

# Hi-C contig processing

Alice Risely

23/10/2023

## Contents

<b>Info</b>	<b>2</b>
Import packages . . . . .	3
<b>Import data</b>	<b>4</b>
<b>Filter and assign identity</b>	<b>7</b>
Remove links that involve an unidentified contigs . . . . .	7
Remove transposons . . . . .	8
Venn diagram after filtering transposons . . . . .	8
Assign remaining contigs to either MAG, plasmid, or resistance gene . . . . .	9
Add contig assignment to links DF . . . . .	9
Remove MAG-MAG links . . . . .	10
<b>Cluster plasmids and link to AMR</b>	<b>10</b>
Cluster plasmids . . . . .	10
Identify plasmid cluster memberships . . . . .	11
Connect plasmid clusters to resistance genes . . . . .	12
Supplementary figure of plasmid clusters . . . . .	15
Calculate plasmid length . . . . .	16
<b>Filter and merge</b>	<b>17</b>
Keep only MAG-PLASMID associations . . . . .	17
Add MAG bin assignment info to link df . . . . .	18
Merge by MAG AND plasmid cluster . . . . .	18
Remove singletons . . . . .	18
Add resistance metadata . . . . .	18

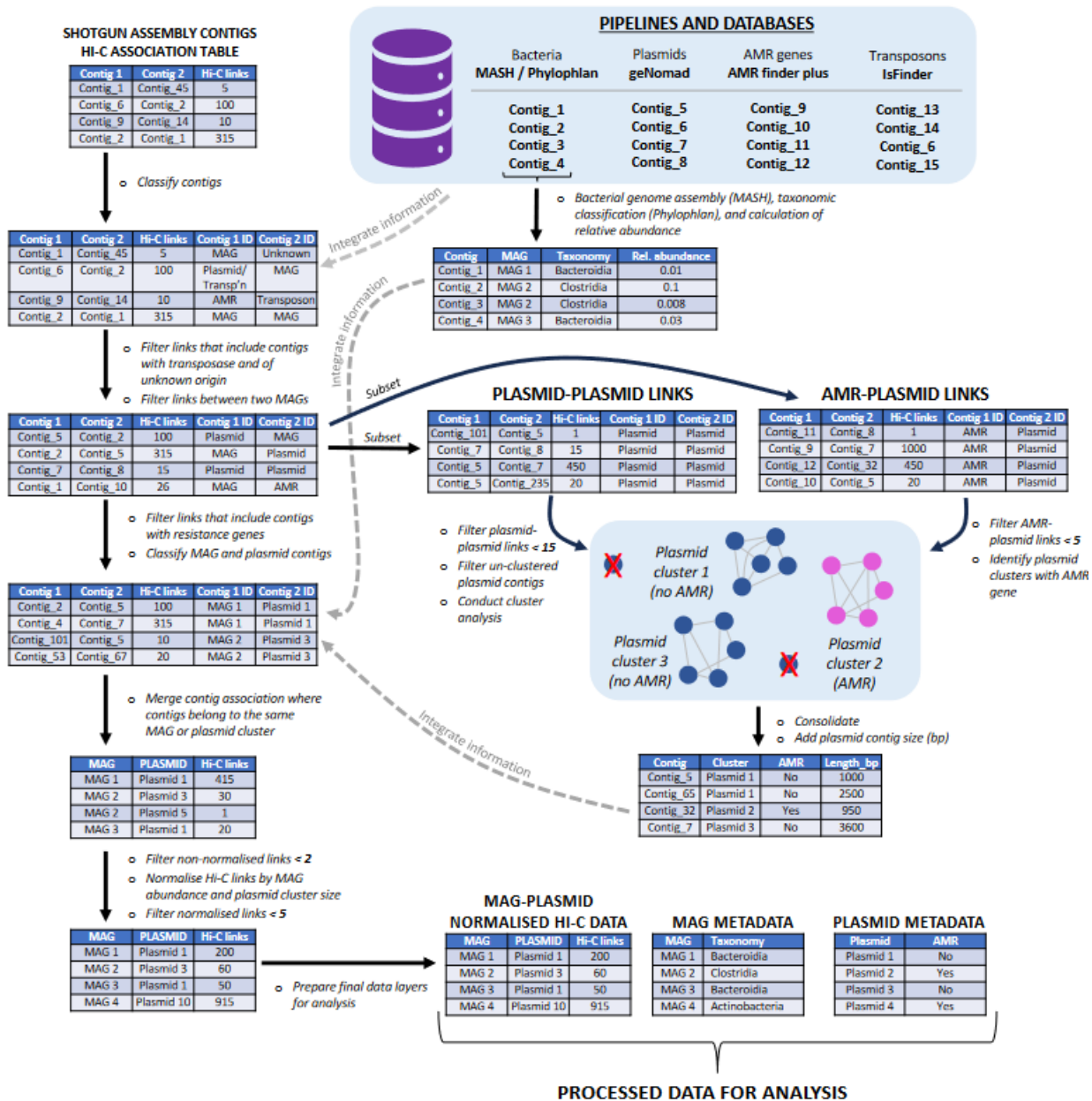
<b>Normalise data</b>	<b>19</b>
Normalise by MAG abundance . . . . .	19
Normalise by plasmid size . . . . .	19
<b>Process data for final analysis</b>	<b>19</b>
Convert count table into adjacency matrix . . . . .	19
Re-add MAGs that don't associate with any plasmids . . . . .	20
Generate MAG metadata . . . . .	21
Generate plasmid metadata . . . . .	21
Convert all layers into phyloseq object . . . . .	21

## Info

Rmarkdown report for the analysis to go with the manuscript “AMR gene presence predicts plasmid network structure in wastewater” by Alice Risely, Thibault Stalder, Benno I. Simmons, Eva M. Top, Angus Buckling, and Dirk Sanders

Data generated by: Stalder et al. “Linking the resistome and plasmidome to the microbiome.” The ISME journal 13.10 (2019): 2437-2446.

Contig processing steps performed under ‘Contig processing’. See Fig S3 for flowchart:



## Import packages

```
library(tidyverse)
library(data.table)
library(phyloseq)
library(igraph)
library(network)
library(expss)
library(here)
library(ggnetwork)
library(RColorBrewer)
library(ggvenn)
```

```
library(ggrepel)
library(ggpubr)

memory.limit(1000000)
```

```
## [1] 1e+06
```

## Import data

### Import HiC data

- NOT RUN
- First few basic filtering steps are skipped as they take a lot of RAM.
- These include filtering out links that are duplicates and between the same contigs.

```
## import association table

WW_links <- read.delim(here("DATA", "WW_links.txt"), header=FALSE)
WW_links_DT<-as.data.table(WW_links) # convert to data table
rm(WW_links)
```

```
# remove contigs attached to themselves

WW_links_DT$self_link<-WW_links_DT$V1 == WW_links_DT$V2
WW_links_DT2<-subset(WW_links_DT, self_link == F)

## remove duplicates
WW_links_filt2<-WW_links_DT2 %>%
  group_by(grp = paste(pmax(V1, V2), pmin(V1, V2), sep = "_")) %>%
  slice(1) %>%
  ungroup() %>%
  select(-grp)
```

### Remove duplicates

- Now import pre-filtered HiC links dataframe, called “WW\_links\_filt2”
- All steps from this point largely involve filtering this dataset of noise so that by the end, only meaningful links remain for analysis

```
# import dataset where reverse duplicates have been excluded, as well as any contigs attached to them

setwd("C:/Users/risel/Dropbox/Sommer postdoc/Plasmid project/PlasmidProjectAnalysis/Updated analysis2")
WW_links_filt2<-readRDS("DATA/WW_links_filt.RDS")

head(WW_links_filt2)
```

```
## # A tibble: 6 x 4
##   V1          V2          V3 self_link
##   <chr>      <chr>      <int> <lgl>
## 1 k141_1000386 k141_1000196     1 FALSE
## 2 k141_1000616 k141_1000543     1 FALSE
## 3 k141_1000630 k141_1000774     1 FALSE
## 4 k141_1000590 k141_1000833     3 FALSE
## 5 k141_1000728 k141_1001032     1 FALSE
## 6 k141_1001172 k141_1000706     1 FALSE
```

```
dim(WW_links_filt2) # 28 million rows
```

```
## [1] 28111659      4
```

```
setwd(here("DATA", "MAGS"))
```

```
myfiles<-list.files()
myfiles[1:5]
```

## Import MAG contigs

```
## [1] "bin_1.fasta" "bin_10.fasta" "bin_100.fasta" "bin_101.fasta"
## [5] "bin_102.fasta"
```

```
dataFiles <- lapply(myfiles, read.table)
myfiles<-str_remove(myfiles, ".fasta") # remove 'fasta' string
length(dataFiles) #379 MAGs
```

```
## [1] 379
```

```
#change names
names(dataFiles)<-myfiles

## loop to extract contigs per cluster data

mag_list<-list()

for (i in 1:length(myfiles)){

  cluster_x<-dataFiles[[i]]
  selectedRows <- cluster_x[grepl(">k141_", cluster_x$V1), ]
  contigs<-substring(selectedRows, 2)
  df<-data.frame(contigs)
  df$cluster<-myfiles[i]
  mag_list[[i]]<-df
}

names(mag_list)<-myfiles
```

```

mag_data<-do.call(rbind, mag_list)
mag_assignment<-mag_data
mag_list <- as.character(mag_assignment$contigs)

setwd("C:/Users/risel/Dropbox/Sommer postdoc/Plasmid project/PlasmidProjectAnalysis/Updated analysis2")

```

## Import predited plasmid IDs

- Import results from Genomad

```

genomad_plasmids <- read.delim("C:/Users/risel/Dropbox/Sommer postdoc/Plasmid project/PlasmidProjectAna
plasmid_list<- as.character(genomad_plasmids$seq_name)

```

```

transposons <- read.delim(here("DATA","ISfinder_best_match_transposons.csv"), header=TRUE, sep = ",")
transposon_list<-as.character(transposons$contig)

```

## Import transposon list

```

# import AMR gene data
amr_genes <- read.delim(here("DATA","amr_contigs_plassclass_and_plasflow.tsv"))
amr_genes <-amr_genes[,c("contig", "Gene.symbol", "Sequence.name", "Element.type", "Element.subtype")]

```

## Import resistance gene list

```

## generate list of all unique contigs

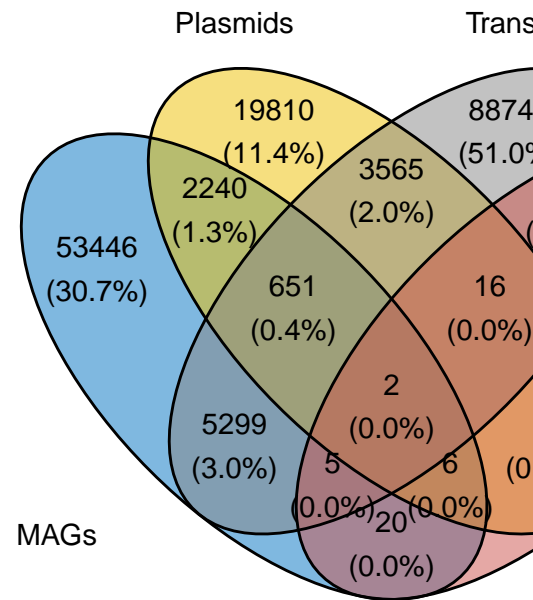
allContigs<-c(unique(WW_links_filt2$V1), unique(WW_links_filt2$V2))
allContigs<-unique(allContigs)

mag_list2<- mag_list[mag_list%in%allContigs]
plasmid_list2<- plasmid_list[plasmid_list%in%allContigs]
transposon_list2<- transposon_list[transposon_list%in%allContigs]
resistance_list2<- amr_genes$contig[amr_genes$contig%in%allContigs]

x <- list(
  MAGs = mag_list2,
  Plasmids = plasmid_list2,
  Transposons = transposon_list2,
  Resistance = resistance_list2
)

```

```
ggvenn(
  x,
  fill_color = c("#0073C2FF", "#EFC000FF", "#868686FF", "#CD534CFF"),
  stroke_size = 0.5, set_name_size = 4
)
```



Summarize contig assignments with Venn Diagram

## Filter and assign identity

Remove links that involve an unidentified contigs

- Assign all contigs to whether they are a MAG, Plasmid, or resistance gene.

```
allContigs_df<-data.frame(allContigs)
names(allContigs_df)<-"Contig"

allContigs_df$MAG<- allContigs_df$Contig %in% mag_list
allContigs_df$Plasmid<- allContigs_df$Contig %in% plasmid_list
allContigs_df$Transposon<- allContigs_df$Contig %in% transposon_list
allContigs_df$Resistance<- allContigs_df$Contig %in% amr_genes$contig

allContigs_df$Remove<- allContigs_df$MAG==F & allContigs_df$Plasmid==F & allContigs_df$Resistance==F

allContigs_filt<-subset(allContigs_df, Remove == F)
```

- Remove links from HiC links dataframe between contigs that are not identified as anything.
- Because we are not interested in these.

```
WW_links_filt2$Keep<- (WW_links_filt2$V1 %in% allContigs_filt$Contig) & (WW_links_filt2$V2 %in% allContigs_filt$Contig)
WW_links_filt3<-subset(WW_links_filt2, Keep == T)
```

## Remove transposons

- Remove any links that involve a transposon

```
WW_links_filt3$Transposon <- WW_links_filt3$V1 %in% transposon_list | WW_links_filt3$V2 %in% transposon_list
WW_links_filt4<- subset(WW_links_filt3, Transposon == F)
```

- So far removed: links that are 1) duplicates, 2) contigs attached to themselves, 3) involve transposons, 4) involve any unidentifiable contigs (not mags/plasmids/AMR, etc)

## Venn diagram after filtering transposons

```
## list of contigs left
allContigs<-c(unique(WW_links_filt4$V1), unique(WW_links_filt4$V2))
allContigs<-unique(allContigs)

## venn diagram

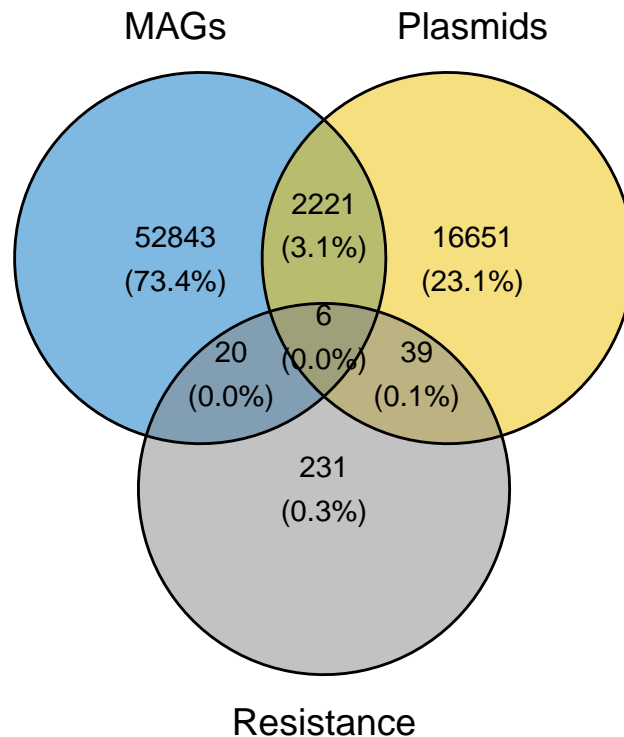
mag_list2<- mag_list[mag_list%in%allContigs]
plasmid_list2<- plasmid_list[plasmid_list%in%allContigs]
resistance_list2<- amr_genes$contig[amr_genes$contig%in%allContigs]

x <- list(
  MAGs = mag_list2,
  Plasmids = plasmid_list2,
  Resistance = resistance_list2
)

ggvenn(
  x,
  fill_color = c("#0073C2FF", "#EFC000FF", "#868686FF", "#CD534CFF"),
  stroke_size = 0.5, set_name_size = 5, text_size = 4
)+ggtitle("Contig assignment overlap")
```



## Contig assignment overlap



## Assign remaining contigs to either MAG, plasmid, or resistance gene

```
allContigs_df<-data.frame(allContigs)
names(allContigs_df)<-"Contig"

allContigs_df$MAG<- allContigs_df$Contig %in% mag_list
allContigs_df$Plasmid<- allContigs_df$Contig %in% plasmid_list
allContigs_df$Resistance<- allContigs_df$Contig %in% amr_genes$contig

# final assignment
allContigs_df$Assignment <- ifelse(allContigs_df$Plasmid == TRUE, "PLASMID", "MAG")
allContigs_df$Assignment <- ifelse(allContigs_df$Resistance == TRUE, "AMR", allContigs_df$Assignment)
```

## Add contig assignment to links DF

```
WW_links_filt4$contig1_assignment <- vlookup(WW_links_filt4$V1, allContigs_df, lookup_column = "Contig")
WW_links_filt4$contig2_assignment <- vlookup(WW_links_filt4$V2, allContigs_df, lookup_column = "Contig")

# remove extra columns
WW_links_filt4<-WW_links_filt4[,c(1,2,3,7,8)]
```

## Remove MAG-MAG links

- After removing mag-mag links, we have a HiC links dataframe which includes Mag-plasmid links, plasmid-plasmid links, and plasmid-amr links, and mag-amr links.
- We will need this later for the plasmid clustering process

```
WW_links_filt5 <- WW_links_filt4[!(WW_links_filt4$contig1_assignment=="MAG" & WW_links_filt4$contig2_assignment=="MAG")]
```

## Cluster plasmids and link to AMR

### Cluster plasmids

- Filter links just between putative plasmid contigs to cluster them

```
links_plasmids <- subset(WW_links_filt5, contig1_assignment == "PLASMID" & contig2_assignment == "PLASMID")
links_plasmids <- links_plasmids %>% arrange(-V3)
```

```
# Links should be robust. Therefore require at least 15 Hi-C connections to assume real genetic connect
```

```
WW_links_plasmids_filtered<-subset(links_plasmids, V3 >14)
```

```
WW_links_plasmids_filtered<-WW_links_plasmids_filtered[,1:3] # keep only first 3 columns
```

```
unique_plasmids<-c(WW_links_plasmids_filtered$V1,WW_links_plasmids_filtered$V2)
```

```
# remove 33 contigs that are unlikely to be contigs (based on gene content)
```

```
gene_content <- read.csv("C:/Users/risel/Dropbox/Sommer postdoc/Plasmid project/PlasmidProjectAnalysis/PlasmidProjectAnalysis.csv")
unique(gene_content$remove)
```

```
## [1] ""      "yes"
```

```
remove_df<-subset(gene_content, remove == "yes")
dim(remove_df)
```

```
## [1] 34  9
```

```
contigs_remove<-as.character(remove_df$Contig)
```

```
WW_links_plasmids_filtered$Remove<- WW_links_plasmids_filtered$V1 %in% contigs_remove | WW_links_plasmids_filtered$V2 %in% contigs_remove
```

```
table(WW_links_plasmids_filtered$Remove)
```

```
##
## FALSE  TRUE
##   366    2
```

```

WW_links_plasmids_filtered<-subset(WW_links_plasmids_filtered, Remove == F)

#####
#####
#####
#####

# convert into network object
# convert into network object
# convert into network object

igraph_net <- graph.data.frame(WW_links_plasmids_filtered[,c('V1','V2')])

# add number of links the the edge weight

E(igraph_net)$weight<-WW_links_plasmids_filtered$V3

igraph_net<-as.undirected(igraph_net) # make undirected

V(igraph_net)$degree<-igraph::degree(igraph_net) # add degree as a node characteristic

```

## Identify plasmid cluster memberships

- Use walktrap method to assign cluster membership

```

# steps = 10
wt <- walktrap.community(igraph_net, weights = E(igraph_net)$weight, steps = 10)

cluster.membership<-membership(wt)

# check how many contigs are assigned to each cluster
cluster_freq<- data.frame(table(cluster.membership))
cluster_freq<-cluster_freq[order(-cluster_freq$Freq),]

# add cluster to graph metadata
V(igraph_net)$ClusterMembership<-as.factor(membership(wt))

# plot network

layout_fr <- layout_with_fr(igraph_net, niter = 10000)
#layout_dh <- layout_with_dh(igraph_net, weight.edge.lengths = edge_density(igraph_net)/1)

n<-ggnetwork(igraph_net, layout = layout_fr)
#n<-ggnetwork(igraph_net)
n$ClusterMembership<-factor(n$ClusterMembership)

# make large colour vector
mypal1<-brewer.pal(12,"Paired")
mypal2<-brewer.pal(12,"Dark2")

```

```
mypal3<-c(mypal1, mypal2, mypal1, mypal2, mypal1, mypal2,mypal1, mypal2, mypal1, mypal2, mypal1, mypal2)
mypal3<-c(mypal3, mypal3)
```

## Connect plasmid clusters to resistance genes

- We've now clustered plasmid contigs, but which ones are also connected to resistance genes?
- Return to HiC links df with MAGs, plasmids, and resistance genes again
- This time keep only links between plasmid contigs and resistance genes

```
links_resistance <- subset(WW_links_filt5, contig1_assignment != "MAG" & contig2_assignment != "MAG")
links_resistance <- subset(links_resistance, (contig1_assignment == "PLASMID" & contig2_assignment == "PLASMID"))

# manipulate dataframe so all plasmids in left column and all resistance contigs in right column

plasmid_contig1<-subset(links_resistance, contig1_assignment == "PLASMID")
plasmid_contig2<-subset(links_resistance, contig2_assignment == "PLASMID")

plasmid_contig2<-plasmid_contig2[,c(2,1,3,5,4)]
names(plasmid_contig2)<-names(plasmid_contig1)

links_resistance2<-rbind(plasmid_contig1, plasmid_contig2)

links_resistance2<-subset(links_resistance2, V3>4) # only considered an AMR plasmid if found connected to resistance gene

head(links_resistance2)
```

```
## # A tibble: 6 x 5
##   V1          V2          V3 contig1_assignment contig2_assignment
##   <chr>      <chr>      <int> <chr>          <chr>
## 1 k141_1739103 k141_1474880    7 PLASMID      AMR
## 2 k141_1772484 k141_2087656    6 PLASMID      AMR
## 3 k141_2194155 k141_2245618    5 PLASMID      AMR
## 4 k141_2481168 k141_1333187    7 PLASMID      AMR
## 5 k141_2621312 k141_1809171    8 PLASMID      AMR
## 6 k141_2768091 k141_1665904    5 PLASMID      AMR
```

```
## what type of resistance is the AMR gene?
```

```
links_resistance2$Resistance<- vlookup(links_resistance2$V2, amr_genes, lookup_column = "contig", result_var = "Resistance")

links_resistance2$AMR_gene<- vlookup(links_resistance2$V2, amr_genes, lookup_column = "contig", result_var = "AMR_gene")

head(links_resistance2)
```

```
## # A tibble: 6 x 7
##   V1          V2          V3 contig1_assignment contig2_a~1 Resis~2 AMR_g~3
##   <chr>      <chr>      <int> <chr>          <chr>      <chr> <chr>
## 1 k141_1739103 k141_1474880    7 PLASMID      AMR        AMR     tet(A)
```

```
## 2 k141_1772484 k141_2087656 6 PLASMID AMR AMR blaAER
## 3 k141_2194155 k141_2245618 5 PLASMID AMR AMR aph(6)~
## 4 k141_2481168 k141_1333187 7 PLASMID AMR AMR tet(W)
## 5 k141_2621312 k141_1809171 8 PLASMID AMR AMR icr-Mo
## 6 k141_2768091 k141_1665904 5 PLASMID AMR METAL ncrA
## # ... with abbreviated variable names 1: contig2_assignment, 2: Resistance,
## # 3: AMR_gene
```

```
# make column indicating whether resistance gene in an AMR gene (rather than metal resistance, etc)
```

```
links_resistance2$Resistance2<- links_resistance2$V2 %in% subset(amr_genes, Element.type == "AMR")$contig2
```

```
head(links_resistance2)
```

```
## # A tibble: 6 x 8
##   V1          V2          V3 contig1_assi~1 conti~2 Resis~3 AMR_g~4 Resis~5
##   <chr>      <chr>      <int> <chr>          <chr>    <chr>    <chr>    <lgl>
## 1 k141_1739103 k141_1474880 7 PLASMID AMR      AMR      tet(A)  TRUE
## 2 k141_1772484 k141_2087656 6 PLASMID AMR      AMR      blaAER  TRUE
## 3 k141_2194155 k141_2245618 5 PLASMID AMR      AMR      aph(6)~ TRUE
## 4 k141_2481168 k141_1333187 7 PLASMID AMR      AMR      tet(W)  TRUE
## 5 k141_2621312 k141_1809171 8 PLASMID AMR      AMR      icr-Mo  TRUE
## 6 k141_2768091 k141_1665904 5 PLASMID AMR      METAL    ncrA    FALSE
## # ... with abbreviated variable names 1: contig1_assignment,
## # 2: contig2_assignment, 3: Resistance, 4: AMR_gene, 5: Resistance2
```

```
# only keep links that involve AMR resistance
```

```
links_resistance3<-subset(links_resistance2, Resistance2 == TRUE)
```

```
head(links_resistance3)
```

```
## # A tibble: 6 x 8
##   V1          V2          V3 contig1_assi~1 conti~2 Resis~3 AMR_g~4 Resis~5
##   <chr>      <chr>      <int> <chr>          <chr>    <chr>    <chr>    <lgl>
## 1 k141_1739103 k141_1474880 7 PLASMID AMR      AMR      tet(A)  TRUE
## 2 k141_1772484 k141_2087656 6 PLASMID AMR      AMR      blaAER  TRUE
## 3 k141_2194155 k141_2245618 5 PLASMID AMR      AMR      aph(6)~ TRUE
## 4 k141_2481168 k141_1333187 7 PLASMID AMR      AMR      tet(W)  TRUE
## 5 k141_2621312 k141_1809171 8 PLASMID AMR      AMR      icr-Mo  TRUE
## 6 k141_1905885 k141_307872 21 PLASMID AMR      AMR      aadA27  TRUE
## # ... with abbreviated variable names 1: contig1_assignment,
## # 2: contig2_assignment, 3: Resistance, 4: AMR_gene, 5: Resistance2
```

```
##### now lets put this info back into plasmid link table
```

```
# make dataframe with cluster and resistance info for each (clustered) plasmid contig
```

```
cluster_df<- n[,c(3,5)]
cluster_df<-unique(cluster_df)
```

```
# add column with whether contig is connected to an AMR gene
cluster_df$Resistance<-cluster_df$name %in% links_resistance3$V1
cluster_df<-cluster_df%>% arrange(ClusterMembership)
cluster_df$Gene <- vlookup(cluster_df$name, links_resistance3, lookup_column = "V1", result_column = "A")

head(cluster_df)
```

```
##           name ClusterMembership Resistance  Gene
## 372 k141_515203             1      TRUE tet(Q)
## 381 k141_973004             1     FALSE <NA>
## 386 k141_190742             1     FALSE <NA>
## 390 k141_971894             1     FALSE <NA>
## 395 k141_1856898           1     FALSE <NA>
## 403 k141_1145966           1     FALSE <NA>
```

```
table(cluster_df$Gene)
```

```
##
##      aadA27      aadS aph(6)-Id      blaAER      blaMCA      cmlA5      mph(A)
##          4          1          2          1          1          1          1
##      msr(E) qacEdelta1      qnrS2      tet(A)      tet(Q)
##          37          1          5          4          4
```

```
subset(amr_genes, Gene.symbol == "msr(E)")
```

```
##           contig Gene.symbol                               Sequence.name
## 364 k141_505817      msr(E) ABC-F type ribosomal protection protein Msr(E)
##      Element.type Element.subtype
## 364          AMR          AMR
```

```
subset(amr_genes, Gene.symbol == "tet(Q)")
```

```
##           contig Gene.symbol
## 198 k141_238138      tet(Q)
## 410 k141_775292      tet(Q)
##
##                               Sequence.name Element.type
## 198 tetracycline resistance ribosomal protection protein Tet(Q)      AMR
## 410 tetracycline resistance ribosomal protection protein Tet(Q)      AMR
##      Element.subtype
## 198          AMR
## 410          AMR
```

```
# make list of plasmid clusters that are connected to a resistance gene
resistance_clusters2<-subset(cluster_df, Resistance==T)
resistance_clusters<-unique(resistance_clusters2$Cluster)

distinct(resistance_clusters2, ClusterMembership, Gene)
```

```
##      ClusterMembership      Gene
## 372             1      tet(Q)
```

```
## 210          2      blaAER
## 253          2    aph(6)-Id
## 333          3      msr(E)
## 189          4      msr(E)
## 195          4      aadA27
## 2051         5        aadS
## 359          6      msr(E)
## 485          8      aadA27
## 487          8      msr(E)
## 278          9      msr(E)
## 235         12      msr(E)
## 107         14      msr(E)
## 4           17      msr(E)
## 2171         17      aadA27
## 311         18      msr(E)
## 56          19      msr(E)
## 482         21      qnrS2
## 34          22      msr(E)
## 73          24      msr(E)
## 410         27    qacEdelta1
## 13          28      msr(E)
## 89          30      tet(A)
## 475         33      msr(E)
## 274         51      msr(E)
## 551         54      qnrS2
## 343         64      msr(E)
## 37          70      msr(E)
## 44          76      msr(E)
## 329         79    aph(6)-Id
## 507         82      aadA27
## 528         83      blaMCA
## 540         91      msr(E)
## 439         99      qnrS2
## 2831        100      msr(E)
## 379        104      mph(A)
## 2421        104      cmlA5
```

```
n$Resistance<-n$ClusterMembership %in% resistance_clusters
```

```
cluster_df$Resistance_cluster<-cluster_df$ClusterMembership %in% resistance_clusters
```

```
# saveRDS(cluster_df, "C:/Users/risel/Dropbox/Sommer postdoc/Plasmid project/PlasmidProjectAnalysis/Upd
```

## Supplementary figure of plasmid clusters

```
p1<-ggplot(n, aes(x = x, y = y, xend = xend, yend = yend, label = ClusterMembership)) +
  geom_edges( color = "black", alpha = 0.5) +
  theme_blank()+
  geom_nodes(aes( fill = ClusterMembership), pch = 21, size =3)+
  scale_size(range = c(2,6))+
# ggtitle("Putative plasmid clusters")+
  scale_fill_manual(values = mypal3)+
```

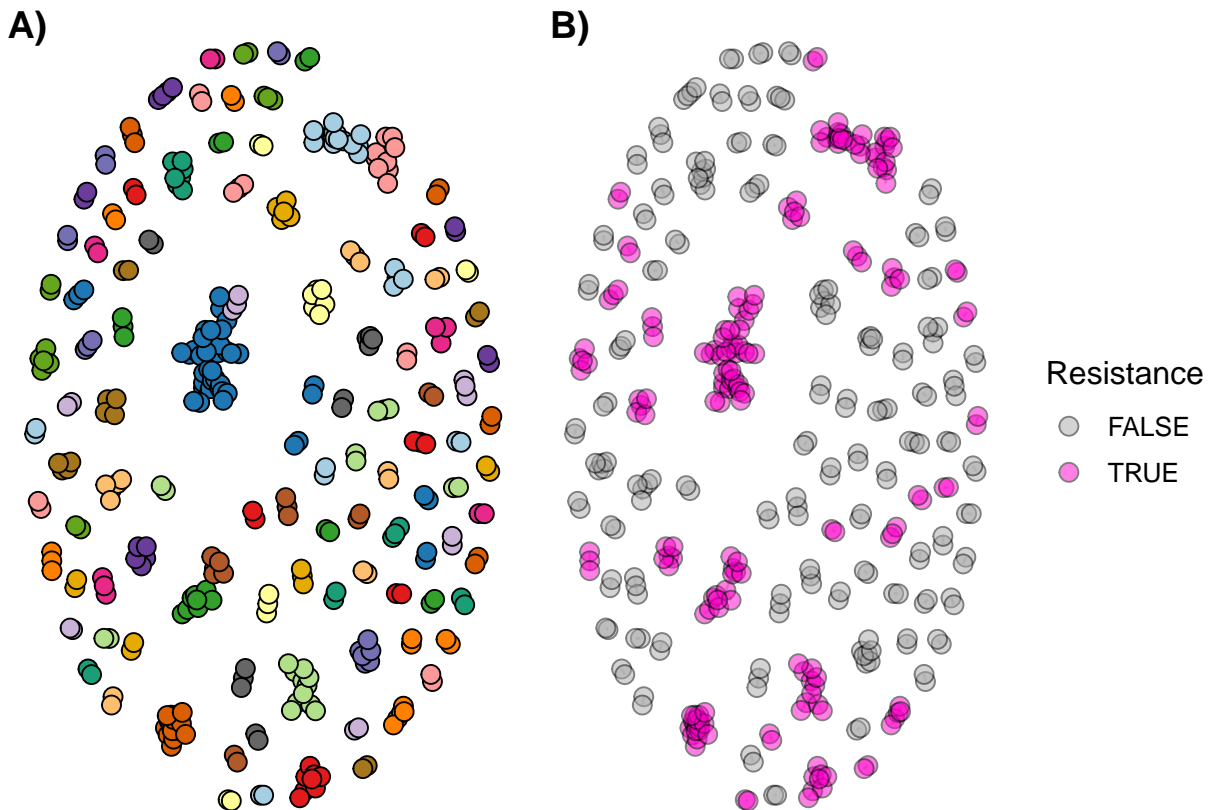
```

theme(legend.position = "none")

p2<-ggplot(n, aes(x = x, y = y, xend = xend, yend = yend, label = name)) +
  geom_edges( color = "grey", alpha = 0.7) +
  theme_blank()+
  geom_nodes(aes(fill = Resistance), pch = 21, alpha = 0.5, size = 3)+
  scale_size(range = c(1.5,6))+
  # ggtitle("Plasmid-plasmid cluster network coloured by AMR presence")+
  scale_fill_manual(values = c("darkgrey", "#ff00cc"))

ggarrange(p1, p2, labels = c("A)", "B)", widths = c(1,1.3))

```



```

#ggsave("C:/Users/risel/Dropbox/Sommer postdoc/Plasmid project/PlasmidProjectAnalysis/Updated analysis2,
#check k141_736244

```

## Calculate plasmid length

```

## add number of contigs that make up each cluster

contig_no<-data.frame(table(cluster_df$ClusterMembership))
cluster_df$ContigNo<-expss::vlookup(cluster_df$ClusterMembership, contig_no, lookup_column = "Var1", re

```



```
## add contig length
contig_length <- read.table("C:/Users/risel/Dropbox/Sommer postdoc/Plasmid project/PlasmidProjectAnalysis/contig_lengths.txt")

cluster_df$LengthKB<- vlookup(cluster_df$name, contig_length, lookup_column = 1, result_column = 2)

summary(cluster_df$LengthKB)

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      206   1984   3703   5570   6878   47938

plasmid_length<-cluster_df %>% group_by(ClusterMembership) %>% summarise(TotalLengthKB = sum(LengthKB))

summary(plasmid_length$TotalLengthKB)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      1351   4845   8772   19368   21611   240077
```

## Filter and merge

### Keep only MAG-PLASMID associations

- Ultimately, we are interested in Mag-plasmid connections
- So at this point, we filter down our HiC links df to include only links between MAG contigs and plasmid contigs
- We couldn't do this before, because we didn't know which plasmid contigs to keep (based on clustering)

```
# keep only links that involve MAGs, and make sure they are all in one column
# at the moment they are spread out across the left and right columns

mag1<- subset(WW_links_filt5, contig1_assignment=="MAG")
mag2<- subset(WW_links_filt5, contig2_assignment=="MAG")

# change columns of mag2 around so they match mag1
mag2<-mag2[,c(2,1,3,5,4)]
names(mag2)<-names(mag1)

WW_links_filt6<-rbind(mag1, mag2)

# change column names
names(WW_links_filt6)[1:3]<-c("contigs_mags", "contigs_plasmids", "Count")

table(WW_links_filt6$contig2_assignment) # still AMR genes in there. Remove
```

```
##
##      AMR PLASMID
##      7333  243014
```

```
WW_links_filt6<-subset(WW_links_filt6, contig2_assignment == "PLASMID")
```

- Only keep plasmid contigs that are clustered
- This information is stored in the object “cluster\_df”

```
WW_links_filt6$Cluster<- vlookup(WW_links_filt6$contigs_plasmids, cluster_df, lookup_column = "name", r
length(unique(WW_links_filt6$Cluster)) # how many clusters?
```

```
## [1] 110
```

```
WW_links_filt6$Cluster<-factor(WW_links_filt6$Cluster)
# remove any plasmid inks that are not assigned a cluster
WW_links_filt7<-na.omit(WW_links_filt6)
```

## Add MAG bin assignment info to link df

```
WW_links_filt7$MAG_assignment<-vlookup(WW_links_filt7$contigs_mags, mag_assignment, lookup_column = "con
```

## Merge by MAG AND plasmid cluster

```
WW_links_filt8<- WW_links_filt7 %>% group_by(MAG_assignment, Cluster) %>% summarise(Count = sum(Count))
```

## Remove singletons

```
WW_links_filt9<-subset(WW_links_filt8, Count >1) # changed
```

## Add resistance metadata

- Plasmid clusters that are associated with AMR are stored in the object “resistance\_clusters”

```
WW_links_filt9$Resistance<-WW_links_filt9$Cluster %in% resistance_clusters
# how many unique plasmid clusters associate with AMR?
table(unique(WW_links_filt9[,c(2,4)])$Resistance)
```

```
##
## FALSE  TRUE
##    77    32
```

## Normalise data

### Normalise by MAG abundance

- MAGs vary in their abundance, and this will affect the number of links
- We want the counts normalised in a way that assumes all MAGs were present at the same abundance
- To get this ‘theoretical’ same abundance, I use the mean abundance across MAGs
- If the mean abundance is 1%, but there is a MAG with 2% abundance, I normalise the count by multiplying it by  $(1/2 = 0.5)$ .
- In this case, 0.5 is called the ‘scaling factor’ that I multiply counts by
- The scaling factor for each MAG is the mean MAG abundance divided by the specific MAG abundance
- However, I always add a pseudocount of 1, to make sure when rounded, there are no zero counts (minimum count should always be 1)
- Same as just dividing by MAG abundance, but then you get  $<0$  which is problematic for networks

```
MAG_metadata <- read.csv(here("DATA", "MAG_metadata.csv"))

MAG_metadata<-MAG_metadata[,1:8]

WW_links_filt9$Abundance<-vlookup(WW_links_filt9$MAG_assignment, MAG_metadata, lookup_column = "cluster_

# generate scaling factor to normalise by

WW_links_filt9$Scaling_factor<- mean(WW_links_filt9$Abundance)/WW_links_filt9$Abundance

WW_links_filt9$Count_normalised<-WW_links_filt9$Count*WW_links_filt9$Scaling_factor
WW_links_filt9$Count_normalised<-WW_links_filt9$Count_normalised+1 # add pseudocount of one so we can ro

WW_links_filt9$Count_normalised<-round(WW_links_filt9$Count_normalised,0)
```

### Normalise by plasmid size

```
WW_links_filt9$PlasmidLength<- vlookup(WW_links_filt9$Cluster, plasmid_length, lookup_column = 1, resul

WW_links_filt9$Scaling_factor_length<- mean(WW_links_filt9$PlasmidLength)/WW_links_filt9$PlasmidLength

WW_links_filt9$Count_normalised1<-WW_links_filt9$Count_normalised*WW_links_filt9$Scaling_factor_length
WW_links_filt9$Count_normalised1<-WW_links_filt9$Count_normalised1+1 # add pseudocount of one so we can

WW_links_filt9$Count_normalised1<-round(WW_links_filt9$Count_normalised1,0)
WW_links_filt9$Count_normalised<-WW_links_filt9$Count_normalised1
```

## Process data for final analysis

### Convert count table into adjacency matrix

We have finished filtering, but at this point we need to generate a few bits of final information so that we can put it all together into a phyloseq object. Phyloseq is an R package that is used to handle 16S microbiome data, but it can also be used to handle other sorts of data like bacteria-plasmid associations.

We need: 1) A MAG x Plasmid count table/adjacency matrix 2) A dataframe with metadata for each MAG (eg Taxonomy) 3) a dataframe with metadata for each plasmid (ie Whether it has a resistance gene or not)

```
# first we make the MAG x plasmic count table
```

```
WW_links_clustered2<-WW_links_filt9[,c("MAG_assignment", "Cluster", "Count_normalised")]
```

```
count_table_clustered<- pivot_wider( WW_links_clustered2, names_from = MAG_assignment, values_from = Count)
```

```
##turn NAs to zeros
```

```
count_table_clustered_dt<-as.data.table(count_table_clustered)
```

```
count_table_clustered_dt[is.na(count_table_clustered_dt)] <- 0
```

```
count_table_clustered_dt[1:5, 1:5]
```

```
##      Cluster bin_1 bin_10 bin_103 bin_104
## 1:         2     4      8       7      0
## 2:         5    17      0      0    418
## 3:        30     6   1059      0      0
## 4:         1     0      2      0    241
## 5:         3     0      3     49      0
```

```
count_table_clustered_df<-data.frame(count_table_clustered_dt)
```

```
#count_table_clustered_df[1:5,1:5]
```

```
#make first col row names
```

```
row.names(count_table_clustered_df)<-count_table_clustered_df$Cluster
```

```
# remove first column
```

```
count_table_clustered_df<-count_table_clustered_df[,-1]
```

```
count_table_clustered_df[1:5,1:5]
```

```
##      bin_1 bin_10 bin_103 bin_104 bin_105
## 2        4      8       7      0      15
## 5       17      0      0     418      0
## 30       6   1059      0      0     52
## 1        0      2      0     241      0
## 3        0      3     49      0      0
```

```
# plasmid clusters are rows, MAGs are columns
```

```
# remove normalised links under 5
```

```
count_table_clustered_df[count_table_clustered_df < 5] <- 0
```

## Re-add MAGs that don't associate with any plasmids

- MAGs which don't associate with any plasmids were filtered out, therefore we need to add these back in

```

# add column for bacterial species that are not associated with any plasmids
# these got removed as they had zero counts
mag_IDs<-unique(mag_assignment$cluster)
mags_to_add<-data.frame(mag_IDs)
mags_to_add$Included<-mags_to_add$mag_IDs %in% names(count_table_clustered_df)
mags_to_add<-subset(mags_to_add, Included==FALSE)
df_to_add<-data.frame(matrix(0, nrow = nrow(count_table_clustered_df), ncol = nrow(mags_to_add)))
names(df_to_add)<-mags_to_add$mag_IDs
row.names(df_to_add)<-row.names(count_table_clustered_df)
new_count_table_clustered<-cbind(count_table_clustered_df, df_to_add)

```

## Generate MAG metadata

```

phylophlan_taxonomy <- read.csv(here("DATA","phylophlan_taxonomy_updated.csv"))

MAG_metadata<-MAG_metadata[,1:8]

new_mag_metadata<-merge(MAG_metadata, phylophlan_taxonomy, by.x = "cluster_id", by.y = "Bin")
row.names(new_mag_metadata)<-new_mag_metadata$cluster_id

```

## Generate plasmid metadata

```

plasmid_metadata_clustered<-data.frame(unique(WW_links_filt9$Cluster))
names(plasmid_metadata_clustered)<- "contigs_plasmids"

plasmid_metadata_clustered$Resistance<- plasmid_metadata_clustered$contigs_plasmids %in% resistance_clusters

row.names(plasmid_metadata_clustered)<-plasmid_metadata_clustered$contigs_plasmids

# turn it into a tax table object
plasmid_metadata_clustered<-tax_table(plasmid_metadata_clustered)
taxa_names(plasmid_metadata_clustered)<-data.frame(plasmid_metadata_clustered)$ta1

```

## Convert all layers into phyloseq object

```

OTU = otu_table(new_count_table_clustered, taxa_are_rows = TRUE)
dim(new_count_table_clustered)

## [1] 109 379

plasmid_ps_clustered<-merge_phyloseq(OTU, sample_data(new_mag_metadata), plasmid_metadata_clustered)

plasmid_ps_clustered

## phyloseq-class experiment-level object
## otu_table() OTU Table: [ 109 taxa and 379 samples ]

```

```
## sample_data() Sample Data:      [ 379 samples by 15 sample variables ]  
## tax_table()   Taxonomy Table:   [ 109 taxa by 2 taxonomic ranks ]
```

```
## saveRDS(plasmid_ps_clustered, "plasmid_ps_clustered_genomad_final.RDS")
```

```
# saveRDS(plasmid_ps_clustered, "C:/Users/risel/Dropbox/Sommer postdoc/Plasmid project/PlasmidProjectAn
```