Regression for Microbiome Data: Multinomial Mixture Models

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Dirichlet Multinomial Mixtures

Implementating DMM in R

ICU Community Types

DMM & Regression





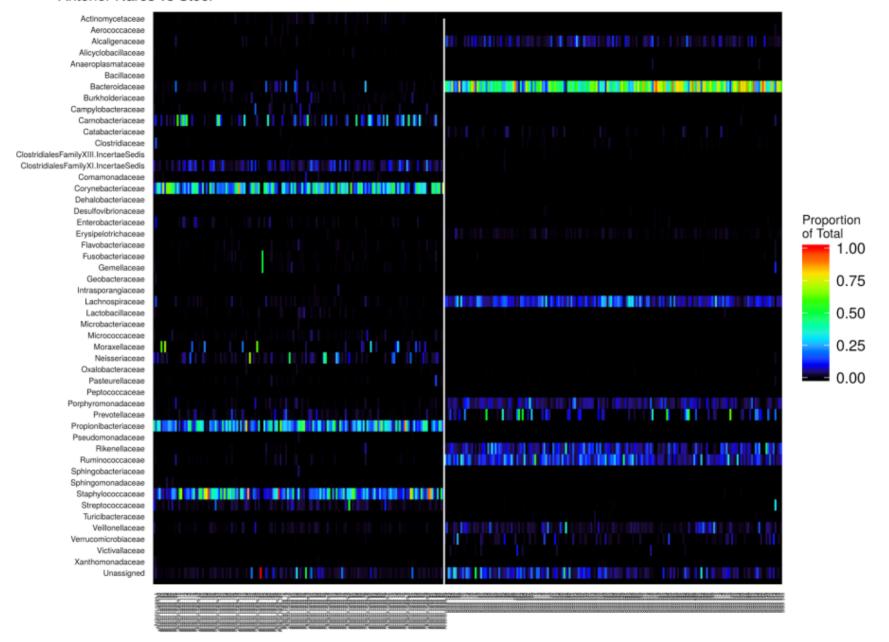
High Dimensional Microbiome Data

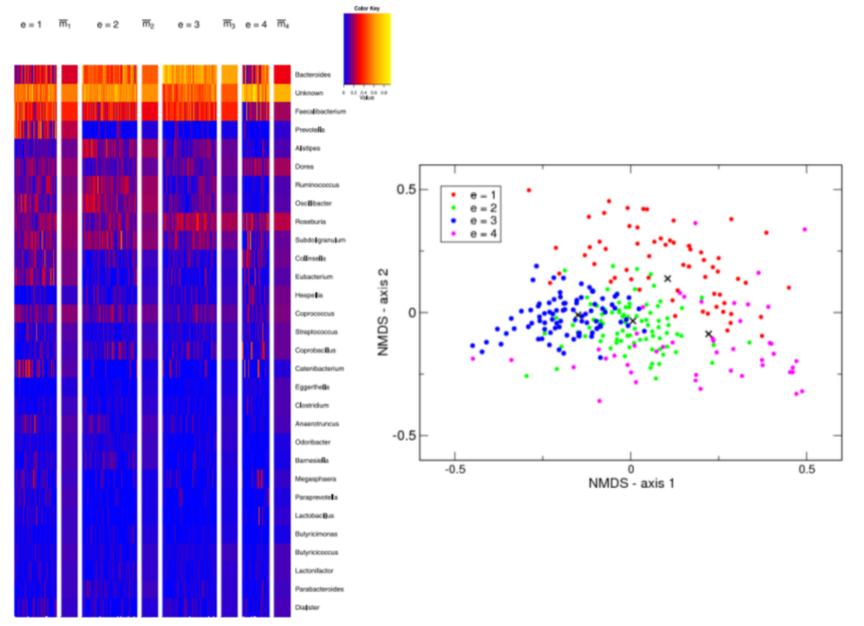
##		700013549	700014386	700014403	700014409	700014412	700014415
##	OTU_97.1	0	0	0	0	0	0
##	OTU_97.10	0	0	6	4	1	5
##	OTU_97.100	0	0	133	7	1	4
##	OTU_97.1000	0	0	0	0	0	0
##	OTU_97.10000	0	0	0	0	0	0
##	OTU_97.10001	0	0	0	0	0	1
##	OTU_97.10002	0	0	0	0	0	0
##	OTU_97.10003	0	0	0	0	0	0
##	OTU_97.10004	0	0	0	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)

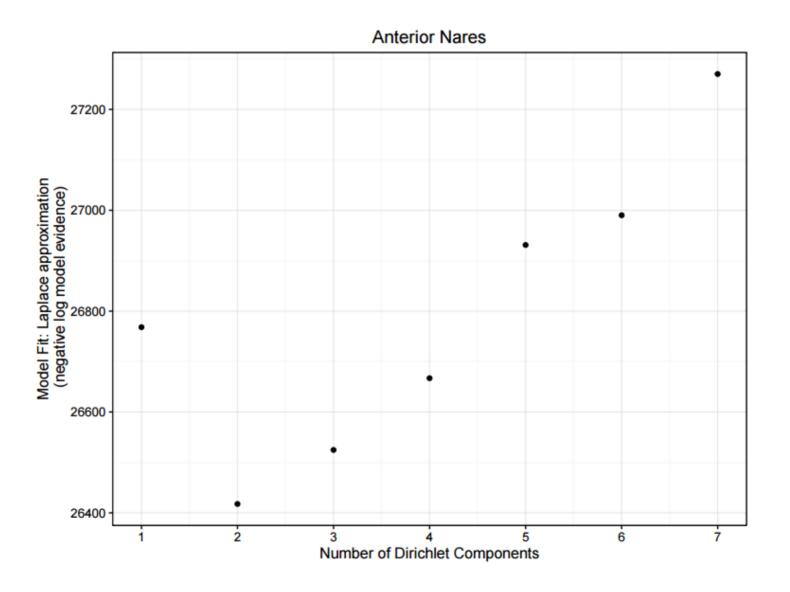
Anterior Nares vs Stool

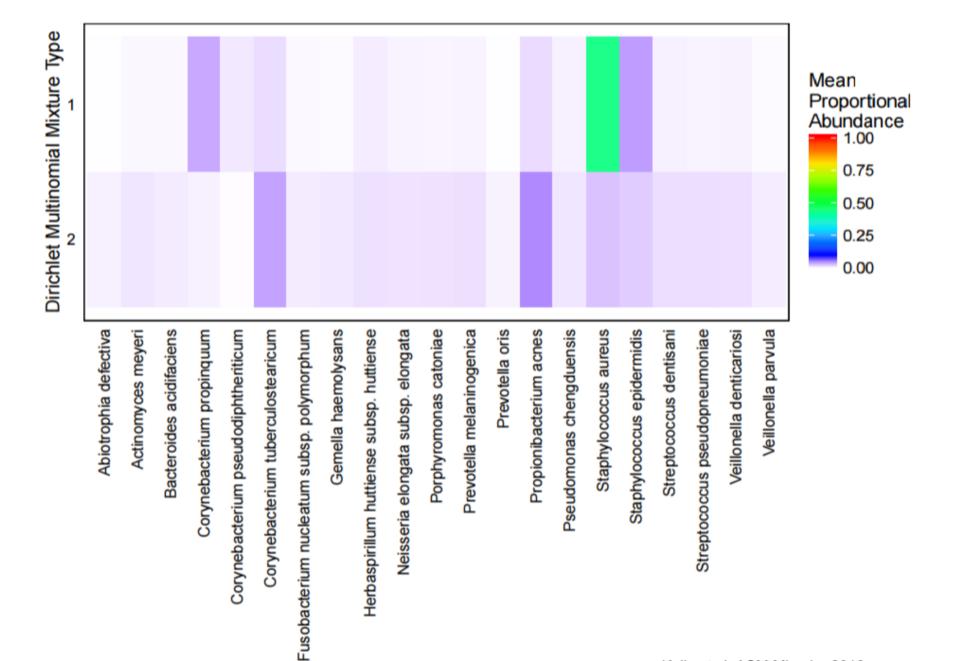


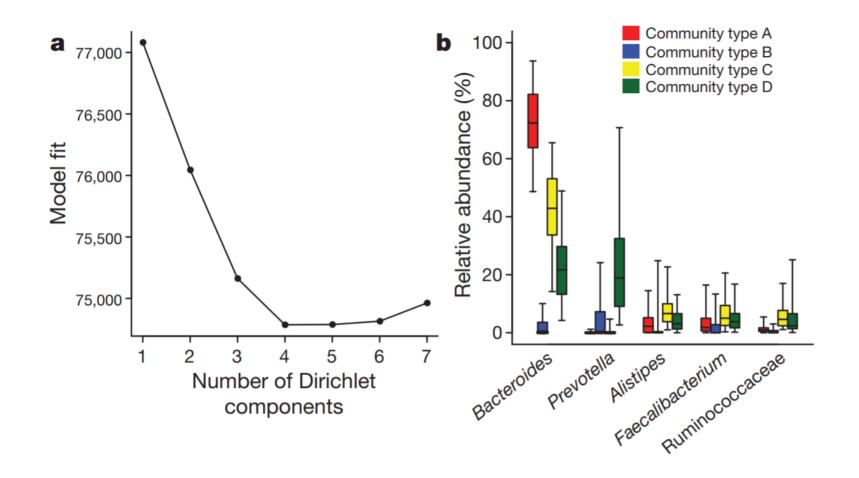


Dirichlet-Multinomial Mixtures

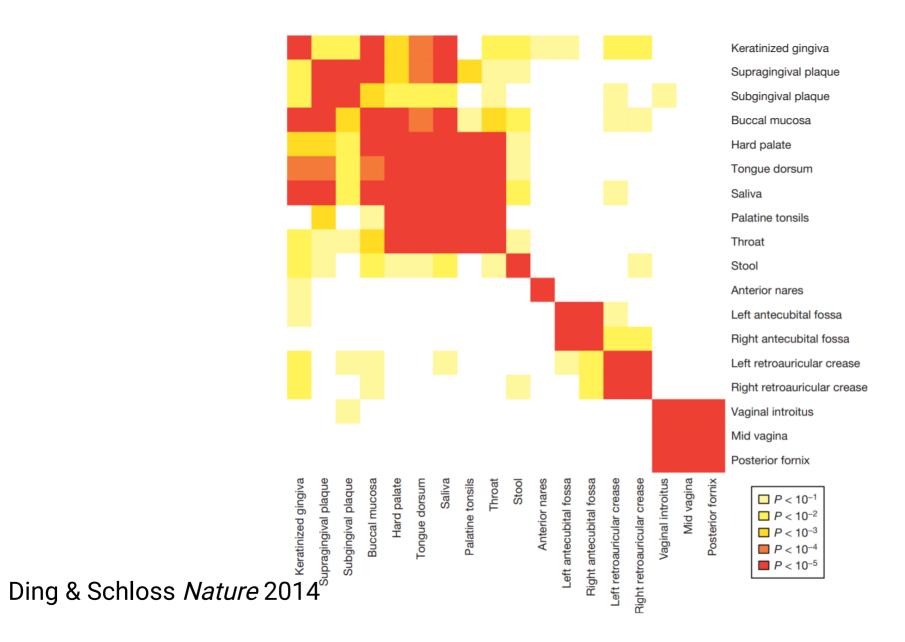
- Dirichlet-multinomial distribution:
 - compound probability distribution
 - o probability vector drawn from Dirichlet distribution (generalized beta)
 - observation drawn from multinomial distribution (generalized binomial)
- D-M mixture modelling:
 - each sample ~ multinomial from one Dirichlet vector
 - vector number: minimize -log(model evidence, Laplace approx)
 - Dirichlet probability vectors = "community types"

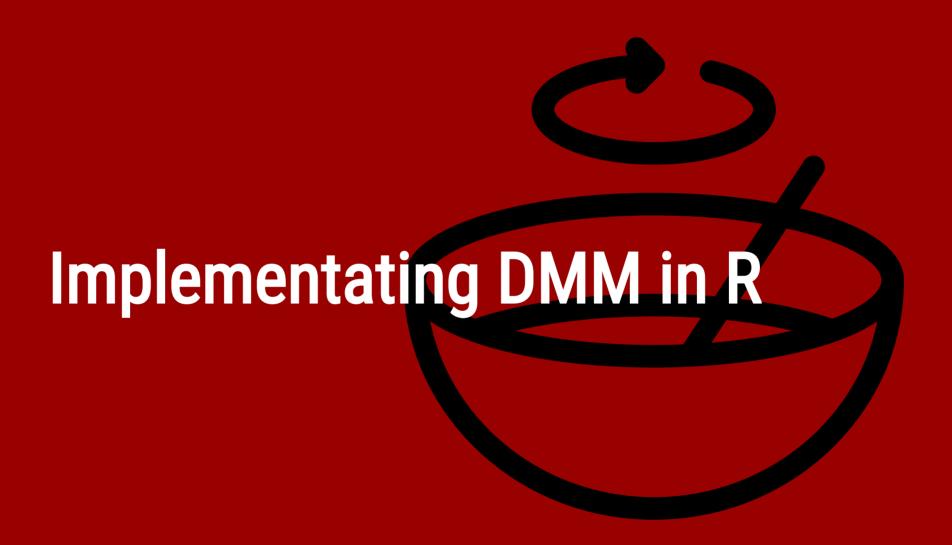






Ding & Schloss Nature 2014



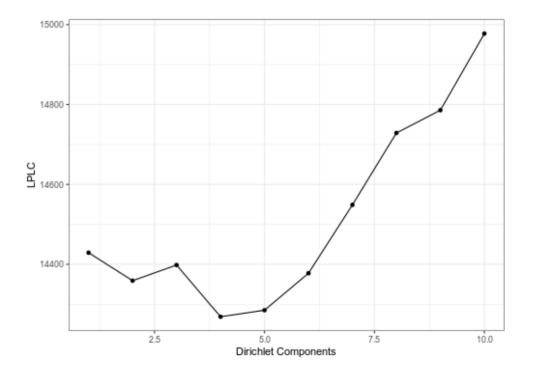


Preparation for DMM

```
# install tidyverse ...
# install.packages("tidyverse")
library(tidyverse)
# new package for heatmap color schemes...
# install.packages("viridis")
library(viridis)
# install package from Bioconductor...
# install.packages("BiocManager")
# BiocManager::install("DirichletMultinomial")
library(DirichletMultinomial)
set.seed(16) # for consistent DMM results
icu_matrix_et <- read_rds(</pre>
 path = "./data/icu_ET_specimen_otu_table.rds"
icu_matrix_et[1:16,1:2]
```

##		VAP.001.ET.20130726	VAP.001.ET.20130729
##	denovo1	0	0
##	denovo10004	0	0
##	denovo10011	0	0
##	denovo10015	0	0
##	denovo10018	0	0
##	denovo10022	0	0
##	denovo10039	0	0
##	denovo1004	0	0
##	denovo10042	0	0
##	denovo10049	0	0
##	denovo10065	0	0
##	denovo10078	3	2
##	denovo10080	0	0
##	denovo10089	0	3
##	denovo10091	0	0
##	denovo10092	2	0

DirichletMultinomial



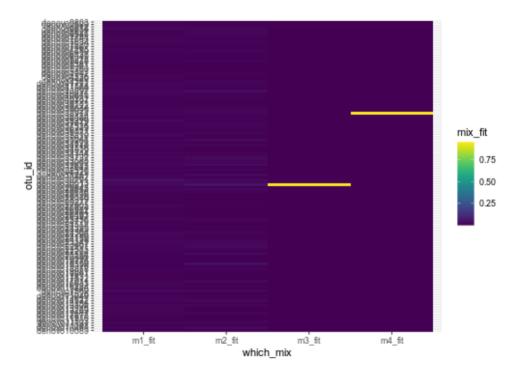


DMM Assignments

```
specimen
                           m1_prob m2_prob
                                              m3_prob m4_prob assignme
      <chr>
                             <dbl>
                                      <dbl>
                                                <dbl>
                                                        <dbl>
                                                                    <i
   1 VAP.001.ET.20130726 3.46e-13 1.00e+ 0 0.
   2 VAP.001.ET.20130729 2.70e-24 1.00e+ 0 0.
   3 VAP.001.ET.20130731 1.37e-15 1.00e+ 0 0.
   4 VAP.002.ET.20130729 1.00e+ 0 2.32e-31 0.
   5 VAP.002.ET.20130731 1.00e+ 0 4.47e-36 0.
   6 VAP.002.ET.20130802 1.00e+ 0 3.47e-31 0.
   7 VAP.002.ET.20130805 3.05e-19 1.00e+ 0 0.
   8 VAP.003.ET.20130730 1.52e-22 1.00e+ 0 5.33e-310
   9 VAP.004.ET.20130808 1.00e+ 0 1.73e-69 0.
## 10 VAP.005.ET.20130814 9.91e-28 4.02e-12 1.00e+ 0
## # ... with 32 more rows
```

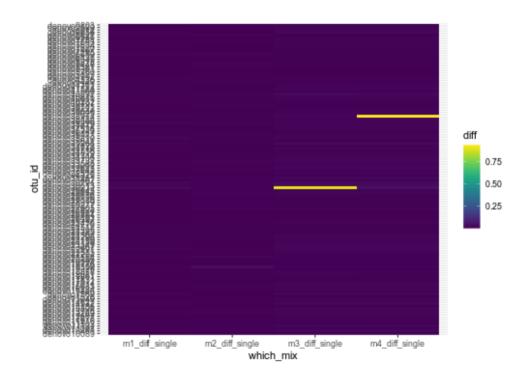
A tibble: 42 x 6

DMM Mixture Fits



Difference From Single-Mixture

```
abs(fitted(best_dmm, scale=TRUE) -
      as.vector(fitted(dmm[[1]].
                       scale=TRUE))) %>%
# scale indicates whether fits scaled by the...
# ... variability of mixturewt parameter theta
 as_tibble(rownames = "otu_id") %>%
 rename_at(.vars = vars(contains("V")),
            .funs = function(x)
              paste0(gsub("V","m",x),"_diff_single")) ->
 icu_et_dmm_otu_diff_single
icu_et_dmm_otu_diff_single %>%
 gather(key = which_mix,
        value = diff,
        -otu_id) %>%
 ggplot(data = .) +
 geom_tile(mapping = aes(x = which_mix,
                          y = otu_id,
                          fill = diff)) +
 scale_fill_viridis()
```





DMM & Regression?

DMM community types as exposure variable:

```
\circ easy \rightarrow lm() or glm()
```

- \circ (like α -diversity or β -diversity PC1)
- DMM community types as outcome variables:
 - e.g., categorical logistic regression
- Biological validity of DMM community types? Reproducibility?



Thank you!

Slides available: github.com/bjklab

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