Bayesian inference of an individual-based mutualistic network 01_02

Net 01 02

```
library(BayesianNetworks)
library(network.tools)
library(tidyverse)
theme_set(theme_minimal())
options(mc.cores = 4)
```

Data

Load dataset and sampling effort per individual plant:

lgl (2): height_cm, se_cam_h

```
web <- readr::read_csv(here::here("data/nets_raw", paste0(params$net, "_int.csv"))) |>
  arrange(ind)
## Rows: 40 Columns: 17
## -- Column specification
## Delimiter: ","
## dbl (17): ind, Chloris_chloris, Erithacus_rubecula, Sylvia_melanocephala, Cyanopica_cooki, Phoenicur
## i Use 'spec()' to retrieve the full column specification for this data.
## i Specify the column types or set 'show_col_types = FALSE' to quiet this message.
mat <- as.matrix(web[, -1])</pre>
mat <- apply(mat, c(1,2), as.integer)</pre>
rownames(mat) <- web$ind</pre>
# create numeric vector of sampling effort for each plant with names = plant id
effort <- readr::read_csv(here::here("data/nets_attr", paste0(params$net, "_attr.csv"))) |>
  select(ind, starts_with("se_")) |>
  filter(ind %in% web$ind) |>
  arrange(ind)
## Rows: 40 Columns: 15
## -- Column specification -----
## Delimiter: ","
## chr (2): fruit_type, fruit_color
## dbl (11): ind, canopy_cover_m2, crop, x, y, fruit_d1_mm, fruit_d2_mm, fruit_mass_mg, seeds_per_fruit
```

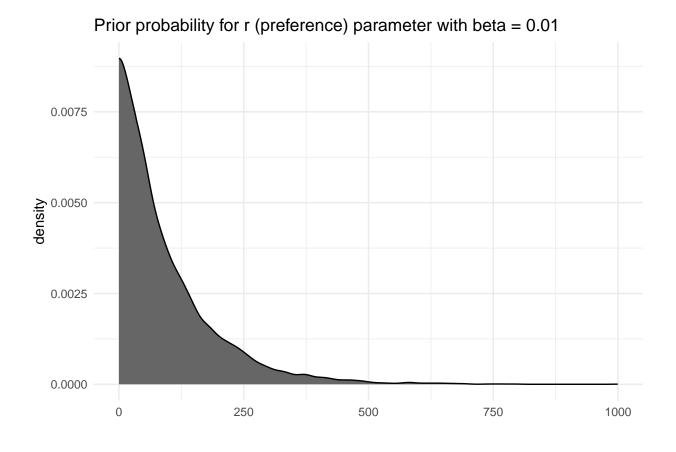
```
## i Use 'spec()' to retrieve the full column specification for this data.
## i Specify the column types or set 'show_col_types = FALSE' to quiet this message.
## If there is only one column with sampling effort, use it:
if (!net %in% c("01_01", "01_02", "02_01", "02_02", "02_03",
                "10_01", "15_01", "18_01", "18_02", "20_01", "21_01", "21_02")) {
  effort <- effort |>
   pull(starts_with("se_"), name = "ind")
}
# Otherwise, select sampling effort column in some specific nets:
if (net == "10 01") {
 effort <- effort |>
   mutate(se_cam_days = se_cam_h/24) |>
   pull(se_cam_days, name = "ind")
}
if (net == "15_01") {
 effort <- effort |>
   pull(se_cam_days, name = "ind")
}
if (net %in% c("18_01", "18_02", "20_01")) {
 effort <- effort |>
   mutate(se_bc_months = se_bc_days/30) |>
   pull(se_bc_months, name = "ind")
}
if (net %in% c("21_01", "21_02")) {
  effort <- effort |>
   pull(se_obs_h, name = "ind")
# For Pistacia and Juniperus, use constant sampling effort
if (net %in% c("01_01", "01_02", "02_01", "02_02", "02_03")) {
  effort <- rep(10, nrow(mat))
 names(effort) <- web$ind</pre>
}
## Some nets may require adjusting of the count data or effort values
# if (net %in% c("01_01", "01_02", "02_01", "02_02", "02_03")) {
# mat <- mat/10 # divide counts by 10 to make modelling feasible
\# mat[mat > 0 & mat < 1] <- 1 \# don't miss rare counts
# mat <- round(mat)</pre>
  mat \leftarrow apply(mat, c(1,2), as.integer)
# }
stopifnot(identical(length(effort), nrow(mat)))
stopifnot(identical(names(effort), rownames(mat)))
# summary(mat)
summary(as.numeric(mat))
```

##

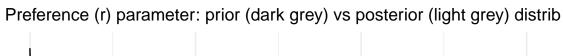
```
##
      Min. 1st Qu. Median
                            Mean 3rd Qu.
##
      0.00
              0.00
                      0.00
                             86.23
                                      0.00 4017.00
# if (max(mat) > 1000) {
    stop("More than 1000 counts in some cell(s)")
summary(effort)
##
      Min. 1st Qu. Median
                              Mean 3rd Qu.
                                              Max.
##
        10
                10
                        10
                                10
                                        10
                                                10
if (max(effort) > 500) {
  stop("Sampling effort > 500 for some plants")
}
```

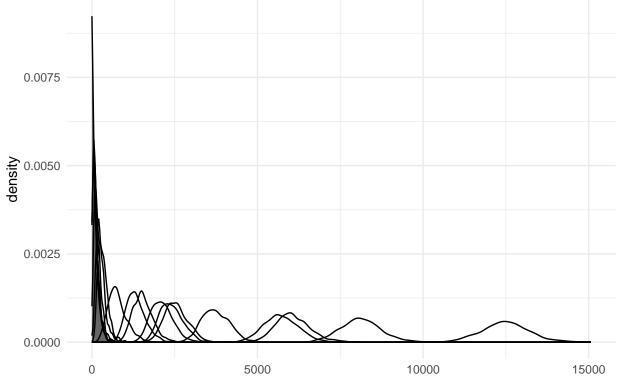
Bayesian inference of network structure

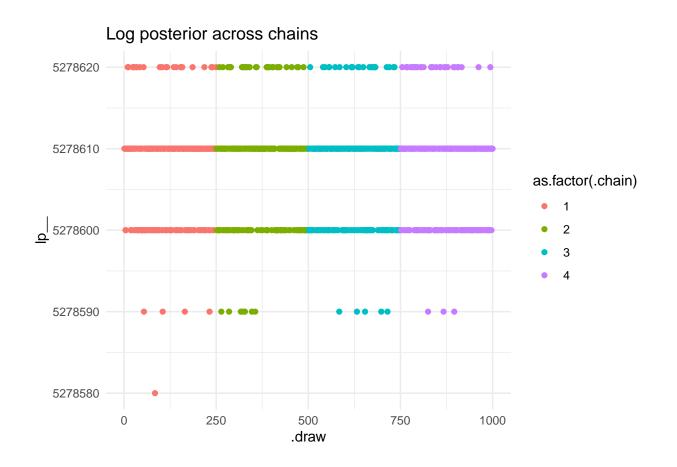
```
dt <- prepare_data(mat, sampl.eff = effort)
plot_prior(params$beta)</pre>
```



```
fit <- fit_model(dt,</pre>
                 refresh = 0,
                 beta = params$beta,
                 model = params$model,
                 \# max\_treedepth = 15,
                 \# init = function() list(r = runif(1, 0, 20000)),
                 iter_warmup = params$iter,
                 iter_sampling = params$iter,
                 thin = 4 * params$iter / 1000)
## Running MCMC with 4 parallel chains...
## Chain 1 finished in 100.5 seconds.
## Chain 4 finished in 100.8 seconds.
## Chain 3 finished in 103.2 seconds.
## Chain 2 finished in 103.3 seconds.
## All 4 chains finished successfully.
## Mean chain execution time: 102.0 seconds.
## Total execution time: 103.5 seconds.
get_seed(fit)
## [1] 594933602
check_model(fit, data = dt)
## Processing csv files: C:/Users/frodr/AppData/Local/Temp/Rtmp4CoIrr/varying_preferences-202406251122-
##
## Checking sampler transitions treedepth.
## Treedepth satisfactory for all transitions.
## Checking sampler transitions for divergences.
## No divergent transitions found.
## Checking E-BFMI - sampler transitions HMC potential energy.
## E-BFMI satisfactory.
##
## Effective sample size satisfactory.
## Split R-hat values satisfactory all parameters.
## Processing complete, no problems detected.
```







Posteriors

Get posterior distributions:

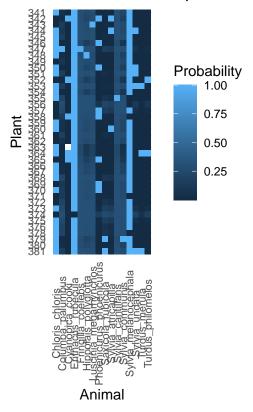
```
post <- get_posterior(fit, dt)
head(post)</pre>
```

```
## # A tibble: 6 x 11
## # Groups:
               Animal, Plant [6]
##
     Plant Animal
                       .chain .iteration .draw connectance preference plant.abund animal.abund int.pr
     <chr> <chr>
                         <int>
                                     <int> <int>
                                                       <dbl>
                                                                   <dbl>
                                                                               <dbl>
                                                                                            <dbl>
                                                                                                       <db
                                                       0.294
                                                                   6832.
                                                                             0.0186
## 1 341
           Chloris_chl~
                                         1
                                                                                            0.111 1
                             1
                                               1
                                                                                                       e+
## 2 342
           Chloris_chl~
                             1
                                         1
                                               1
                                                       0.294
                                                                   6832.
                                                                             0.0343
                                                                                            0.111 7.95e-1
## 3 343
           Chloris_chl~
                             1
                                        1
                                               1
                                                       0.294
                                                                  6832.
                                                                             0.00881
                                                                                            0.111 4.54e-
## 4 344
           Chloris_chl~
                             1
                                        1
                                               1
                                                       0.294
                                                                   6832.
                                                                             0.0120
                                                                                            0.111 1
                                                                                                      e+
           Chloris_chl~
## 5 345
                             1
                                         1
                                               1
                                                       0.294
                                                                   6832.
                                                                             0.00680
                                                                                            0.111 1
## 6 346
           Chloris_chl~
                             1
                                         1
                                               1
                                                       0.294
                                                                   6832.
                                                                             0.0838
                                                                                            0.111 1
                                                                                                      e+
```

Mean edge probability:

```
plot_interaction_prob(post)
```

Mean interaction probability

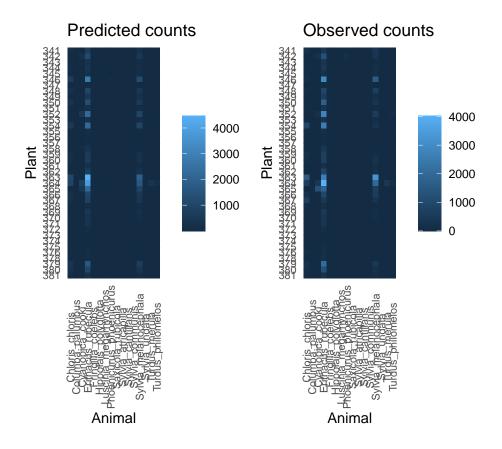


Generate predicted visits for each pairwise interaction

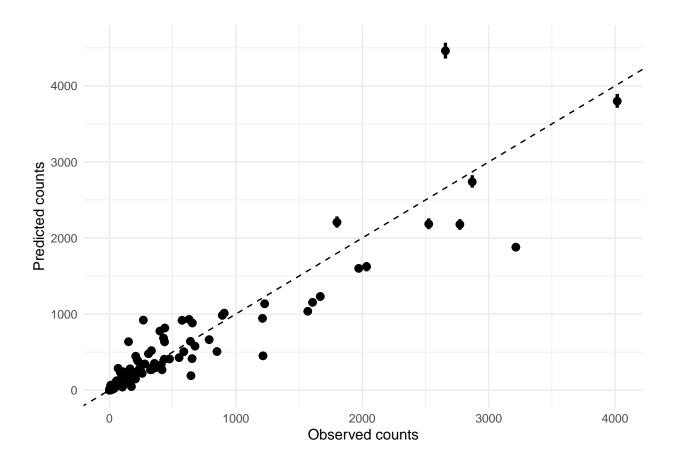
```
post.counts <- predict_counts(fit, dt)</pre>
```

Compare observed and predicted visits by the model:

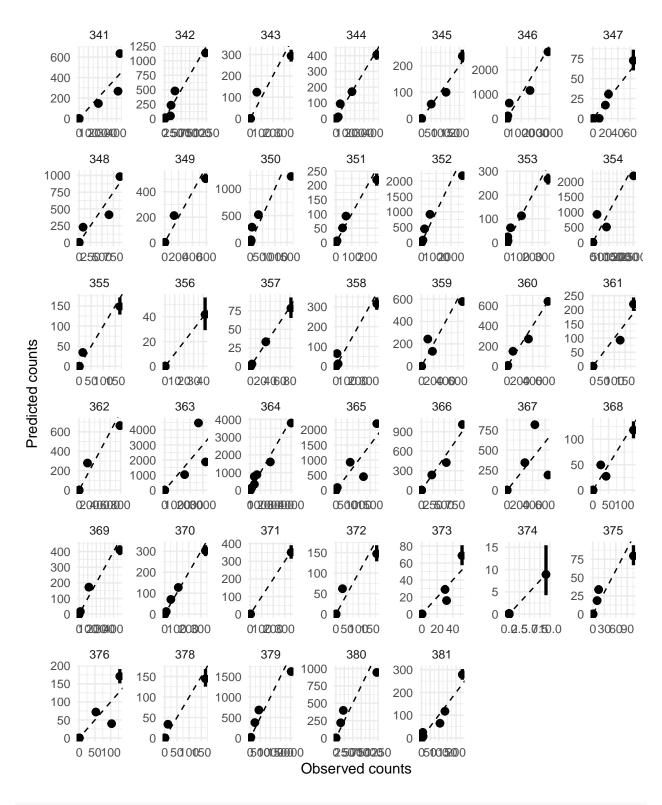
```
p <- plot_counts_pred(post.counts, sort = FALSE)
o <- plot_counts_obs(mat, sort = FALSE, zero.na = FALSE)
library(patchwork)
p + o</pre>
```



plot_counts_pred_obs(post.counts, dt)



plot_counts_pred_obs(post.counts, dt, byplant = TRUE, scales = "free")



saveRDS(post.counts, here::here(paste0("data/nets_post/", params\$net, "_post_counts.rds")))