were further imported into the *R* software (Team 2016), where we analyzed it using the packages '*RAM*' (Chen *et al.*, 2016), '*vegan*' (Oksanen *et al.*, 2016) and '*Hmisc*' (Harrell Jr *et al.*, 2016).

281           The identification of the core microbial community is conventionally obtained by  
282   defining limits of frequency across the samples, *i.e.* a core community could be defined  
283   as microorganisms occurring in all samples (100% of occurrence frequency) or in a part  
284   of the samples (varying from 30% to 90% of frequency). For example, Ainsworth *et al.*,  
285   (2015) identified the ubiquitous endosymbiont bacterial community (or core  
286   community) associated with corals using a 30% occurrence frequency cut-off.  
287   Similarly, the human and grapevine studies were used determined the core community,  
288   respectively at levels of 100%, 100% and 75% occurrence frequency across the  
289   samples. We used a range of limits - 30, 40, 50, 60,70, 80, 90 and 100% occurrence  
290   frequency - based on the OTU tables across the samples to verify the difference in the  
291   core microbial community selected by these methods.

292           The method proposed here is based on the probability test for the distribution of  
293   each microbial taxon (OTU) among samples. This probability test is based on the  
294   Poisson distribution, which is a discrete random probability regression model. The  
295   Poisson distribution expresses the probability of an event taking place at a given point  
296   in time (Rao and Rubin, 1964). Here we treat events as OTUs across a series of  
297   collected samples. The Poisson distribution has previously been used in biogeographic  
298   studies to predict the abundance of species in a given ecosystem (Vincent and Haworth,  
299   1983; Guisan and Zimmermann, 2000).

300           Following the idea proposed in the Phylotype Sampling Model (Turnbaugh *et*  
301   *al.*, 2009), the Poisson distribution was used to verify the sampling error expected given  
302   the sample size and the probability of observing the minimum abundance of a  
303   microorganism in any sample. However, the major difference from the previously  
304   methods including the Phylotype Sampling Model is that our proposed method does not  
305   present abundance or frequency thresholds. The probability (***P***) of Poisson distribution

306 is obtained by  $P(x) = \lambda^x e^{-\lambda} / x!$ , where the lambda ( $\lambda$ ) and  $x$  represent the average of  
 307 relative abundance and the occurrence frequency of each taxon across the communities,  
 308 respectively. Using this formula, we have tested two hypotheses:  $H_0$  – the individual  
 309 (OTU) fits in the Poisson distribution and thus likely occurs in every sample (95% of  
 310 confidence), indicating that it cannot be excluded from the core microbial community;  
 311  $H_1$  – the individual does not fit in the Poisson distribution, and thus is unlikely to occur  
 312 in every sample, supporting its exclusion from the core microbial community.

313 The calculation starts with the determination of the average of sequences per  
 314 community source ( $N$ ), the average relative abundance of each taxon across  
 315 communities ( $p$ ) and the occurrence frequency of each taxon across communities ( $f$ ).  
 316 The  $p$  and  $f$  are calculated with values of  $A$  and  $rich > 0$ , and they are used in the  
 317 Poisson distribution, where the  $\lambda$  is obtained per OTU by the formula  $\lambda = N \times p$ .

318 The goodness-of-fit of the Poisson model to distribution of OTUs were  
 319 determined from the  $R^2$  (adjusted) and  $p$ -value. The goodness of fit ( $R^2$ ) indicates the  
 320 level of variance of an OTU's relative abundance explained by the Poisson distribution,  
 321 which in this case is correlated with the proportion of microbial community that could  
 322 be not excluded as possible member of the core microbial group. The  $p$ -value is used to  
 323 calculate the significance of OTUs predicted as probable core members by the Poisson  
 324 distribution.

325 The arbitrary (thresholds of 30, 40, 50, 60, 70, 80, 90 and 100%) and the  
 326 proposed (Poisson distribution) methods resulted in OTU tables for the core microbial  
 327 community and the “variable” community (made of those that do not belong to the core  
 328 community). The statistical analyses comparing the results were performed using the R  
 329 software version 3.2.2 (R Core Team, 2015), including the Shannon index. We also  
 330 developed a function in R, which identifies a core microbial community by the method

331 based on the Poisson distribution. The R script of this function is available in  
332 Supplementary Code Simplified file, and the description is available in Supplementary  
333 Code Description file.

334

## 335 ACKNOWLEDGEMENTS

336 We thank FAPESP for the projects funding, 2014/22845-5 and 2013/18529-8. We are  
337 grateful to the students in Brendan J.M. Bohannan's laboratory and the students from the  
338 Institute of Ecology and Evolution for support. We thank the members of the Earth Microbiome  
339 Project and the authors that made the database available. We also acknowledge the comments  
340 and discussion provided by Annelise Mendes Nascimento, Clarisse Betancourt, Ademir Durrer,  
341 and Trish Pasby throughout the manuscript preparation.

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440



441 **Table legends**

442 **Table 1** – Databases selected from EMP on the *Qiita platform*.

443

444 **Table 2** – Number of OTU's identified by the arbitrary and proposed method (based on  
445 the Poisson distribution) across the datasets

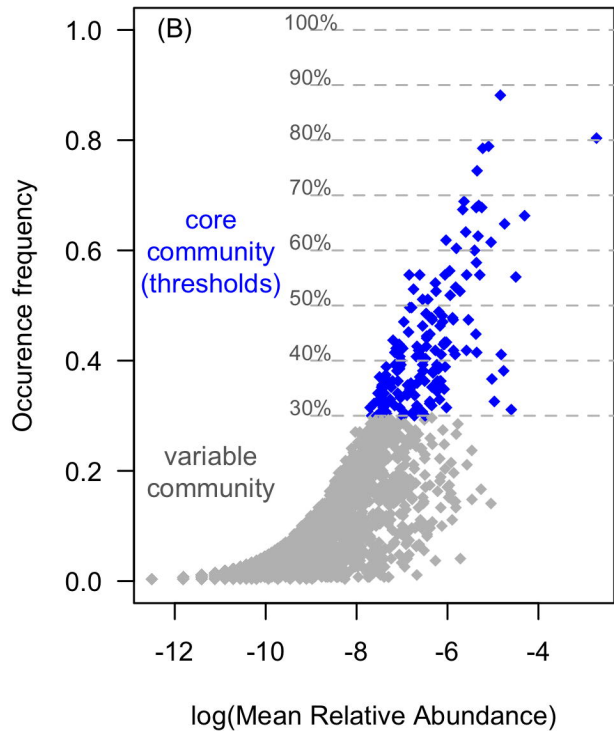
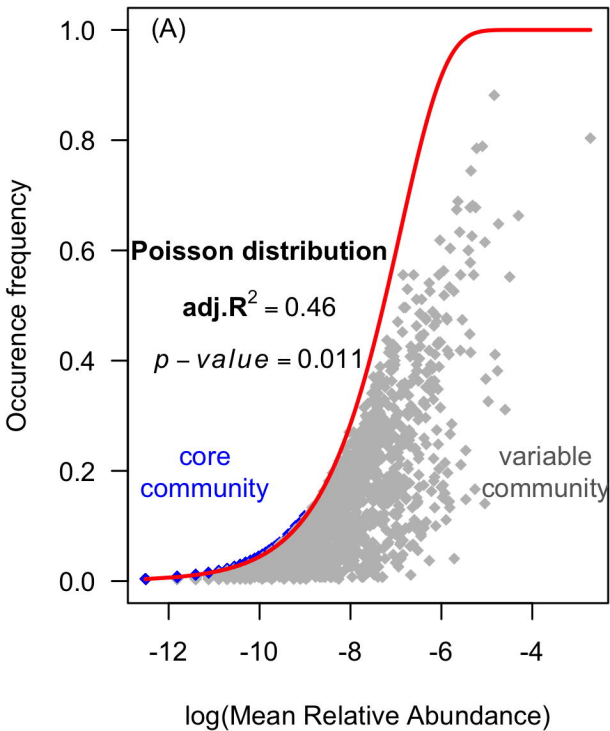
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448 **Figure legends**

449 **Figure 1** – The core and variable communities of the mice microbiome  
450 determined by (A) our proposed method based on the Poisson distribution and (B) an  
451 arbitrary, threshold-based method.

452 **Figure 2** – Percentage of the relative abundance of the core communities of the  
453 mice database determined by arbitrary methods (thresholds of 30,40,50,60,70,80,90 and  
454 100%) and by our proposed method (Core Poisson).



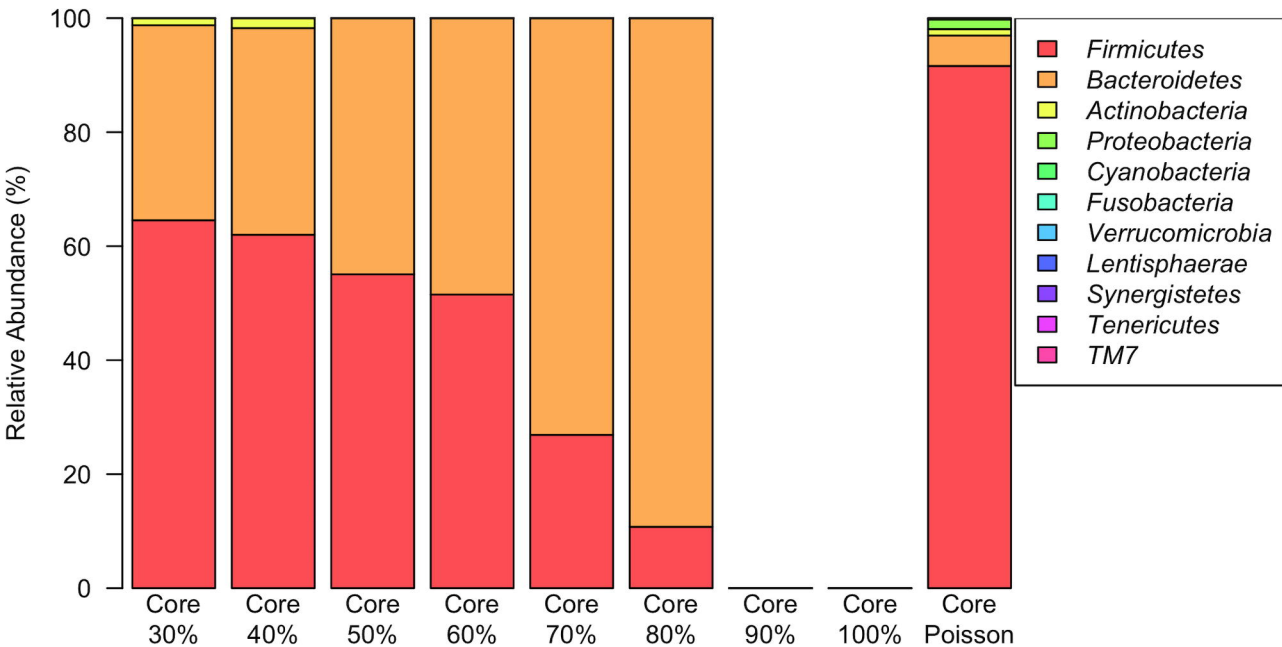


Table 1 – Databases selected from EMP on Qiita platform

	Databases selected from EMP			
	Grape	Maize	Human	Mice
<b>Study EMP – ID</b>	2382	1792	550	77
<b>Qiita Link</b>	<a href="https://qiita.ucsd.edu/study/description/2382">https://qiita.ucsd.edu/study/description/2382</a>	<a href="https://qiita.ucsd.edu/study/description/1792">https://qiita.ucsd.edu/study/description/1792</a>	<a href="https://qiita.ucsd.edu/study/description/550">https://qiita.ucsd.edu/study/description/550</a>	<a href="https://qiita.ucsd.edu/study/description/77">https://qiita.ucsd.edu/study/description/77</a>
<b>Title</b>	The Soil Microbiome Influences Grapevine-Associated Microbiota	Diversity and heritability of the maize rhizosphere microbiome under field conditions	Moving pictures of the human microbiome	A core gut microbiome in obese and lean twins
<b>Number of samples</b>	401	442	1,736	271
<b>Data Type</b>	16S - HiSeq	16S – 454 FLX	16S – 454 FLX	16S – 454 FLX
<b>Number of reads / sample</b>	1,000	2,080	5,000	1,000
<b>OTUs</b>	8,583	10,747	16,129	4,495
<b>Reference</b>	(Zarraonaindia <i>et al.</i> , 2015)	(Peiffer <i>et al.</i> , 2013)	(Caporaso <i>et al.</i> , 2011)	(Turnbaugh <i>et al.</i> , 2009)

Table 2 – Number of OTU's identified by the arbitrary and proposed method (based on the Poisson distribution) across the datasets

		Databases							
		Grapevine		Maize		Human		Mice	
Methods		Core community	Variable community	Core community	Variable community	Core community	Variable community	Core community	Variable community
Conventional method	30%	211	8,372	272	10,475	206	15,923	170	4,325
	40%	109	8,474	145	10,602	93	16,036	82	4,413
	50%	40	8,543	80	10,667	42	16,087	35	4,460
	60%	15	8,568	39	10,708	24	16,105	19	4,476
	70%	5	8,578	19	10,728	12	16,117	5	4,490
	80%	0	8,583	5	10,742	2	16,127	2	4,493
	90%	0	8,583	3	10,744	0	16,129	0	4,495
	100%	0	8,583	0	10,747	0	16,129	0	4,495
Proposed method		5,039	3,544	5,294	5,453	8,751	7,378	1,717	2,778