



Learning from Human Microbiome

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Human Microbiome

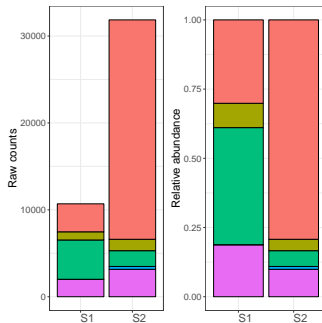


Credit: Antoine Doré

Microbiome Data



- ▶ $\mathbf{X} = (x_{ij})_{n \times p}$ matrix of microbiome data for n samples and p taxa
- ▶ Due to sample differences, often work with relative abundances





Exploratory analysis

- ▶ Dimension reduction (Ordination)
- ▶ Microbial interactions
- ▶ Controlling batch effects
- ▶ ...

Supervised learning

- ▶ Is the microbiota associated with an outcome?
- ▶ Which taxa are associated with an outcome?
- ▶ ...



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Dimension Reduction

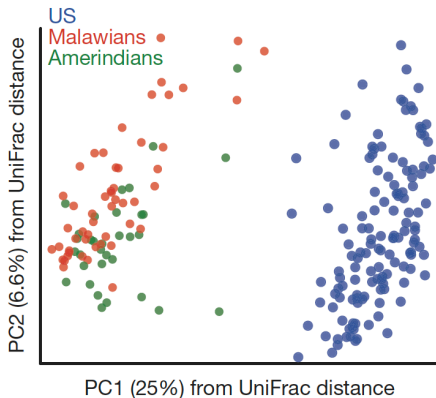


Figure: PCoA of unweighted unifracs distances for the fecal microbiota of adults¹

¹Yatsunenkeno et al. Nature, 2012

Dimension Reduction



Existing methods:

- ▶ PCoA (aka MDS), DPCoA

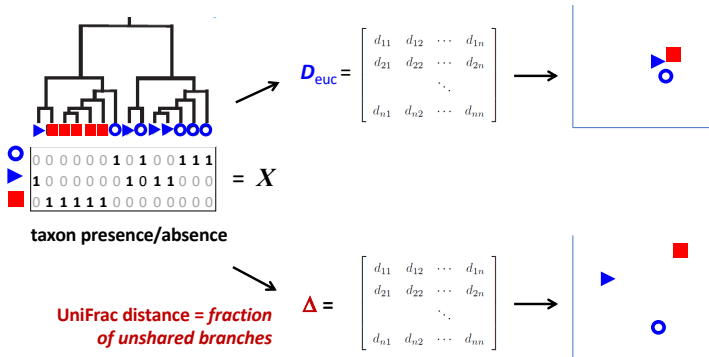
Limitations:

- ▶ unable to visualize both samples and variables.
- ▶ unable to account for two-way structures.

Two-way Structures



- ▶ Similarities among **samples** better captured by **phylogenetic tree**
- ▶ Many methods for capturing phylogenetic distances, e.g. UniFrac dist.

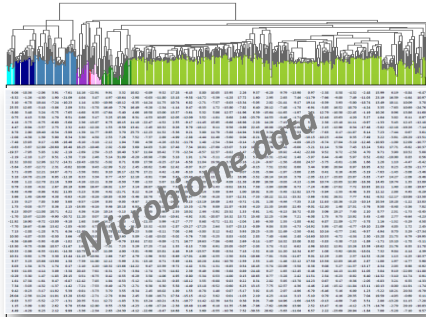


Two-way Structures



- The phylogenetic tree also captures similarities among **taxa**.
Alternatively, can consider information from **metabolic pathways**.

$Q =$



$X =$

GMD Biplot



First recall PCA biplot

$$\begin{array}{c}
 \text{p variables} \\
 \text{n samples}
 \end{array}
 \begin{array}{|c|} \hline X \\ \hline \end{array}
 \approx
 \begin{array}{|c|} \hline u_1 \\ \hline \end{array}
 \begin{array}{|c|} \hline v_1^T \\ \hline \end{array}
 +
 \begin{array}{|c|} \hline u_2 \\ \hline \end{array}
 \begin{array}{|c|} \hline v_2^T \\ \hline \end{array}$$

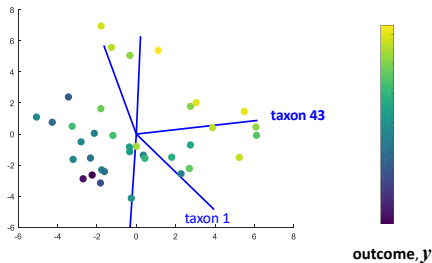
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 X \\
 (n \times p)
 \end{array}
 \approx
 \begin{array}{c}
 u_1 u_2 \\
 \begin{array}{|c|} \hline U \\ \hline \end{array}
 \end{array}
 \begin{array}{c}
 v_1 v_2 \\
 \begin{array}{|c|} \hline V \\ \hline \end{array}
 \end{array}$$

$$\begin{array}{c}
 \text{n samples' coords} \\
 \text{p variables' coords}
 \end{array}$$

GMD Biplot



First recall PCA biplot



$$X \approx u_1 v_1^\top + u_2 v_2^\top$$



- ▶ SVD gives $\mathbf{X} = \mathbf{USV}^T$ by solving

$$\arg \min_{\mathbf{U}, \mathbf{S}, \mathbf{V}} \|\mathbf{X} - \mathbf{USV}^T\|_F$$

where $\|\mathbf{A}\|_F = \text{trace}(\mathbf{A}^T \mathbf{A})$.



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- ▶ Consider instead a general norm to incorporate \mathbf{H} and \mathbf{Q} :

$$\|\mathbf{X} - \mathbf{USV}^T\|_{\mathbf{H}, \mathbf{Q}}$$

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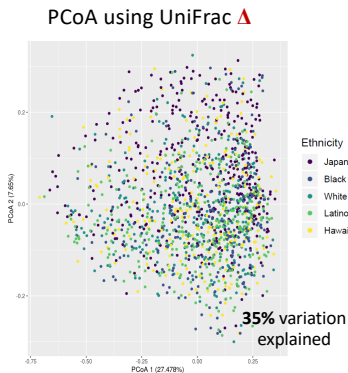
- ▶ The GMD (Gen'zd Matrix Decomp²) gives $\mathbf{X} = \mathbf{USV}^T$ such that $\mathbf{U}^T \mathbf{H} \mathbf{U} = \mathbf{V}^T \mathbf{Q} \mathbf{V} = \mathbf{I}_K$, and \mathbf{S} is the diagonal matrix of GMD values.

²Allen et al. JASA, 2014

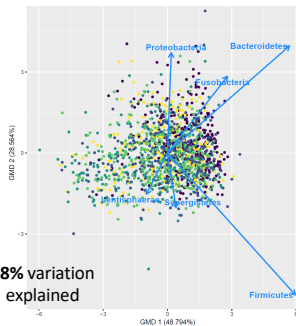
GMD Biplot



The GMD-biplot³ displays **samples** and **variables** using columns of U and V



PCoA using X and UniFrac Δ ;
phyla (arrows) from **GMD biplot**



³Yue et al. mSystems, 2019

Supervised Learning with GMD



- ▶ GMD generalizes SVD for doubly structured data
- ▶ Can thus use GMD for supervised learning, similar to PCR

GMD Regression and Inference



- ▶ Linear model $y = \mathbf{X}\beta + \varepsilon$
- ▶ Incorporating \mathbf{H} and \mathbf{Q}

$$y = \mathbf{U}\mathbf{S}\mathbf{V}^T\beta + \varepsilon$$

- ▶ Coefficient

$$\hat{\beta}_{GMD} = \mathbf{Q}\mathbf{V}\mathbf{W}\mathbf{S}^{-1}\mathbf{U}^T\mathbf{H}y,$$

where \mathbf{W} is a diagonal matrix of weights:

- ▶ $\mathbf{W}_j = \mathbf{1}_{j \in \mathcal{J}} \rightarrow \hat{\beta}_{GMDR}(\mathcal{J}), \mathcal{J} \subset \{1, \dots, p\}$
- ▶ $\mathbf{W} = \mathbf{S}^2(\mathbf{S}^2 + \lambda \mathbf{I}_n)^{-1} \rightarrow \hat{\beta}_{KPR} = \arg \min_{\beta} \{\|y - \mathbf{X}\beta\|_{\mathbf{H}}^2 + \lambda \|\beta\|_{\mathbf{Q}^{-1}}^2\}$ ⁴

⁴Randolph et al. AOAS, 2018

⁵Yue et al. Submitted, 2020

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- ▶ GMD inference (GMDI⁵) $H_{0,j} : \beta_j^* = 0$.

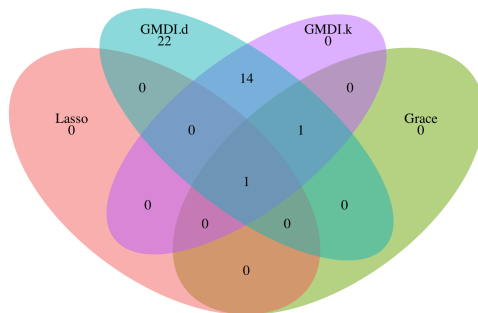
⁴Randolph et al. AOAS, 2018

⁵Yue et al. Submitted, 2020

Application to Yatsunenko Data



- ▶ Which bacteria are associated with age?
- ▶ Significant associations from multivariate methods⁶ (FDR=0.1)

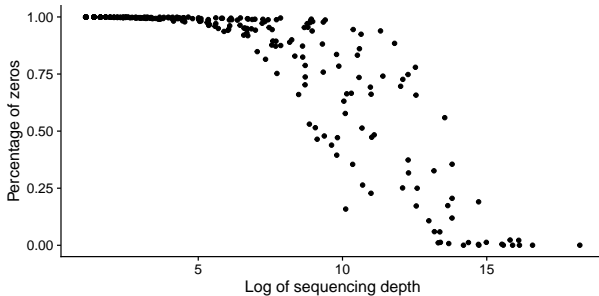


⁶Ridge test by Bühlmann (2013) returns 0 sig association.

Open Questions: Missing Data



- ▶ Microbiome data are zero-inflated.
- ▶ Zeros are not missing at random.



Open Questions: Microbial Network Analysis



We previously worked on constructing microbial co-occurrence network from presence/absence data⁷.

⁷Cai et al. Biometrika, 2019

Open Questions: Microbial Network Analysis



We previously worked on constructing microbial co-occurrence network from presence/absence data⁷.

- ▶ How to define dependence between two taxa?
- ▶ Marginal vs. conditional?
- ▶ How to jointly analyze microbiome and metabolomic data?

⁷Cai et al. Biometrika, 2019

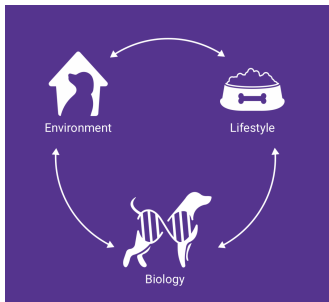


Microbiome by environment interaction

$$y_i = \alpha_0 + \alpha' E_i + \beta' G_i + \gamma E_i G_i + \epsilon_i,$$

- ▶ E_i : low-dim covariates.
- ▶ G_i : high-dim genetic markers.
- ▶ Interest in testing whether the interaction $\gamma = 0$.
- ▶ Existing variance components test fails to control type I error if G_i is high-dimensional.

The Dog Aging Project



- ▶ Co-led by University of Washington and Texas A&M University.
- ▶ To understand how genes, lifestyle, and environment influence aging.
- ▶ Multiple data types: survey data, electronic medical records, omics data, etc.



- ▶ Differential Markov random field analysis with an application to detecting differential microbial community networks. *Biometrika*. 2019
- ▶ The GMD-biplot and its application to microbiome data. *mSystems*. 2019
- ▶ Generalized matrix decomposition: estimation and inference for two-way structured data. 2020+

Thank You!

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