Microbial Bile Acid Metabolism Shapes T Cell Responses During Inflammation

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Chapter 1

Introduction: load the datasets

1.1 Load packages

```
library(janitor)
library(readxl)
library(tidyverse)
library(ggpubr)
library(data.table)
```

1.2 Load datasets

```
#patient cohort
cohort_BAS<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/cohort_BAS.csv")
ursodiol<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/ursodiol.csv")

#metabolomics data
#concentrations
conc_all_filtered<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/conc_all_filtered_combined_table<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/filtered#annotations
ba_families<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/ba_families.csv")

#16s data</pre>
```

counts_samples <-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/countasv_annotation_blast_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/asv_alpha_all<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/asv_alpha_asv_annotation_blast_color_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_insv_annotation_blast_color_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_insv_annotation_blast_color_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_insv_annotation_blast_color_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_insv_annotation_blast_color_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_insv_annotation_blast_color_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_insv_annotation_blast_color_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_insv_annotation_blast_color_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_insv_annotation_blast_color_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_insv_annotation_blast_color_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_insv_annotation_blast_color_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_insv_annotation_blast_color_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_insv_annotation_blast_color_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_insv_annotation_blast_color_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_insv_annotation_blast_color_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_insv_annotation_blast_color_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_insv_annotation_blast_color_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_insv_annotation_blast_color_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_insv_annotation_blast_color_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_insv_annotation_blast_color_ag<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_insv_annotation_blast_color_ag<-read_csv("/

#shotqun data

BSH_metalphlan <-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/BSH_mbai_genes_clean<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/bai_gtaxa_bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/taxa_bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/taxa_bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/taxa_bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/taxa_bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/bai_gtaxa_bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/bai_gtaxa_bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/bai_gtaxa_bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/bai_gtaxa_bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/bai_gtaxa_bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/bai_gtaxa_bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/bai_gtaxa_bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/bai_gtaxa_bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/bai_gtaxa_bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/bai_gtaxa_bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/bai_gtaxa_bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/bai_gtaxa_bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/bai_gtaxa_bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/bai_gtaxa_bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/bas_later<-read_csv("/Volumes/vandenbrinklab/Oriana/BAs_pub

#ursodiol cohort: double check that it's ok to share
patients_urso_CIF<- read_csv("/Volumes/vandenbrinklab/Oriana/BAs_published_datasets/patients_urso_cif*</pre>

Chapter 2

Analyze the effect of UDCA administration on the bile acid pool (supplementary figure 5)

```
#summarize bile acid pools
both_conc<- cohort_BAS %>% select(-ursodiol)%>%
  left_join(conc_all_filtered) %>% clean_names()
*prep dataset prepping each BA depending on its classifications
both_conc_pools<-both_conc %>%
  gather("bile_acid", "value", names(.)[8]:names(.)[ncol(.)]) %>%
  select(-gi_gvhd, -later, -periengr) %>%
  left_join(ba_families) %>%
  filter(bile_acid!="beta_muricholic_acid") %>% #removing because it's not measured in all sample
  filter(bile_acid!="omega_muricholic_acid") %>% #removing because it's not measured in all samp
  mutate(primary_pool=ifelse(prim_vs_sec=="Primary", value, 0)) %>%
  mutate(secondary_pool=ifelse(prim_vs_sec=="Secondary", value, 0)) %>%
  mutate(sulfated_pool=ifelse(sulfated=="Y", value, 0)) %>%
  mutate(conjugated_pool=ifelse(amidated=="Y" & sulfated=="N", value, 0)) %>%
  mutate(unconjugated_pool=ifelse(amidated=="N" & sulfated=="N", value, 0)) %>%
  mutate(secondary_nonUDCA=ifelse(prim_vs_sec=="Secondary" & udca=="N", value, 0)) %>%
  mutate(total_BAs=value) %>%
  mutate(total_nonUDCA_pool=ifelse(udca=="N", value, 0)) %>%
  mutate(glycine_pool=ifelse(glycine=="Y" & sulfated=="N", value, 0)) %%
  mutate(taurine_pool=ifelse(taurine=="Y" & sulfated=="N", value, 0)) %>%
```

```
mutate(taurine_SBA_pool=ifelse(taurine=="Y" & prim_vs_sec=="Secondary" & sulfated=="!"
mutate(taurine_PBA_pool=ifelse(taurine=="Y" & prim_vs_sec=="Primary" & sulfated=="N"
mutate(glycine_SBA_pool=ifelse(glycine=="Y" & prim_vs_sec=="Secondary" & sulfated=="N"
mutate(glycine_PBA_pool=ifelse(glycine=="Y" & prim_vs_sec=="Primary" & sulfated=="N",
select(-colnames(ba_families), -value)

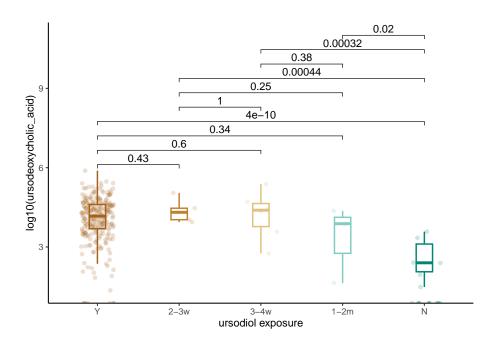
both_conc_pools_final<-both_conc_pools %>%
group_by(sampleid) %>%
summarise(across(where(is.numeric), sum)) %>%
left_join(ursodiol)

#rearrange ursodiol
both_conc_pools_final$ursodiol <-factor(both_conc_pools_final$ursodiol,
levels=c("Y","2-3w","3-4w","1-2m", "N"))</pre>
```

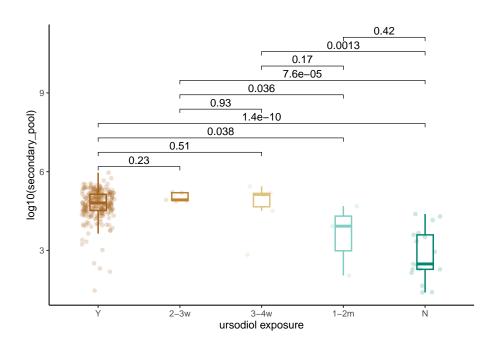
##Evaluation of ursodiol exposure and UDCA concentration

```
ursodiol_BAs<-both_conc %>%
 left_join(ursodiol)
#rearrange ursodiol
ursodiol BAs$ursodiol <-factor(ursodiol BAs$ursodiol,
                           levels=c("Y","2-3w","3-4w","1-2m", "N"))
ursodiol_BAs %>%
  ggplot(aes(x=ursodiol, y=log10(`ursodeoxycholic_acid`), color=ursodiol)) +
  geom_boxplot(width=0.2, outlier.shape =NA, lwd=.7)+
 geom_jitter(width=0.2, alpha=0.2)+
 theme_classic() +
 xlab("ursodiol exposure")+
  stat_compare_means(comparisons=list( c("Y", "2-3w"),c("3-4w", "Y"), c("Y", "1-2m"),
                                       c("3-4w", "2-3w"), c("1-2m", "2-3w"), c("N", "2-3w")
                                       c("1-2m", "3-4w"), c("N", "3-4w"),
                                       c("N", "1-2m")
  ),
  #label="p.signif",
 method="wilcox.test",
 correct=FALSE)+
 scale color manual(values=c("#a6611a", "#bf812d", "#dfc27d", "#80cdc1", "#018571"))+
 theme(legend.position="none")
```

2.1. PLOT URSODIOL EXPOSURE AND SECONDARY BAS CONCENTRATIONS9



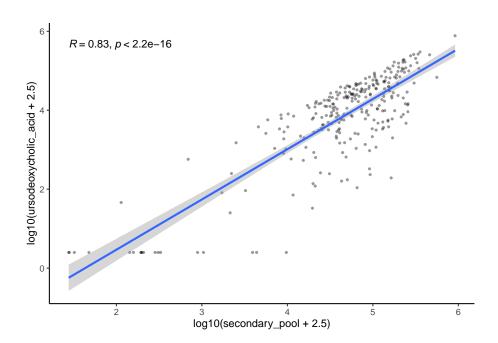
2.1 Plot ursodiol exposure and secondary BAs concentrations



2.2 Plot correlation of ursodiol with other bile acid pools: plot conjugated UDCA (taurour-sodeoxycholic_acid+glycoursodeoxycholic_acid), TBAs (total_BAs), PBAs (primary_pool), SBAs (secondary_pool), nonUDCA total BAs (total_nonUDCA_pool), nonUDCA SBAs (secondary_nonUDCA), secondary/primary ratio (SP_ratio)

```
both_conc_pools_final %>%
  mutate(SP_ratio=secondary_pool/primary_pool) %>%
  mutate(SP_ratio_nonUDCA=secondary_nonUDCA/primary_pool) %>%
  left_join(both_conc %>% select(sampleid, glycoursodeoxycholic_acid, tauroursodeoxychoggplot(aes(y=log10(`ursodeoxycholic_acid`+2.5), x=log10(secondary_pool+2.5)))+
  geom_point(size=0.8, alpha=0.4)+
  geom_smooth(method="lm")+
  stat_cor(method = "pearson")+
  #ylab("log10(UDCA)")+
```

```
#xlab("log10(PS_nonUDCA)")+
theme_classic()
```

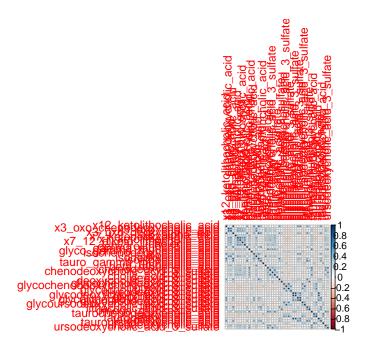


2.3 Create correlation plots to evaluate association of UDCA with all individual BAs

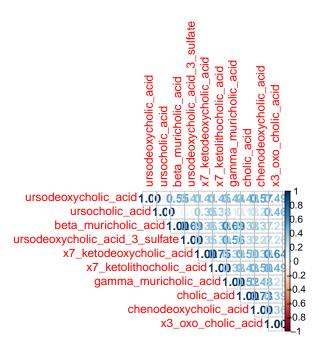
```
library(corrplot)

precor_data<- filtered_combined_table %>%
    column_to_rownames("sampleid")
cor_data<-cor(precor_data, use = "complete.obs")

corrplot(cor_data)</pre>
```



2.3.1 Visualization of significant correlations of UDCA with individual BAs (R>0.4)



14CHAPTER 2. ANALYZE THE EFFECT OF UDCA ADMINISTRATION ON THE BILE ACID POC

Chapter 3

Create the bile acid pools (figure 4, supplementary figure 6,8)

3.1 Create BA pools first for peri-GVHD-onset timepoint

```
later<- cohort BAS %>%filter(later=="Y") %>%
  filter(ursodiol=="Y") %>%
  select(sampleid, GI_GVHD) %>%
  left_join(conc_all_filtered)
#prep dataset prepping each BA depending on its classifications
later_pools<-later %>%
  gather("bile_acid", "value", names(.)[5]:names(.)[ncol(.)]) %>%
  left_join(ba_families) %>%
  mutate(primary_pool=ifelse(prim_vs_sec=="Primary", value, 0)) %>%
  mutate(secondary_pool=ifelse(prim_vs_sec=="Secondary", value, 0)) %>%
  mutate(sulfated_pool=ifelse(sulfated=="Y", value, 0)) %>%
  mutate(conjugated_pool=ifelse(amidated=="Y" & sulfated=="N", value, 0)) %%
  mutate(unconjugated_pool=ifelse(amidated=="N" & sulfated=="N", value, 0)) %>%
  mutate(secondary_nonUDCA=ifelse(prim_vs_sec=="Secondary" & udca=="N", value, 0)) %>%
  mutate(total_BAs=value) %>%
  mutate(total_nonUDCA_pool=ifelse(udca=="N", value, 0)) %>%
  mutate(glycine_pool=ifelse(glycine=="Y" & sulfated=="N", value, 0)) %%
  mutate(taurine_pool=ifelse(taurine=="Y" & sulfated=="N", value, 0)) %>%
```

```
mutate(taurine_SBA_pool=ifelse(taurine=="Y" & prim_vs_sec=="Secondary" & sulfated=="!"
mutate(taurine_PBA_pool=ifelse(taurine=="Y" & prim_vs_sec=="Primary" & sulfated=="N"
mutate(glycine_SBA_pool=ifelse(glycine=="Y" & prim_vs_sec=="Secondary" & sulfated=="N"
mutate(glycine_PBA_pool=ifelse(glycine=="Y" & prim_vs_sec=="Primary" & sulfated=="N", select(-colnames(ba_families), -value)

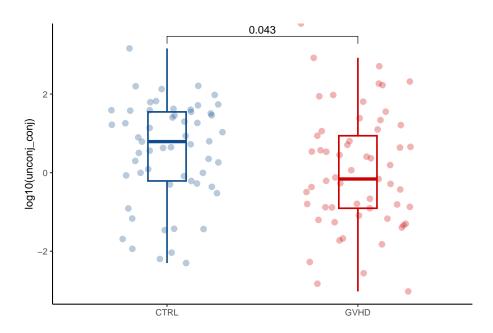
#replace NAs with 0 to be able to add sums
later_pools[is.na(later_pools)]<-0

later_pools_final<-later_pools %>%
    #gather("bile_acid", "value", names(.)[2]:names(.)[ncol(.)]) %>%
#summarise(sum_group=sum(value))
group_by(sampleid) %>%
summarise(across(where(is.numeric), sum))
```

3.1.1 Plot: TBAs (total_BAs), PBAs (primary_pool), SBAs (secondary_pool), nonUDCA SBAs (secondary_nonUDCA), conjugated (conjugated_pool), unconjugated (unconjugated_pool), sulfated (sulfated pool)

```
later_pools_final %>%
  left_join(cohort_BAS) %>%
 mutate(GI_GVHD=ifelse(GI_GVHD=="Y", "GVHD", "CTRL")) %>%
 mutate(sp_ratio=secondary_pool/primary_pool) %>%
 mutate(sp_nonUDCA_ratio=secondary_nonUDCA/primary_pool) %>%
 mutate(unconj_conj=unconjugated_pool/conjugated_pool) %>%
  ggplot(aes(x=GI_GVHD, y=log10(unconj_conj), colour=GI_GVHD))+
  geom_boxplot(width=0.2, lwd=0.8, outlier.shape = NA) +
  geom_jitter(width=0.3, alpha=0.3, size=2.5)+
 ylab("log10(unconj_conj)")+
 xlab("")+
 theme classic()+
  stat_compare_means(comparisons=list(c("CTRL", "GVHD")),
                     method="wilcox.test",
                     correct=FALSE)+
  scale color manual(values=c("dodgerblue4", "red3"))+
  theme(legend.position="none")
```

3.1. CREATE BA POOLS FIRST FOR PERI-GVHD-ONSET TIMEPOINT17



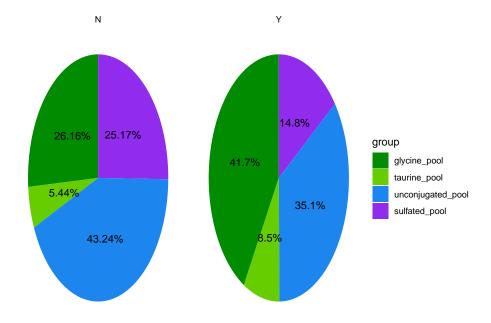
3.1.2 Create pies

dataset_pre<-later_pools_final %>%

```
gather("BA_pool", "value", names(.)[2]:names(.)[ncol(.)]) %>%
  left_join(cohort_BAS %>%
              select(sampleid, GI_GVHD, later, ursodiol)) %>%
  filter(later=="Y") %>%
  filter(ursodiol=="Y") %>%
  select(-ursodiol, -later) %>%
  group_by(GI_GVHD, BA_pool) %>%
  summarise(ave_pool=ave(value)) %>% slice(1)
## Joining with `by = join_by(sampleid)`
## Warning: Returning more (or less) than 1 row per `summarise()` group was deprecated in
## dplyr 1.1.0.
## i Please use `reframe()` instead.
## i When switching from `summarise()` to `reframe()`, remember that `reframe()`
     always returns an ungrouped data frame and adjust accordingly.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```

```
## `summarise()` has grouped output by 'GI_GVHD', 'BA_pool'. You can override
## using the `.groups` argument.
```

```
dataset_pre2<-dataset_pre %>%
  #filter(BA_pool=="primary_pool"|BA_pool=="secondary_nonUDCA") %>% #to evaluate nonUD
  #filter(BA_pool=="primary_pool"|BA_pool=="secondary_pool") %>% #to evaluate total se
  filter(BA_pool=="glycine_pool"|BA_pool=="taurine_pool"|BA_pool=="sulfated_pool"|BA_p
  rename(group=BA_pool) %>%
 rename(value=ave_pool) %>%
 ungroup() %>%
  group_by(GI_GVHD) %>%
 mutate(sum_value=sum(value)) %>%
 mutate(perc=value/sum_value) %>%
 mutate(labels = scales::percent(perc)) %>%
  ungroup()
#only run below when evaluating glycine/taurine conjugation as wel
#define order of piechart for glycine/taurin conjugation
dataset_pre2$group <- factor(dataset_pre2$group, levels = c("glycine_pool", "taurine_p
cp<-coord_polar(theta="y")</pre>
cp$is_free<-function()TRUE</pre>
ggplot(dataset_pre2, aes(x="", y=perc, fill=group))+
 geom_bar(stat="identity", width=1)+cp+
  facet_wrap(.~GI_GVHD, scales="free")+
  geom_text(aes(label = labels),
            position = position_stack(vjust = 0.5)) +
  theme_void()+
  theme(axis.ticks=element_blank(),
        axis.title=element_blank(),
        axis.text.y=element_blank())+
  scale_fill_manual(values=c("green4", "chartreuse3", "dodgerblue2", "purple2")) #to eval
```



3.2 Create BA pools for peri-engraftment timepoint

```
periengr_conc<- cohort_BAS %>%filter(periengr=="Y") %>%
  filter(ursodiol=="Y") %>%
  select(sampleid, GI_GVHD) %>%
  left_join(conc_all_filtered) %>%
  select(-`beta_muricholic_acid`, -`omega_muricholic_acid`) #remove since it is not measured in a
#prep dataset prepping each BA depending on its classifications
periengr_pools<-periengr_conc %>%
  gather("bile_acid", "value", names(.)[3]:names(.)[ncol(.)]) %>%
  left_join(ba_families) %>%
  mutate(primary_pool=ifelse(prim_vs_sec=="Primary", value, 0)) %>%
  mutate(secondary_pool=ifelse(prim_vs_sec=="Secondary", value, 0)) %>%
  mutate(sulfated_pool=ifelse(sulfated=="Y", value, 0)) %>%
  mutate(conjugated_pool=ifelse(amidated=="Y" & sulfated=="N", value, 0)) %>%
  mutate(unconjugated_pool=ifelse(amidated=="N" & sulfated=="N", value, 0)) %>%
  mutate(secondary_nonUDCA=ifelse(prim_vs_sec=="Secondary" & udca=="N", value, 0)) %%
  mutate(total BAs=value) %>%
  mutate(total_nonUDCA_pool=ifelse(udca=="N", value, 0)) %>%
```

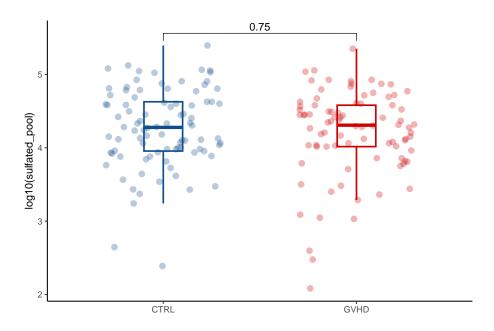
```
mutate(glycine_pool=ifelse(glycine=="Y" & sulfated=="N", value, 0)) %>%
mutate(taurine_pool=ifelse(taurine=="Y" & sulfated=="N", value, 0)) %>%
mutate(taurine_SBA_pool=ifelse(taurine=="Y" & prim_vs_sec=="Secondary" & sulfated=="""
mutate(taurine_PBA_pool=ifelse(taurine=="Y" & prim_vs_sec=="Primary" & sulfated=="N"
mutate(glycine_SBA_pool=ifelse(glycine=="Y" & prim_vs_sec=="Secondary" & sulfated=="N"
mutate(glycine_PBA_pool=ifelse(glycine=="Y" & prim_vs_sec=="Primary" & sulfated=="N", select(-colnames(ba_families), -value)

#replace NAs with 0 to be able to add sums
periengr_pools[is.na(periengr_pools)]<-0

#final table with each group sum
periengr_pools_final<-periengr_pools %>%
    group_by(sampleid) %>%
    summarise(across(where(is.numeric), sum))
```

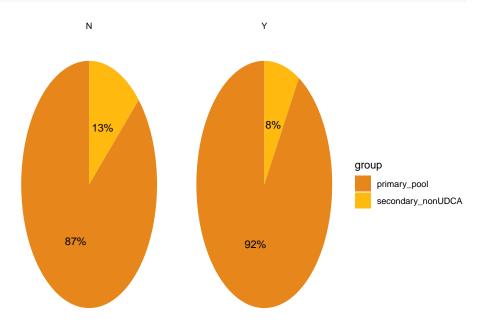
3.2.1 Plot BA pools and GVHD; can plot total BAs (total_BAs), PBAs (primary_pool), SBAs (secondary_pool), nonUDCA SBAs (secondary_nonUDCA), conjugated (conjugated_pool), unconjugated (unconjugated_pool), sulfated_pool, secondary/primary ratio and secondary*/primary ratio

```
periengr_pools_final %>%
  left_join(cohort_BAS) %>%
 mutate(GI_GVHD=ifelse(GI_GVHD=="Y", "GVHD", "CTRL"))  %>%
 mutate(sp_ratio=secondary_pool/primary_pool) %>%
 mutate(sp_nonUDCA_ratio=secondary_nonUDCA/primary_pool) %>%
  ggplot(aes(x=GI_GVHD, y=log10(sulfated_pool), colour=GI_GVHD))+
  geom_boxplot(width=0.2, lwd=0.8, outlier.shape = NA) +
  geom_jitter(width=0.3, alpha=0.3, size=2.5)+
  #ylab("log10(sulfated_pool)")+
  xlab("")+
  theme classic()+
  stat_compare_means(comparisons=list(c("CTRL", "GVHD")),
                     method="wilcox.test",
                     correct=FALSE)+
  scale color manual(values=c("dodgerblue4", "red3"))+
  theme(legend.position="none")
```



3.2.2 Create pies

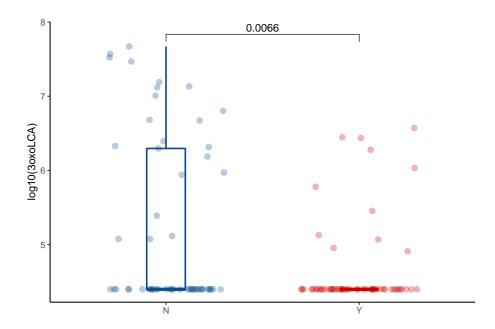
```
dataset_pre<-periengr_pools_final %>%
      gather("BA_pool", "value", names(.)[2]:names(.)[ncol(.)]) %>%
      left_join(cohort_BAS %>% select(sampleid, GI_GVHD, ursodiol)) %>%
      filter(ursodiol=="Y") %>%
      group_by(GI_GVHD, BA_pool) %>%
      summarise(ave_pool=ave(value)) %>% slice(1)
dataset_pre2<-dataset_pre %>%
      filter(BA_pool=="primary_pool"|BA_pool=="secondary_nonUDCA") %>% #to evaluate nonUDCA secondary
       #filter(BA_pool=="primary_pool"|BA_pool=="secondary_pool") %>% #to evaluate total secondary
       \#filter(BA\_pool == "glycine\_pool" | BA\_pool == "taurine\_pool" | BA\_pool == "sulfated\_pool" | BA\_pool == "unconstant" | BA\_pool == "sulfated\_pool" | BA\_pool == "unconstant" | BA\_pool == "sulfated\_pool" | BA\_pool == "unconstant" | BA\_pool == "unconstant" | BA\_pool == "sulfated\_pool" | BA\_pool == "unconstant" | BA\_pool == "uncons
      rename(group=BA_pool) %>%
      rename(value=ave_pool) %>%
      ungroup() %>%
      group_by(GI_GVHD) %>%
      mutate(sum_value=sum(value)) %>%
      mutate(perc=value/sum_value) %>%
      mutate(labels = scales::percent(perc)) %>%
      ungroup()
#only run to evaluate glycine/taurine conjugation
```



Chapter 4

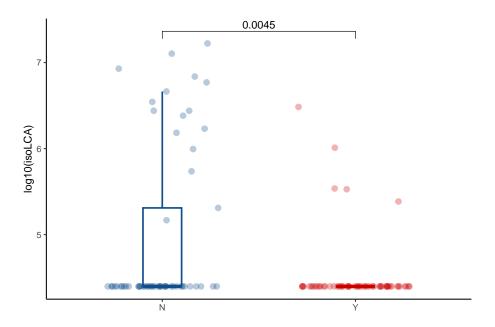
Evaluate T cell modulatory BAs in patients with GVHD vs controls (figure 4)

4.1 3oxoLCA

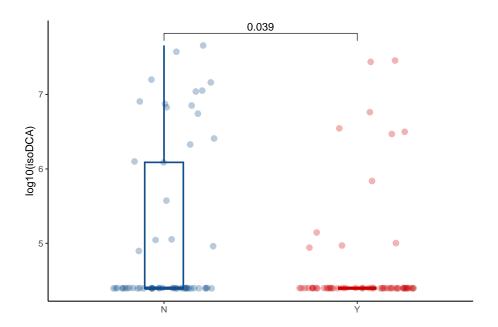


4.2 isoLCA

4.3. ISODCA 25

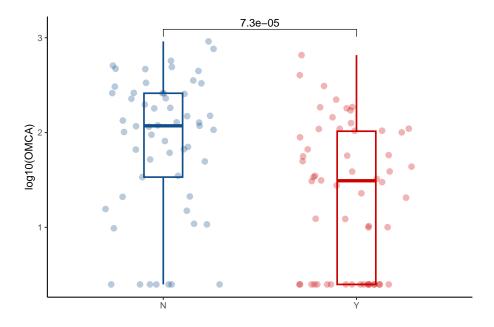


4.3 isoDCA



4.4 OMCA

4.4. OMCA 27



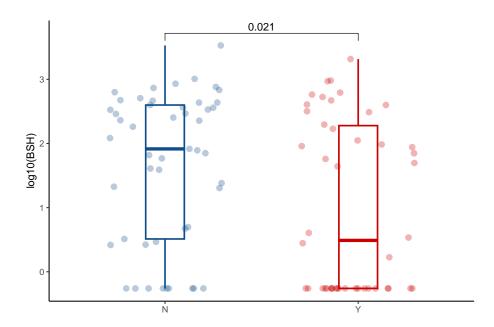
28CHAPTER 4. EVALUATE T CELL MODULATORY BAS IN PATIENTS WITH GVHD VS CONTR

Chapter 5

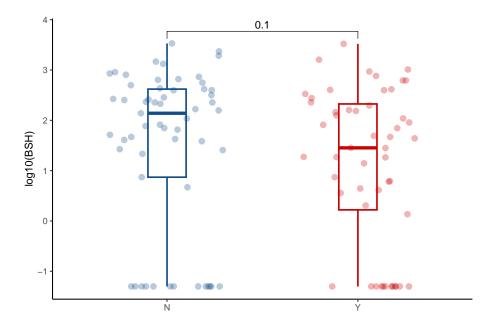
Shotgun metagenomic sequencing: Evaluate genes of interest (figure 5, supplement figure 10)

5.1 BSH

5.1.1 Evaluate BSH abundance at peri-GVHD onset



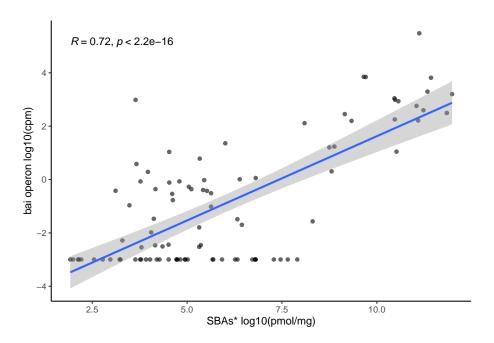
5.1.2 Evaluate BSH abundance at peri-engraftment time point



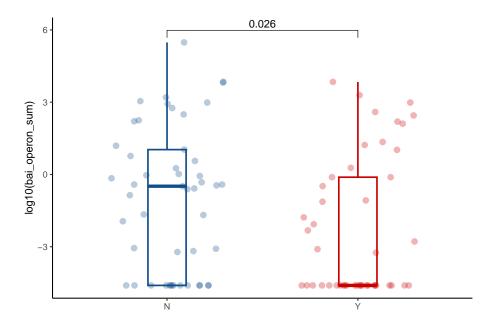
5.2 Bai operon gene

5.2.1 Evaluate correlation of bai operon gene sum and nonUDCA secondary BAs

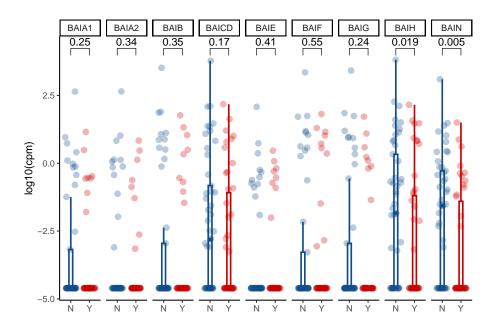
```
bai_genes_clean %>%
  distinct(sampleid, bai_operon_sum ) %>%
  inner_join(both_conc_pools_final) %>%
  ggplot(aes(x=log(secondary_nonUDCA), y=log(bai_operon_sum+0.05)))+
  geom_point(alpha=0.6)+
  stat_cor(method="pearson")+
  geom_smooth(method="lm")+
  theme_classic()+
  ylab("bai operon log10(cpm)")+
  xlab("SBAs* log10(pmol/mg)")
```



5.2.2 Bai operon gene sum in peri-GVHD onset

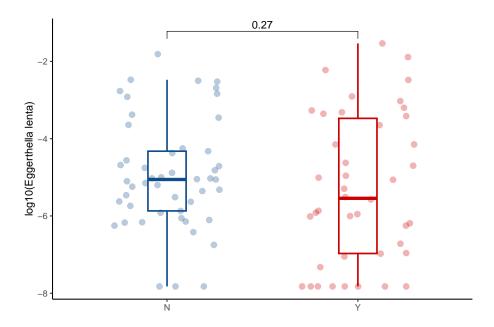


5.2.3 Bai operon individual gene abundance

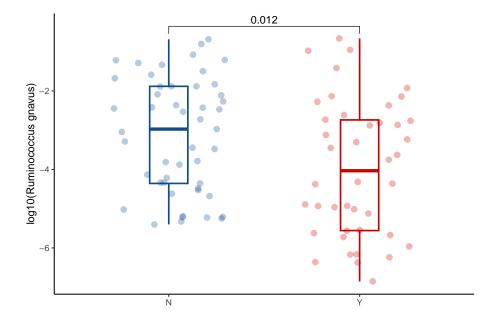


5.3 Bile acid related bacteria

5.3.1 Eggerthella lenta



5.3.2 Ruminococcus gnavus



Chapter 6

Create landscape of all peri-GVHD-onset samples (figure 5)

6.1 Define sample order from higher nonUDCA secondary BAs to lower

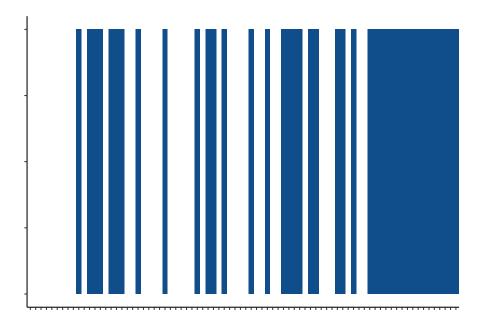
```
samples_key<-BSH_metalphlan %>% distinct(sampleid) %>%
  left_join(later_pools_final %>% select(sampleid, secondary_nonUDCA)) %>%
  left_join(cohort_BAS) %>%
  filter(later=="Y") %>%
  arrange(desc(secondary_nonUDCA)) %>%
  left_join(ursodiol) %>% filter(ursodiol2=="Y")

level_order <- samples_key$sampleid</pre>
```

6.2 GI GVHD plot

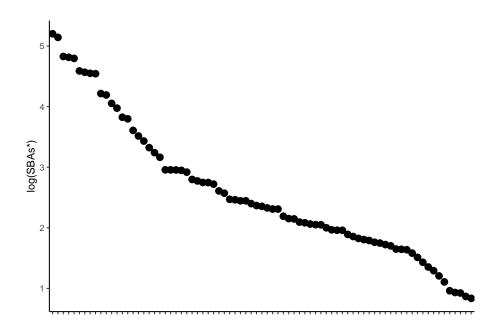
```
gi_gvhd_plot<-cohort_BAS %>%
filter(later=="Y") %>%
ggplot((aes(x = factor(sampleid, levels = level_order), y = 1, fill = GI_GVHD))) +
geom_raster(color = "black", size = 0.5) +
theme_classic()+ theme(axis.text.x=element_blank())+
```

```
xlab("")+
ylab("")+
scale_fill_manual(values=c("white", "dodgerblue4"))+
theme(axis.text.y = element_blank())+
theme(legend.position = "none") #only for plotting reasons
gi_gvhd_plot
```



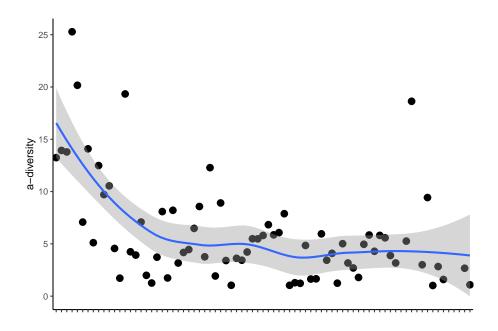
6.3 SBA plot

```
sba_plot<-ggplot(samples_key, aes(x=factor(sampleid, level=level_order), y=log10(second geom_point(size=3)+theme_classic()+
   ylab("log(SBAs*)")+
   theme(axis.text.x=element_blank())+
   xlab("")
sba_plot</pre>
```



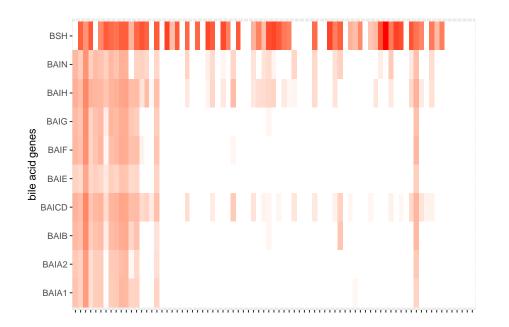
6.4 A-diversity plot

```
adiv_pre<-cohort_BAS %>%
 filter(later=="Y") %>%
 left_join(asv_alpha_all) %>% #add a-diversity
  inner_join(samples_key) %>%
  arrange(desc(secondary_nonUDCA)) %>%
          mutate(rank = 1:nrow(.))
adiv_plot \leftarrow ggplot(adiv_pre, aes(x = rank, y = simpson_reciprocal)) +
  geom_point(size=3) +
  geom_smooth(method = "loess") +
  theme_classic() +
 ylab("a-diversity") +
  #xlab("sampleid") +
 theme(axis.text.x = element_blank()) +
 xlab("") +
 scale_x_discrete(limits = adiv_pre$rank[order(-adiv_pre$rank)])
adiv_plot
```



6.5 Bile acid related genes

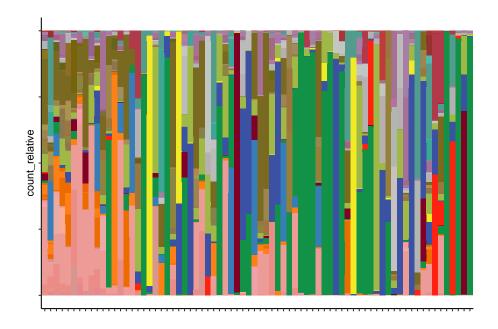
```
bai_genes_clean$sampleid <-gsub("FMT_", "FMT.", bai_genes_clean$sampleid)</pre>
ba_genes_pre<-samples_key %>%
  select(sampleid, GI_GVHD, secondary_nonUDCA) %>%
  left_join(BSH_metalphlan %>%
              select(sampleid, cpm, KOID)) %>%
  rename(gene=KOID) %>%
  mutate(gene=ifelse(gene=="K01442", "BSH", NA)) %>%
  distinct() %>%
  spread(key=gene, value=cpm, fill=0)
operon_genes_pre<-samples_key %>%
  left_join(bai_genes_clean) %>%
  select(sampleid, cpm, gene) %>%
  distinct() %>%
  spread(key=gene, value=cpm, fill=0)
pre_bai_plot<-ba_genes_pre %>%
  left_join(operon_genes_pre) %>%
  select(-GI_GVHD, -secondary_nonUDCA) %>%
```



6.6 Microbiome composition

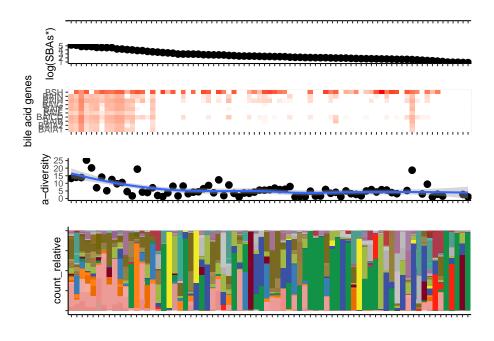
```
setDT(asv_annotation_blast_color_ag)
asv_color_base_set = unique(asv_annotation_blast_color_ag[,.(color_label_group,color_base)])
color_base_set_asv_carT = asv_color_base_set$color_base
names(color_base_set_asv_carT) = asv_color_base_set$color_label_group;
gg = ggplot(asv_color_base_set, aes(color_label_group,y=1,fill=color_label_group)) + geom_tile()
    scale_fill_manual(values = color_base_set_asv_carT) +
```

```
theme_classic() +
  theme(axis.text.x = element_text(angle=60,hjust = 1)) +
  theme(legend.position = "none")
#color_set_asv_carT maps each distinct taxonomic group to its corresponding color.
asv_color_set = unique(asv_annotation_blast_color_ag[,.(color,color_label_group_disting)
color_set_asv_carT = asv_color_set$color
names(color_set_asv_carT) =asv_color_set$color_label_group_distinct;
setDT(counts_samples)
setDT(asv_annotation_blast_color_ag)
m = merge(counts_samples[,.(asv_key,sampleid,
                         count, count relative, count total)],
          asv_annotation_blast_color_ag[,.(asv_key,color_label_group_distinct)]);
sample_composition <- m %>%
  left_join(cohort_BAS %>% select(PID, sampleid)) %>%
  left_join(cohort_BAS) %>%
  filter(later=="Y")
m1<-sample_composition %>%
  group_by(sampleid, color_label_group_distinct) %>%
  inner_join(samples_key) %>%
  mutate(sampleid = fct_reorder(sampleid, desc(secondary_nonUDCA)))
m1$color_label_group_distinct = factor(m1$color_label_group_distinct,levels = sort(uni-
gg_composition = ggplot(m1,
                        aes(x=factor(sampleid, levels=level_order),
                            y=count relative,
                            fill=color_label_group_distinct) ) +
  geom_bar(stat = "identity",position="fill",width = 1) +
  theme_classic() +
  theme(axis.text.x = element_blank(),
        axis.text.y = element_blank(),
        legend.position = "none") +
  xlab("")+
  scale_fill_manual(values = color_set_asv_carT);
print(gg_composition)
```



6.7 Add all plots together

$44 CHAPTER\ 6.\ CREATE\ LANDSCAPE\ OF\ ALL\ PERI\ GVHD-ONSET\ SAMPLES\ (FIGURE\ 5)$



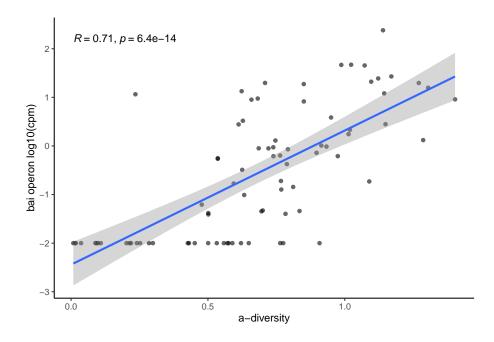
Chapter 7

Diversity, bai operon and domination

7.1 Evaluate correlation of a-diversity and bai operon sum

```
data_ba<- asv_alpha_all %>%
  inner_join(bai_genes_clean %>% distinct(sampleid, bai_operon_sum)) %>%
  left_join(cohort_BAS) %>%
  filter(ursodiol=="Y")

data_ba %>%
ggplot(aes(x=log10(simpson_reciprocal), y=log10(bai_operon_sum+0.01)))+
  geom_point(alpha=0.6)+
  stat_cor(method="pearson")+
  geom_smooth(method="lm")+
  theme_classic()+
  ylab("bai operon log10(cpm)")+
  xlab("a-diversity")
```

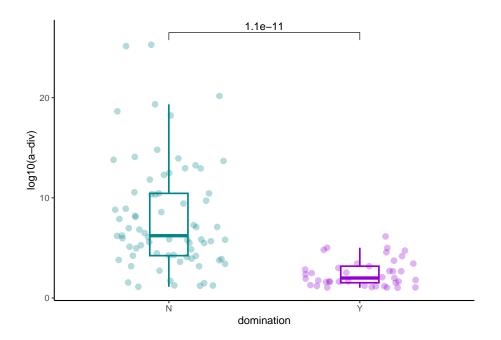


7.2 Identify patients with monodomination by 16S

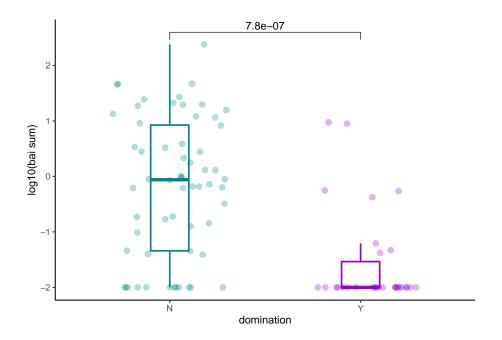
```
#create dataset with asv
samples_asv<-cohort_BAS %>%
  filter(later=="Y") %>%
  select(sampleid) %>%
  inner_join(counts_samples %>%
               select(sampleid, asv_key, count, count_total)) %>%
  inner_join(asv_annotation_blast_ag %>%
               select(asv_key, kingdom, phylum, class, ordr, family, genus)) %>%
  mutate(relab=count/count_total) %>%
  group_by(sampleid, genus)
pathogens_pre<- samples_asv %>%
  filter(genus=="Enterococcus"|genus=="Streptococcus"|phylum=="Proteobacteria") %>%
  mutate(enterococcus=ifelse(genus=="Enterococcus", relab, 0)) %>%
  mutate(streptococcus=ifelse(genus=="Streptococcus", relab, 0)) %>%
  mutate(proteobacteria=ifelse(phylum=="Proteobacteria", relab, 0)) %>%
  mutate(enterococcus_dom=ifelse(enterococcus>=0.3, "Y", "N")) %>%
  mutate(streptococcus_dom=ifelse(streptococcus>=0.3, "Y", "N")) %>%
   mutate(proteobacteria_dom=ifelse(proteobacteria>=0.3, "Y", "N")) %>%
```

```
mutate(any_dom=ifelse(enterococcus_dom=="Y"|streptococcus_dom=="Y"|proteobacteria_dom=="Y", "Y'
group_by(sampleid) %>%
arrange(desc(any_dom)) %>% slice(1)
```

7.3 Domination and a-diversity

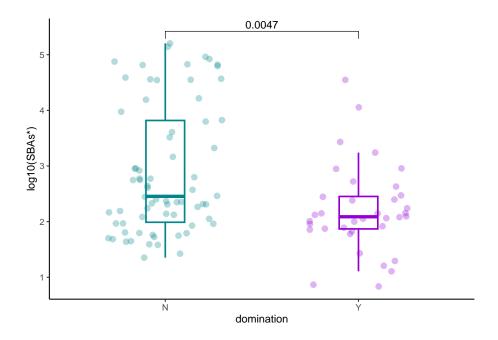


7.4 Domination and bai operon



7.5 SBAs and domination

```
pathogens_pre %>% inner_join(later_pools_final) %>%
   ggplot(aes(x=any_dom, y=log10(secondary_nonUDCA), color=any_dom))+
   geom_boxplot(width=0.2, lwd=0.8, outlier.shape = NA) +
```



Chapter 8

##

##

Censored

624

Evaluation of UDCA exposure and clinical outcomes

8.1 Prepare the patient outcome table

Other

100

386

GRM Relapse/PoD

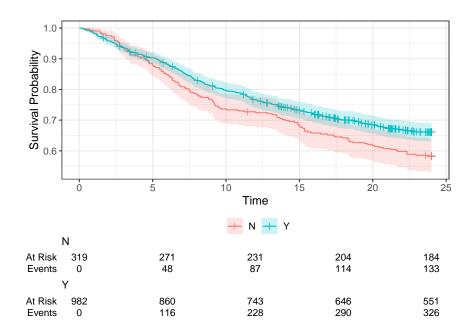
191

```
patients_urso_CIF2$GRM_time <- patients_urso_CIF2$OS</pre>
patients_urso_CIF2$GRM_time[patients_urso_CIF2$relapse==T & patients_urso_CIF2$pod=="N
patients_urso_CIF2$GRM_time[patients_urso_CIF2$relapse==F & patients_urso_CIF2$pod=="Y
patients_urso_CIF2$GRM_time[patients_urso_CIF2$relapse==T & patients_urso_CIF2$pod=="Y
patients_urso_CIF2$TRM_time <- patients_urso_CIF2$OS</pre>
patients_urso_CIF2$TRM_time[patients_urso_CIF2$relapse==T & patients_urso_CIF2$pod=="N
patients_urso_CIF2$TRM_time[patients_urso_CIF2$relapse==F & patients_urso_CIF2$pod=="Y
patients_urso_CIF2$TRM_time[patients_urso_CIF2$relapse==T & patients_urso_CIF2$pod=="Y
patients_urso_CIF2 <- patients_urso_CIF2 %>%
  mutate(GRM_mortality_2yr = ifelse(GRM_time > 24,1,GRM_mortality),
         GRM_time_2yr = ifelse(GRM_time > 24,24,GRM_time),
         TRM_mortality_2yr = ifelse(TRM_time > 24,1,TRM_mortality),
         TRM_time_2yr = ifelse(TRM_time > 24,24,TRM_time),
         death_2yr = ifelse(OS > 24,FALSE,death),
         OS_2yr = ifelse(OS > 24,24,OS),
         GRM_mortality_2yr = factor(GRM_mortality_2yr,levels=1:4,labels=c("Censored","
         TRM_mortality_2yr = factor(TRM_mortality_2yr,levels=1:3,labels=c("Censored",
patients_urso_CIF2 <- patients_urso_CIF2 %>% mutate(donor_new=ifelse(donor_match=="MMR
```

8.2 Evaluate ursodiol exposure and overall survival

8.2.1 Univariable analysis

```
KM.OS <- survfit2(Surv(OS_2yr,as.numeric(death_2yr))~ursodiol2,data=patients_urso_CIF2
KM.OS %>% ggsurvfit() +
  add_censor_mark() +
  add_confidence_interval() +
  add_risktable(times=c(0,6, 12, 18, 24))
```



8.2.2 Multivariable analysis

Characteristic	**HR**	**95% CI**	**p-value**
age	1.03	1.02, 1.04	<0.001
sex			
F	_	_	
M	0.95	0.79, 1.15	0.6
donor_match			
haplo		_	
haplo/MMUD	1.20	0.57, 2.51	0.6
MMRD	1.23	0.16, 9.28	0.8
MMUD	1.23	0.73, 2.07	0.4
MRD	0.74	0.45, 1.21	0.2
MUD	0.82	0.51, 1.32	0.4
graft			
BM	_	_	
CD34	0.89	0.60, 1.33	0.6
PBSC	1.15	0.80, 1.67	0.5
UCB	0.75	0.44, 1.28	0.3
intensity			
Ablative	_	_	
Nonablative	0.49	0.33, 0.73	<0.001
Reduced Intensity	1.00	0.74, 1.35	>0.9
ursodiol2			
N		_	
Y	0.69	0.55, 0.85	<0.001

8.3 Evaluation of cumulative incidences

8.3.1 Cumulative incidence of GVHD-related mortality

```
gray.test.GRM <- cuminc(Surv(GRM_time_2yr, GRM_mortality_2yr)~ursodiol2, data=patients]
gray.test.GRM %>% tbl_cuminc(times= c(6,12,18,24),outcome="GRM") %>%
  add_p() %>%
  add_n() %>%
  modify_caption("Outcome: GRM")

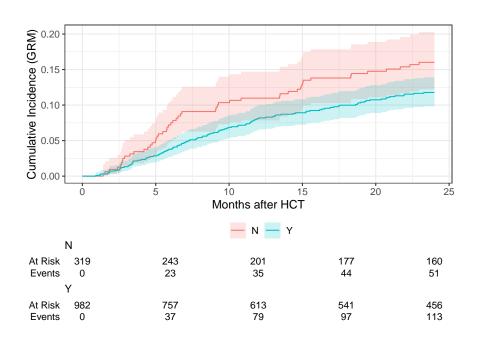
gray.test.GRM %>% ggcuminc(outcome="GRM") +
```

```
gray.test.GRM %>% ggcuminc(outcome="GRM") +
labs(
    x = "Months after HCT",
    y = "Cumulative Incidence (GRM)"
) +
```

Table 8.1: Outcome: GRM

Characteristic	**N**	**Time 6**	**Time 12**	**Time 18**	**Time 24**	*
ursodiol2	1,301					
N		7.2% (4.7%, 10%)	11% (7.8%, 15%)	14% (10%, 18%)	16% (12%, 20%)	
Y		3.8% (2.7%, 5.1%)	8.1% (6.5%, 9.9%)	10% (8.2%, 12%)	12% (9.8%, 14%)	

```
add_confidence_interval() +
add_risktable(times=c(0,6,12,18,24))
```



$8.3.2 \quad {\bf Cumulative \ incidence \ of \ Relapse/progression \ of \ disease }$

```
gray.test.GRM %>% tbl_cuminc(times= c(6,12,18,24),outcome="Relapse/PoD") %>%
add_p() %>%
add_n() %>%
modify_caption("Outcome: Relapse/PoD")
```

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Table 8.2: Outcome: Relapse/PoD

Characteristic	**N**	**Time 6**	**Time 12**	**Time 18**	**Time 24
ursodiol2	1,301				
N		12% (8.9%, 16%)	18% (14%, 23%)	22% (17%, 26%)	23% (18%, 28
Y		15% (13%, 17%)	24% (21%, 26%)	26% (24%, 29%)	28% (25%, 3

Table 8.3: Outcome: Other

Characteristic	**N**	**Time 6**	**Time 12**	**Time 18**	**Ti
ursodiol2	1,301				
N		4.7% (2.7%, 7.4%)	7.2% (4.7%, 10%)	8.8% (6.0%, 12%)	11% (7
Y		4.1% (3.0%, 5.4%)	5.0% (3.8%, 6.5%)	5.4% (4.1%, 7.0%)	5.6% (4

8.3.3 Cumulative incidence of mortality non-related to GVHD or relapse/progression of disease

```
gray.test.GRM %>% tbl_cuminc(times= c(6,12,18,24),outcome="Other") %>%
  add_p() %>%
  add_n() %>%
  modify_caption("Outcome: Other")
```

8.3.4 Multivariable analysis of GVHD-related mortality

fgmodel.GRM <- crr(Surv(GRM_time_2yr,GRM_mortality_2yr)~age+sex+donor_match+graft+inter
fgmodel.GRM %>% tbl_regression(exponentiate=TRUE) %>% bold_p()

Characteristic	**HR**	**95% CI**	**p-value**
age	1.02	1.01, 1.04	0.002
sex			
F			
M	0.77	0.56, 1.05	0.10
donor_match			
haplo	_		
haplo/MMUD	1.78	0.57, 5.59	0.3
MMRD	0.00	0.00, 0.00	<0.001
MMUD	1.52	0.65, 3.58	0.3
MRD	0.58	0.26, 1.28	0.2
MUD	0.74	0.35, 1.59	0.4
graft			
BM	_	_	
CD34	1.28	0.59, 2.79	0.5
PBSC	1.64	0.85, 3.16	0.14
UCB	0.88	0.36, 2.19	0.8
intensity			
Ablative	_	_	
Nonablative	0.95	0.53, 1.71	0.9
Reduced Intensity	1.25	0.75, 2.09	0.4
ursodiol2			
N			
Y	0.66	0.46, 0.94	0.022