

# Ongoing Microbiome Research lines

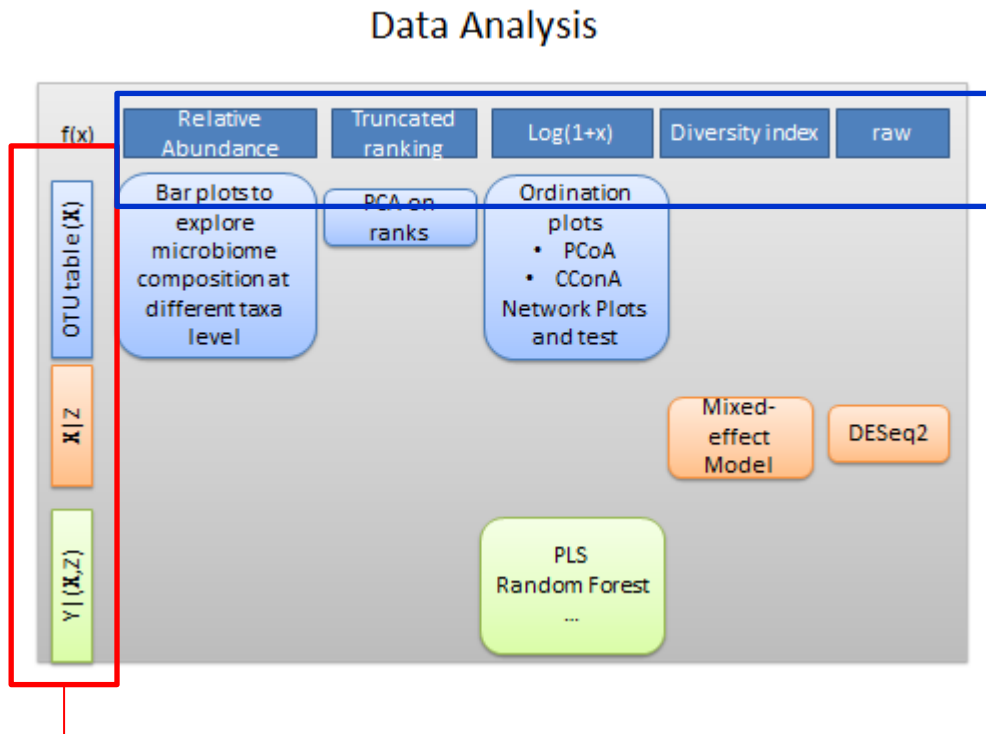
Ziv Shkedy

CenStat/I-BioStat, Hasselt University, Belgium

January, 16, 2017

# Rsearch lines

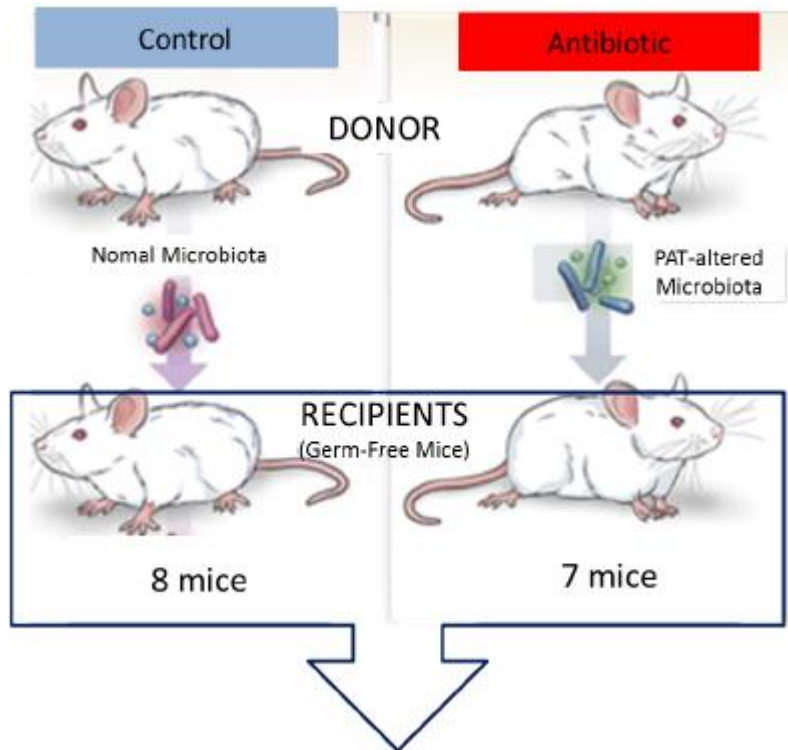
Nolen's presentation:



Similar to Omics data and other high dimensional data:

- Different type of data.
- Different rsearch settings.

# Main interest: intervention studies

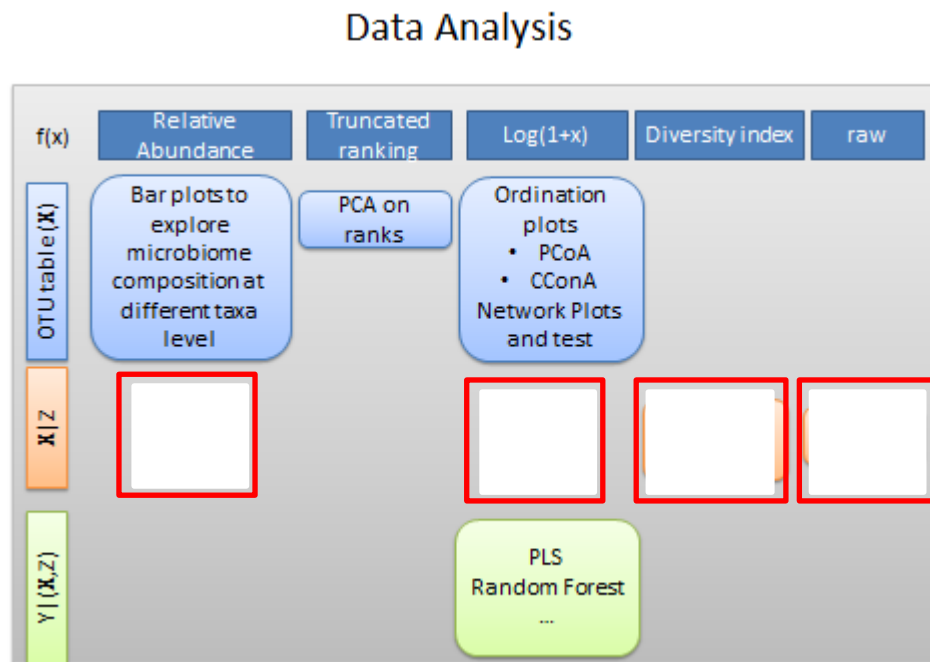


- Transfer microbiome of the donors to the recipient.
- Two groups of donors: treated and control.

Measurements:

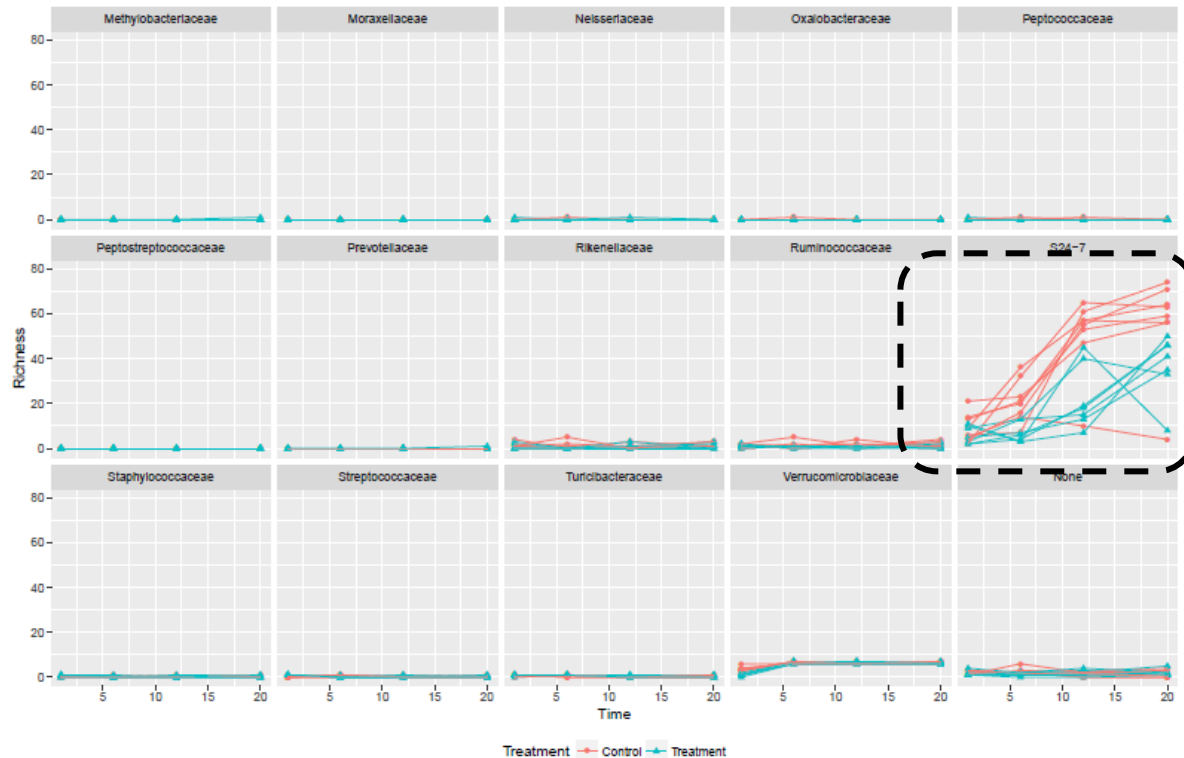
1. Microbiome data.
2. Clinical response(s).

# 1. Longitudinal analysis of microbiome data



- X: microbiome data.
- Z: treatment.
- Repeated measurements over time.

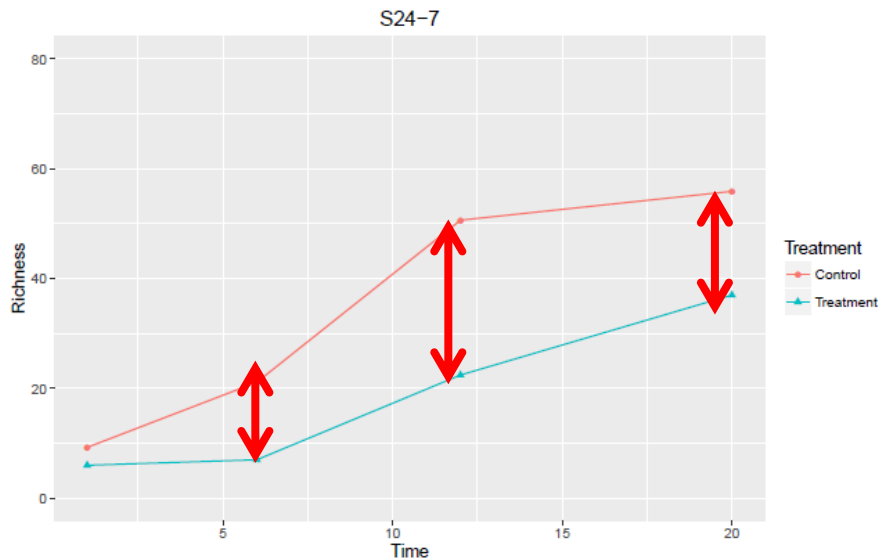
# Family-level Richness – Subject Profiles



- Richness: the number of non zero OTUs per subject (per family).
- Two treatment groups.

Not all families are active !!

# Modeling richness over time: family level

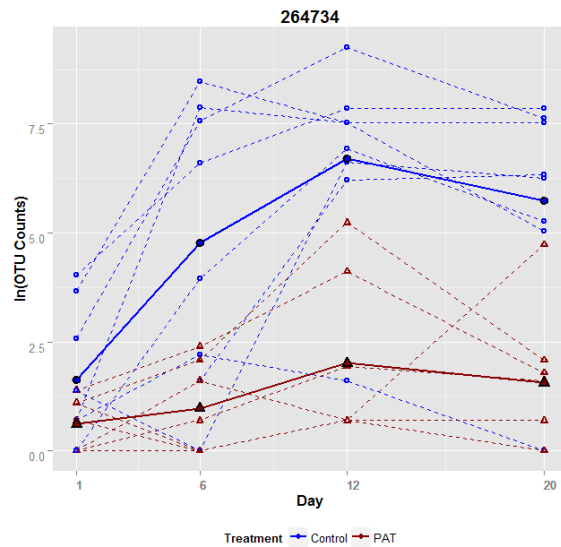


Response: number of active OTUs in the family.

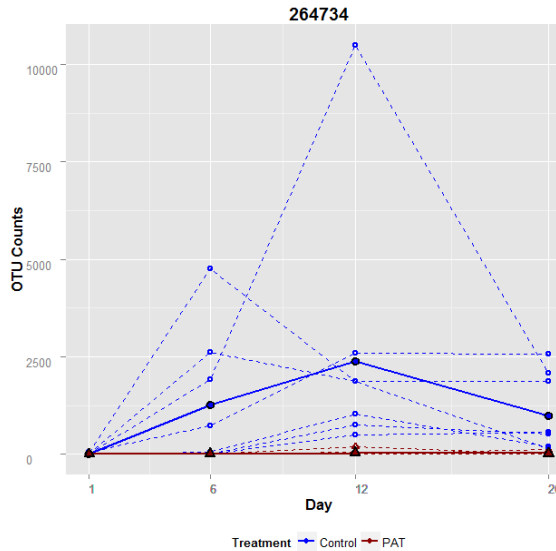
Treatment effect over time ?

# Effect of microbiota transfer on OTU Level: 264734

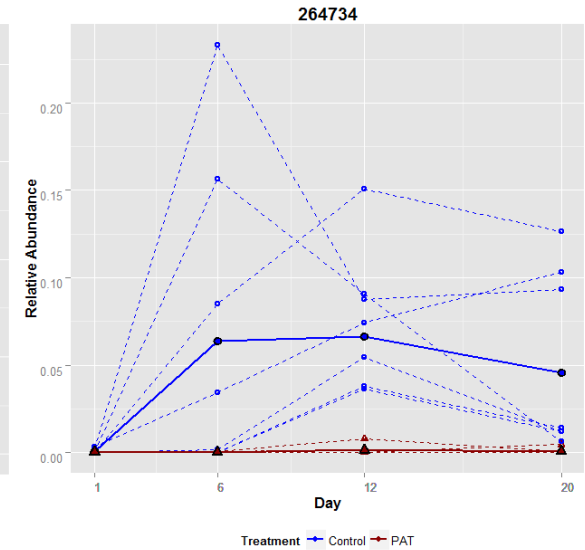
Log(Raw counts+1)



Raw counts

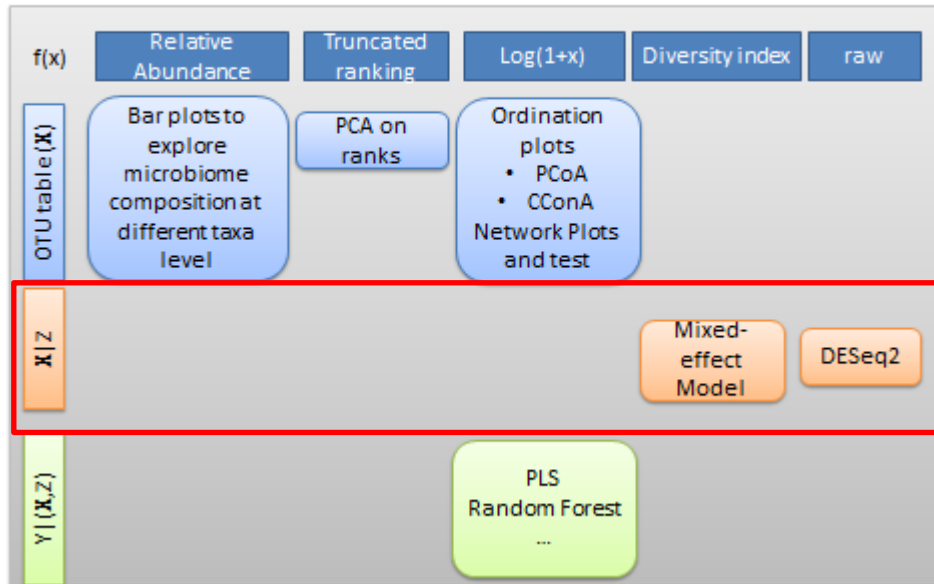


Relative abundance



# Longitudinal analysis of microbiome data

## Data Analysis



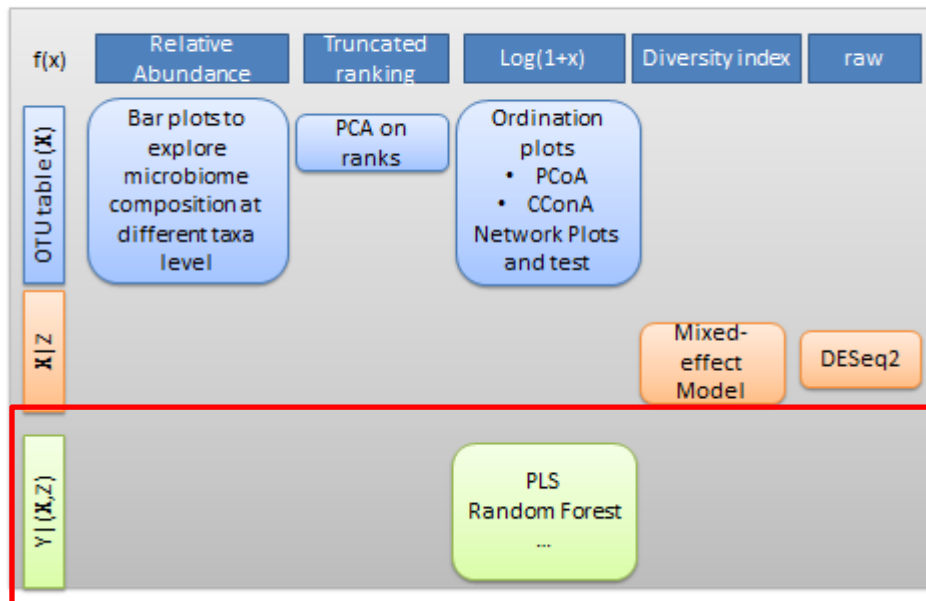
## Issues:

- Zero inflated longitudinal data:
  - Continuous.
  - Counts.
  - Binary
- Over-dispersion data.



## 2. Development of Biomarkers

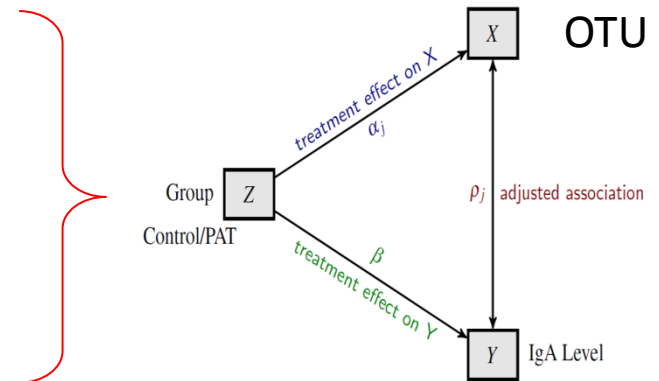
### Data Analysis



Modeling the effect of microbiome on **clinical variables** taking into account intervention.

# The biomarker setting

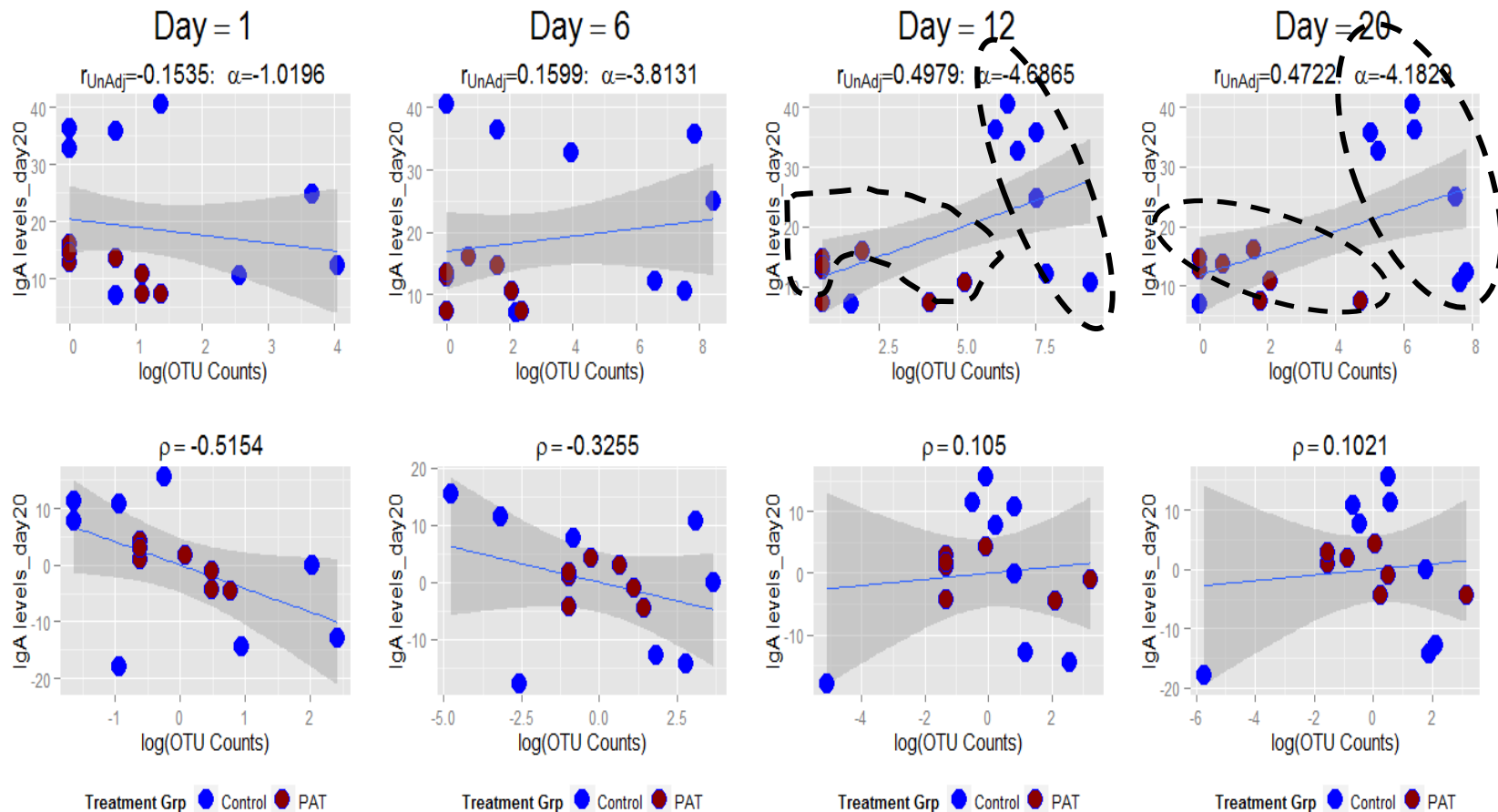
- PAT study: IgA and microbiome.
- Analysis at each time point:
  - Joint modeling
    - Log(count)
    - Row counts.
    - Relative abundance.
  - Non-parametric methods.
  - Methods for zero-inflated count data.
- T1D: survival/log(survival)



Feature specific models

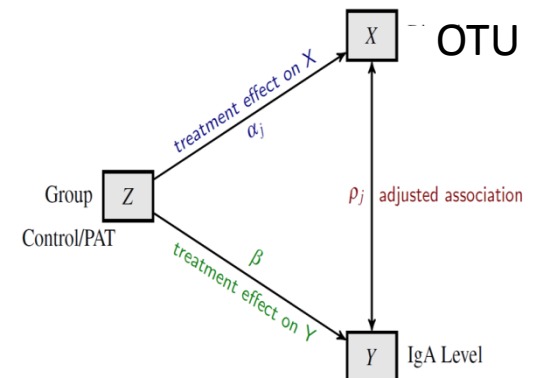
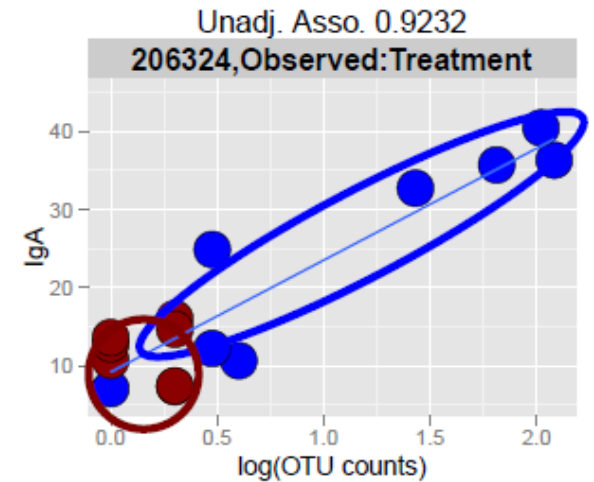
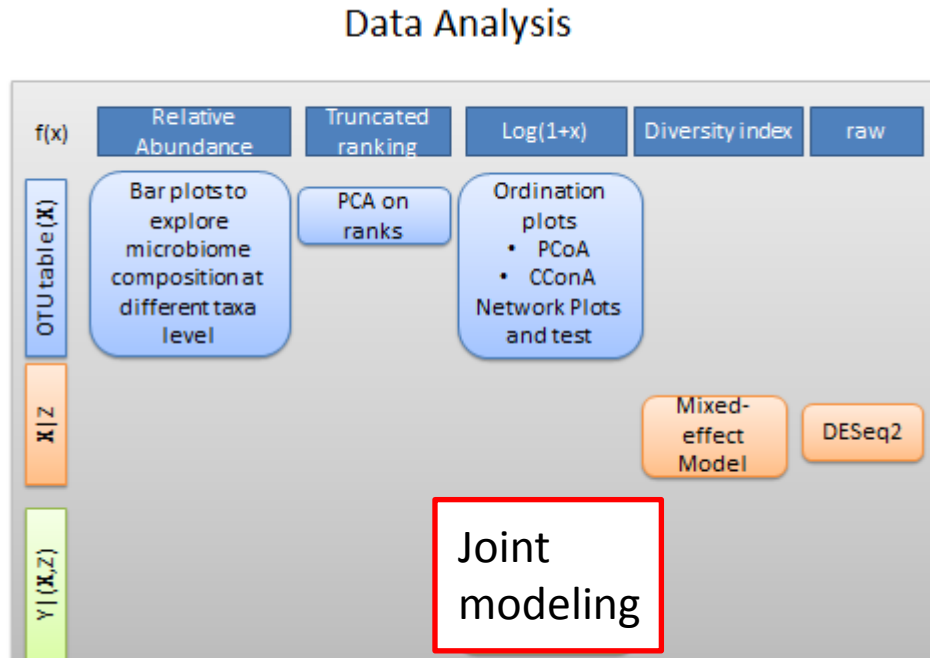
# Results for OTU 264734

Evolution of treatment effect over time.



differentially abundant from day 12 10

## 2.1: A joint model: OUT 206324

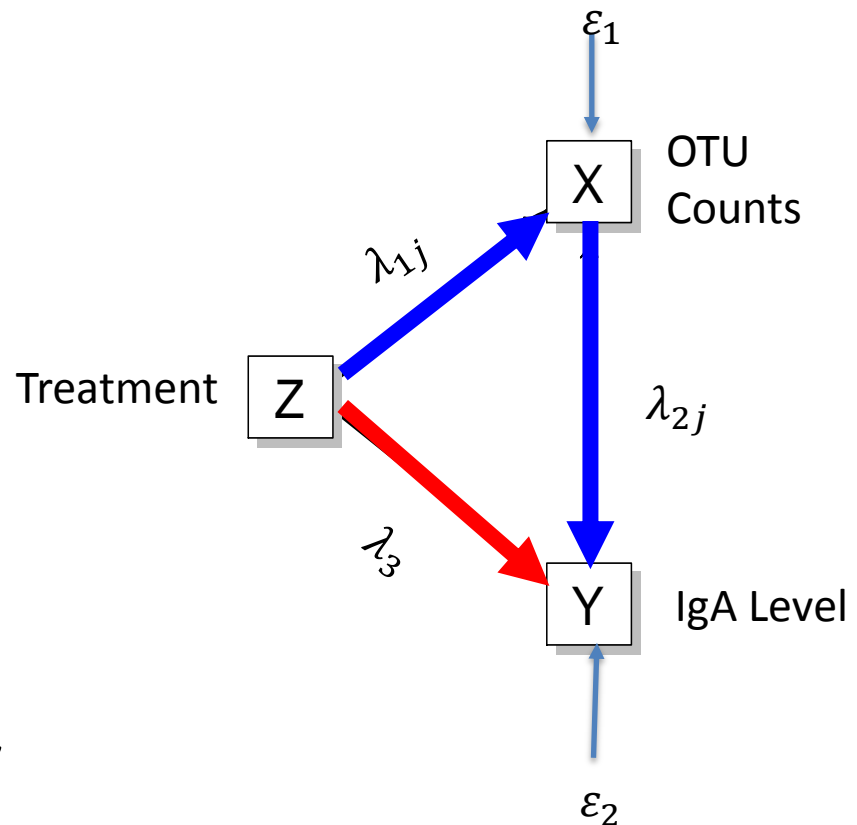


## 2.2: Structural equations modeling

Modeling direct and indirect effect of the treatment on the clinical outcome:

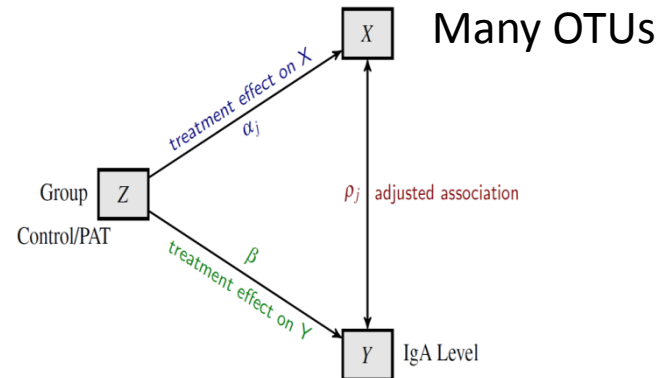
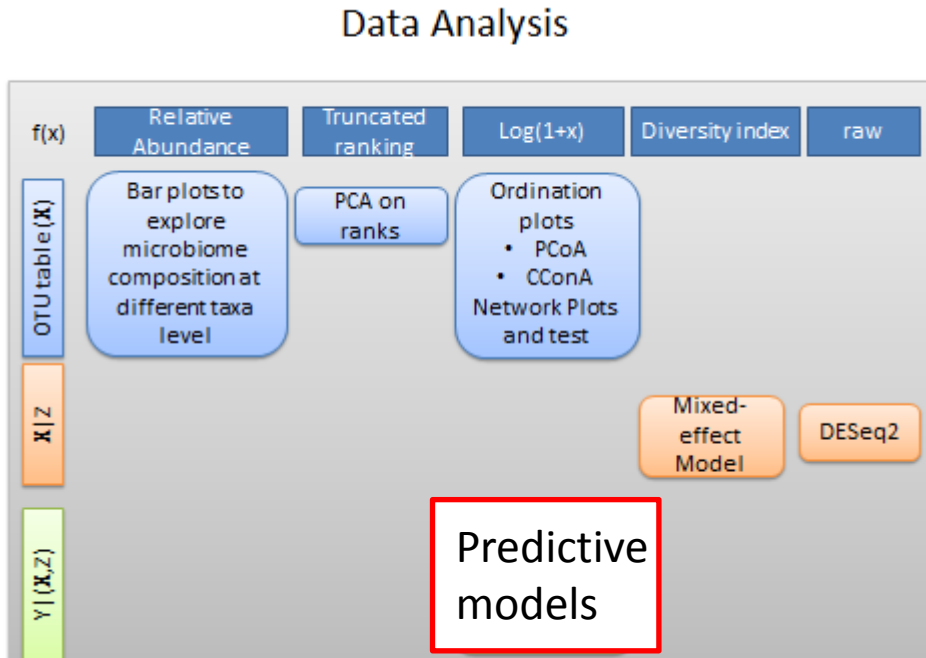
$$X_{ij} = \lambda_{1j}Z_i + \varepsilon_{1i},$$

$$Y_i = \lambda_3 Z_i + \lambda_{2j} X_{ij} + \varepsilon_{2i}.$$



➡ Example: Rudradev

## 2.3: Predictive models

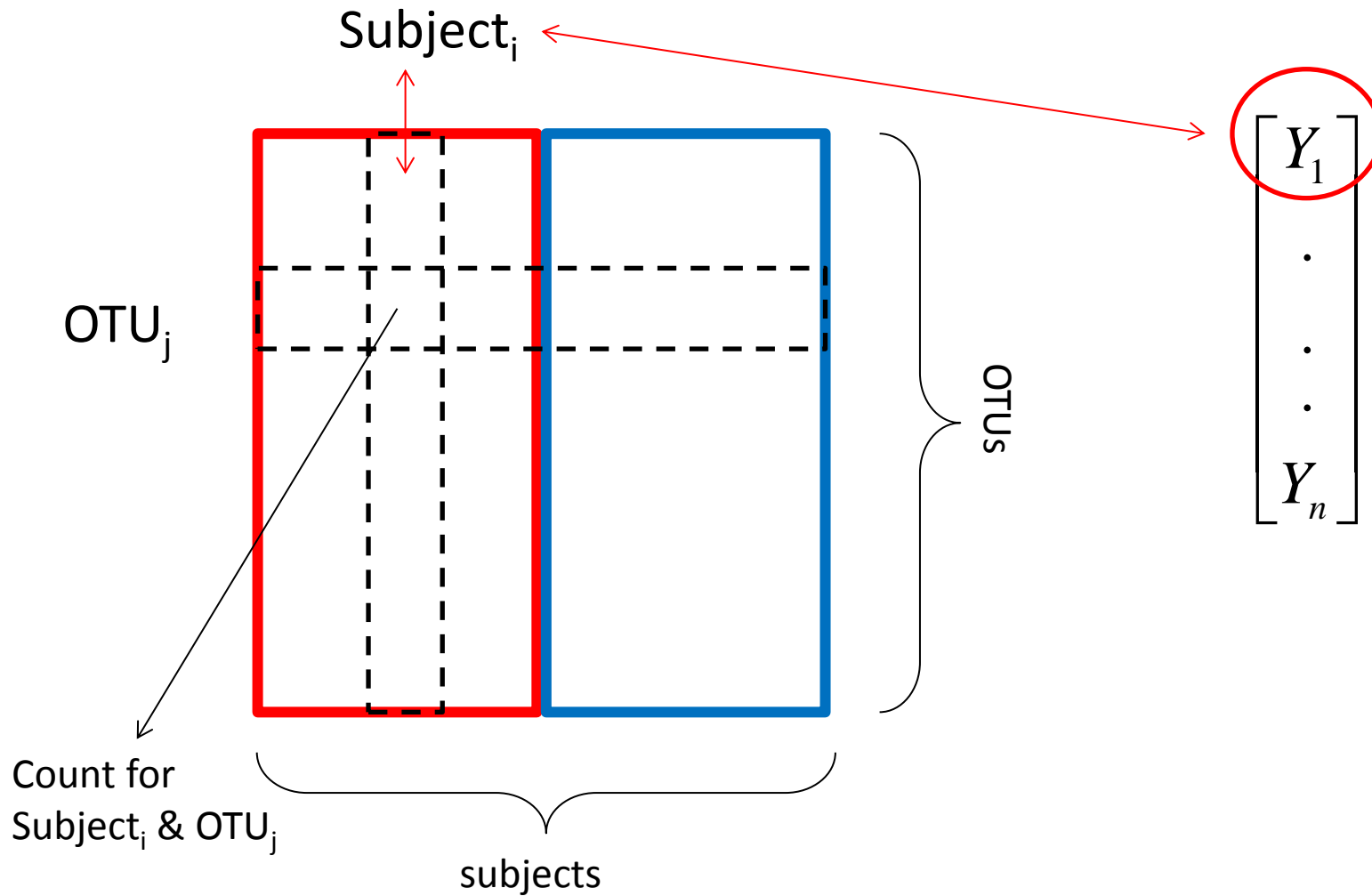


Can we predict the clinical outcome using microbiome data (taking into account the treatment effect) ?

# Data Structure

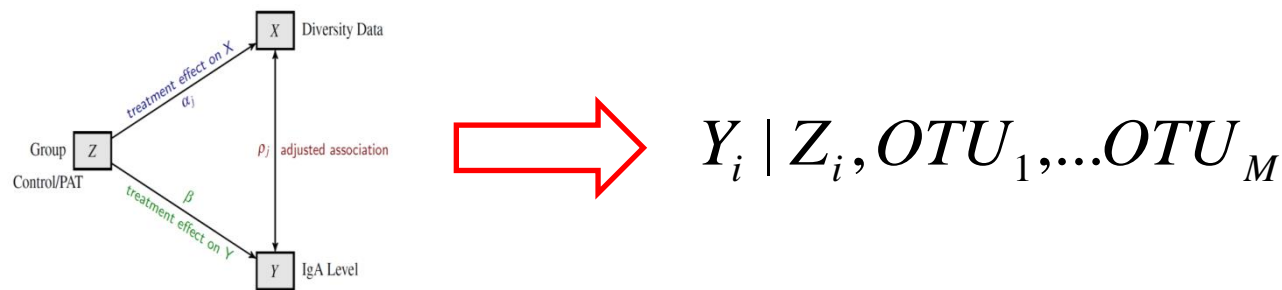
Microbiome

Clinical outcome



# Predictive models for clinical outcomes

Analysis at each time point:



Predictive models for clinical outcome:

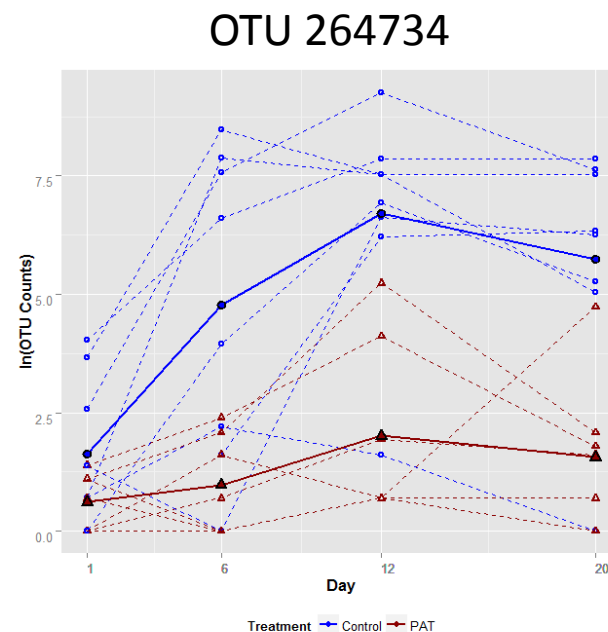
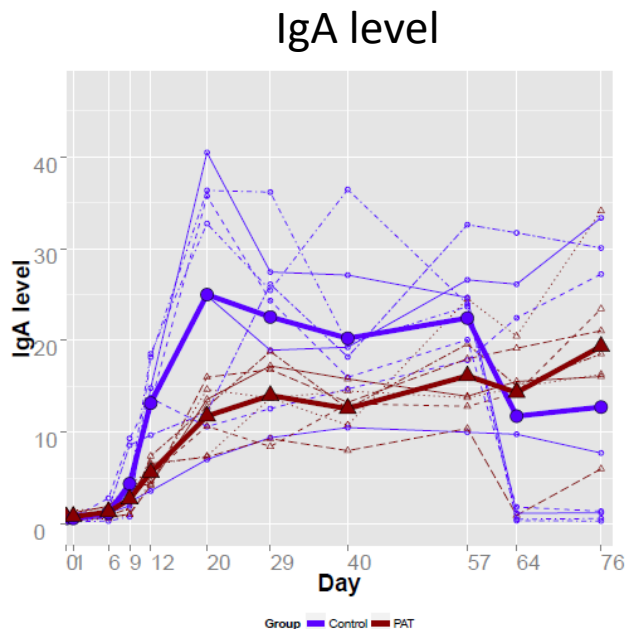
$$Y_i = Z\gamma + \sum_{j=1}^M \beta_j OTU_{ij} + error_i$$

$$E(Y_i) = f(treatment, OTU_1, OTU_2, \dots, OTU_K)$$

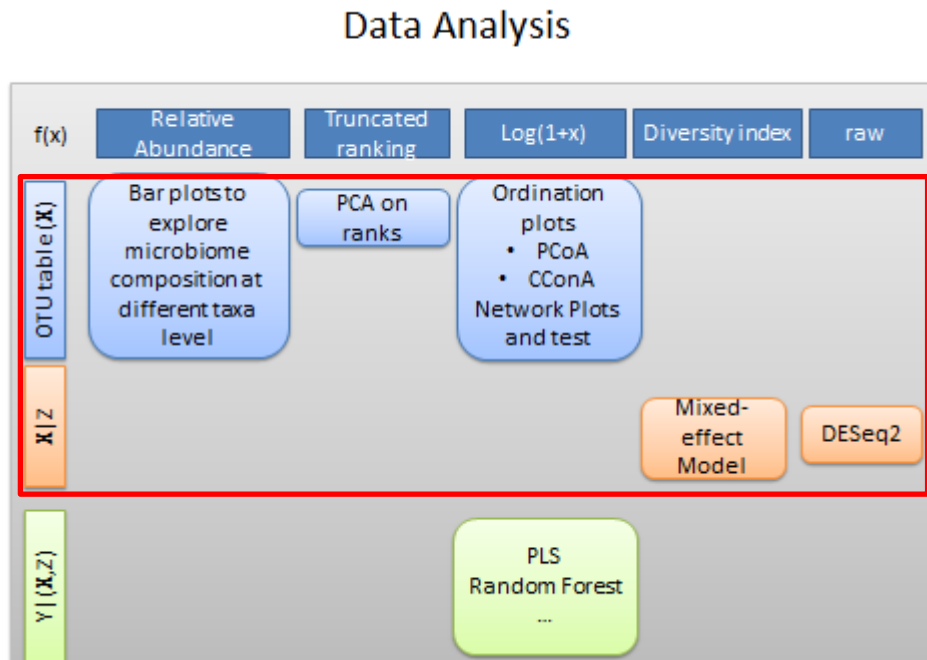


## 2.4: A joint modeling - longitudinal data

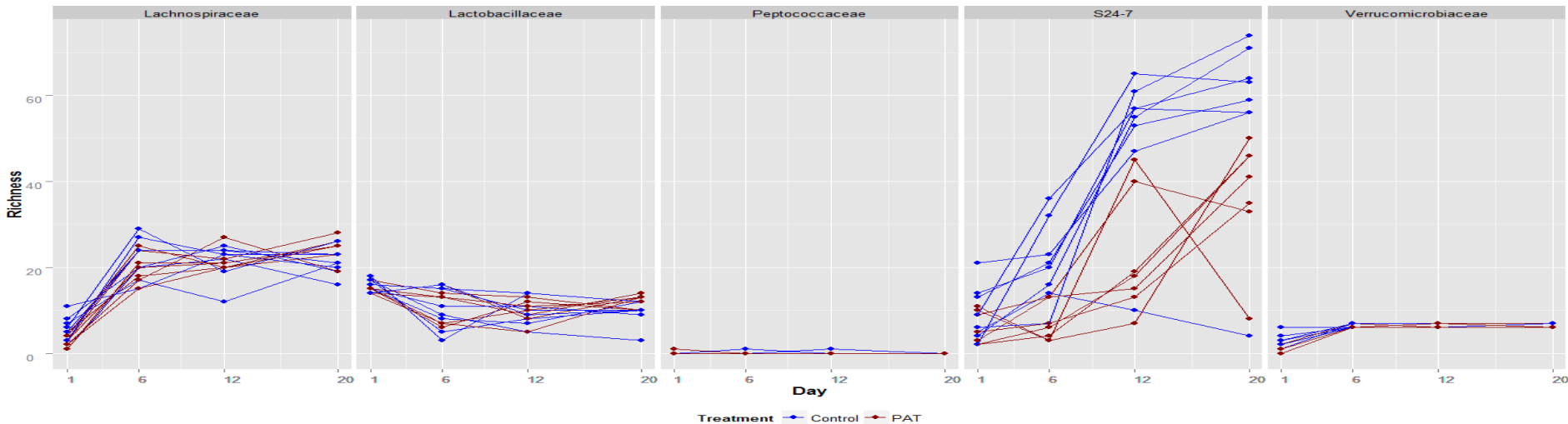
- Joint model for the longitudinal data.
  - Joint models for IgA and counts/relative abundance/abundance.
  - Evolution of treatment effects over time.



### 3. Population models for the evolution over time by family



## 3.1: Family-based analysis: richness

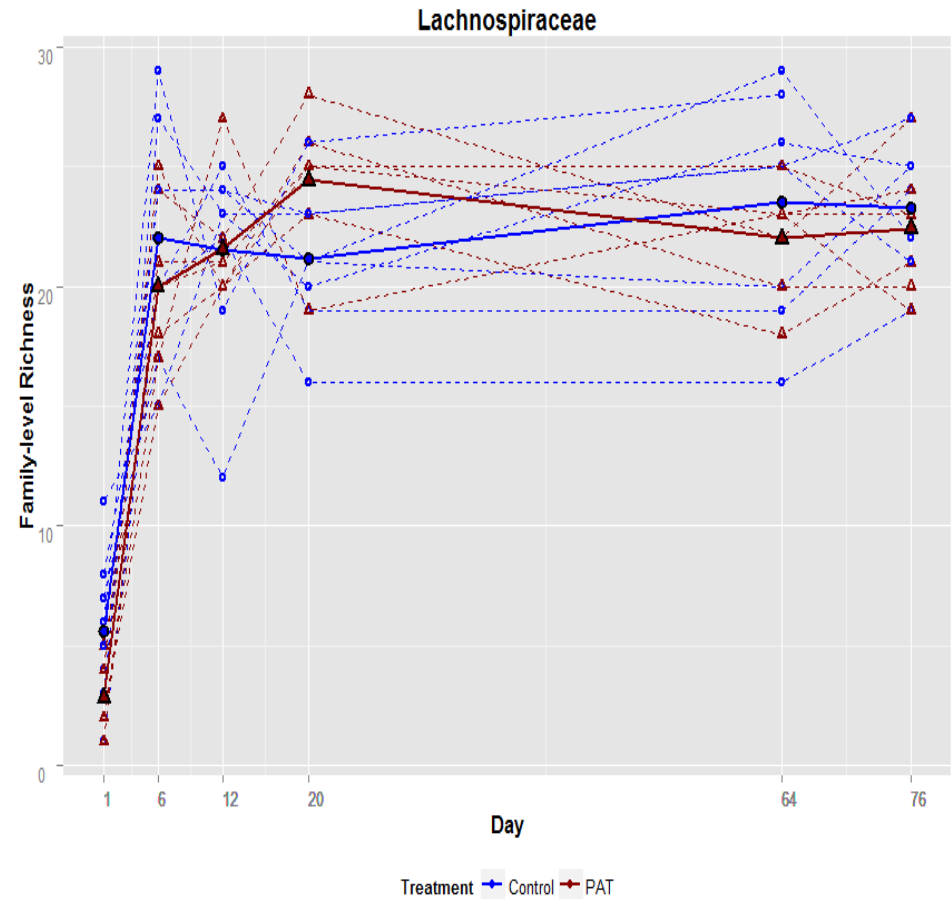
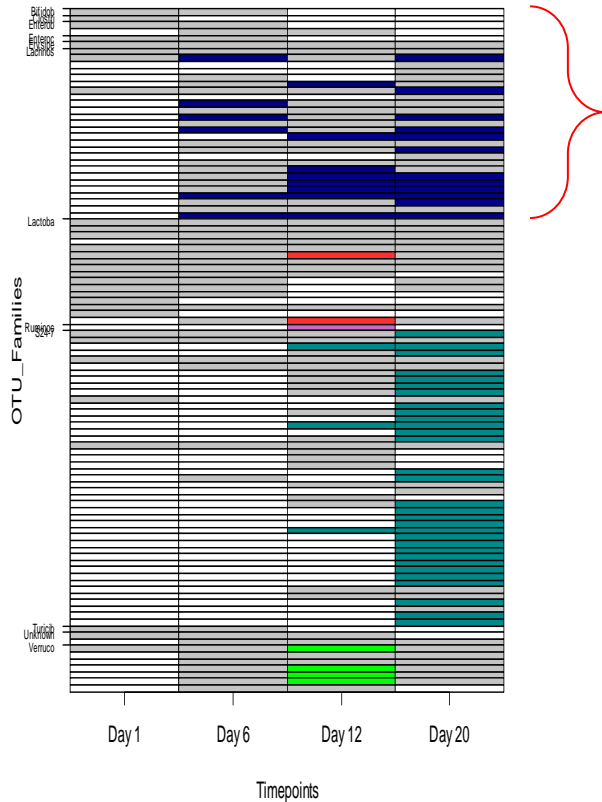


$$\frac{\partial N(t)}{\partial t} = f(\text{time}, \text{treatment})$$

- Non linear mixed effects modeling for the richness (family size in terms of OTUs activity).
- Modeling intervention.

# The Lachnospiraceae Family

### Significant OTUs based on Adjusted Asso. - 70%





## 3.2: correlation among OTUs

- Modeling interaction between OTUs

$$\Delta Y_i(t) = \log(Y_i(t)) - \log(Y_i(t-1))$$

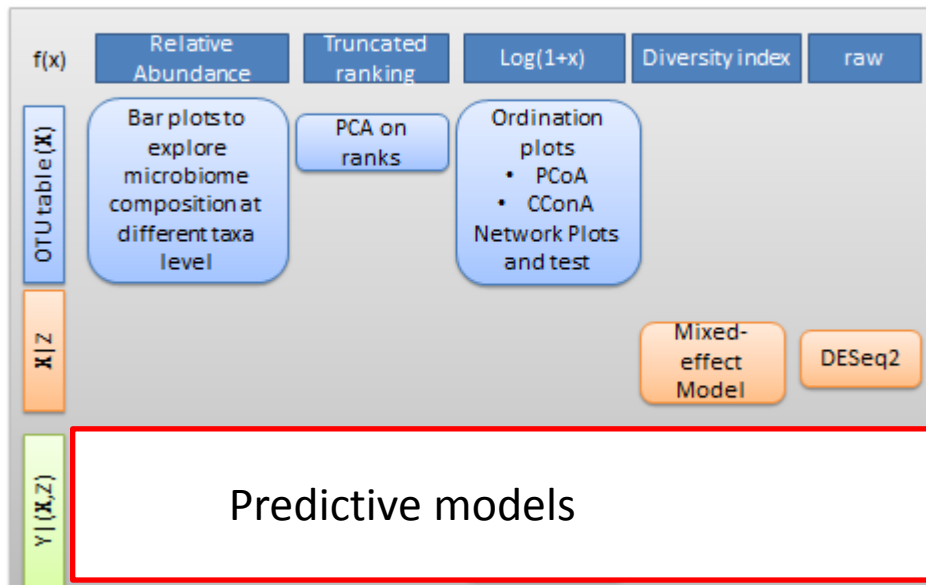
$$\tilde{Y}_i(t) = \frac{\Delta Y_i(t)}{\Delta t}$$

$$\tilde{Y}_i(t) = \beta_0 + \sum_{k=1}^K \alpha_{ik} Y_k + \varepsilon_{it}$$

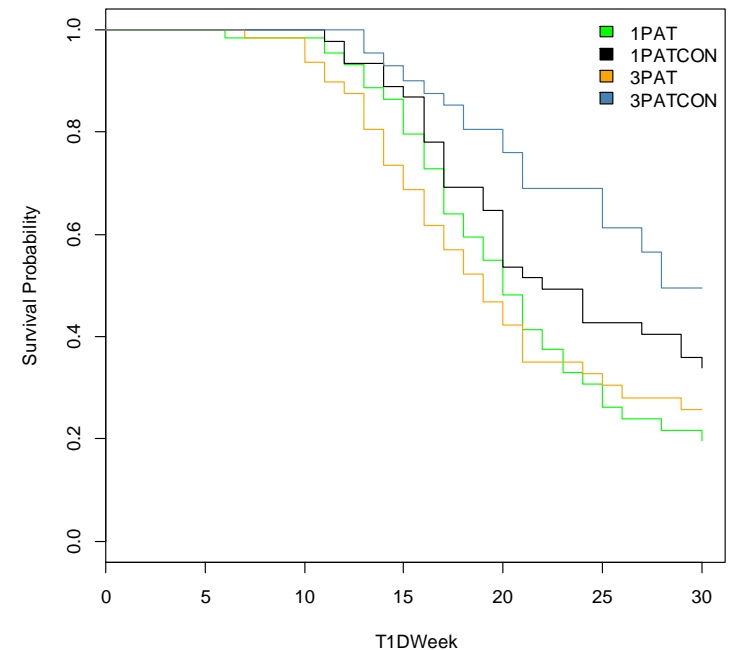
- LASSO/EN models.

# 3.4: Predictive models for diabetes based on microbiome data

## Data Analysis



## Clinical response: time to event data



Can we predict the time to event using microbiome data ?

## 3.5: Risk score for diabetes

- Modeling high/low risk for diabetes using microbiome risk score.

$$R_i = f(OTU_1, OTU_2, \dots, OTU_K)$$

Risk score to develop diabetes

$$\text{Risk group} = \begin{cases} low & R_i \leq \theta \\ high & R_i > \theta \end{cases}$$

$$S(t) = f(RG_i)$$

Can we find a significant different between the risk group in terms the time to developing diabetes ?