

Regression for Microbiome Data: Moving From Diversity to Inference



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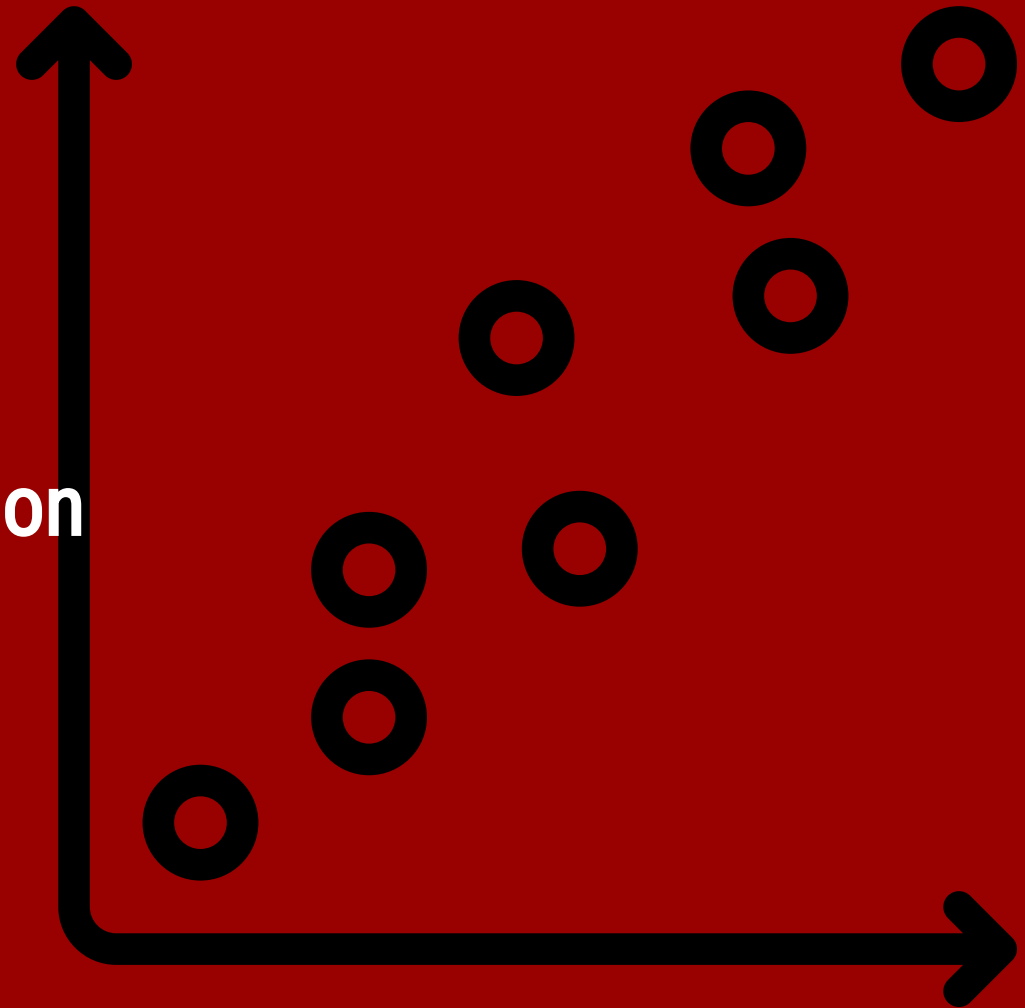
Review α -diversity

Review β -diversity

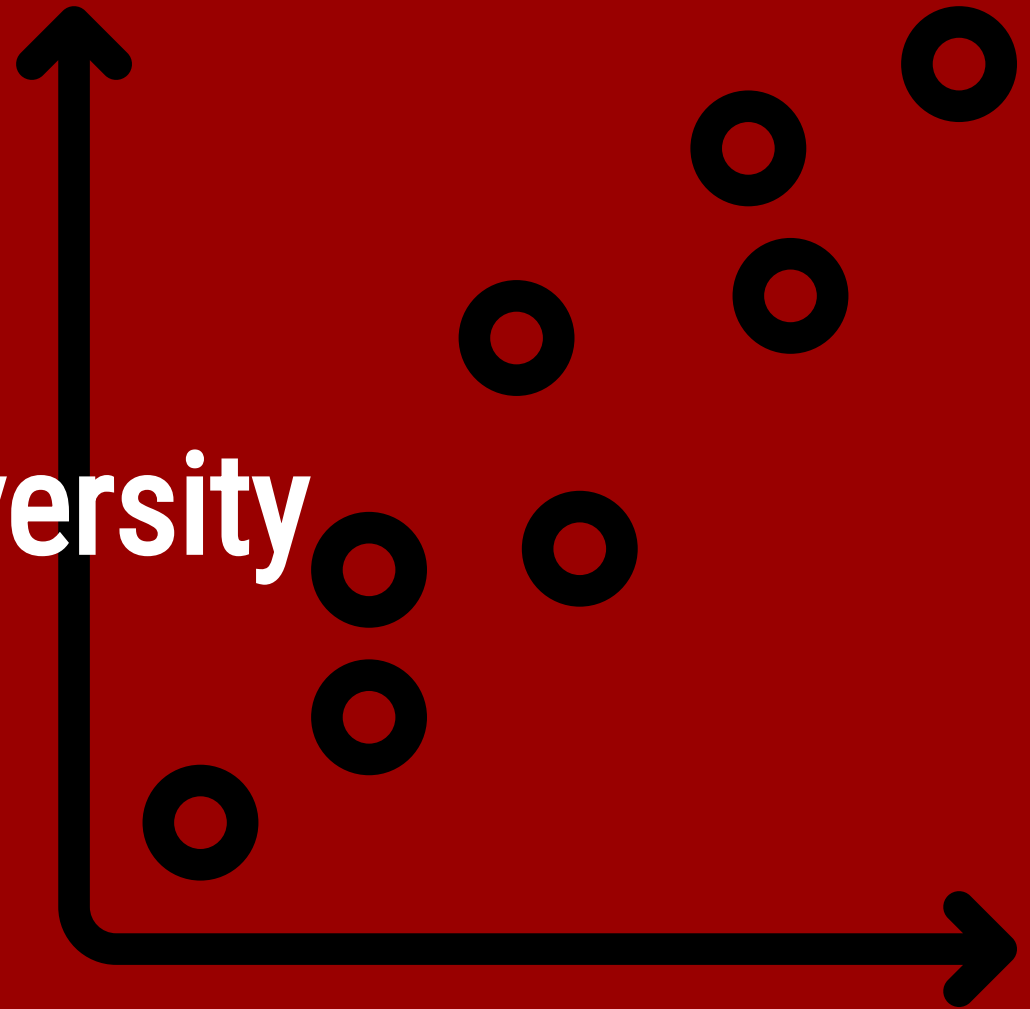
α/β -diversity \rightarrow linear regression

β -diversity \rightarrow PERMANOVA

Compositional data?



α -diversity



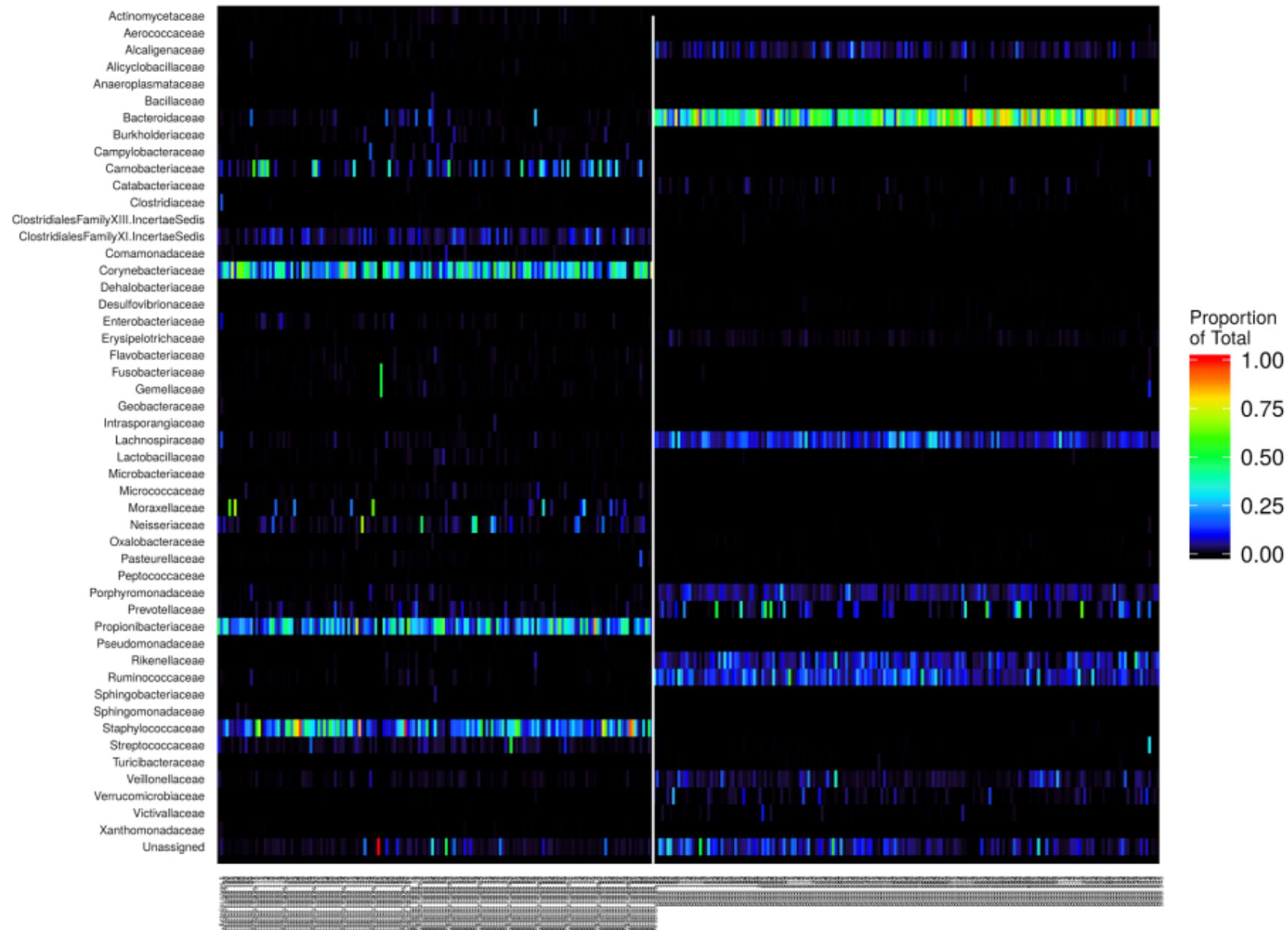
High Dimensional Microbiome Data

##	700013549	700014386	700014403	700014409	700014412	700014415
## OTU_97.1	0	0	0	0	0	0
## OTU_97.10	0	0	6	4	1	5
## OTU_97.100	0	0	133	7	1	4
## OTU_97.1000	0	0	0	0	0	0
## OTU_97.10000	0	0	0	0	0	0
## OTU_97.10001	0	0	0	0	0	1
## OTU_97.10002	0	0	0	0	0	0
## OTU_97.10003	0	0	0	0	0	0
## OTU_97.10004	0	0	0	0	0	0
## OTU_97.10005	0	0	0	0	0	0
## OTU_97.10006	0	0	0	0	0	0
## OTU_97.10007	0	0	0	0	0	0
## OTU_97.10008	0	1	0	0	0	0
## OTU_97.10009	0	0	1	0	0	0
## OTU_97.1001	0	0	0	0	0	0
## OTU_97.10010	0	0	0	0	0	0

High Dimensional Microbiome Data

- How to deal with high-dimensional microbiome data?
- **Descriptive (e.g., heatmaps and stacked barplots)**
- Test a priori hypotheses regarding specific OTUs/taxa
- Reduce dimensions:
 - single summary statistic (alpha diversity)
 - pairwise distances (beta diversity) with PCoA or PERMANOVA
 - community types (mixture modeling)

Anterior Nares vs Stool



High Dimensional Microbiome Data

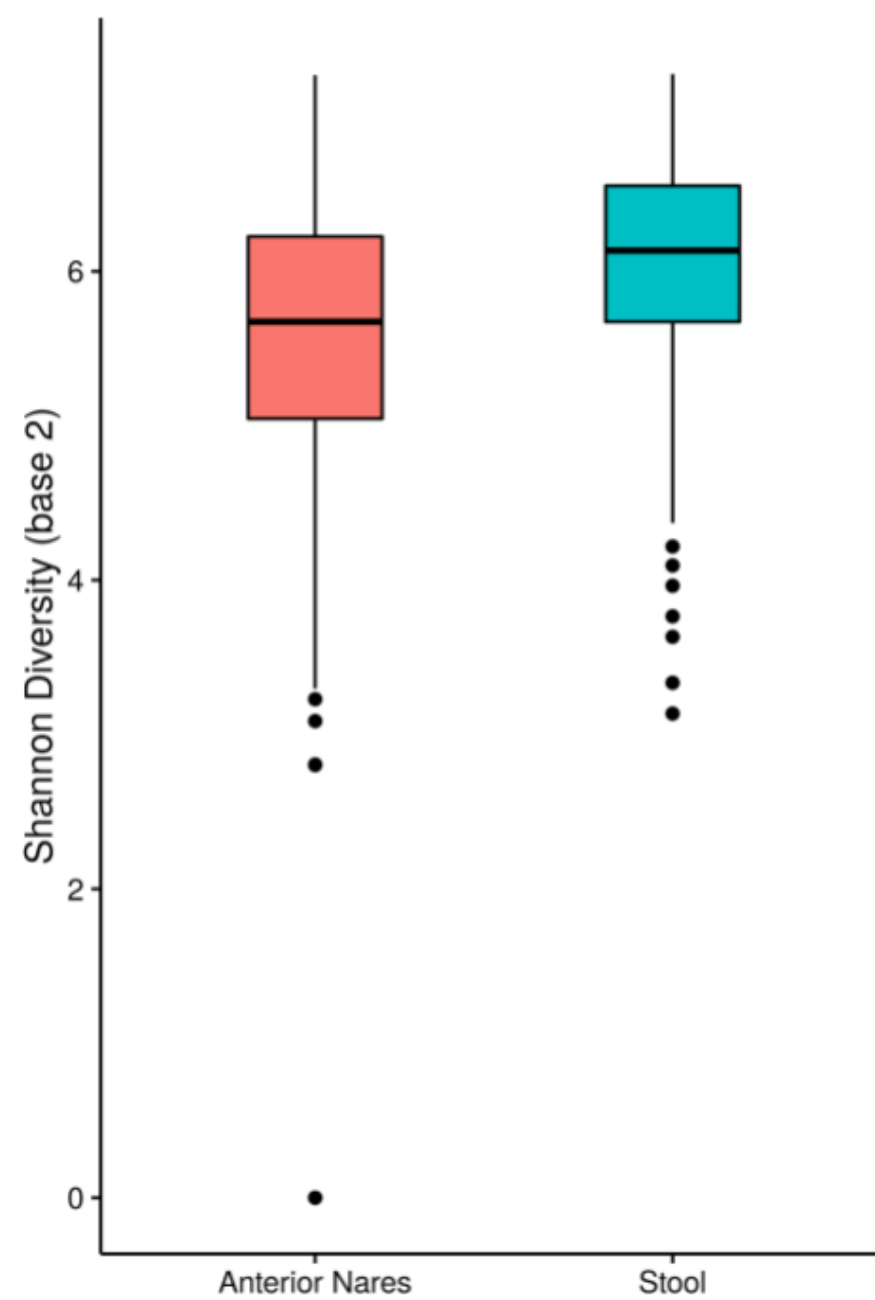
- How to deal with high-dimensional microbiome data?
- Descriptive (e.g., heatmaps and stacked barplots)
- Test a priori hypotheses regarding specific OTUs/taxa
- **Reduce dimensions:**
 - **single summary statistic (alpha diversity)**
 - pairwise distances (beta diversity) with PCoA or PERMANOVA
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Shannon Diversity

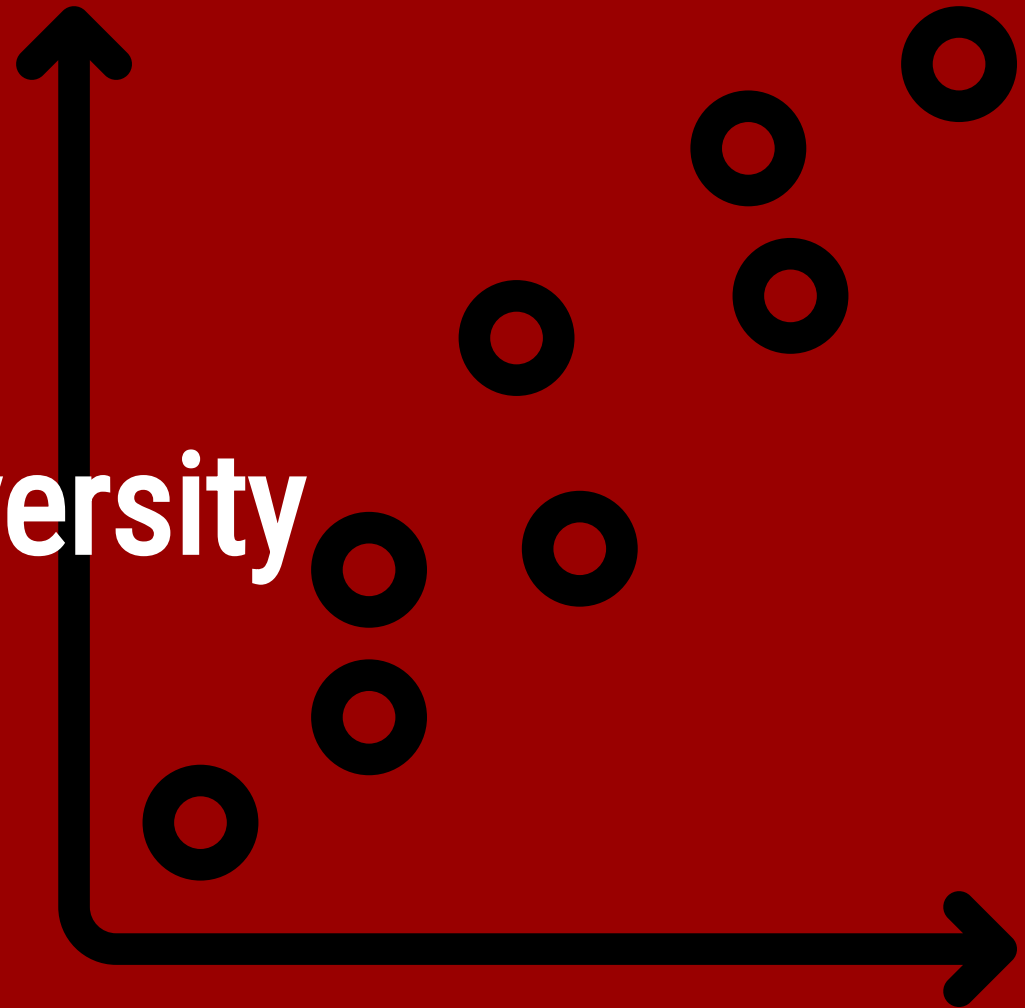
- **Richness** & **evenness**
- Shannon diversity:

$$H' = - \sum p_i * \log_b (p_i)$$

- "The uncertainty contained in a probability distribution is the average log-probability of an event." (McElreath *Statistical Rethinking*, 2nd 2020)



β -diversity

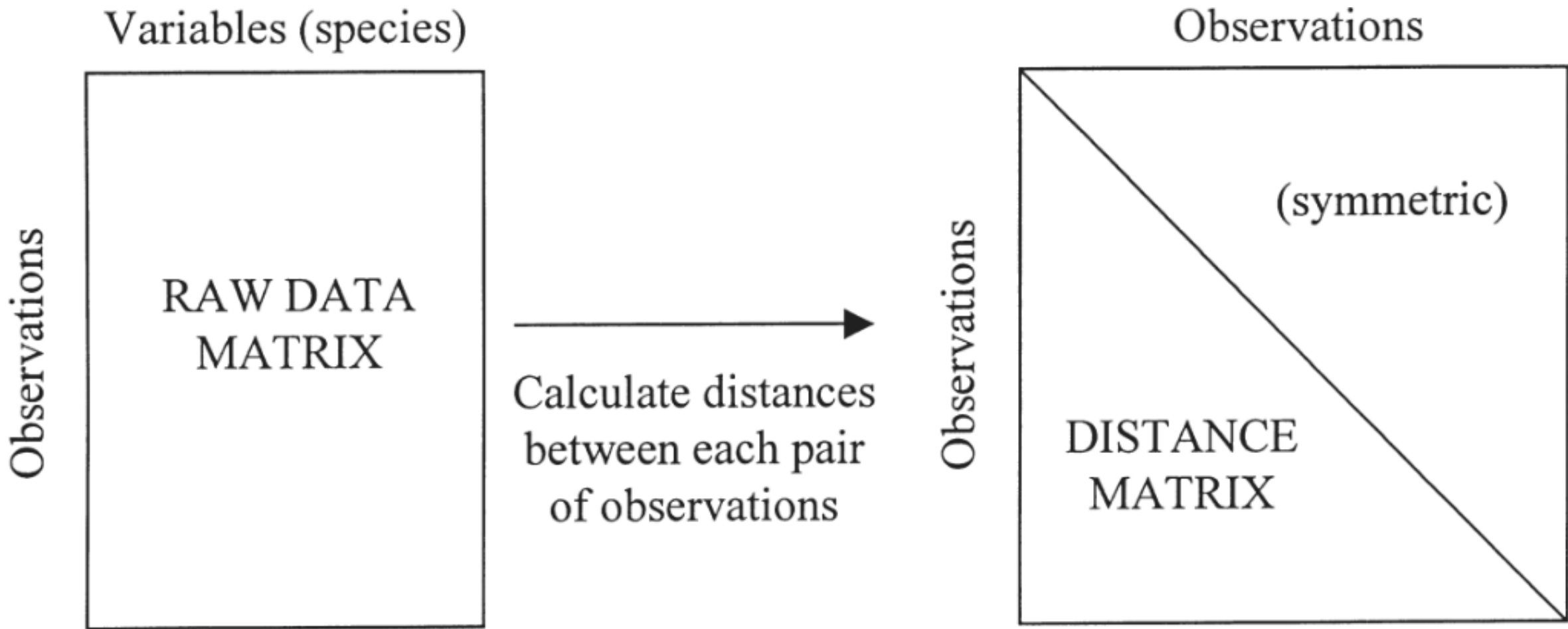


High Dimensional Microbiome Data

- How to deal with high-dimensional microbiome data?
- Descriptive (e.g., heatmaps and stacked barplots)
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 - **pairwise distances (beta diversity) with PCoA or PERMANOVA**
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Beta Diversity as Dimension Reduction

- Summarize each sample's relationship to other samples:
 - pairwise distances
 - OTU table → square matrix
- Many beta diversity metrics:
 - just counts versus counts + phylogeny
 - weighted versus unweighted



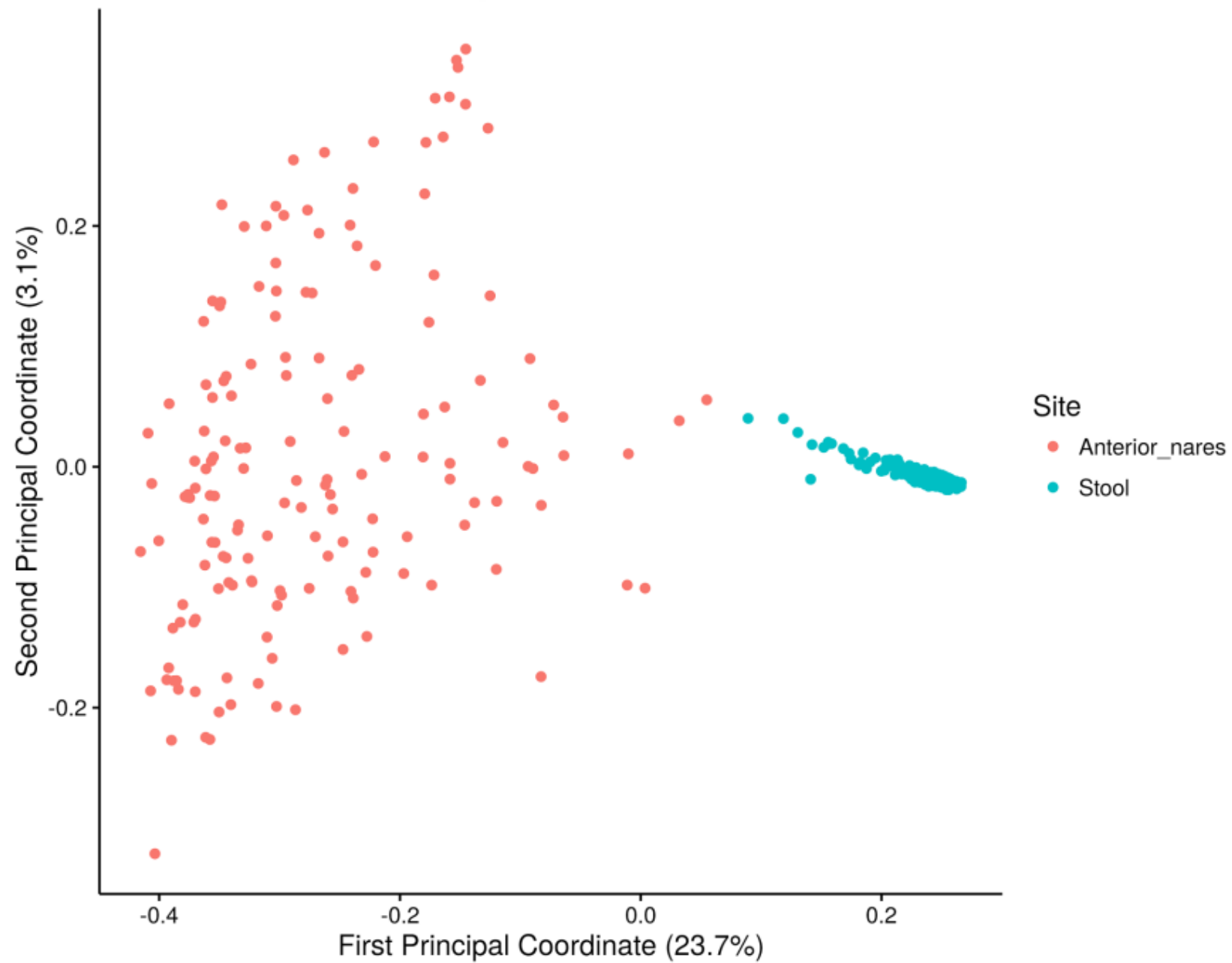
Distance Metrics for Beta Diversity

- Just counts versus counts + phylogeny:
 - Jaccard: $J(A, B) = \frac{A \cap B}{A \cup B}$ & $d_J(A, B) = 1 - J(A, B)$
 - UniFrac: fraction of unique branch length in tree
- Weighted versus unweighted:
 - weighted: counts matter
 - unweighted: binary (presence-absence)

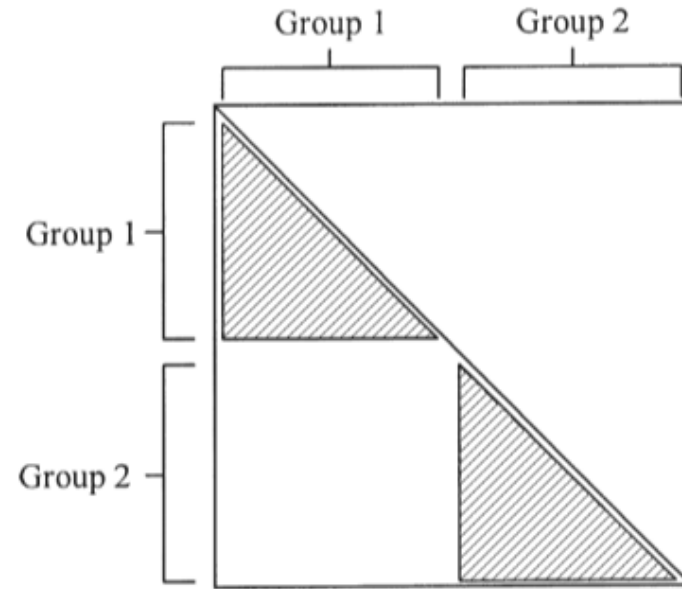
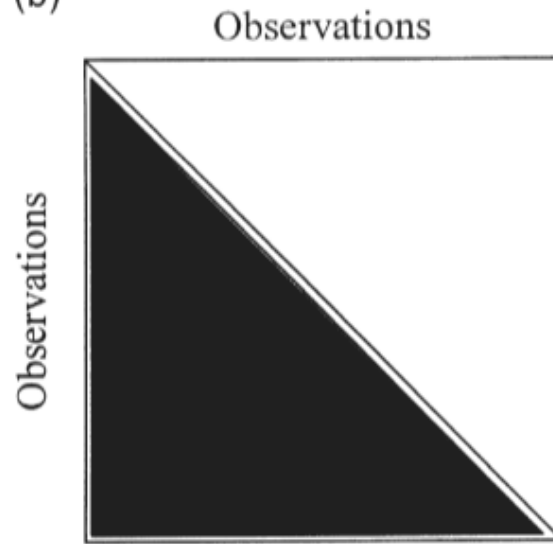
Pairwise Distances → PCoA

- PCoA: principal coordinate analysis
 - any metric distance, even if non-Euclidean
 - like PCA, eigenvalue decomposition (maximum variance) but mediated by distance function (no original descriptors)
 - unlike PCA, does not allow projection of original descriptors in reduced-dimension space

Weighted UniFrac

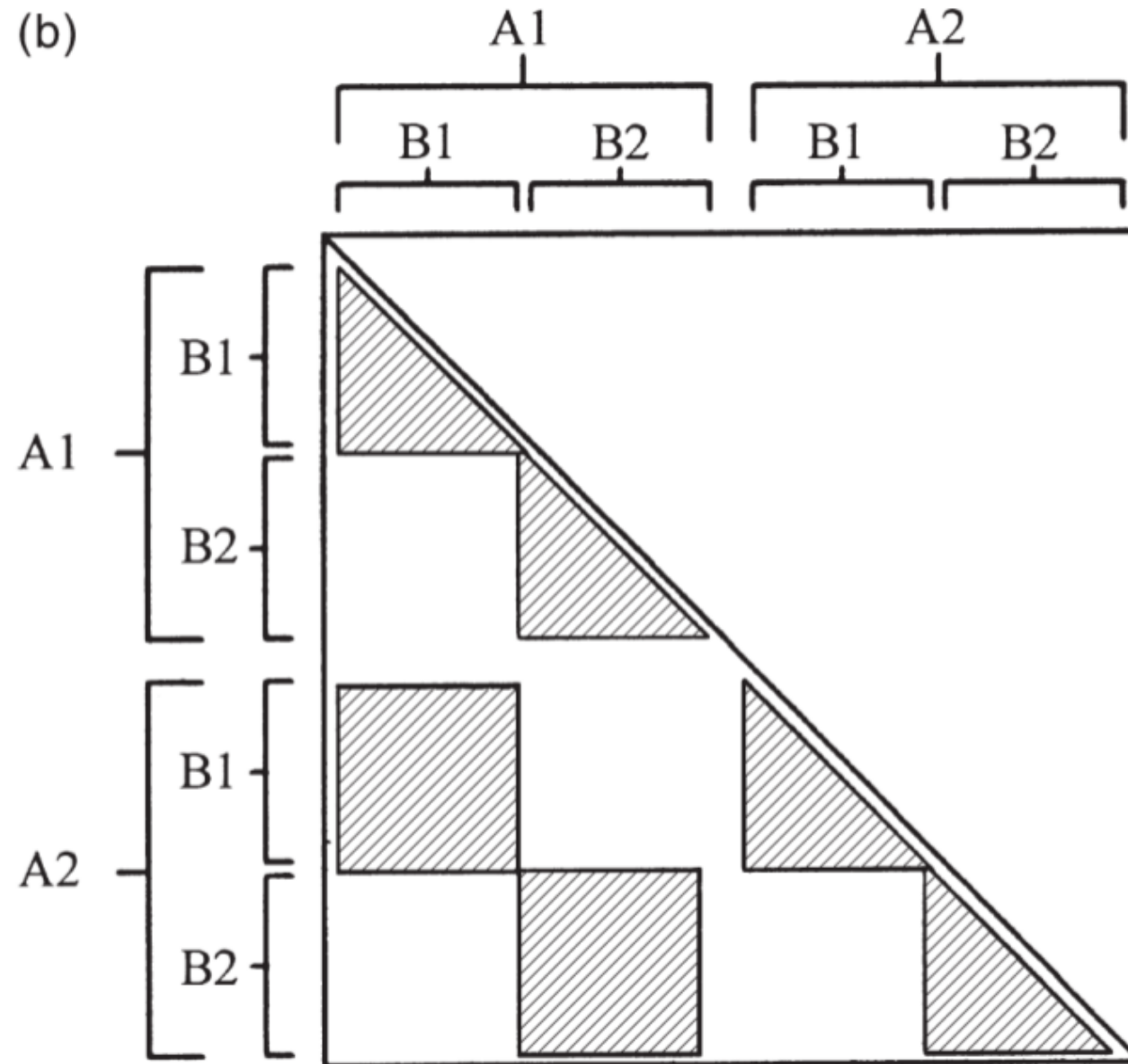


(b)



$$F = \frac{SS_A / (a - 1)}{SS_W / (N - a)}$$

(b)



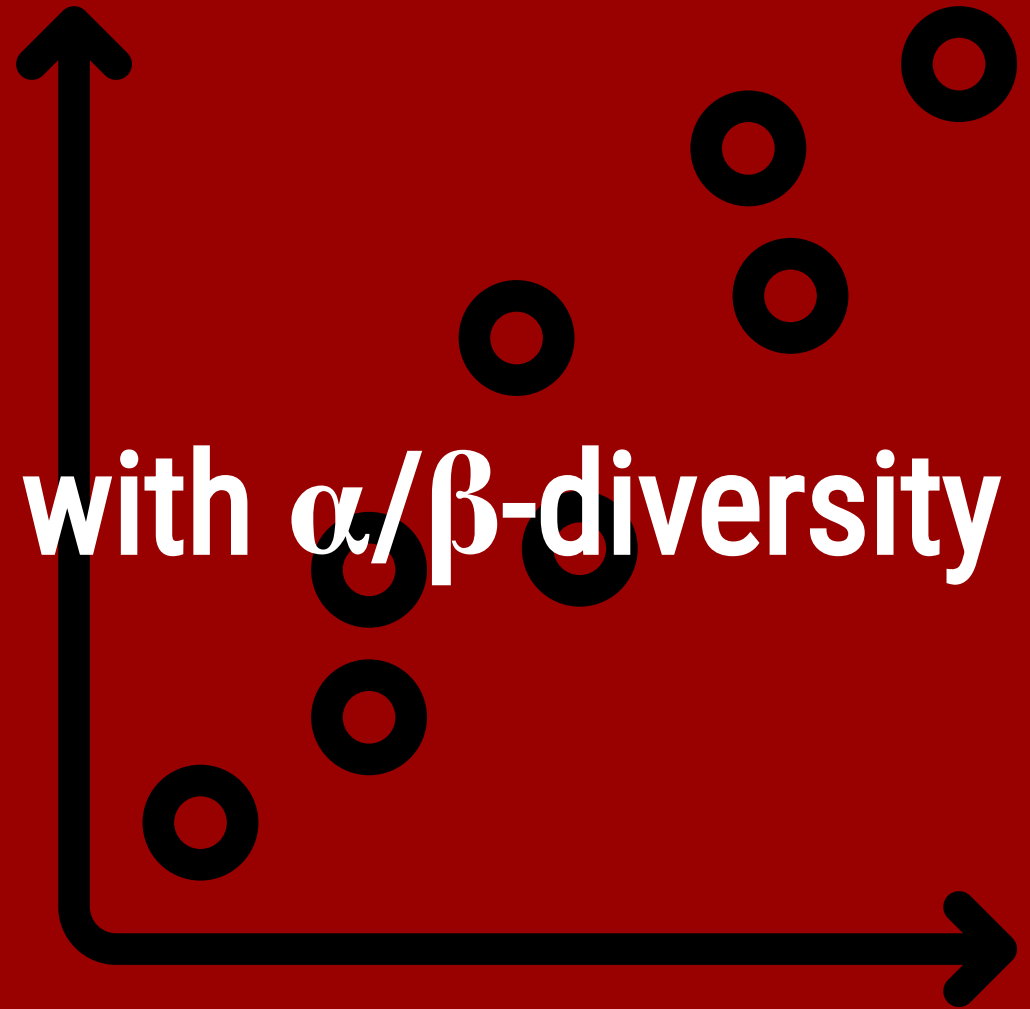
$$R^2 = 1 - \frac{SS_W}{SS_W + SS_A} = \frac{SS_A}{SS_T}$$

$$\omega^2 = \frac{SS_A - (a-1) \frac{SS_W}{N-a}}{SS_T + \frac{SS_W}{N-a}}$$

Table 1. Effect sizes observed from various exposures/interventions in studies of various microbiome sampling sites are shown as measured by omega-squared (ω^2) statistics, together with the *P*-values from PERMANOVA test

Site	Comparison groups		ω^2/P -value				Reference
	Control	Exposure	Weighted UniFrac	Unweighted UniFrac	Weighted Jaccard	Unweighted Jaccard	
Nares	Non-smoker (33)	Smoker (29)	0.042/0.001	0.009/0.001	0.023/0.001	0.007/0.001	Charlson <i>et al.</i> (2010)
Oral	Non-smoker (33)	Smoker (29)	0.032/0.001	0.008/0.001	0.024/0.001	0.007/0.001	Charlson <i>et al.</i> (2010)
Gut	Before feeding (10)	After feeding (10)	0.056/0.138	0.013/0.986	0/0.989	0.014/0.985	Wu <i>et al.</i> (2011)
Oral	No azithromycin (42)	Azithromycin (6)	0.063/0.01	0.039/0.001	0.099/0.004	0.032/0.001	Charlson <i>et al.</i> (2012)
Lung	No azithromycin (34)	Azithromycin (6)	0.065/0.005	0.038/0.001	0.019/0.089	0.033/0.001	Charlson <i>et al.</i> (2012)
Skin	Left retroauricular (186)	Right retroauricular (187)	0.000/0.828	0.0001/0.327	0.000/0.986	0.000/1.000	HMP Consortium (2012b)
Human	Anterior nares (161)	Stool (187)	0.567/0.001	0.201/0.001	0.230/0.001	0.117/0.001	HMP Consortium (2012b)

Linear regression with α/β -diversity



Linear Regression with **lm()**

```
# install.packages("tidyverse")
library(tidyverse)

# install.packages("vegan")
library(vegan)

# install.packages("ape")
library(ape)

set.seed(16)

otu_tab <- read_rds(
  "./data/HMP_OTU_table_matrix_stool_nares.rds"
)

otu_tab %>%
  str(vec.len = 3)
```

```
## num [1:43140, 1:10] 0 0 0 0 0 0 0 0 ...
## - attr(*, "dimnames")=List of 2
## ..$ : chr [1:43140] "OTU_97.1" "OTU_97.10" "OTU_97.100" ...
## ..$ : chr [1:10] "700014718" "700014767" "700014923" ...
```

Linear Regression with **lm()**

```
otu_tab %>%  
  as_tibble(rownames = "otu_id") %>%  
  gather(key = "specimen_id",  
         value = "read_count",  
         -otu_id) %>%  
  distinct() -> otu_long  
  
otu_long
```

```
## # A tibble: 431,400 x 3  
##   otu_id      specimen_id read_count  
##   <chr>      <chr>          <dbl>  
## 1 OTU_97.1    700014718            0  
## 2 OTU_97.10   700014718            0  
## 3 OTU_97.100  700014718            0  
## 4 OTU_97.1000 700014718            0  
## 5 OTU_97.10000 700014718            0  
## 6 OTU_97.10001 700014718            0  
## 7 OTU_97.10002 700014718            0  
## 8 OTU_97.10003 700014718            0  
## 9 OTU_97.10004 700014718            0  
## 10 OTU_97.10005 700014718            0  
## # ... with 431,390 more rows
```

Linear Regression with `lm()`

```
read_tsv(file = "../data/v13_map_uniquebyPSN.txt.bz2") %>%
  rename_all(.funs = ~ gsub("#", "", tolower(.x))) %>%
  rename(specimen_id = sampleid) %>%
  distinct() -> specimen_data

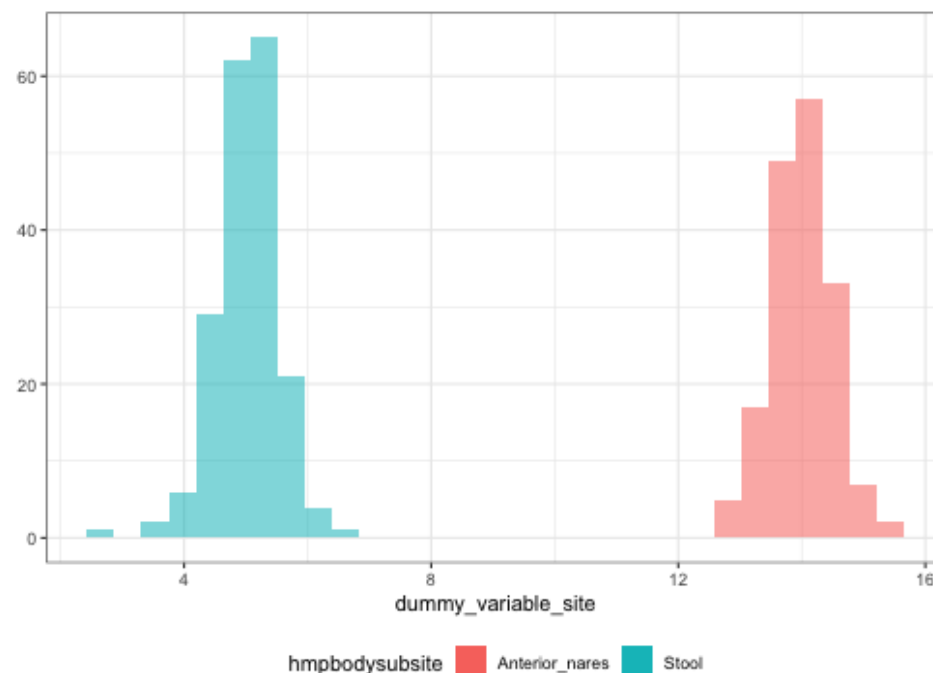
specimen_data %>%
  group_by(hmpbodysubsite) %>%
  mutate(dummy_variable_site =
    rnorm(n = length(hmpbodysubsite),
          mean = nchar(unique(hmpbodysubsite)),
          sd = 0.5)) %>%
  ungroup() %>%
  filter(hmpbodysubsite %in%
    c("Anterior_nares", "Stool")) %>%
  select(specimen_id,
    hmpbodysubsite,
    dummy_variable_site) %>%
  mutate(specimen_id = as.character(specimen_id)) %>%
  distinct() -> specimen_data

specimen_data
```

```
## # A tibble: 361 x 3
##   specimen_id hmpbodysubsite dummy_variable_site
##   <chr>      <chr>                <dbl>
## 1 700013549    Stool                    5.87
## 2 700014386    Stool                    4.68
## 3 700014445    Anterior_nares          14.2
## 4 700014488    Stool                    4.95
## 5 700014497    Stool                    5.36
## 6 700014527    Anterior_nares          13.9
## 7 700014555    Stool                    4.39
## 8 700014718    Stool                    4.10
## 9 700014767    Anterior_nares          14.5
## 10 700014797    Anterior_nares          13.3
## # ... with 351 more rows
```

Linear Regression with **lm()**

```
specimen_data %>%  
  qplot(data = .,  
        x = dummy_variable_site,  
        fill = hmpbodysubsite,  
        alpha = 0.8,  
        geom = "histogram",  
        position = "identity") +  
  scale_alpha(guide = FALSE) +  
  theme_bw() +  
  theme(legend.position = "bottom")
```



Linear Regression with `lm()`

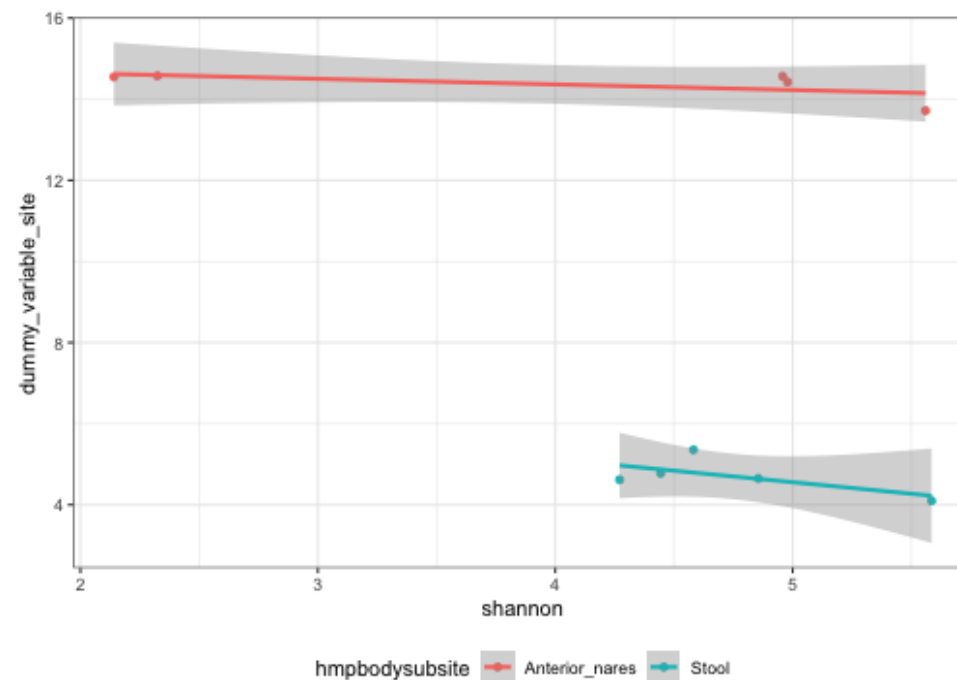
```
otu_long %>%
  group_by(specimen_id) %>%
  summarise(shannon = diversity(x = read_count,
                              index = "shannon")) %>%
  ungroup() %>%
  left_join(specimen_data, by = "specimen_id") %>%
  mutate(dummy_variable_shannon =
    rnorm(n = length(shannon),
          mean = 0,
          sd = 0.2) +
    shannon) %>%
  distinct() -> shannon_summary

shannon_summary
```

```
## # A tibble: 10 x 5
##   specimen_id shannon hmpbodysubsite dummy_variable_site dummy_var
##   <chr>      <dbl> <chr>                <dbl>
## 1 700014718    5.58 Stool                4.10
## 2 700014767    2.14 Anterior_nares      14.5
## 3 700014923    2.32 Anterior_nares      14.6
## 4 700016920    4.96 Anterior_nares      14.6
## 5 700023706    4.98 Anterior_nares      14.4
## 6 700038343    5.56 Anterior_nares      13.7
## 7 700095956    4.86 Stool                4.65
## 8 700105834    4.58 Stool                5.36
## 9 700107189    4.27 Stool                4.62
## 10 700109383    4.44 Stool                4.78
```

Linear Regression with `lm()`

```
shannon_summary %>%  
  qplot(data = .,  
        x = shannon,  
        y = dummy_variable_site,  
        color = hmpbodysubsite,  
        geom = c("point", "smooth"),  
        method = "lm") +  
  theme_bw() +  
  theme(legend.position = "bottom")
```



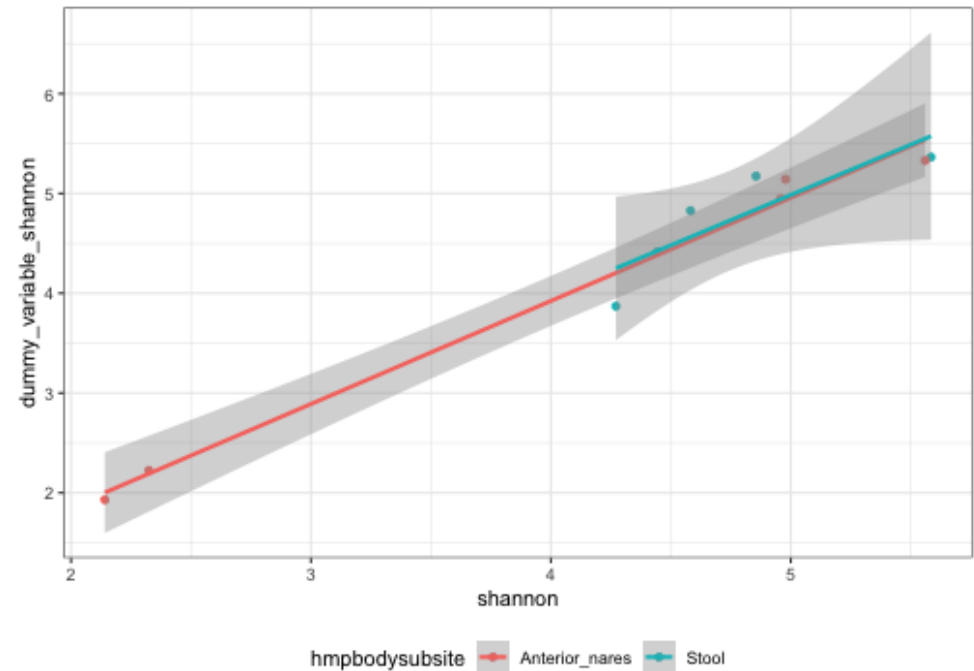
Linear Regression with **lm()**

```
shannon_summary %>%  
  lm(formula = dummy_variable_site ~ shannon,  
     data = .) %>%  
  summary()
```

```
##  
## Call:  
## lm(formula = dummy_variable_site ~ shannon, data = .)  
##  
## Residuals:  
##      Min       1Q   Median       3Q      Max   
## -5.0672 -4.0586 -0.9973  4.8409  6.0355   
##  
## Coefficients:  
##              Estimate Std. Error t value Pr(>|t|)      
## (Intercept)   16.328     6.301   2.591   0.032 *      
## shannon       -1.555     1.395  -1.115   0.297      
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## Residual standard error: 5.041 on 8 degrees of freedom  
## Multiple R-squared:  0.1345,    Adjusted R-squared:  0.02627   
## F-statistic: 1.243 on 1 and 8 DF,  p-value: 0.2973
```

Linear Regression with **lm()**

```
shannon_summary %>%  
  qplot(data = .,  
        x = shannon,  
        y = dummy_variable_shannon,  
        color = hmpbodysubsite,  
        geom = c("point", "smooth"),  
        method = "lm") +  
  theme_bw() +  
  theme(legend.position = "bottom")
```



Linear Regression with `lm()`

```
shannon_summary %>%  
  lm(formula = dummy_variable_shannon ~ shannon,  
     data = .) %>%  
  summary()
```

```
##  
## Call:  
## lm(formula = dummy_variable_shannon ~ shannon, data = .)  
##  
## Residuals:  
##      Min       1Q   Median       3Q      Max   
## -0.34993 -0.18375  0.01602  0.14710  0.34814   
##  
## Coefficients:  
##              Estimate Std. Error t value Pr(>|t|)      
## (Intercept) -0.20539    0.30165  -0.681    0.515      
## shannon      1.03619    0.06678  15.515 2.96e-07 ***  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## Residual standard error: 0.2413 on 8 degrees of freedom  
## Multiple R-squared:  0.9678,    Adjusted R-squared:  0.9638   
## F-statistic: 240.7 on 1 and 8 DF,  p-value: 2.965e-07
```

Linear Regression with **lm()**

```
shannon_summary %>%  
  lm(formula = dummy_variable_shannon ~ shannon +  
      hmpbodysubsite,  
      data = .) %>%  
  summary()
```

```
##  
## Call:  
## lm(formula = dummy_variable_shannon ~ shannon + hmpbodysubsite,  
##      data = .)  
##  
## Residuals:  
##      Min       1Q   Median       3Q      Max   
## -0.3688 -0.1690  0.0134  0.1674  0.3323   
##  
## Coefficients:  
##              Estimate Std. Error t value Pr(>|t|)      
## (Intercept)   -0.20055    0.32224  -0.622    0.553      
## shannon         1.03088    0.07540  13.672 2.64e-06 ***  
## hmpbodysubsiteStool 0.03673    0.17233   0.213   0.837      
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## Residual standard error: 0.2572 on 7 degrees of freedom  
## Multiple R-squared:  0.968,    Adjusted R-squared:  0.9589   
## F-statistic: 106 on 2 and 7 DF,  p-value: 5.834e-06
```

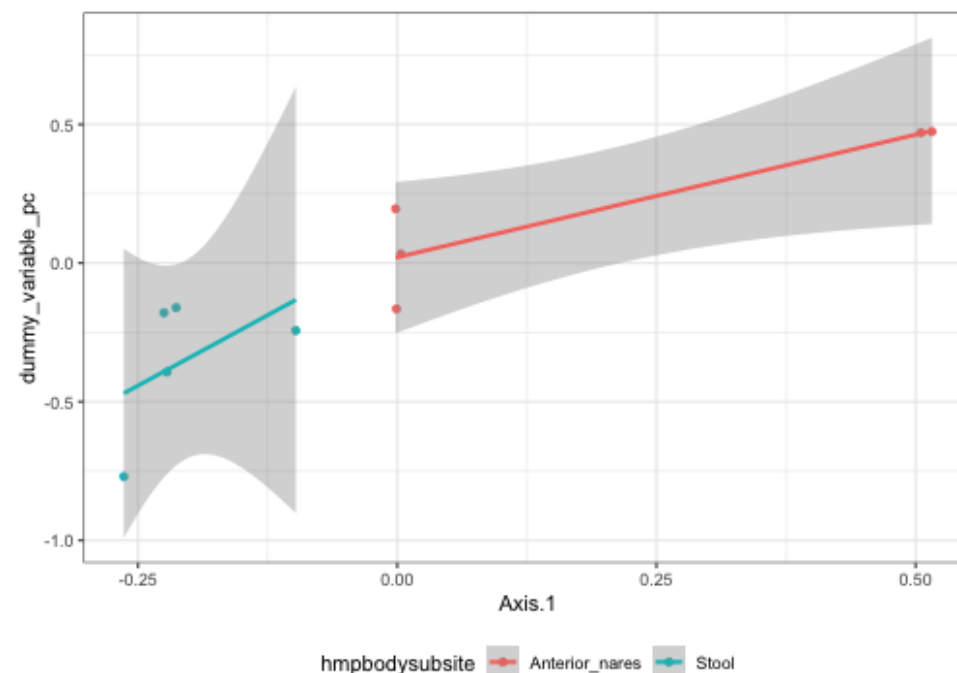
Linear Regression with `lm()`

```
otu_tab %>%  
  t() %>% # TRANSPOSE  
  vegdist(x = ., method = "jaccard") %>%  
  pcoa(D = .) -> pc  
  
pc$Vectors %>%  
  as_tibble(rownames = "specimen_id") %>%  
  select(specimen_id, Axis.1, Axis.2) %>%  
  left_join(shannon_summary, by = "specimen_id") %>%  
  mutate(dummy_variable_pc =  
    rnorm(n = length(shannon),  
          mean = 0,  
          sd = 0.2) +  
    Axis.1) %>%  
  distinct() -> pc_summary  
  
pc_summary
```

```
## # A tibble: 10 x 8  
##   specimen_id Axis.1 Axis.2 shannon hmpbodysubsite dummy_variab  
##   <chr>      <dbl> <dbl> <dbl> <chr> <dbl>  
## 1 700014718 -2.64e-1 0.222 5.58 Stool 1  
## 2 700014767 5.16e-1 0.174 2.14 Anterior_nares 1  
## 3 700014923 5.05e-1 0.183 2.32 Anterior_nares 1  
## 4 700016920 3.50e-3 -0.434 4.96 Anterior_nares 1  
## 5 700023706 -8.28e-4 -0.290 4.98 Anterior_nares 1  
## 6 700038343 -1.54e-3 -0.435 5.56 Anterior_nares 1  
## 7 700095956 -2.22e-1 0.189 4.86 Stool  
## 8 700105834 -2.25e-1 0.174 4.58 Stool  
## 9 700107189 -9.78e-2 0.0363 4.27 Stool  
## 10 700109383 -2.13e-1 0.180 4.44 Stool  
## # ... with 2 more variables: dummy_variable_shannon <dbl>,  
## # dummy_variable_pc <dbl>
```

Linear Regression with **lm()**

```
pc_summary %>%  
  qplot(data = .,  
        x = Axis.1,  
        y = dummy_variable_pc,  
        color = hmpbodysubsite,  
        geom = c("point", "smooth"),  
        method = "lm") +  
  theme_bw() +  
  theme(legend.position = "bottom")
```



Linear Regression with `lm()`

```
pc_summary %>%  
  lm(formula = dummy_variable_pc ~ Axis.1,  
      data = .) %>%  
  summary()
```

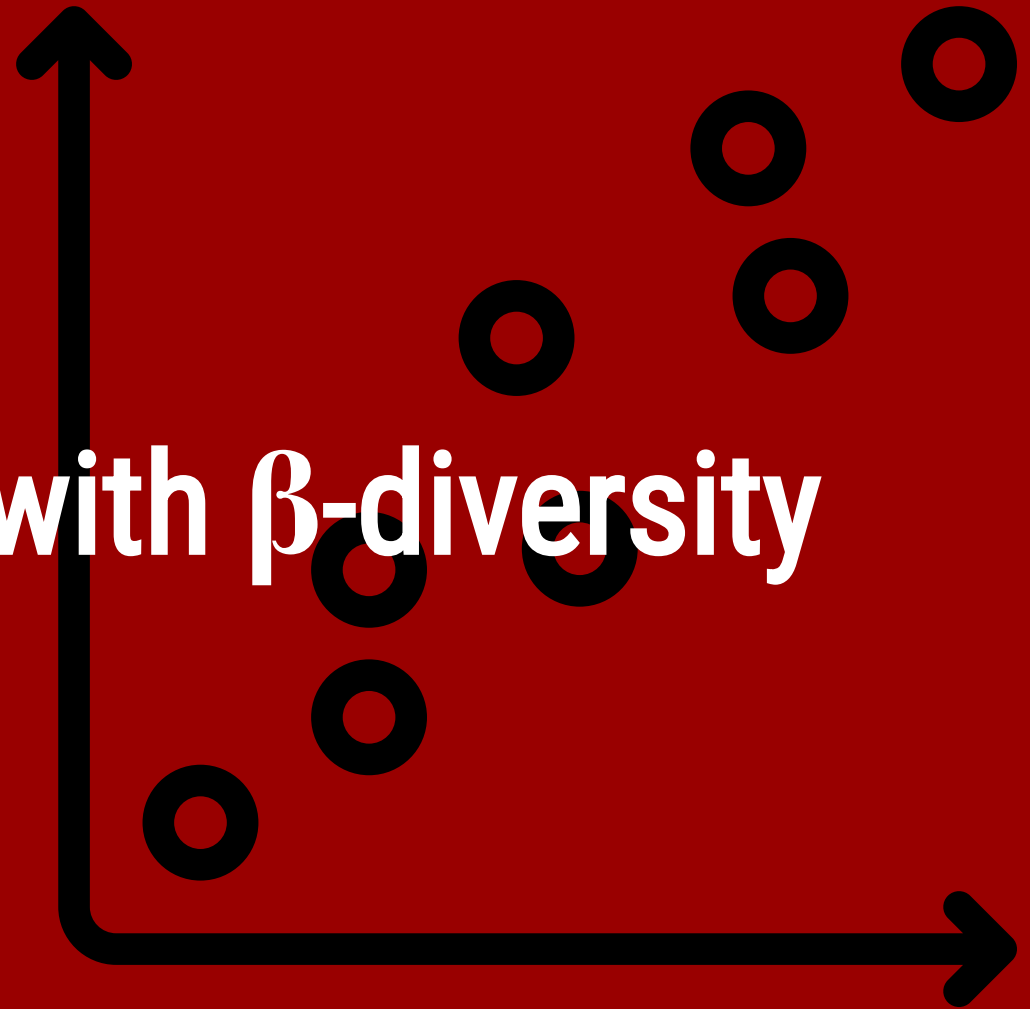
```
##  
## Call:  
## lm(formula = dummy_variable_pc ~ Axis.1, data = .)  
##  
## Residuals:  
##      Min       1Q   Median       3Q      Max   
## -0.38811 -0.05846 -0.04998  0.14369  0.27116   
##  
## Coefficients:  
##              Estimate Std. Error t value Pr(>|t|)      
## (Intercept) -0.07387    0.06180  -1.195  0.266241      
## Axis.1       1.16777    0.22633   5.160  0.000864 ***  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## Residual standard error: 0.1954 on 8 degrees of freedom  
## Multiple R-squared:  0.7689,    Adjusted R-squared:  0.74   
## F-statistic: 26.62 on 1 and 8 DF,  p-value: 0.0008641
```

Linear Regression with **lm()**

```
pc_summary %>%  
  lm(formula = dummy_variable_pc ~ Axis.2,  
    data = .) %>%  
  summary()
```

```
##  
## Call:  
## lm(formula = dummy_variable_pc ~ Axis.2, data = .)  
##  
## Residuals:  
##      Min       1Q   Median       3Q      Max   
## -0.63113 -0.17200 -0.04452  0.10175  0.59896   
##  
## Coefficients:  
##              Estimate Std. Error t value Pr(>|t|)      
## (Intercept) -0.07387    0.12574  -0.587    0.573      
## Axis.2      -0.29223    0.48408  -0.604    0.563      
##  
## Residual standard error: 0.3976 on 8 degrees of freedom  
## Multiple R-squared:  0.04357,    Adjusted R-squared:  -0.07598   
## F-statistic: 0.3644 on 1 and 8 DF,  p-value: 0.5628
```

PERMANOVA with β -diversity



PERMANOVA with **adonis()**

```
otu_tab %>%  
  t() %>% # TRANSPOSE  
  vegdist(x = ., method = "jaccard") -> otu_dist  
  
otu_dist %>%  
  str(vec.len = 2)
```

```
## 'dist' num [1:45] 1 0.996 ...  
## - attr(*, "Size")= int 10  
## - attr(*, "Labels")= chr [1:10] "700014718" "700014767" ...  
## - attr(*, "Diag")= logi FALSE  
## - attr(*, "Upper")= logi FALSE  
## - attr(*, "method")= chr "jaccard"  
## - attr(*, "call")= language vegdist(x = ., method = "jaccard")
```

PERMANOVA with `adonis()`

```
labels(otu_dist) %>% #match order from dist
  enframe(value = "specimen_id") %>%
  select(specimen_id) %>%
  left_join(pc_summary, by = "specimen_id") %>%
  mutate(dummy_category = Axis.1 > mean(Axis.1)) %>%
  distinct() -> sorted_summary

sorted_summary
```

```
## # A tibble: 10 x 9
##   specimen_id  Axis.1  Axis.2 shannon hmpbodysubsite dummy_variab
##   <chr>      <dbl>  <dbl>  <dbl> <chr>
## 1 700014718   -2.64e-1  0.222    5.58 Stool
## 2 700014767    5.16e-1  0.174    2.14 Anterior_nares
## 3 700014923    5.05e-1  0.183    2.32 Anterior_nares
## 4 700016920    3.50e-3 -0.434    4.96 Anterior_nares
## 5 700023706   -8.28e-4 -0.290    4.98 Anterior_nares
## 6 700038343   -1.54e-3 -0.435    5.56 Anterior_nares
## 7 700095956   -2.22e-1  0.189    4.86 Stool
## 8 700105834   -2.25e-1  0.174    4.58 Stool
## 9 700107189   -9.78e-2  0.0363    4.27 Stool
## 10 700109383   -2.13e-1  0.180    4.44 Stool
## # ... with 3 more variables: dummy_variable_shannon <dbl>,
## #   dummy_variable_pc <dbl>, dummy_category <lgl>
```

PERMANOVA with **adonis()**

```
# distance matrix is response variable
```

```
adonis(otu_dist ~ hmpbodysubsite,  
       data = sorted_summary)
```

```
##  
## Call:  
## adonis(formula = otu_dist ~ hmpbodysubsite, data = sorted_summary)  
##  
## Permutation: free  
## Number of permutations: 999  
##  
## Terms added sequentially (first to last)  
##  
##           Df SumsOfSqs MeanSqs F.Model    R2 Pr(>F)  
## hmpbodysubsite 1    0.7036 0.70364  1.5719 0.16422 0.014 *  
## Residuals      8    3.5811 0.44764          0.83578  
## Total          9    4.2847          1.00000  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

PERMANOVA with **adonis()**

```
# multivariable possible...  
adonis(otu_dist ~ hmpbodysubsite + dummy_category,  
       data = sorted_summary)
```

```
##  
## Call:  
## adonis(formula = otu_dist ~ hmpbodysubsite + dummy_category,      data = sorted_summary)  
##  
## Permutation: free  
## Number of permutations: 999  
##  
## Terms added sequentially (first to last)  
##  
##           Df SumsOfSqs MeanSqs F.Model      R2 Pr(>F)  
## hmpbodysubsite 1    0.7036 0.70364  1.6100 0.16422 0.002 **  
## dummy_category 1    0.5218 0.52180  1.1939 0.12178 0.125  
## Residuals      7    3.0593 0.43704          0.71400  
## Total          9    4.2847          1.00000  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

PERMANOVA with **adonis()**

```
# ... but order matters!!!
```

```
adonis(otu_dist ~ dummy_category + hmpbodysubsite,  
       data = sorted_summary)
```

```
##
```

```
## Call:
```

```
## adonis(formula = otu_dist ~ dummy_category + hmpbodysubsite,      data = sorted_summary)
```

```
##
```

```
## Permutation: free
```

```
## Number of permutations: 999
```

```
##
```

```
## Terms added sequentially (first to last)
```

```
##
```

	Df	SumsOfSqs	MeanSqs	F.Model	R2	Pr(>F)
## dummy_category	1	0.6329	0.63293	1.4482	0.14772	0.018 *
## hmpbodysubsite	1	0.5925	0.59251	1.3557	0.13828	0.036 *
## Residuals	7	3.0593	0.43704		0.71400	
## Total	9	4.2847			1.00000	

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```


PERMANOVA with **adonis()**

```
# ... do you mean strata?  
adonis(otu_dist ~ dummy_category,  
       strata = sorted_summary$hmpbodysubsite,  
       data = sorted_summary)
```

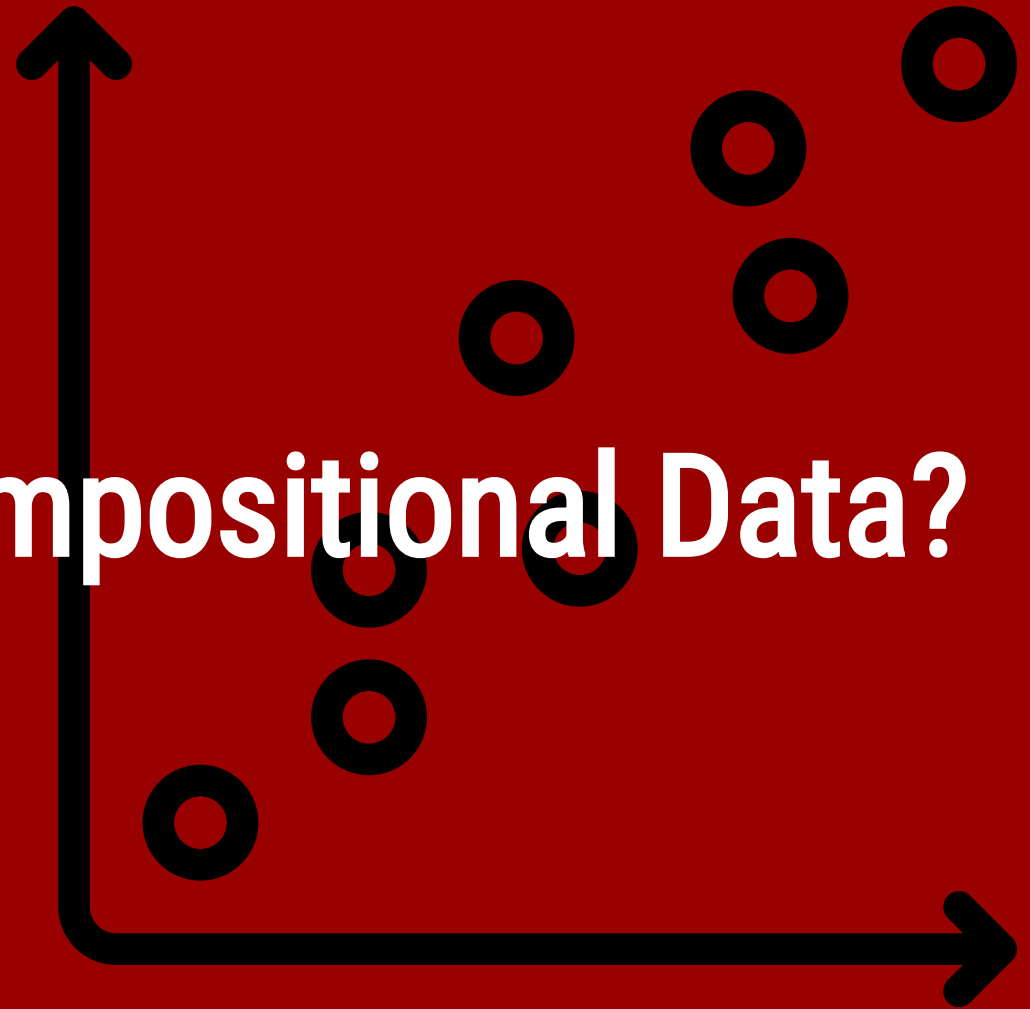
```
##  
## Call:  
## adonis(formula = otu_dist ~ dummy_category, data = sorted_summary,      strata = sorted_summary$hmpbodysubsite)  
##  
## Blocks:  strata  
## Permutation: free  
## Number of permutations: 999  
##  
## Terms added sequentially (first to last)  
##  
##           Df SumsOfSqs MeanSqs F.Model    R2 Pr(>F)  
## dummy_category  1    0.6329 0.63293  1.3865 0.14772 0.291  
## Residuals      8    3.6518 0.45648      0.85228  
## Total          9    4.2847      1.00000
```

PERMANOVA with **adonis()**

```
# ... or do you mean nestedness?  
adonis(otu_dist ~ dummy_category / hmpbodysubsite,  
       data = sorted_summary)
```

```
##  
## Call:  
## adonis(formula = otu_dist ~ dummy_category/hmpbodysubsite, data = sorted_summary)  
##  
## Permutation: free  
## Number of permutations: 999  
##  
## Terms added sequentially (first to last)  
##  
##  
##          Df SumsOfSqs MeanSqs F.Model    R2 Pr(>F)  
## dummy_category      1    0.6329 0.63293   1.4482 0.14772 0.009 **  
## dummy_category:hmpbodysubsite 1    0.5925 0.59251   1.3557 0.13828 0.023 *  
## Residuals          7    3.0593 0.43704         0.71400  
## Total              9    4.2847         1.00000  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Regression & Compositional Data?

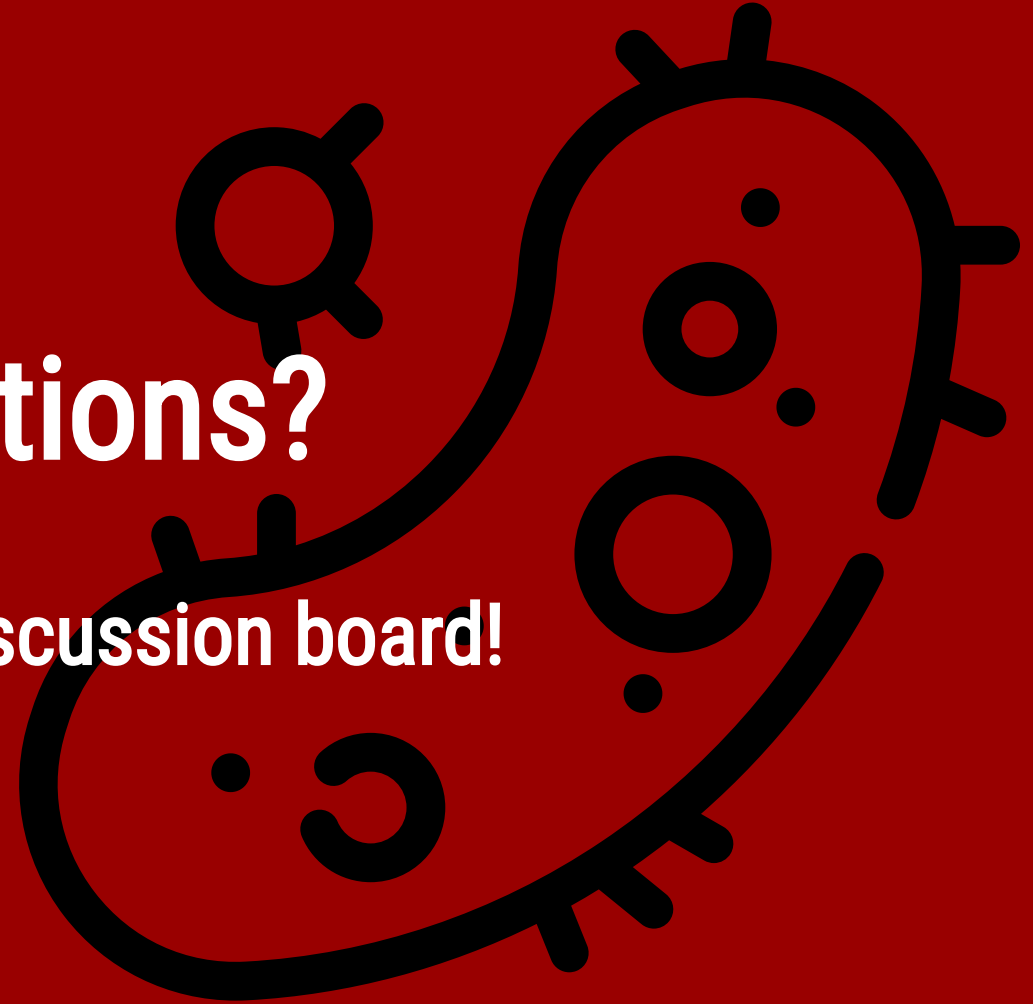


Regression & Compositional Data?

- Compositional data approaches correct OTU dependency:
 - e.g., `compositions::clr()` or `philr::philr()`
 - $p \gg n$ challenges persist
- Must pair compositional transform with regularization:
 - `glmnet::glmnet` for LASSO/ridge/elastic net
 - Bayesian methods

Questions?

Post to the discussion board!



Thank you!

Slides available: github.com/bjklab

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