

MiDAS_course_2025

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Note: This is an R markdown report see this cheat sheet for more information on how to make nice Rmarkdown documents.

Background to the project

The dataset contains timeseries data from 4 Danish Wastewater Treatment Plants (WWTPs) from year 2020 collected in the frame of MiDAS project. The following excersices aim to get you familiar with the main microbial community analysis using the `ampvis2` package, and other auxiliary packages such as `ggplot2` for nice plots and `dplyr` for data wrangling.

Install ampvis2

Installation instructions and guides for `ampvis2` can be found on the associated homepage. If you need to install it, please execute the code from the first chunk below (for windows users you need to start Rstudio as administrator).

Note: `eval=F` in the `code chunk` header means that it is not evaluated (run) when the html is build.

Load the packages

Remember to load the packages before you try to use the associated functions.

1. Load and prepare the data for analysis

1.1 Set your working directory

1.2 Load the data into R

With `ampvis2` we can load all the necessary files into a single object, to make the further analysis easier and ordered. You can call it anything, but it's best to keep it short but meaningful To make the analysis easy the metadata, taxonomy and asvtable is combined into a single object `d`. You could name it however you like.

```
## Warning: Only 141 of 161 unique sample names match between metadata and otutable. The following unma
## metadata (20):
##  "MQ221006-200", "MQ221006-201", "MQ221006-202", "MQ221006-203", "MQ221006-204", "MQ221006-205", "MQ
```

Q: What does the warning mean?

1.3 Let's explore the original data sets:

ASV-table. It contains the ASV ID (e.g. "ASV15", even though the column name says OTU, it contain ASVs), which can be linked to the original DNA sequence; the sample-identifier (e.g. "MQ201118-152"); the number of reads associated to each ASV in each sample (e.g. "ASV1" is seen 1539 times in sample "MQ201118-152").

```
## # A tibble: 3 x 4
##   '#OTU ID' 'MQ201118-152' 'MQ201118-153' 'MQ211213-113'
##   <chr>      <dbl>      <dbl>      <dbl>
## 1 ASV2      1539      998      3016
## 2 ASV4       863      533      1901
## 3 ASV5       404      246      2204
```

We also load the metadata which contains information on each sample. Note that the **SampleID** is what connects your metadata to your ASV-table.

```
##      SampleID Line SampleContent SampleSite SampleDate
## 1 MQ201030-215  LT           AS Kalundborg 15/01/2020
## 2 MQ201030-216  LT           AS Kalundborg 24/01/2020
## 3 MQ201030-217  LT           AS Kalundborg 27/01/2020
## 4 MQ201030-218  LT           AS Kalundborg 03/02/2020
## 5 MQ201030-219  LT           AS Kalundborg 10/02/2020
## 6 MQ201030-220  LT           AS Kalundborg 17/02/2020
```

We can also check that everything in the `ampvis2` object is correct, and get an overview of the object. Look at the first rows of the ASV table inside the `ampvis2` object:

```
##      MQ201118-152 MQ201118-153 MQ201118-154 MQ201118-155 MQ201118-156
## ASV1           174           147           155           173           232
## ASV2          1539           998           990          2486          1542
## ASV3           430           312           477           498           514
## ASV4           863           533           452           614           597
## ASV5           404           246           257           583           355
## ASV6          1107          1067          1284          1341          1312
##      MQ201118-157 MQ201118-158 MQ201118-159 MQ201118-160 MQ201118-161
## ASV1           249           305           259           232           255
## ASV2          2476          1504          2466          1873          2146
## ASV3           554           705           720           773           854
## ASV4           561           572           658           562           571
## ASV5           533           414           638           501           599
## ASV6          1091          1450          1181          1008           920
##      MQ201118-162 MQ201118-163 MQ201118-164 MQ201118-165 MQ201118-166
## ASV1           280           326           324           285           308
## ASV2          2113          2366          2316          2423          1833
## ASV3          1267          1074          1301          1166          1478
## ASV4           690           575           487           469           514
## ASV5           638           696           898           918           839
## ASV6          1026          1057          1156           986           830
##      MQ201118-167 MQ201118-168 MQ201118-169 MQ201009-287 MQ201009-288
```

##	ASV1	508	431	792	996	633
##	ASV2	798	1059	3593	957	1354
##	ASV3	1308	1905	4163	428	712
##	ASV4	316	518	449	363	303
##	ASV5	279	429	1677	888	797
##	ASV6	561	463	399	170	101
##	MQ201009-289	MQ201009-290	MQ201009-291	MQ201009-292	MQ201009-293	
##	ASV1	552	406	241	241	177
##	ASV2	1134	1270	718	541	464
##	ASV3	666	695	817	1016	1613
##	ASV4	239	274	229	179	153
##	ASV5	812	709	375	290	217
##	ASV6	113	73	64	68	52
##	MQ201009-294	MQ201009-295	MQ210618-86	MQ210618-87	MQ210618-88	MQ210618-89
##	ASV1	251	212	615	1064	613 1541
##	ASV2	400	263	547	671	469 535
##	ASV3	1576	1773	1085	1640	709 477
##	ASV4	142	152	159	232	309 360
##	ASV5	257	171	512	750	477 520
##	ASV6	57	60	79	103	79 70
##	MQ210618-90	MQ210618-91	MQ201118-151	MQ201118-170	MQ201118-171	
##	ASV1	1553	1939	128	485	484
##	ASV2	626	507	849	1156	738
##	ASV3	457	416	290	1582	1706
##	ASV4	367	595	652	220	238
##	ASV5	683	599	196	924	417
##	ASV6	61	63	1321	387	439
##	MQ201118-172	MQ201118-173	MQ201118-174	MQ201118-175	MQ201118-176	
##	ASV1	647	442	391	427	374
##	ASV2	862	401	234	188	169
##	ASV3	2856	1363	1127	1163	1229
##	ASV4	380	160	126	130	183
##	ASV5	582	315	219	196	231
##	ASV6	931	407	349	260	398
##	MQ201118-177	MQ201118-178	MQ201118-179	MQ201118-180	MQ201118-181	
##	ASV1	377	370	307	564	0
##	ASV2	227	184	223	176	2
##	ASV3	1097	1038	1023	1198	0
##	ASV4	156	117	137	151	0
##	ASV5	338	382	365	323	0
##	ASV6	405	432	501	724	0
##	MQ201118-182	MQ201118-183	MQ211213-101	MQ211213-102	MQ211213-103	
##	ASV1	56	0	1115	934	846
##	ASV2	670	1	1145	1356	1146
##	ASV3	108	0	4085	4038	3220
##	ASV4	143	0	226	440	364
##	ASV5	282	0	2103	2660	2130
##	ASV6	133	0	699	527	397
##	MQ201110-288	MQ201110-289	MQ201110-290	MQ201110-291	MQ201110-292	
##	ASV1	1190	957	1022	836	1305
##	ASV2	21	12	18	13	29
##	ASV3	0	0	0	0	0
##	ASV4	326	414	295	425	423
##	ASV5	87	82	56	51	87

##	ASV6	40	41	36	45	47
##	MQ201110-293	MQ201110-294	MQ201110-295	MQ201110-296	MQ201110-297	
##	ASV1	1117	1606	2811	1176	822
##	ASV2	38	56	45	65	92
##	ASV3	0	0	0	0	0
##	ASV4	459	1117	581	934	1044
##	ASV5	133	206	195	235	245
##	ASV6	31	62	35	40	39
##	MQ201110-298	MQ201110-299	MQ201110-300	MQ201110-301	MQ201110-302	
##	ASV1	855	585	589	276	288
##	ASV2	97	92	122	62	55
##	ASV3	0	0	0	0	0
##	ASV4	770	706	813	400	643
##	ASV5	227	214	220	143	139
##	ASV6	36	38	39	16	15
##	MQ201110-303	MQ201110-304	MQ201110-305	MQ201110-306	MQ201110-307	
##	ASV1	274	347	286	682	357
##	ASV2	55	58	46	56	44
##	ASV3	0	0	0	0	0
##	ASV4	519	490	516	374	498
##	ASV5	128	179	180	300	220
##	ASV6	13	9	17	29	19
##	MQ201110-308	MQ201030-232	MQ201030-233	MQ201030-234	MQ201030-235	
##	ASV1	360	0	0	1	1
##	ASV2	41	0	1	0	0
##	ASV3	0	0	0	0	0
##	ASV4	469	147	122	270	122
##	ASV5	248	122	100	146	77
##	ASV6	17	8	4	8	2
##	MQ201030-236	MQ201030-237	MQ201030-238	MQ201030-239	MQ201030-240	
##	ASV1	0	0	0	1	0
##	ASV2	0	0	0	0	0
##	ASV3	0	0	0	0	0
##	ASV4	200	206	289	176	192
##	ASV5	73	75	77	102	77
##	ASV6	5	2	2	7	1
##	MQ201030-241	MQ220601-127	MQ220601-128	MQ220601-129	MQ220601-130	
##	ASV1	0	0	0	0	0
##	ASV2	0	0	1	0	0
##	ASV3	0	0	0	0	0
##	ASV4	169	57	69	58	55
##	ASV5	46	14	9	15	5
##	ASV6	4	1	1	2	1
##	MQ220601-131	MQ220601-132	MQ220601-133	MQ220601-134	MQ220601-135	
##	ASV1	0	0	0	0	0
##	ASV2	0	1	0	0	1
##	ASV3	0	0	0	0	0
##	ASV4	63	71	65	83	116
##	ASV5	4	10	5	4	2
##	ASV6	2	2	3	4	2
##	MQ220601-136	MQ220601-137	MQ220601-138	MQ201009-283	MQ201009-284	
##	ASV1	0	0	0	444	416
##	ASV2	0	0	0	542	450
##	ASV3	1	0	0	180	95

## ASV4	93	167	72	451	573
## ASV5	5	0	1	692	548
## ASV6	4	2	0	83	102
## MQ201009-285	MQ201009-286	MQ211213-114	MQ211213-115	MQ211213-116	
## ASV1	512	623	1465	993	866
## ASV2	804	831	3309	2165	1888
## ASV3	308	266	1736	1104	959
## ASV4	401	384	1954	959	654
## ASV5	687	720	2257	1322	922
## ASV6	114	125	1400	944	855
## MQ211213-117	MQ211213-118	MQ211213-119	MQ211213-120	MQ201110-279	
## ASV1	1210	776	960	1156	986
## ASV2	1949	1132	2148	3033	6
## ASV3	1215	1074	786	1097	0
## ASV4	568	258	1080	2654	560
## ASV5	937	422	800	972	91
## ASV6	1137	1284	964	1214	30
## MQ201110-280	MQ201110-281	MQ201110-282	MQ201110-283	MQ201110-284	
## ASV1	1228	1325	1272	1163	816
## ASV2	13	13	10	11	16
## ASV3	0	0	0	0	0
## ASV4	557	453	369	413	255
## ASV5	84	83	86	82	62
## ASV6	36	35	37	47	44
## MQ201110-285	MQ201110-286	MQ201110-287	MQ201030-215	MQ201030-216	
## ASV1	670	812	1007	0	0
## ASV2	9	12	10	10	9
## ASV3	0	0	0	0	0
## ASV4	239	346	348	409	566
## ASV5	50	61	86	304	363
## ASV6	18	37	25	60	62
## MQ201030-217	MQ201030-218	MQ201030-219	MQ201030-220	MQ201030-221	
## ASV1	1	0	1	0	0
## ASV2	5	3	1	3	4
## ASV3	0	0	0	0	0
## ASV4	483	406	431	666	508
## ASV5	376	390	430	469	347
## ASV6	45	50	42	59	44
## MQ201030-222	MQ201030-223	MQ201030-224	MQ201030-225	MQ201030-226	
## ASV1	1	0	1	0	0
## ASV2	2	3	4	1	0
## ASV3	0	0	0	0	0
## ASV4	437	511	541	566	310
## ASV5	303	321	254	271	175
## ASV6	47	35	42	49	28
## MQ201030-227	MQ201030-228	MQ201030-229	MQ201030-230	MQ201030-231	
## ASV1	0	0	1	0	0
## ASV2	4	1	1	1	1
## ASV3	0	0	0	0	0
## ASV4	286	299	264	363	310
## ASV5	129	154	203	194	170
## ASV6	22	15	10	12	6
## MQ211213-104	MQ211213-105	MQ211213-106	MQ211213-107	MQ211213-108	
## ASV1	773	863	1136	1149	953

```
## ASV2          944          793          1024          1239          791
## ASV3          2238         2072          2146          2327         1806
## ASV4           406          462           473           549          338
## ASV5          1777         1548          1728          1979         1057
## ASV6           445          493           718           909          956
##      MQ211213-109 MQ211213-110 MQ211213-111 MQ211213-112 MQ211213-113
## ASV1           880          766          1248           919         1405
## ASV2           807          863          2018          1957         3016
## ASV3          1314          933          1534          1149         1825
## ASV4           303          420          1132          1179         1901
## ASV5           983         1043          1985          1550         2204
## ASV6           857          808          1181           921         1336
```

Look at the last rows of the metadata inside the ampvis2 object:

```
##      SampleID Line SampleContent SampleSite SampleDate
## MQ211213-108 MQ211213-108 LT          AS      Randers 05/10/2020
## MQ211213-109 MQ211213-109 LT          AS      Randers 14/10/2020
## MQ211213-110 MQ211213-110 LT          AS      Randers 19/10/2020
## MQ211213-111 MQ211213-111 LT          AS      Randers 26/10/2020
## MQ211213-112 MQ211213-112 LT          AS      Randers 04/11/2020
## MQ211213-113 MQ211213-113 LT          AS      Randers 09/11/2020
```

Look at the first rows of the taxonomy table inside the ampvis2 object:

```
##      Kingdom          Phylum          Class          Order
## ASV1 k__Bacteria p__Actinobacteriota c__Actinobacteria o__Micrococcales
## ASV2 k__Bacteria p__Actinobacteriota c__Acidimicrobiia o__Microtrichales
## ASV3 k__Bacteria p__Chloroflexi c__Anaerolineae o__C10-SB1A
## ASV4 k__Bacteria p__Firmicutes c__Bacilli o__Lactobacillales
## ASV5 k__Bacteria p__Actinobacteriota c__Acidimicrobiia o__Microtrichales
## ASV6 k__Bacteria p__Proteobacteria c__Alphaproteobacteria o__Rhodobacterales
##      Family          Genus          Species
## ASV1 f__Intrasporangiaceae g__Ca_Phosphoribacter s__midas_s_5
## ASV2 f__Microtrichaceae g__Ca_Microthrix s__Ca_Microthrix_parvicella
## ASV3 f__Amarolineaceae g__Ca_Amarolinea s__Ca_Amarolinea_dominans
## ASV4 f__Carnobacteriaceae g__Trichococcus s__midas_s_4
## ASV5 f__Microtrichaceae g__Ca_Microthrix s__Ca_Microthrix_subdominans
## ASV6 f__Rhodobacteraceae g__Rhodobacter
##      OTU
## ASV1 ASV1
## ASV2 ASV2
## ASV3 ASV3
## ASV4 ASV4
## ASV5 ASV5
## ASV6 ASV6
```

Q: What are the minimum and maximum number of reads in the dataset?

```
## ampvis2 object with 4 elements.
## Summary of OTU table:
##      Samples      OTUs  Total#Reads  Min#Reads  Max#Reads  Median#Reads
```

```
##          141          12229          6316036          886          127366          42719
##      Avg#Reads
##      44794.58
##
## Assigned taxonomy:
##      Kingdom          Phylum          Class          Order          Family
##  12229(100%) 12159(99.43%) 12117(99.08%) 12019(98.28%) 11839(96.81%)
##      Genus          Species
## 11114(90.88%) 8897(72.75%)
##
## Metadata variables: 5
## SampleID, Line, SampleContent, SampleSite, SampleDate
```

Q: What are the minimum and maximum number of reads in Ribe?

```
## 111 samples and 4341 OTUs have been filtered
## Before: 141 samples and 12229 OTUs
## After: 30 samples and 7888 OTUs
```

```
## ampvis2 object with 4 elements.
## Summary of OTU table:
##      Samples          OTUs      Total#Reads      Min#Reads      Max#Reads      Median#Reads
##          30          7888          1138608          25903          69635          37354.5
##      Avg#Reads
##      37953.6
##
## Assigned taxonomy:
##      Kingdom          Phylum          Class          Order          Family          Genus
##  7888(100%) 7865(99.71%) 7854(99.57%) 7817(99.1%) 7742(98.15%) 7313(92.71%)
##      Species
##  5782(73.3%)
##
## Metadata variables: 5
## SampleID, Line, SampleContent, SampleSite, SampleDate
```

1.4 Add/modify metadata

Sometimes the data types in the metadata columns are not what we want. For example, we would like *SampleDate* to be a Date column, but now is character. This can create some conflicts later on, so it's better to change upfront. Also, you can create a new column in the metadata with the **Month** information (as a character) based on the **SampleDate** column or as a factor if you'd like to have the months names.

```
## 'data.frame': 141 obs. of 5 variables:
## $ SampleID : chr "MQ201118-152" "MQ201118-153" "MQ201118-154" "MQ201118-155" ...
## $ Line : chr "LT" "LT" "LT" "LT" ...
## $ SampleContent: chr "AS" "AS" "AS" "AS" ...
## $ SampleSite : chr "Randers" "Randers" "Randers" "Randers" ...
## $ SampleDate : chr "07/01/2020" "17/01/2020" "21/01/2020" "29/01/2020" ...
```

Check the data types in the metadata after modifications

```
## 'data.frame': 141 obs. of 7 variables:
## $ SampleID : chr "MQ201118-152" "MQ201118-153" "MQ201118-154" "MQ201118-155" ...
## $ Line : chr "LT" "LT" "LT" "LT" ...
## $ SampleContent: chr "AS" "AS" "AS" "AS" ...
## $ SampleSite : chr "Randers" "Randers" "Randers" "Randers" ...
## $ SampleDate : Date, format: "2020-01-07" "2020-01-17" ...
## $ Month : chr "01" "01" "01" "01" ...
## $ MonthName : Factor w/ 12 levels "January","February",...: 1 1 1 1 2 2 2 2 3 3 ...
```

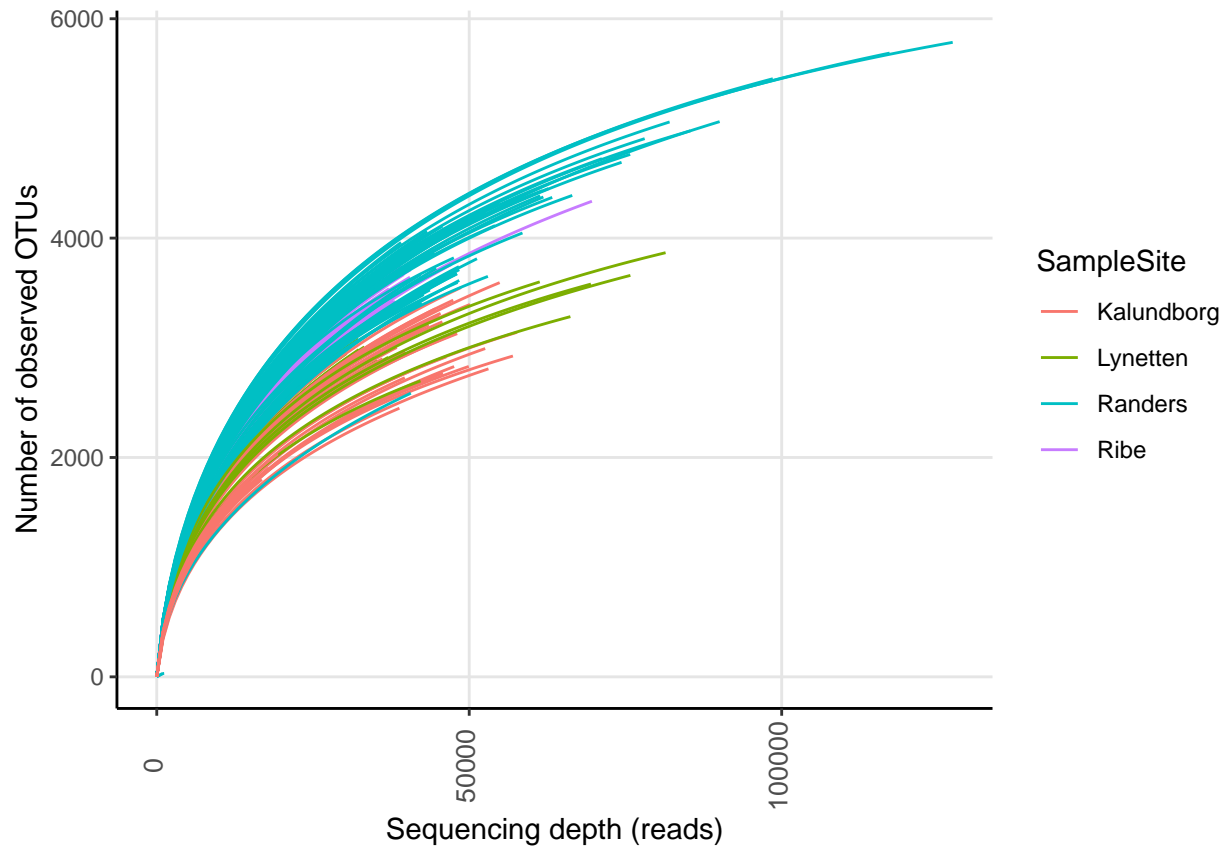
Remove unnecessary files

Basic QC analysis

Evaluation of negative controls: as we often work with tiny amounts of DNA contamination often occur. This could be from other samples, yourself and even the kits/reagents we use. Hence, it is important to take a critical look at the negative controls compared to the real samples. However, in the interest of time you can assume that problematic samples have been removed from the data set.

1. Rarefaction curves

The goal of this analysis is to evaluate if we have sequenced enough reads pr. sample to represent the diversity in the samples. This is often a subjective decision. For every sample, we take 1 read at a time, and evaluate if this belongs to an ASV we have already observed, or if this read represents new diversity (and ASV that has not been observed before). Every time we evaluate a new read we move 1 point on the x-axis and if it is a new ASV we also move 1 point up on the y-axis. When the curve is steep we discover new ASVs often, indicating that we need to sequence more reads to capture the diversity in the sample. When the curve flattens, we rarely observe new ASVs, indicating that we have captured most of the diversity in the sample. Often you have to compromise with the number of reads in order to keep more samples in your analysis.

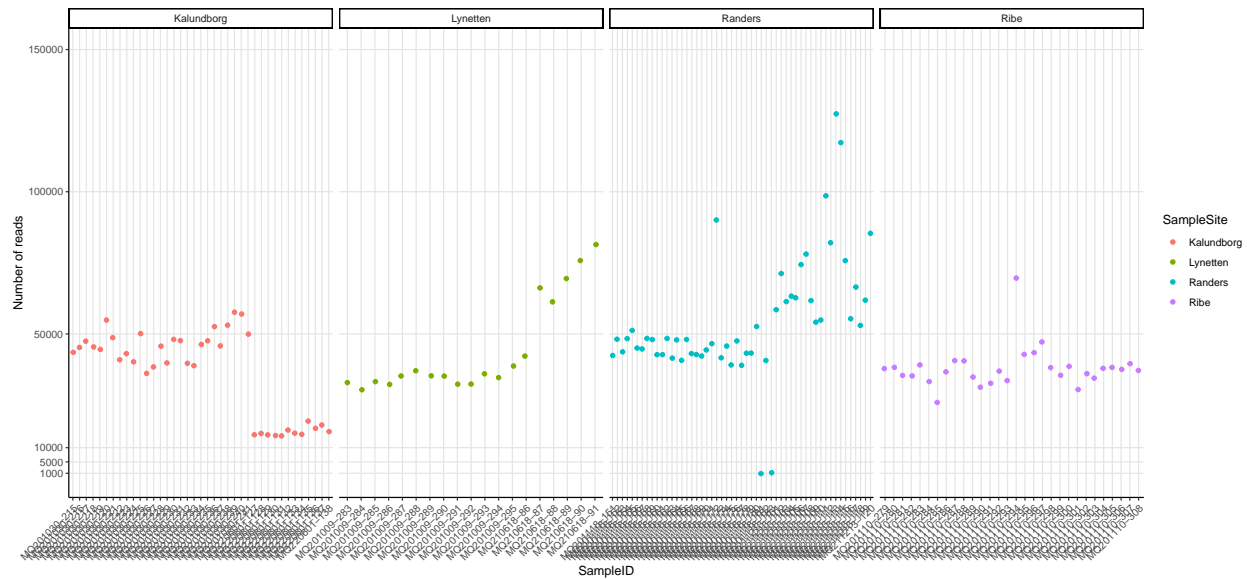


The function `amp_alphadiv` takes the metadata and appends the number of reads and ASVs in each sample which then can be used for further analysis.

```
##           SampleID Line SampleContent SampleSite SampleDate Month
## MQ201118-181 MQ201118-181 LT          AS    Randers 2020-07-27   07
## MQ201118-183 MQ201118-183 LT          AS    Randers 2020-08-11   08
## MQ220601-131 MQ220601-131 LT          AS Kalundborg 2020-10-16  10
## MQ220601-130 MQ220601-130 LT          AS Kalundborg 2020-10-05  10
## MQ220601-129 MQ220601-129 LT          AS Kalundborg 2020-09-30   09
## MQ220601-127 MQ220601-127 LT          AS Kalundborg 2020-09-09   09
##           MonthName Reads uniqueOTUs  Shannon  Simpson invSimpson
## MQ201118-181    July    886         30 2.864474 0.9282824 13.943586
## MQ201118-183   August   1188         31 2.387568 0.8009968  5.025044
## MQ220601-131  October  14136        1776 5.818483 0.9879157 82.752046
## MQ220601-130  October  14258        1771 5.825115 0.9874007 79.369266
## MQ220601-129  September 14497        1689 5.796092 0.9871528 77.838007
## MQ220601-127  September 14532        1743 5.865044 0.9888748 89.885752
```

2. Check the number of reads produced pr. sample.

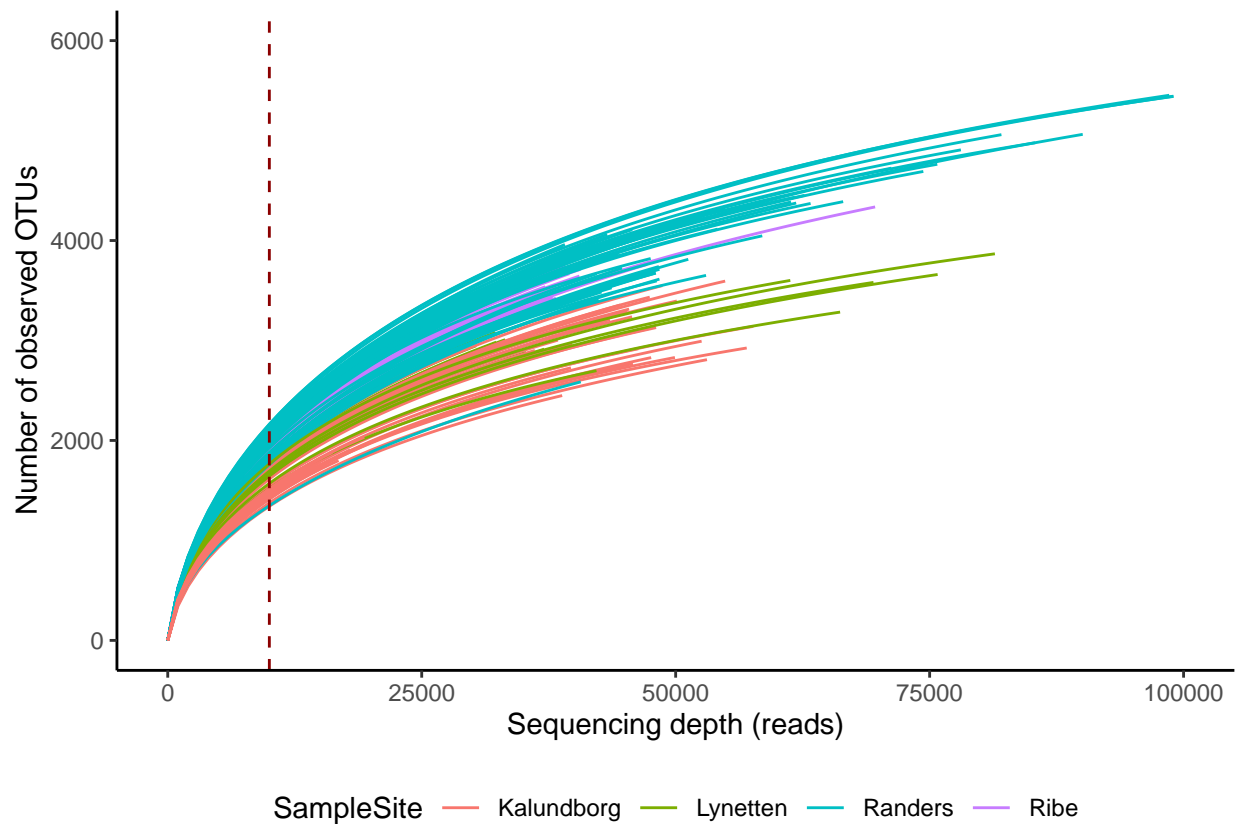
Note: You can use “+” to modify all `ampvis2` plots as behind the surface they are just `ggplot2` objects. Here we change a number of features (e.g. y axis title or x axis label position).



3. Subset to a minimum number of reads per sample

After we have decided that we don't trust that samples with less than 10000 we remove them from our analysis. We store the subset in the object "ds_midast".

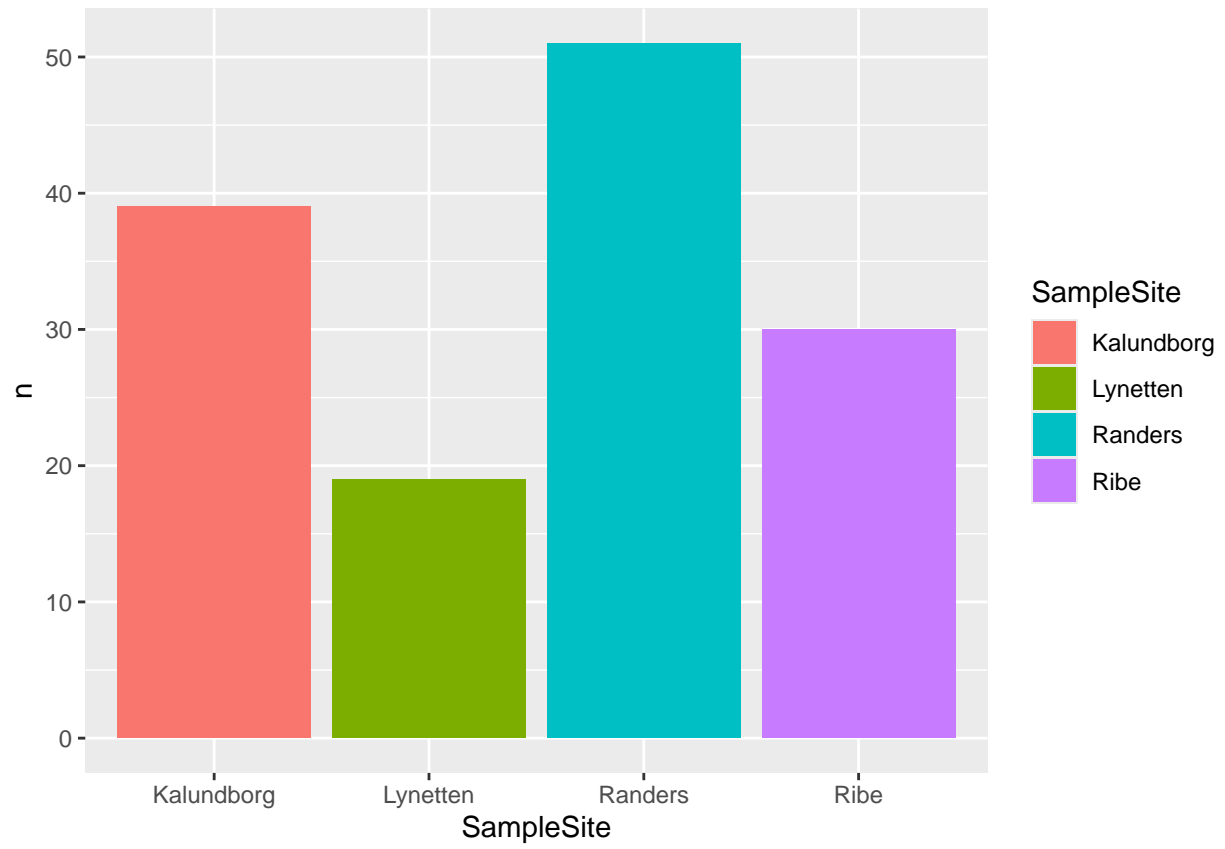
```
## 2 samples and 11 OTUs have been filtered
## Before: 141 samples and 12229 OTUs
## After: 139 samples and 12218 OTUs
```

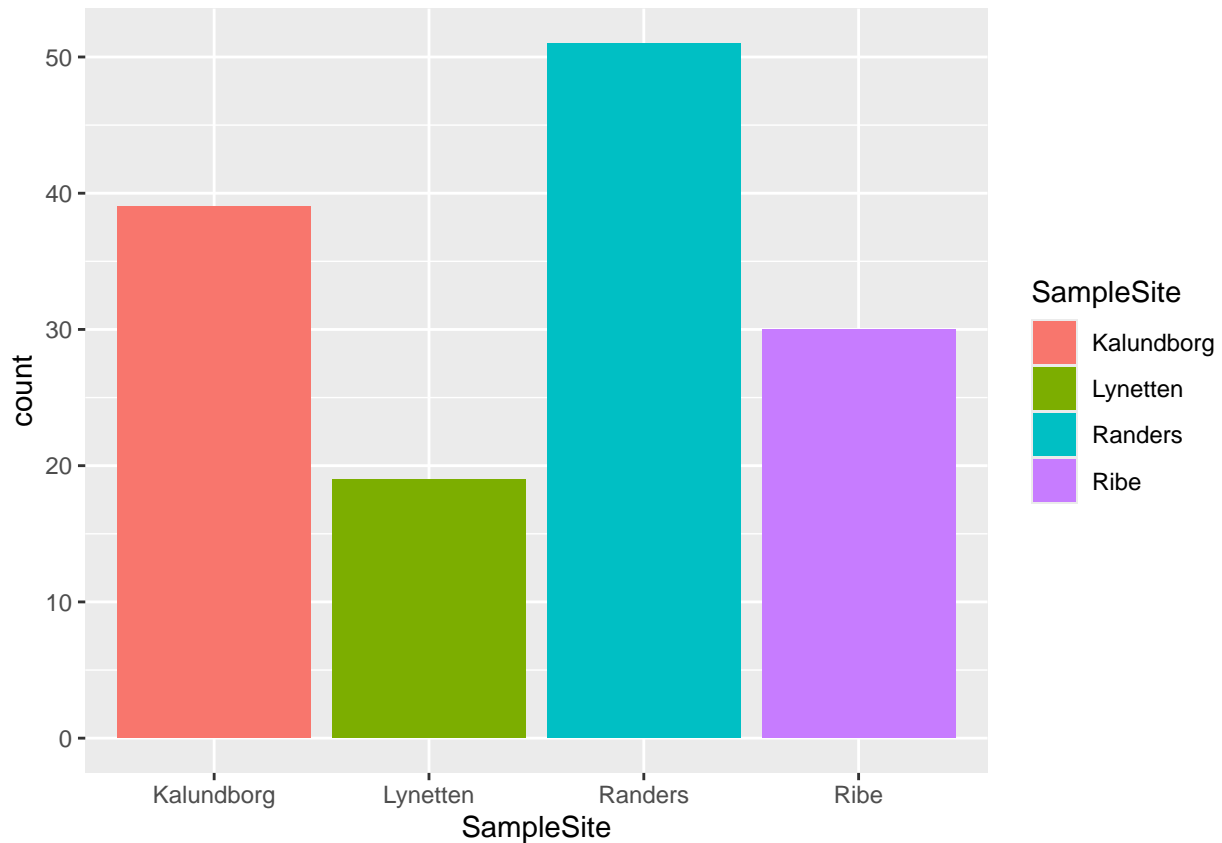


4. Count the number of samples per plant

Use the function `count()` from the `tidyverse` package to summarize how many samples were taken at each WWTP as a simple table. You could also visualize it using e.g. `geom_col()` or `geom_bar()` from the `ggplot2` package.

```
## # A tibble: 4 x 2
## # Groups:   SampleSite [4]
##   SampleSite     n
##   <chr>       <int>
## 1 Kalundborg    39
## 2 Lynetten     19
## 3 Randers      51
## 4 Ribe        30
```





5. Rarefy

For some analyses it is preferable to rarefy the dataset, in other words standardise sequencing depth across samples, to make fair comparisons. It is a topic that gets highly debated in literature since it produces a “data-loss”, but in general it is advisable to use it when performing alpha diversity comparisons.

```
## Warning: The chosen rarefy size (10000) is smaller than the smallest amount of  
## reads in any sample (14136).
```

```
## 0 samples have been filtered.
```

Q: Should we worry about the warning?

6. Normalise

For some analyses we may want to have our ampvis2 object to normalise the ASv read counts to 100 (relative abundance). Many ampvis functions have the option to normalise when calling it.

```
## 0 samples have been filtered.
```

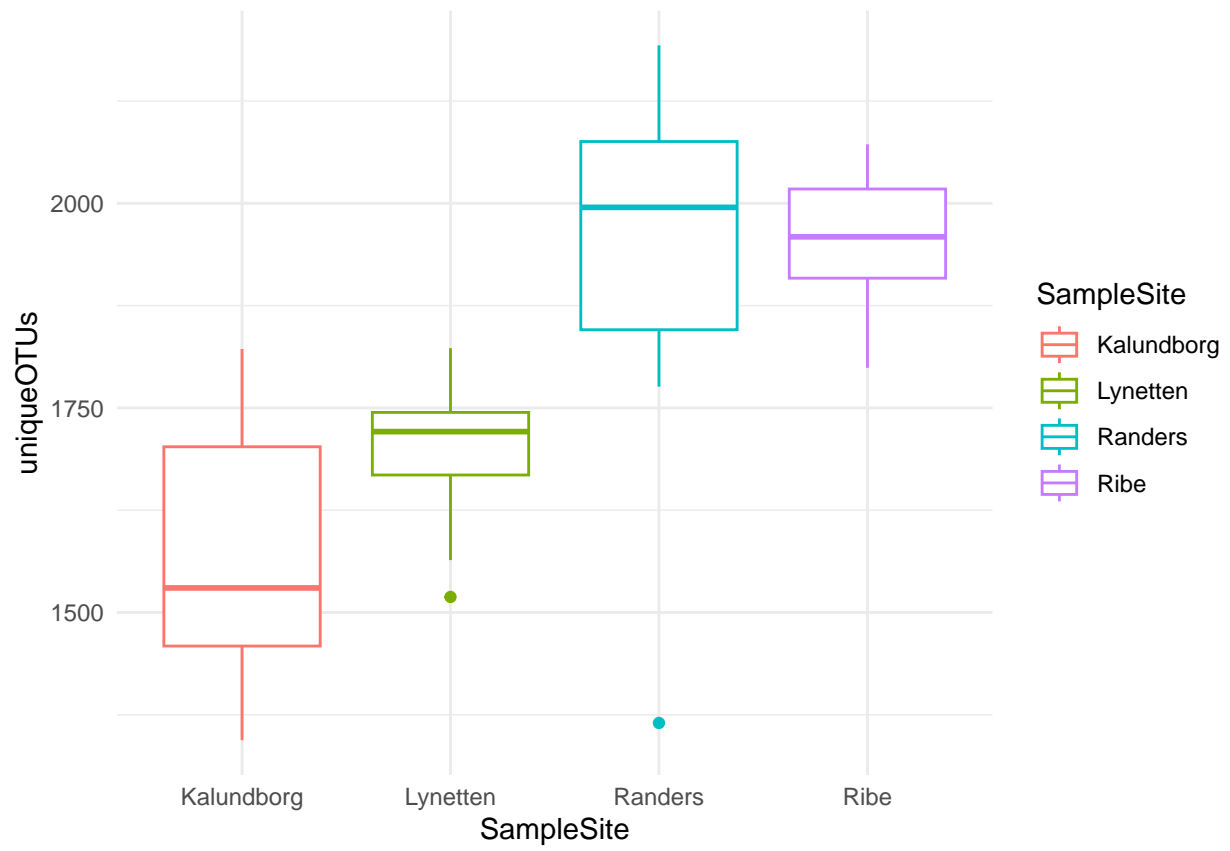
Data analysis

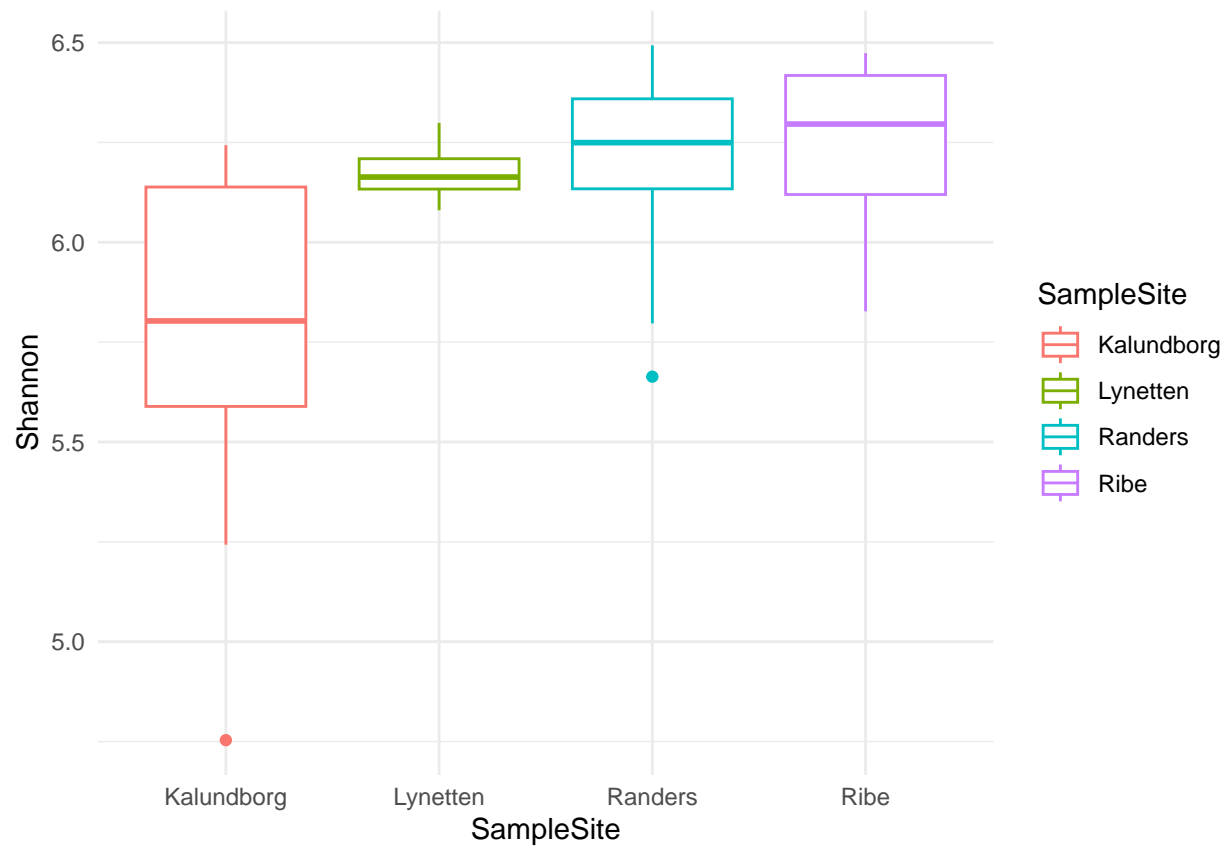
1. Alpha diversity

In microbial community analysis we often also quantify the diversity of the community in any single sample. This can be quantified with a single number that takes into account the number and abundance of the individual taxa. There are numerous ways of calculating these **diversity indices**, and many can be calculated using the `amp_alpha_diversity()` function. The results are appended to the end of metadata as simple columns.

```
##           SampleID Line SampleContent SampleSite SampleDate Month
## MQ201118-152 MQ201118-152 LT          AS      Randers 2020-01-07   01
## MQ201118-153 MQ201118-153 LT          AS      Randers 2020-01-17   01
## MQ201118-154 MQ201118-154 LT          AS      Randers 2020-01-21   01
## MQ201118-155 MQ201118-155 LT          AS      Randers 2020-01-29   01
## MQ201118-156 MQ201118-156 LT          AS      Randers 2020-02-06   02
## MQ201118-157 MQ201118-157 LT          AS      Randers 2020-02-14   02
##           MonthName Reads uniqueOTUs  Shannon  Simpson invSimpson
## MQ201118-152  January 10000        1827 6.198710 0.9932242 147.5832
## MQ201118-153  January 10000        1872 6.196973 0.9928831 140.5098
## MQ201118-154  January 10000        1882 6.109789 0.9916055 119.1262
## MQ201118-155  January 10000        1856 6.126986 0.9917604 121.3657
## MQ201118-156  February 10000        1797 6.125199 0.9923990 131.5613
## MQ201118-157  February 10000        1915 6.161394 0.9916501 119.7613
```

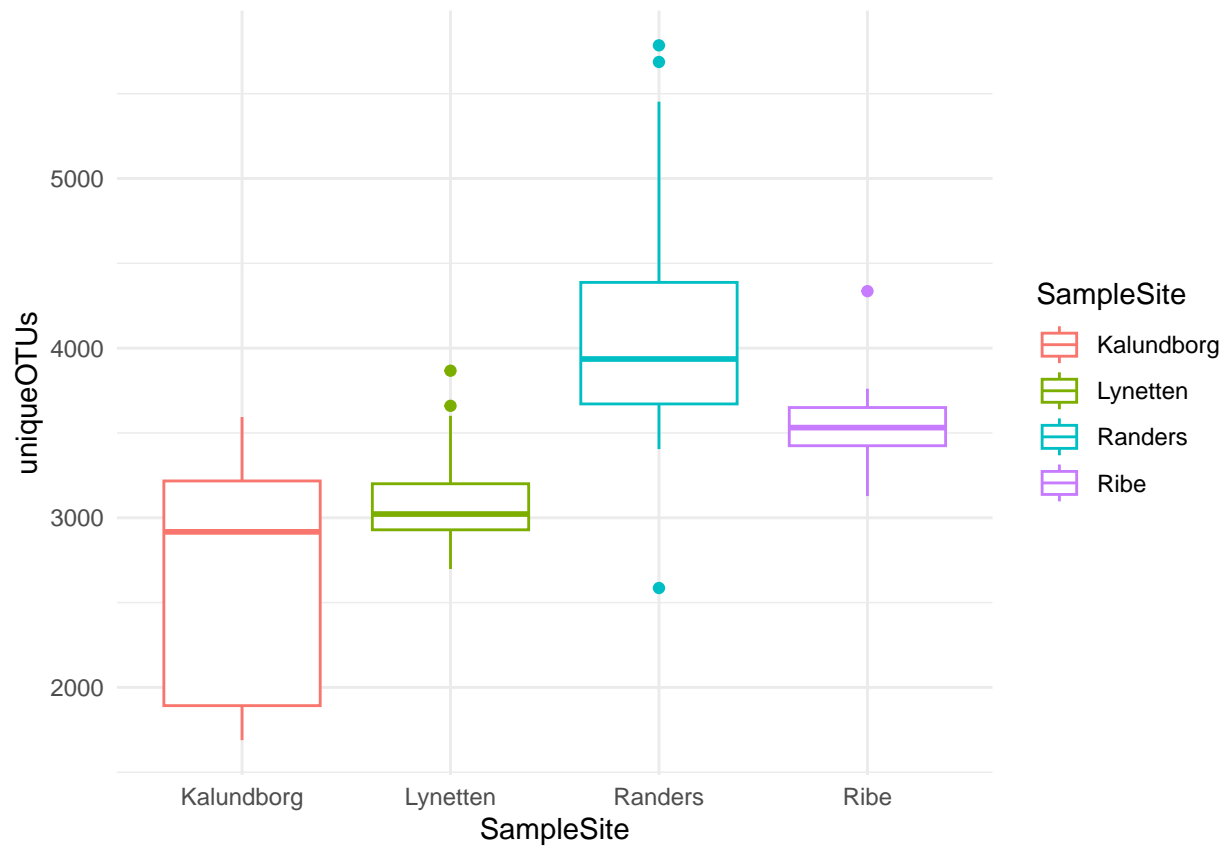
Plot the species richness - **ObservedOTUs** and Shannon diversity of the **alpha** data set using the `geom_boxplot()` from the `ggplot2` package. See e.g. [this example](<http://www.sthda.com/english/wiki/ggplot2-box-plot-quick-start-guide-r-software-and-data-visualization>). In which plant the microbial community is least diverse?

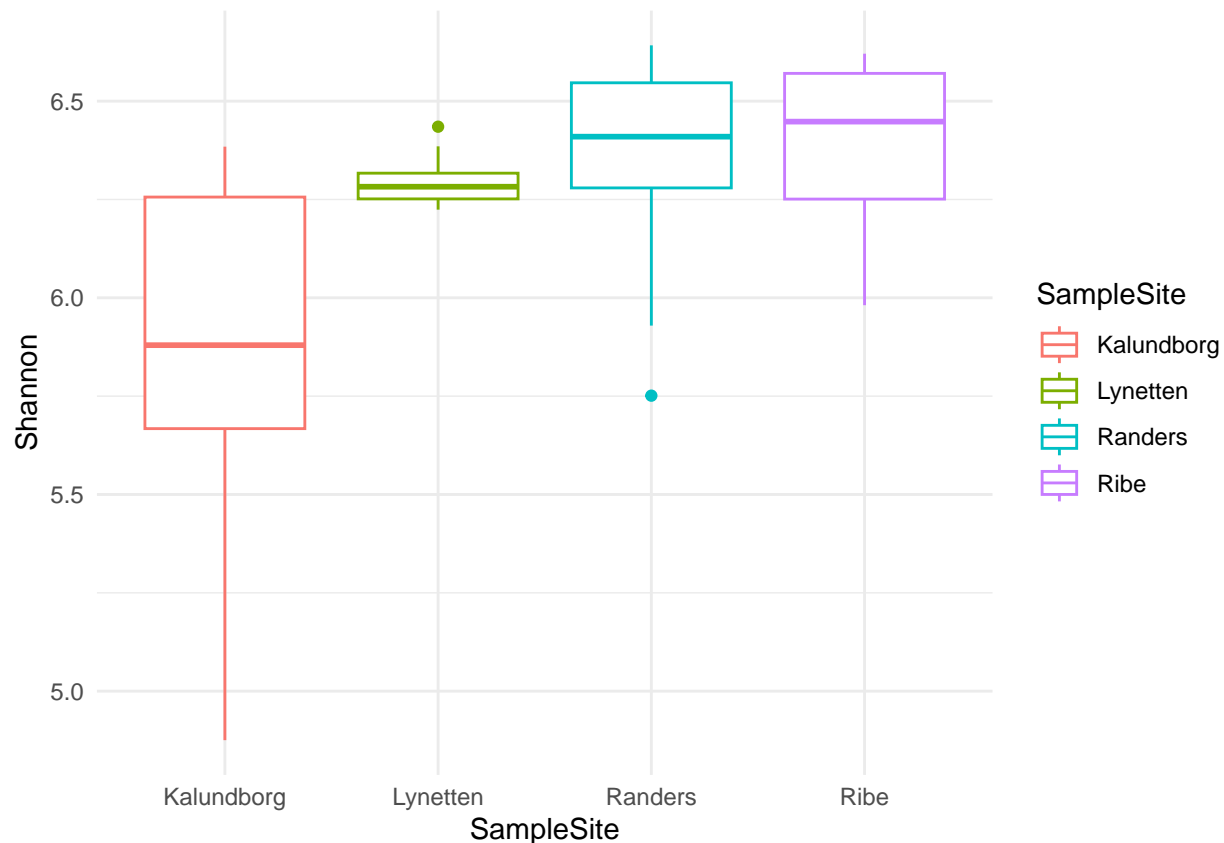




1.1 Alpha-diversity additional tasks

Compare the alpha diversity results using the non-rarefied dataset. What are your observations?





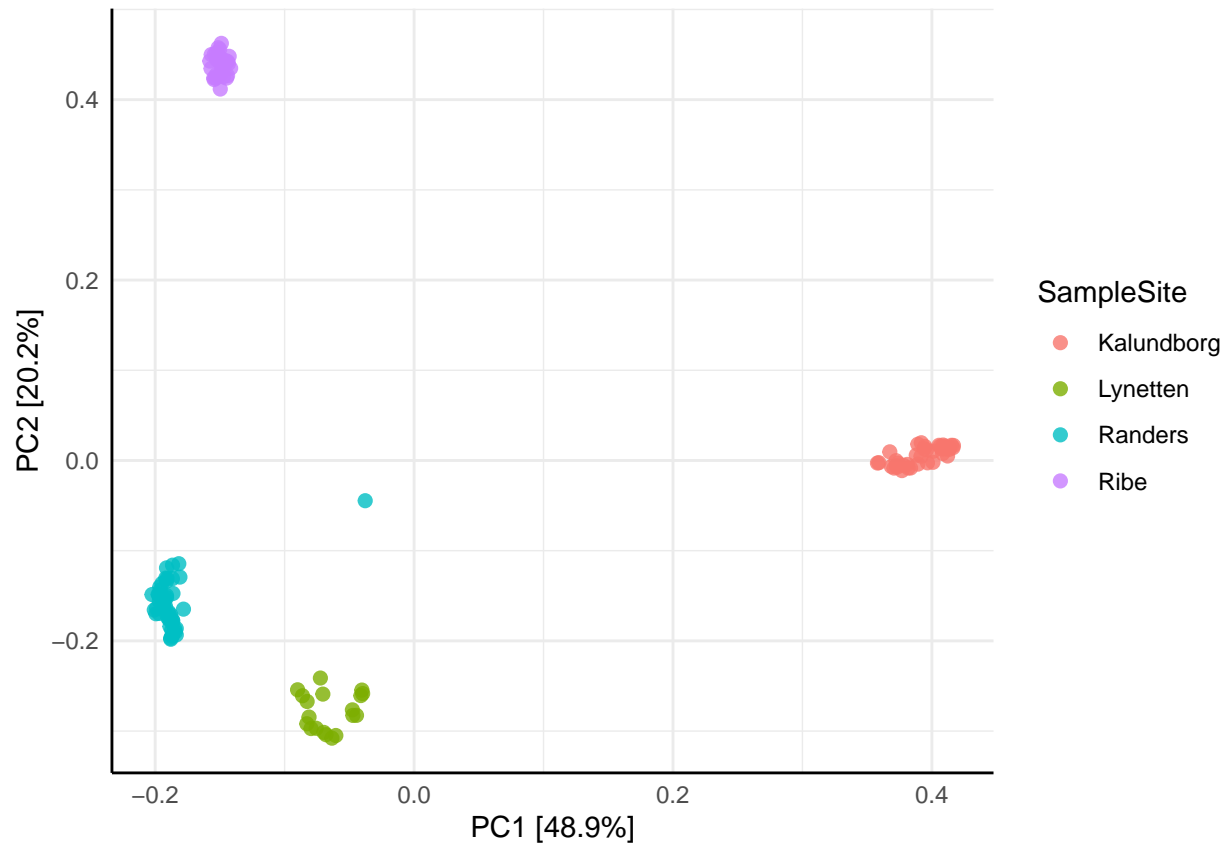
2. Beta diversity

When we are comparing between samples we call it beta-diversity. One of the most common ways of comparing large data sets and identify similarities and differences are using ordination. See this guide for an introduction to the topic. Ordination is trying to show you the largest differences between samples. In ordination we take the ASV table with 1000's of bacteria and try to visualize which samples have similar microbial communities. Samples (colored dots) located close together have similar microbial communities, while samples located far apart have different microbial communities. There are many versions of the ordination. One of the most simple and commonly used is PCA where the raw ASV counts are often transformed using **hellinger** transformation that takes the square root of the relative abundance. See this guide for short intro on **Hellinger** and other data transformations. In addition to transforming the data, different types of ordination can be made (PCoA or NMDS are also often used).

2.1 Perform a PCA

Q: What can you say about the similarity of microbial communities in the 4 WWTPs based on PCA plot?

```
## 10898 OTUs not present in more than 0.1% relative abundance in any sample have been filtered
## Before: 12218 OTUs
## After: 1320 OTUs
```

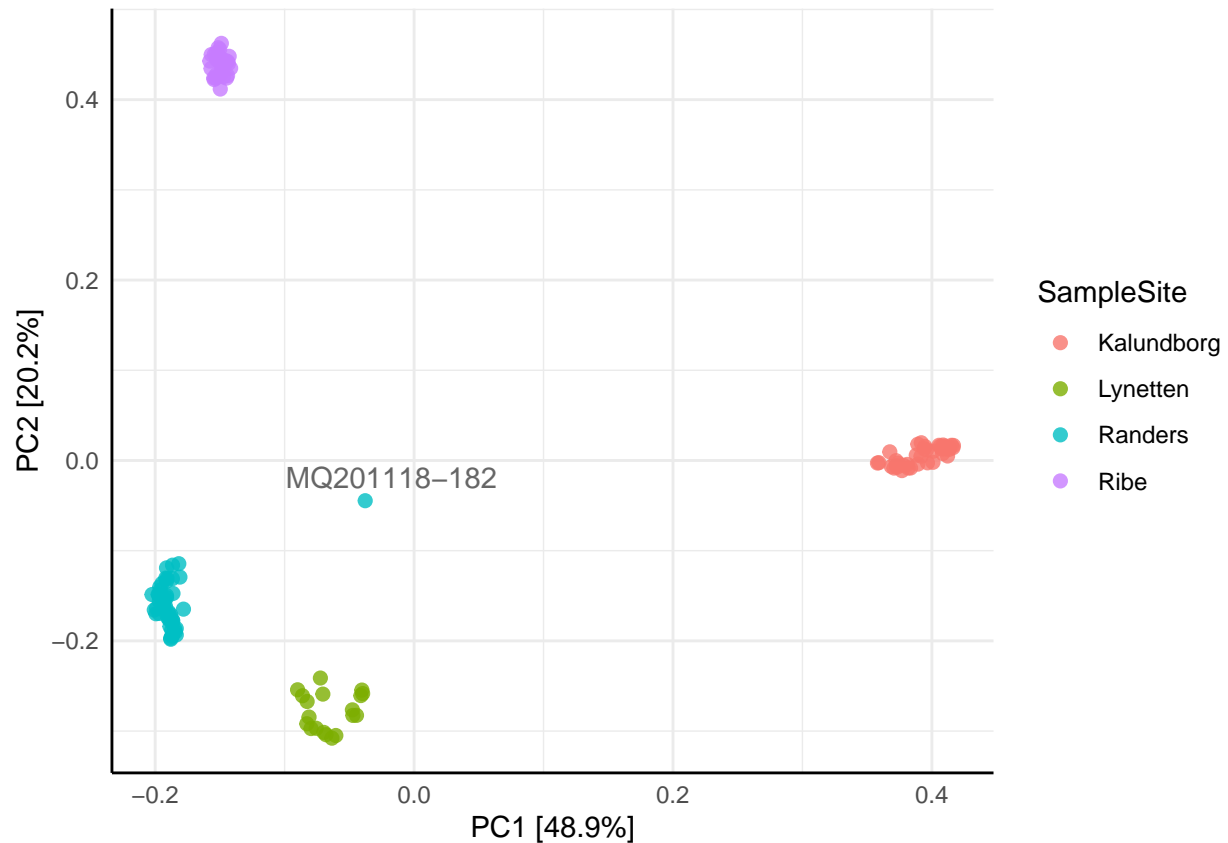


2.2 Problematic samples

Identify the outlier (by e.g. using `amp_ordination` & `sample_label_by` option or `amp_heatmap` & adjusting the “Group_by” parameter to show the “Sample”), subset the dataset to remove the outlier sample and replot the ordination and heatmap.

```
## 10898 OTUs not present in more than 0.1% relative abundance in any sample have been filtered
## Before: 12218 OTUs
## After: 1320 OTUs
```

```
## Warning: ggrepel: 138 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```

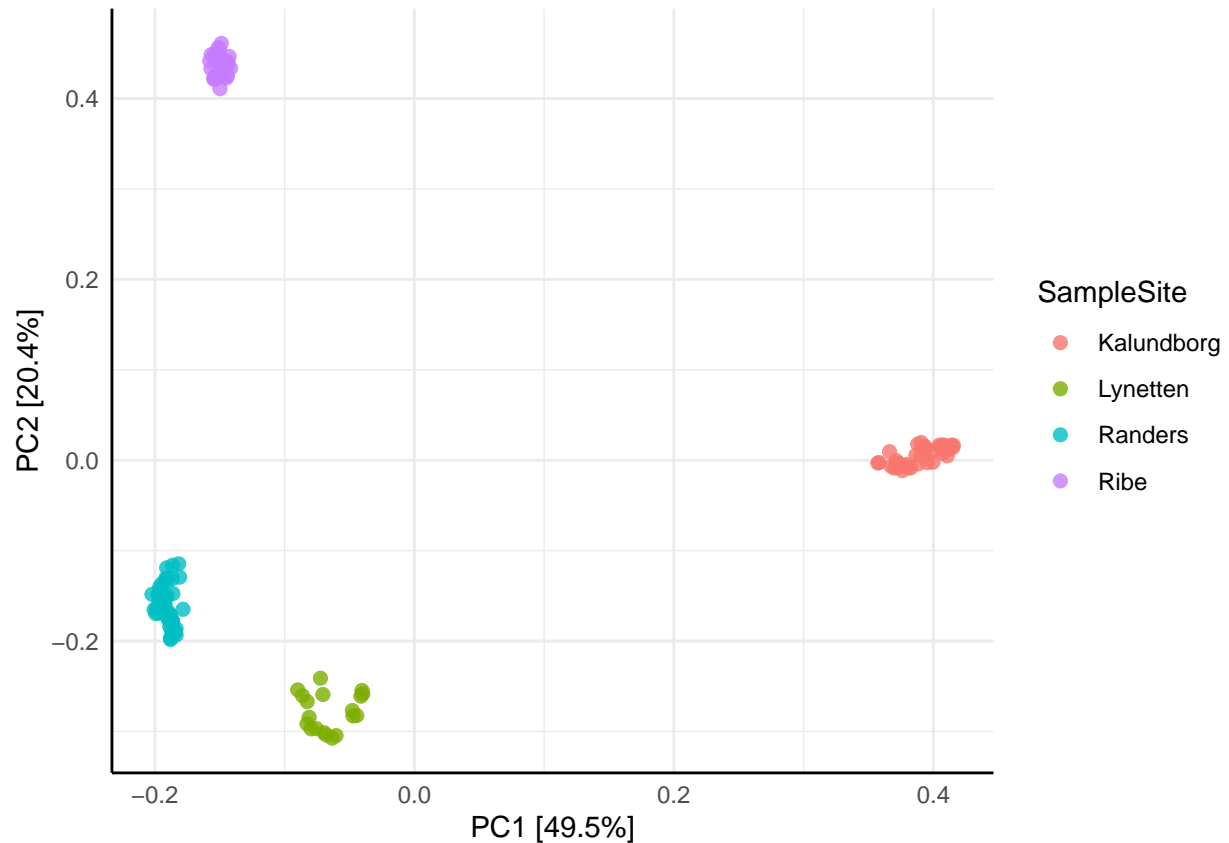


Remove outlier. Depending on which stage of your analysis, it can be necessary to re-do it with the outlier(s) removed from the beginning. For this exercise we will move from here on without the outlier: **Create new ampvis2 object**

```
## 1 samples and 25 OTUs have been filtered
## Before: 139 samples and 12218 OTUs
## After: 138 samples and 12193 OTUs
## 1 samples and 25 OTUs have been filtered
## Before: 139 samples and 12218 OTUs
## After: 138 samples and 12193 OTUs
```

Check that we have effectively removed the outlier

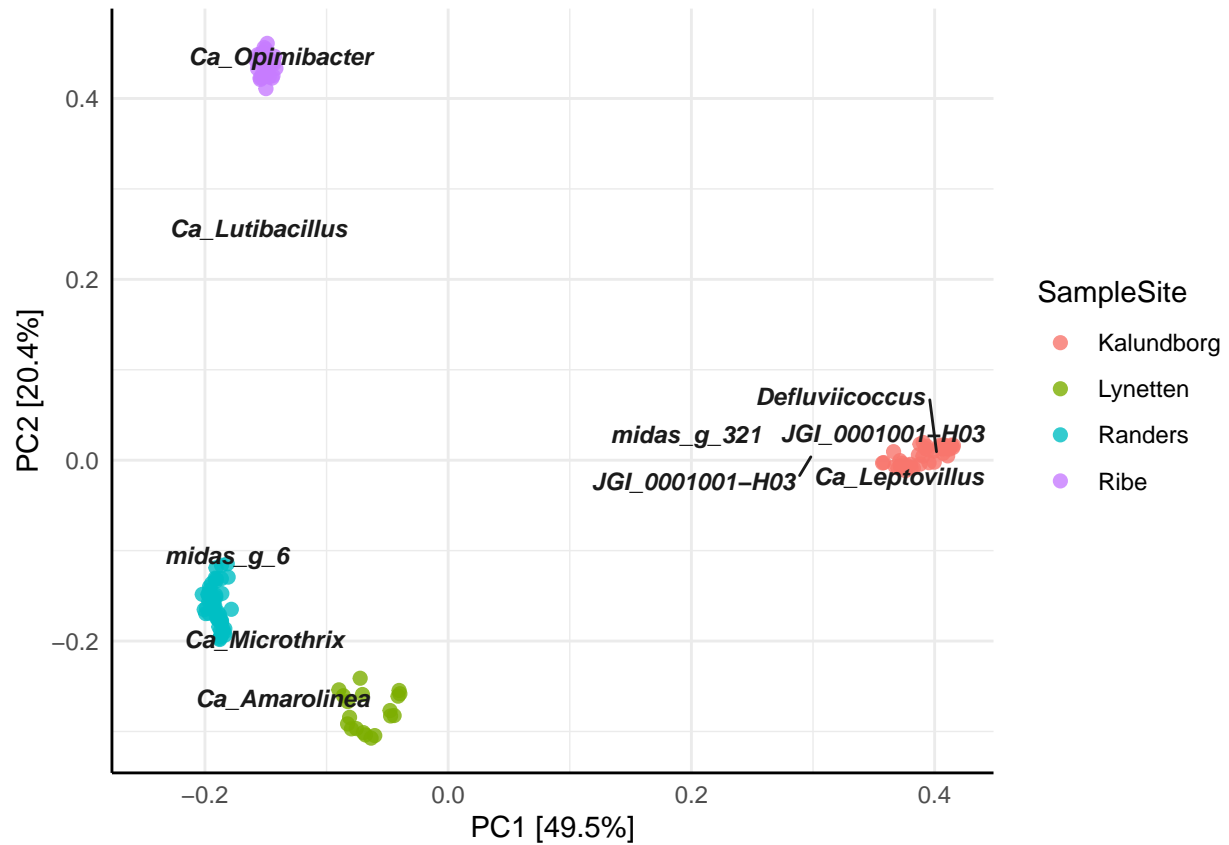
```
## 10986 OTUs not present in more than 0.1% relative abundance in any sample have been filtered
## Before: 12193 OTUs
## After: 1207 OTUs
```



2.3 Explore ordinations

Which bacteria are mainly causing the differences among the observed clusters (hint: try using `species_nlabels` and `species_label_taxonomy`). Keep the ordination results handy, how do the ordination relate the ordination results to your `heatmap`?

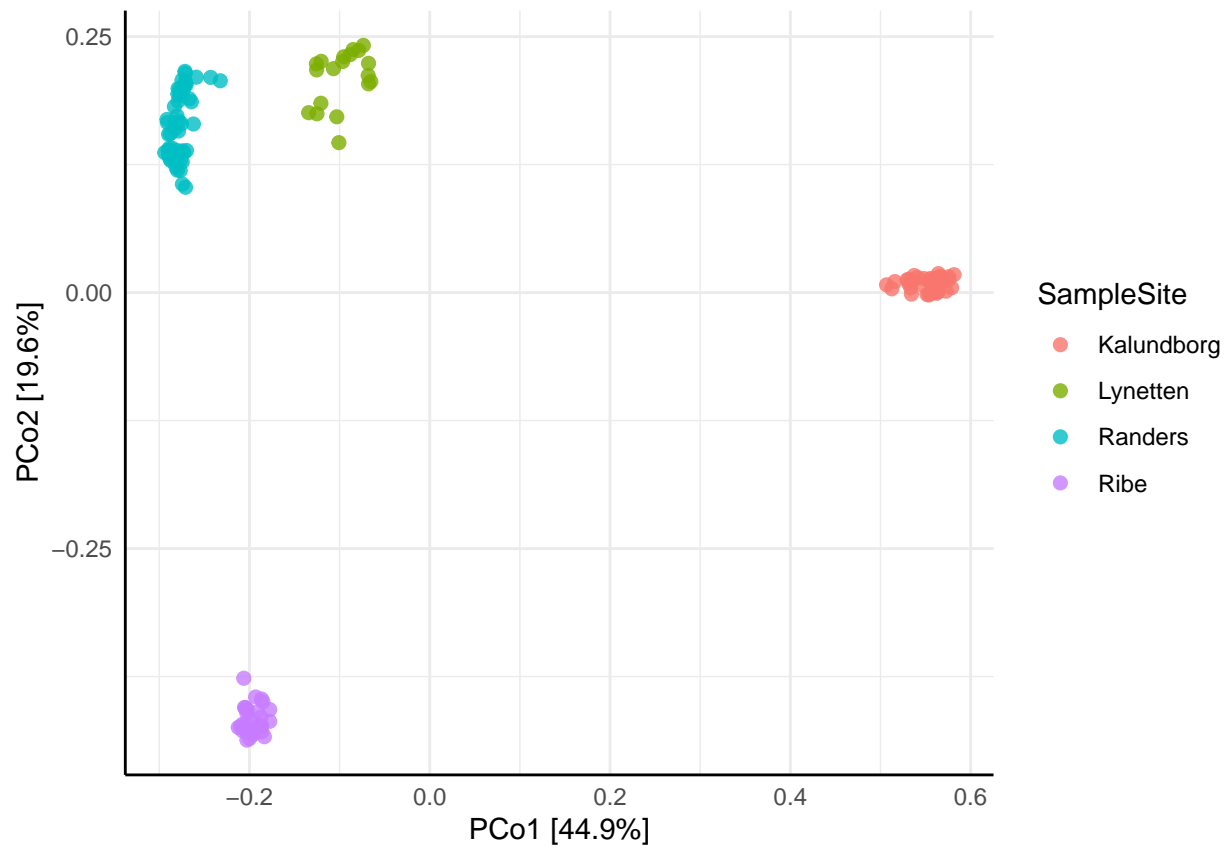
```
## 10986 OTUs not present in more than 0.1% relative abundance in any sample have been filtered
## Before: 12193 OTUs
## After: 1207 OTUs
```



2.4. Beta-diversity additional tasks

Try different ordinations, e.g. PCoA based on bray-curtis distance

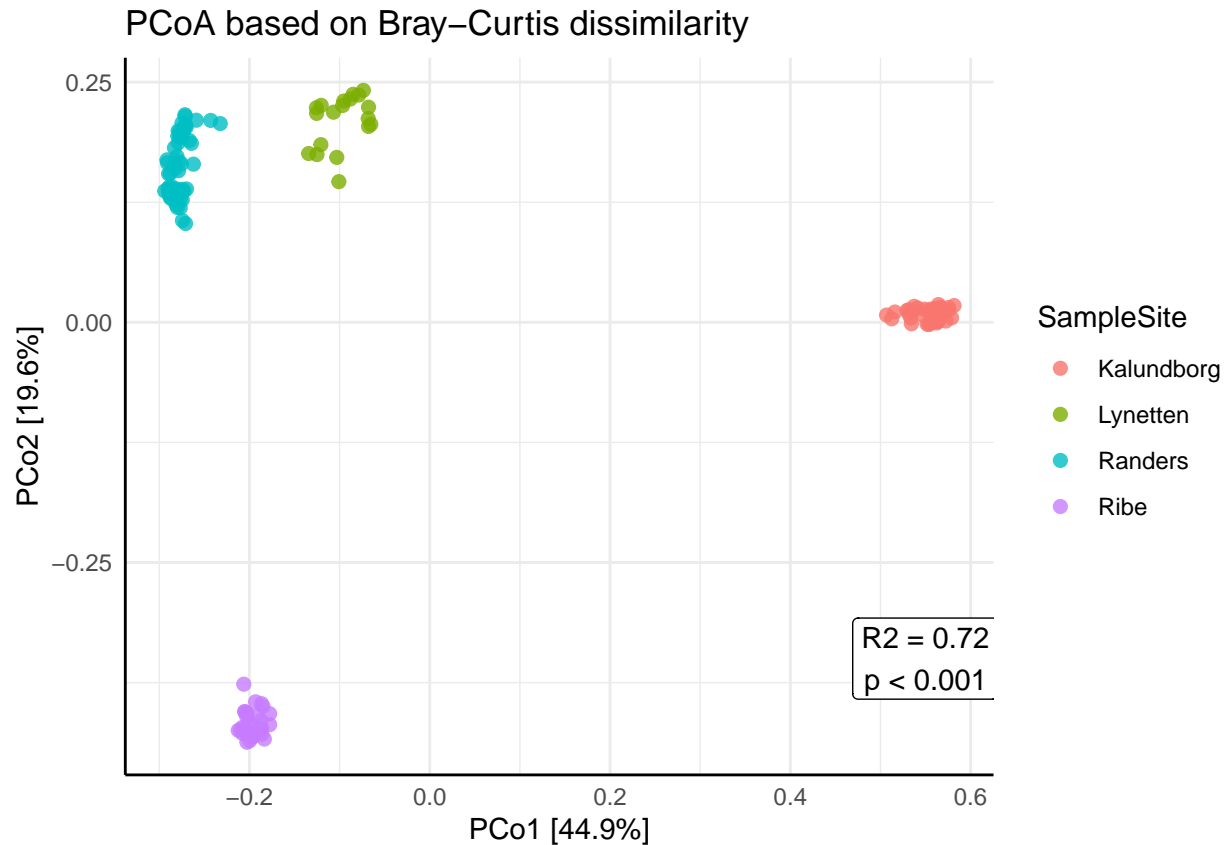
```
## 10986 OTUs not present in more than 0.1% relative abundance in any sample have been filtered
## Before: 12193 OTUs
## After: 1207 OTUs
```



(Advanced) Evaluate the statistical significance Install vegan package (install only if you don't have it)

Plot adding the statistical significance

```
## 10986 OTUs not present in more than 0.1% relative abundance in any sample have been filtered
## Before: 12193 OTUs
## After: 1207 OTUs
```



3. Microbial abundance

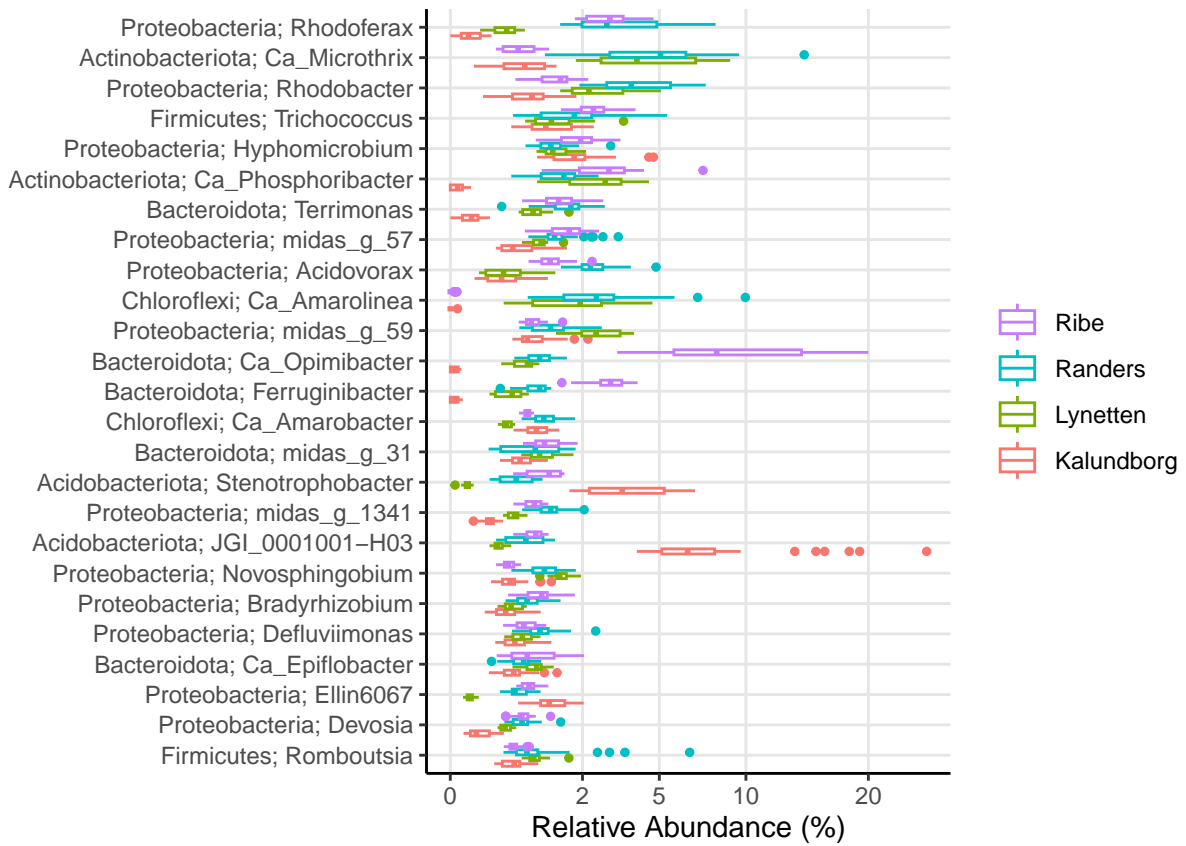
3.1 Which are the 25 most abundant genera in each Plant?

We normally start data analysis by making overview using the `amp_heatmap()` function. Modify the heatmap below using the relevant options - inspirations can be found in the Get started guide.

Top 25 genera using MiDAS 5.3

Ca_Microthrix -	0.6	4.8	4.9	0.6
JGI_0001001-H03 -	8	0.3	0.7	0.8
Ca_Opimibacter -	0	0.6	0.9	10.5
Rhodobacter -	0.7	2.7	4.1	1.3
Rhodoferrax -	0.1	0.4	3.4	2.9
Ca_Leptovillus -	6	0.8	0	0
Trichococcus -	1.2	1.4	1.7	2.5
Hyphomicrobium -	1.9	1.3	1.2	1.9
Ca_Competibacter -	0.6	8.8	0.1	0.3
midas_g_6 -	0.4	0	3.6	0.3
Stenotrophobacter -	3.8	0	0.5	1
Ca_Phosphoribacter -	0	2.6	1.4	2.8
Defluviicoccus -	4.6	0.3	0.1	0.1
Acidovorax -	0.3	0.4	2.4	1.2
midas_g_59 -	0.9	2.6	1.2	0.8
Ca_Amarolinea -	0	2	2.6	0
midas_g_57 -	0.6	0.9	1.4	1.6
Ca_Promineofilum -	0.6	5	0.2	0.4
Terrimonas -	0.1	0.8	1.6	1.4
Ferruginibacter -	0	0.4	0.9	2.9
midas_g_31 -	0.6	1	0.9	1.1
Ca_Sarcinithrix -	2.2	0.9	0.1	0.2
Ca_Amarobacter -	0.9	0.4	1.1	0.7
Ca_Lutibacillus -	0	0.3	0	3.6
midas_g_321 -	2.4	0.2	0.3	0
	Kalundborg -	Lynetten -	Randers -	Ribe -

3.2 Try visualising with a boxplot



3.3 Which are the 25 most abundant genera in each WWTP and month?

[illegible]

3.4 Which genera within Proteobacteria are the most abundant across all samples?

```
## 9123 OTUs have been filtered
```

```
## Before: 12193 OTUs
```

After: 3070 OTUs

[illegible]

3.5 Taxonomic reference database

Compare the results of microbial composition based on MiDAS 5 vs SiLVA 138.2

Q: Does the choice of taxonomic database influence alpha and beta-diversity analysis? When does it matter?

Create an ampvis2 file using Silva taxonomy

```
## Warning: Only 141 of 161 unique sample names match between metadata and otutable. The following unma
## metadata (20):
## "MQ221006-200", "MQ221006-201", "MQ221006-202", "MQ221006-203", "MQ221006-204", "MQ221006-205", "MQ
```

Create the normalised dataset removing the outlier and subsetting for samples with at least 10000 reads (tip: you can do all at once)

```
## 3 samples and 36 OTUs have been filtered
## Before: 141 samples and 12229 OTUs
## After: 138 samples and 12193 OTUs
```

What are the most abundant 25 genera based on silva?

```
## Warning in scale_fill_gradientn(colours = color.pal, trans = plot_colorscale, :
## log-10 transformation introduced infinite values.
```

Top 25 genera using SILVA 138.2

Tetrasphaera -	0	3.2	1.5	6.4
Rhodoferrax -	0.1	0.4	3.2	2.9
f__Saprospiraceae ASV688 -	0	0	0	6.5
Candidatus Microthrix -	0	2.1	2.9	0.1
f__Saprospiraceae ASV69 -	0	0	3.6	0.2
Hyphomicrobium -	1.4	1.2	1.1	1.6
o__C10-SB1A ASV3 -	0	1.9	2.6	0
p__Pseudomonadota ASV2289 -	4.2	0	0	0
f__Blastocatellaceae ASV1503 -	3.9	0	0	0
Terrimonas -	0.1	0.8	1.6	1.4
o__Ardenticatenales ASV398 -	3.6	0	0	0
f__Carnobacteriaceae ASV4 -	0.7	0.8	1	1.4
f__Microtrichaceae ASV5 -	0.3	1.4	1.5	0.4
Fuscovulum -	0.3	0.5	1.9	0.5
OLB8 -	0	0.8	1.6	0.5
Ferruginibacter -	0	0.4	0.6	2.3
f__Blastocatellaceae ASV1320 -	2.8	0	0	0
k__Bacteria ASV20 -	0	0.3	1.9	0.3
Novosphingobium -	0.4	1.3	1	0.4
f__Saprospiraceae ASV2897 -	2.4	0	0	0
Candidatus Nitrosoarchaeum -	0.8	0.6	0.6	0.5
Stenotrophobacter -	1.4	0	0.2	0.5
Candidatus Competibacter -	0.6	2.4	0.1	0.2
f__Paracoccaceae ASV19 -	0	0.3	1	0.7
f__Sphingomonadaceae ASV291 -	0.8	2.2	0	0
	Kalundborg	Lynetten	Randers	Ribe

Q: why is it important to get good taxonomic classifications? What strikes you the most?

4. Additional tasks, timeseries

4.1 Time-series ordinations

Make 2 PCA plots for Kalundborg and Randers using `sample_trajectory` option to see the changes in the community over time. Comment on the stability of the communities in the two WWTPs. What do you think may cause the progression of the communities that you see on the plot?

```
## 88 samples and 2843 OTUs have been filtered
```

```
## Before: 138 samples and 12193 OTUs
```

```
## After: 50 samples and 9350 OTUs
```

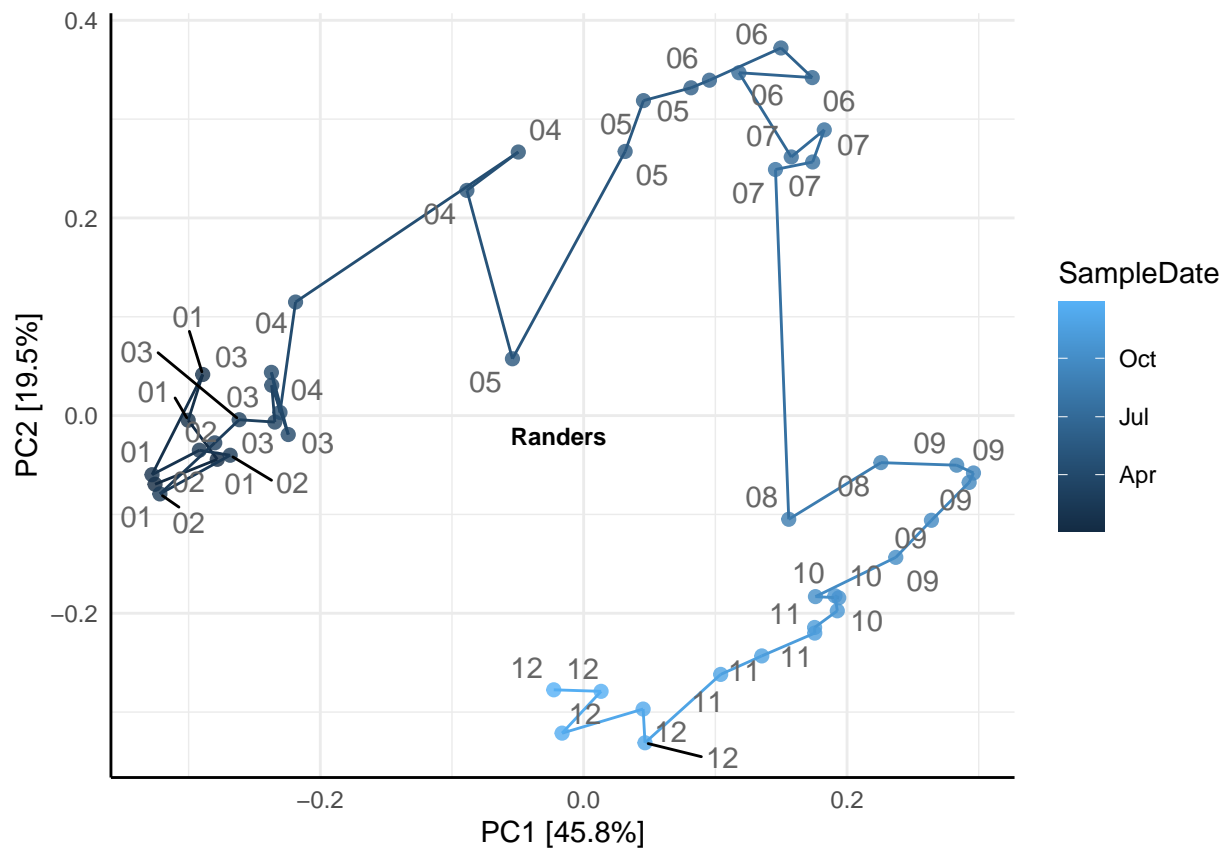
```
## 8906 OTUs not present in more than 0.1% relative abundance in any sample have been filtered
```

```
## Before: 9350 OTUs
```

```
## After: 444 OTUs
```

```
## Warning: ggrepel: 1 unlabeled data points (too many overlaps). Consider
```

```
## increasing max.overlaps
```



```
## 99 samples and 4759 OTUs have been filtered
```

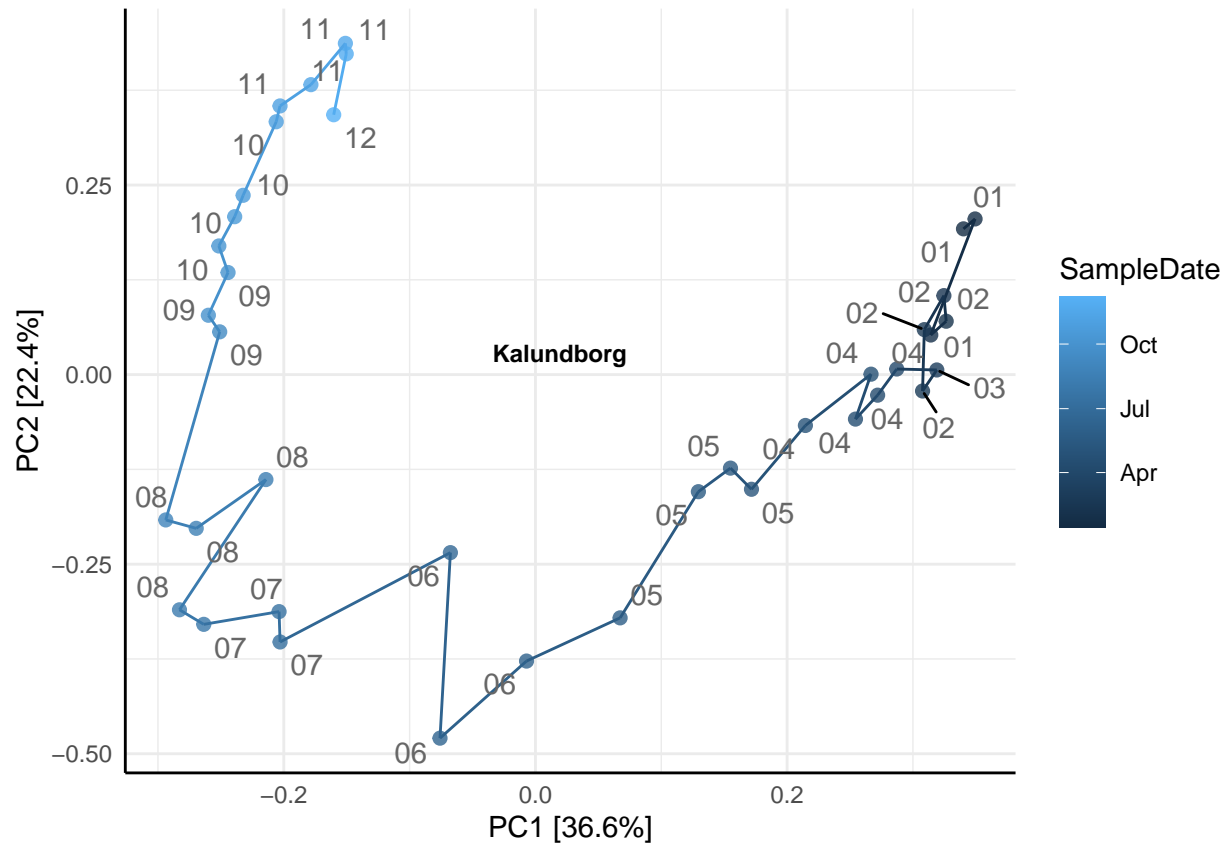
```
## Before: 138 samples and 12193 OTUs
```

```
## After: 39 samples and 7434 OTUs
```

```
## 7021 OTUs not present in more than 0.1% relative abundance in any sample have been filtered
```

```
## Before: 7434 OTUs
```

```
## After: 413 OTUs
```

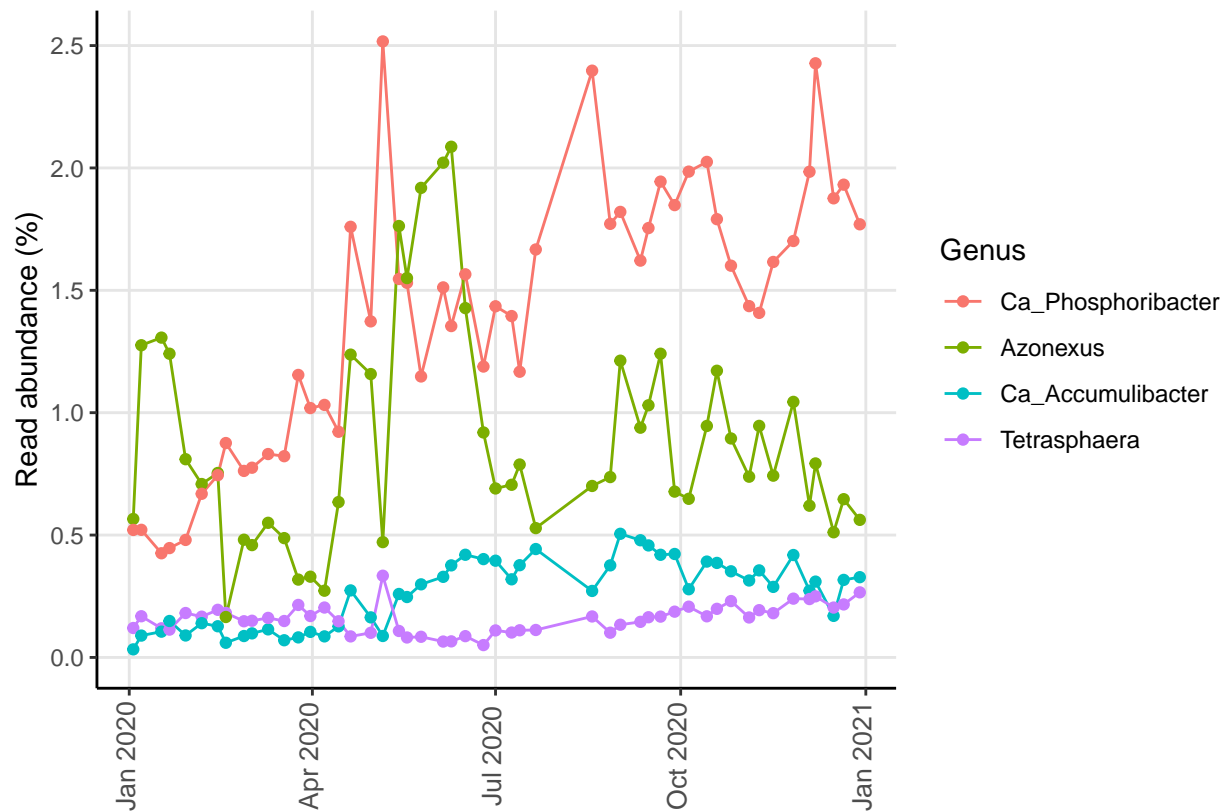


4.2 Timeseries plots

Subset the *Tetrasphaera*, *Ca. Phosphoribacter*, *Azonexus* and *Ca. Accumolibacter* genus data from Randers WWTP using `amp_subset_taxa()` and `amp_timeseries()` functions; and plot the data to identify the temporal dynamics of the different polyphosphate accumulating genera.

```
## 12078 OTUs have been filtered
## Before: 12193 OTUs
## After: 115 OTUs
```

```
## 88 samples and 11 OTUs have been filtered
## Before: 138 samples and 115 OTUs
## After: 50 samples and 104 OTUs
```



4.3 Functional information

Subset the data for Lynetten and plot the heatmap showing the 25 most abundant genera. The `amp_heatmap` function offers the possibility of directly linking the genus-level plot with functional information from midas field guide. To do that, use:

```
option plot_functions = TRUE functions = c("Filamentous", "AOB", "NOB", "PAO", "GAO")
```

How many of the genera have the functional information available? What is the function of the most abundant bacteria in this WWTP?

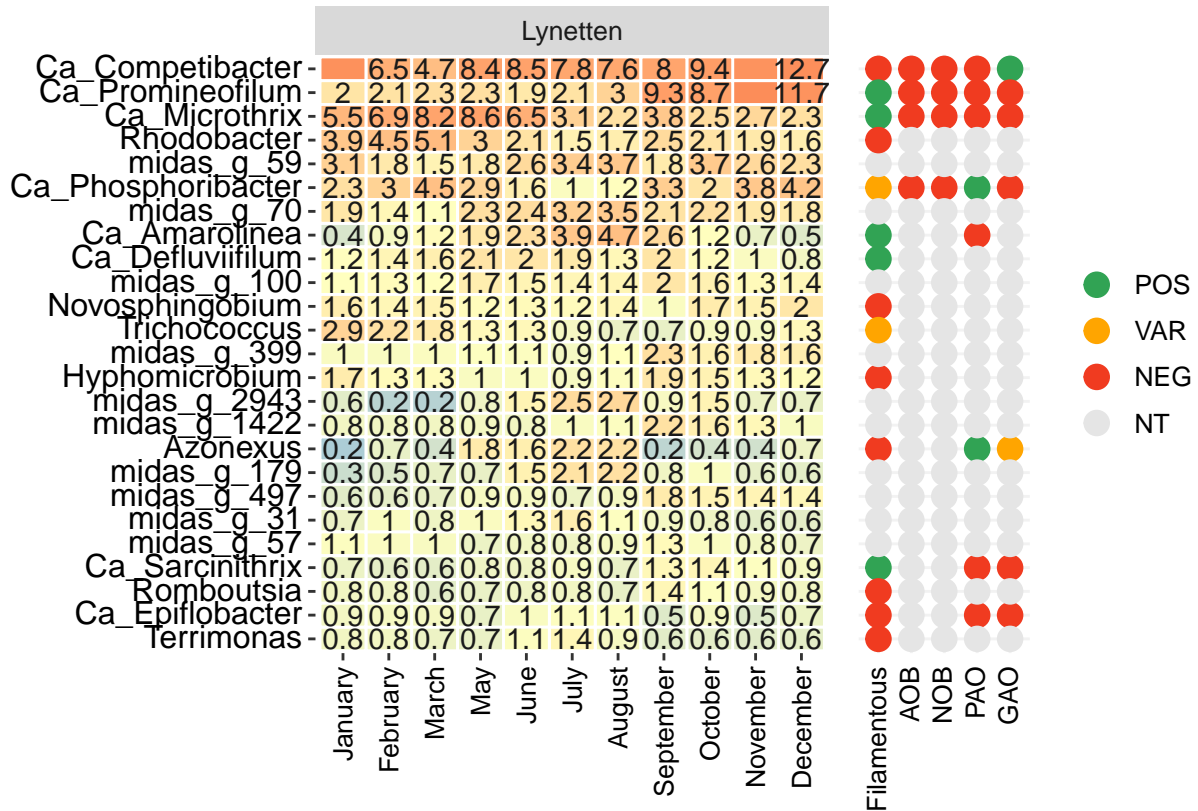
```
## 119 samples and 5157 OTUs have been filtered
## Before: 138 samples and 12193 OTUs
## After: 19 samples and 7036 OTUs

## Warning: package 'jsonlite' was built under R version 4.4.2

##
## Attaching package: 'jsonlite'

## The following object is masked from 'package:purrr':
##
##   flatten

## Warning: package 'patchwork' was built under R version 4.4.2
```



5. Core communities

(Advanced) We will evaluate the core communities in our dataset, First we need to choose the desired taxonomic level. For this exercise we will choose “Species”. The analysis is done outside ampvis2, therefore we will export the ampvis2 object to a long format data.frame

Calculate the relative abundance per species and the mean abundance in each WWTP

```
## # A tibble: 6 x 7
## # Groups:   SampleSite, Species [6]
##   SampleID   OTU   count SampleSite Species          sumSpp meanSppSite
##   <chr>      <chr> <dbl> <chr>      <chr>          <dbl>      <dbl>
## 1 MQ201118-152 ASV1  0.361 Randers    s__midas_s_5      0.364      1.04
## 2 MQ201118-152 ASV2  3.20  Randers    s__Ca_Microthrix_parvi~ 3.22      2.65
## 3 MQ201118-152 ASV3  0.893 Randers    s__Ca_Amarolinea_domin~ 0.900      2.61
## 4 MQ201118-152 ASV4  1.79  Randers    s__midas_s_4      3.38      1.70
## 5 MQ201118-152 ASV5  0.839 Randers    s__Ca_Microthrix_subdo~ 1.09      2.02
## 6 MQ201118-152 ASV7  0      Randers    s__midas_s_220     0          0.000297
```

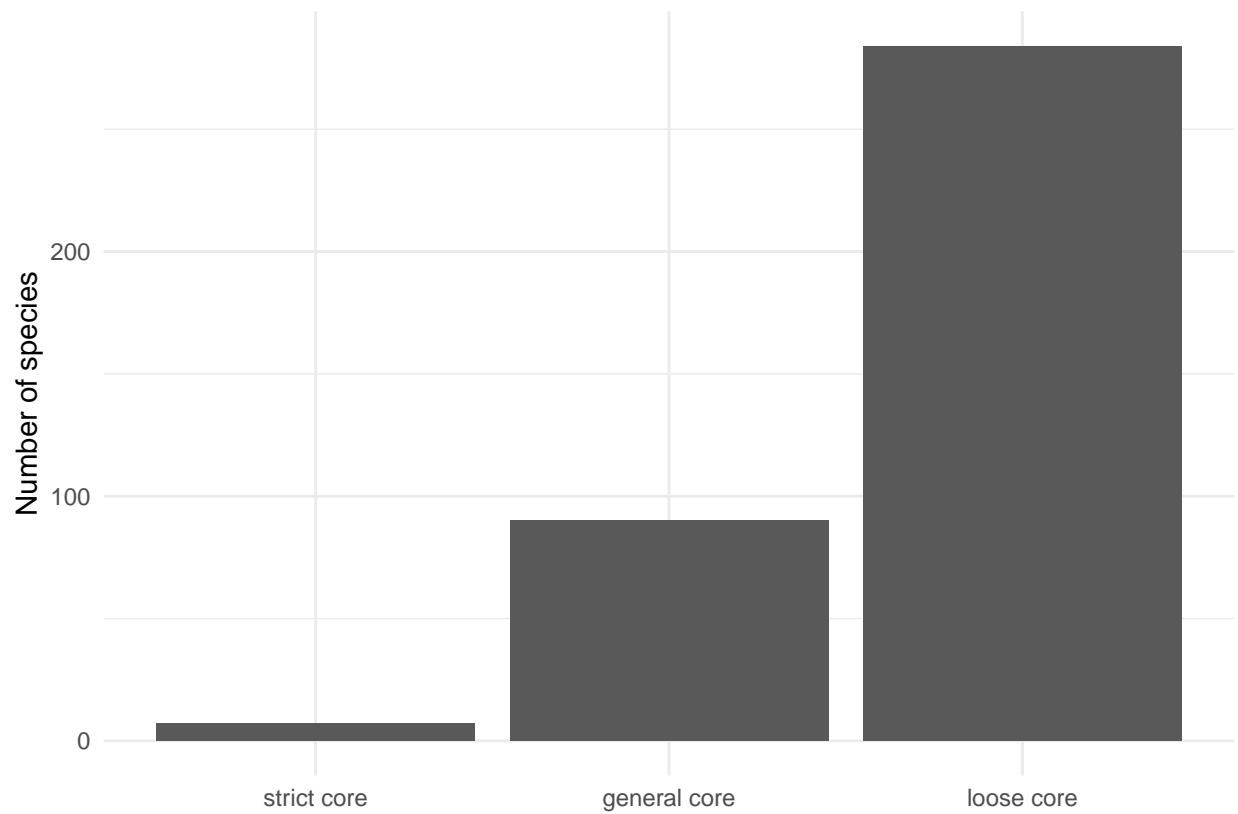
Define core groups based on abundance and create combined data.frame

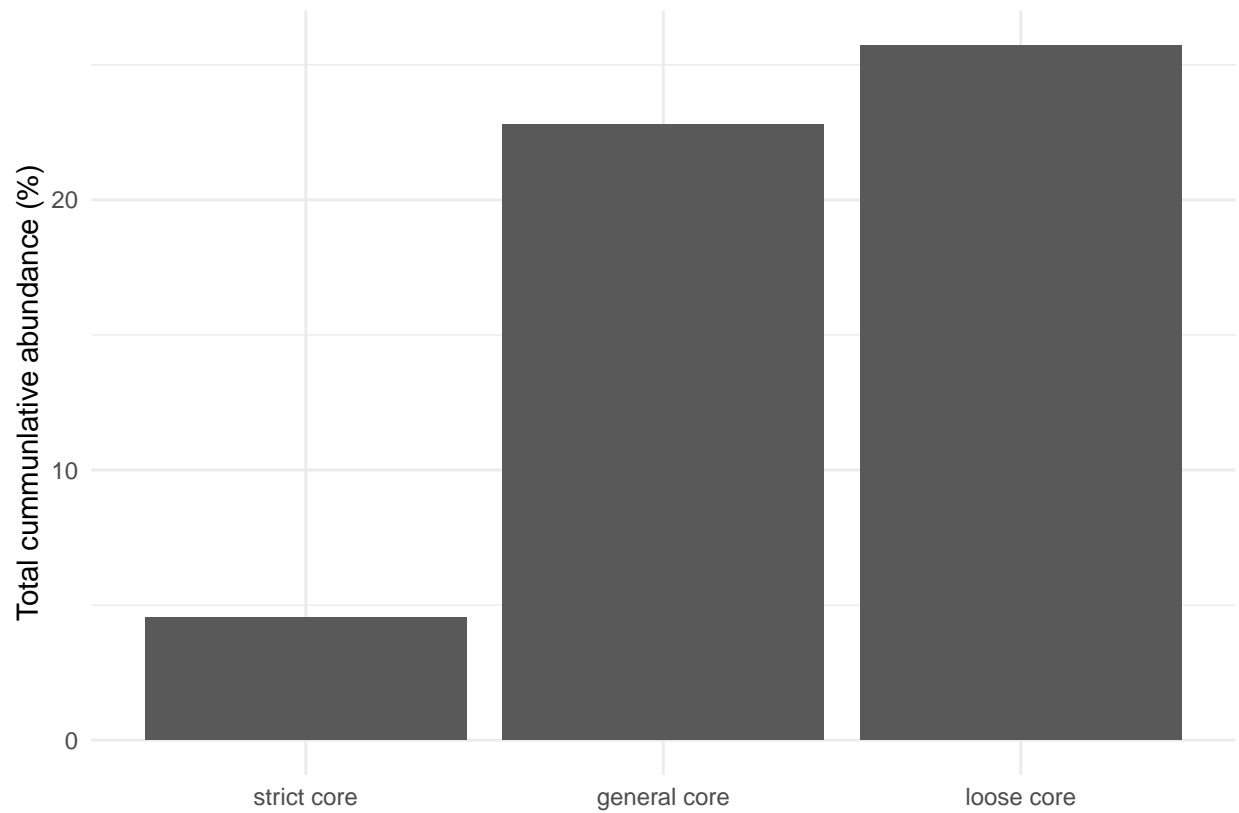
```
## # A tibble: 6 x 9
##   Species          mean_abu Category Kingdom Phylum Class Order Family Genus
##   <chr>          <dbl> <chr>      <chr>      <chr>      <chr> <chr> <chr> <chr>
## 1 s__midas_s_4      1.68  strict ~ k__Bac~ p__Fi~ c__B~ o__L~ f__Ca~ g__T~
```



```
## 2 s__Ca_Microthrix_su~ 1.44 strict ~ k__Bac~ p__Ac~ c__A~ o__M~ f__Mi~ g__C~
## 3 s__midas_s_57 0.573 strict ~ k__Bac~ p__Pr~ c__A~ o__R~ f__Rh~ g__m~
## 4 s__midas_s_1112 0.316 strict ~ k__Bac~ p__Ac~ c__T~ o__T~ f__Th~ g__S~
## 5 s__midas_s_101 0.181 strict ~ k__Bac~ p__Fi~ c__C~ o__C~ f__Cl~ g__C~
## 6 s__midas_s_64 0.179 strict ~ k__Bac~ p__Fi~ c__C~ o__C~ f__Cl~ g__C~
```

Visualise how many species are per core category and the total mean cummulative abundance the three categories explain





5.1 Core community additional tasks

Find the core communities at ASV level and visualise the outcomes

