

Using lm with asremlPlus for the Ladybird example from Welham et al. (2014)

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Introduction

This vignette shows how to use `asremlPlus` (Brien, 2021a), and `dae` (Brien, 2021b), for exploring and presenting predictions from a linear mixed model analysis, the predictions having been produced using `lmerTest` (Kuznetsova et al., 2017), `lm` and `emmeans` (Lenth, 2021). Here, `asremlPlus`, `dae`, `lmerTest` and `emmeans` are packages for the R Statistical Computing environment (R Core Team, 2021) and `lm` is available from `stats` and is included in R.

The context is a three-factor factorial experiment on ladybirds (Welham et al., 2014, Example 8.2) that aims to answer the question “Will ladybirds transfer fungus to aphids on plants?” The experiment consists of 2 runs of 36 containers, each with a plant and aphids. There are three factors that results in 12 treatments: Host plant (beans, trefoil), infected Cadavers (5, 10, 20), Ladybird (-, +). Ther are randomized to the containers within a run so that each is replicated 3 times within a run. The response to be analysed is the logit of the proportion of live aphids that were infected.

Initialize

```
library(knitr)
opts_chunk$set("tidy" = FALSE, comment = NA)
suppressMessages(library(lmerTest))
packageVersion("lmerTest")
```

```
## [1] '3.1.3'
```

```
suppressMessages(library(emmeans))
packageVersion("emmeans")
```

```
## [1] '1.7.1.1'
```

```
suppressMessages(library(asremlPlus))
packageVersion("asremlPlus")
```

```
## [1] '4.3.31'
```

```

suppressMessages(library(dae))
packageVersion("dae")

## [1] '3.2.13'

options(width = 95, show.signif.stars = FALSE)

```

Get data available in asremlPlus

```

data("Ladybird.dat")

```

Do an ANOVA of logits

```

Ladybird.aov <- aov(logitP ~ Host*Cadavers*Ladybird + Error(Run/Plant),
                      data=Ladybird.dat)
summary(Ladybird.aov)

```

```

Error: Run
      Df  Sum Sq Mean Sq F value Pr(>F)
Residuals 1 0.06766 0.06766

Error: Run:Plant
      Df  Sum Sq Mean Sq F value Pr(>F)
Host          1 13.599 13.599 59.172 1.82e-10
Cadavers      2 17.027  8.514 37.044 3.78e-11
Ladybird       1 11.091 11.091 48.257 3.33e-09
Host:Cadavers 2  0.308  0.154  0.670  0.5158
Host:Ladybird   1  0.228  0.228  0.992  0.3234
Cadavers:Ladybird 2  1.735  0.867  3.774  0.0287
Host:Cadavers:Ladybird 2  0.200  0.100  0.435  0.6493
Residuals      59 13.560  0.230

```

The anova table gives the F-tests for the three-factor effects and interactions. Note the `Residuals` `Mean Sq` value for `Run:Plant` of 0.230. Also, it is clear that the `Run` component is negative, given that the `Residuals` `Mean Sq` value for `Run` is less than that for `Run:Plant`; it is $(0.06766 - 0.230) / 36$. From the table it is seen that the only significant interaction is `Cadavers:Ladybird` and that the `Host` main effect is significant.

Use lmerTest and lm to analyse the logits

Mixed model analysis of logits

```

m1.lmer <- lmerTest::lmer(logitP ~ Host*Cadavers*Ladybird + (1|Run),
                           data=Ladybird.dat)

```

```

boundary (singular) fit: see ?isSingular

```

```
summary(m1.lmer)
```

Linear mixed model fit by REML. t-tests use Satterthwaite's method [`'lmerModLmerTest'`]
Formula: logitP ~ Host * Cadavers * Ladybird + (1 | Run)
Data: Ladybird.dat

REML criterion at convergence: 102.8

Scaled residuals:

Min	1Q	Median	3Q	Max
-1.9633	-0.5217	0.1360	0.5789	2.1896

Random effects:

Groups	Name	Variance	Std.Dev.
Run	(Intercept)	0.0000	0.0000
Residual		0.2271	0.4766

Number of obs: 72, groups: Run, 2

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	-1.603097	0.194560	60.000000	-8.240	1.91e-11
Hosttrefoil	-0.870675	0.275149	60.000000	-3.164	0.00244
Cadavers10	0.564771	0.275149	60.000000	2.053	0.04448
Cadavers20	0.919229	0.275149	60.000000	3.341	0.00144
Ladybird+	0.547710	0.275149	60.000000	1.991	0.05109
Hosttrefoil:Cadavers10	-0.212735	0.389120	60.000000	-0.547	0.58661
Hosttrefoil:Cadavers20	-0.120410	0.389120	60.000000	-0.309	0.75806
Hosttrefoil:Ladybird+	0.073153	0.389120	60.000000	0.188	0.85151
Cadavers10:Ladybird+	-0.040048	0.389120	60.000000	-0.103	0.91837
Cadavers20:Ladybird+	0.414204	0.389120	60.000000	1.064	0.29138
Hosttrefoil:Cadavers10:Ladybird+	0.005698	0.550299	60.000000	0.010	0.99177
Hosttrefoil:Cadavers20:Ladybird+	0.449979	0.550299	60.000000	0.818	0.41676

Correlation of Fixed Effects:

	(Intr)	Hsttrf	Cdvr10	Cdvr20	Ldybr+	Hs:C10	Hs:C20	Hst:L+	C10:L+	C20:L+	H:C10:
Hosttrefoil	-0.707										
Cadavers10	-0.707	0.500									
Cadavers20	-0.707	0.500	0.500								
Ladybird+	-0.707	0.500	0.500	0.500							
Hsttrfl:C10	0.500	-0.707	-0.707	-0.354	-0.354						
Hsttrfl:C20	0.500	-0.707	-0.354	-0.707	-0.354	0.500					
Hsttrfl:Ld+	0.500	-0.707	-0.354	-0.354	-0.707	0.500	0.500				
Cdvr10:Ld+	0.500	-0.354	-0.707	-0.354	-0.707	0.500	0.250	0.500			
Cdvr20:Ld+	0.500	-0.354	-0.354	-0.707	-0.707	0.250	0.500	0.500	0.500		
Hstt:C10:L+	-0.354	0.500	0.500	0.250	0.500	-0.707	-0.354	-0.707	-0.707	-0.354	
Hstt:C20:L+	-0.354	0.500	0.250	0.500	0.500	-0.354	-0.707	-0.707	-0.354	-0.707	0.500
optimizer (nloptwrap) convergence code: 0 (OK)											
boundary (singular) fit: see ?isSingular											

As expected the Run component is bound at zero, leading to a singular model. This results in a change in the estimate of the residual variance to 0.227. To allow for a negative estimate we will redo the analysis with Run fixed, because with `lme4` (`lmerTest`) one cannot unconstrain the Run component to allow it to be negative. As Littell et al. (2006, p.150) say

if you do not set the negative variance component estimate to zero, but allow it to remain negative, you get better control over Type I error and, for cases of negative wholeplot error variance estimates, greater power. Therefore, this is the recommended procedure.

Analyse with Reps fixed using lm to make the analysis equivalent to ANOVA

The function `lm` has to be used because there are no random terms; `lme4` cannot be used because it requires at least one random term.

```
 m.lm <- lm(logitP ~ Run + Host*Cadavers*Ladybird,
              data=Ladybird.dat)
(aov.tab <- anova(m.lm))
```

Analysis of Variance Table

```
Response: logitP
          Df  Sum Sq Mean Sq F value    Pr(>F)
Run           1  0.0677  0.0677  0.2944   0.58946
Host          1 13.5992 13.5992 59.1720 1.815e-10
Cadavers      2 17.0274  8.5137 37.0444 3.784e-11
Ladybird       1 11.0907 11.0907 48.2571 3.329e-09
Host:Cadavers 2  0.3078  0.1539  0.6695   0.51579
Host:Ladybird  1  0.2279  0.2279  0.9916   0.32341
Cadavers:Ladybird 2  1.7349  0.8675  3.7744  0.02867
Host:Cadavers:Ladybird 2  0.1999  0.1000  0.4350  0.64932
Residuals     59 13.5596  0.2298
```

Now the Run:Plant variance estimate is equal to that for the Residuals Mean Sq for Run:Plant from the anova table.

Obtain the marginality matrix for the fixed terms

The `pstructure` function from the `dae` package (Brien, 2021b) produce the marginality matrix for a formula as a side effect and we take advantage of that to obtain the matrix required here.

```
Ladybird.pstr <- pstructure(formula = ~ Host*Cadavers*Ladybird,
                           data = Ladybird.dat)
(HCL.marg <- marginality(Ladybird.pstr))
```

	Host	Cadavers	Host:Cadavers	Ladybird	Host:Ladybird	Cadavers:Ladybird	
Host	1	0		1	0	1	0
Cadavers	0	1		1	0	0	1
Host:Cadavers	0	0		1	0	0	0
Ladybird	0	0		0	1	1	1
Host:Ladybird	0	0		0	0	1	0
Cadavers:Ladybird	0	0		0	0	0	1
Host:Cadavers:Ladybird	0	0		0	0	0	0
			Host:Cadavers:Ladybird				
Host				1			
Cadavers				1			
Host:Cadavers				1			

Ladybird	1
Host:Ladybird	1
Cadavers:Ladybird	1
Host:Cadavers:Ladybird	1

This marginality matrix is interpreted by taking a row term and noting that it is marginal to any column term with a one in this row.

Choose marginality-compliant model

```
chosen <- chooseModel(aov.tab, DF = "Df", denDF = 59, p.values = "Pr(>F)" ,
                       terms.marginality = HCL.marg)
(chosen$choose.summary)
```

Sequence of model investigations

	terms	DF	denDF	p	action
1	Host:Cadavers:Ladybird	2	59	0.6493	Nonsignificant
2	Cadavers:Ladybird	2	59	0.0287	Significant
3	Host:Ladybird	1	59	0.3234	Nonsignificant
4	Host:Cadavers	2	59	0.5158	Nonsignificant
5	Host	1	59	0.0000	Significant

```
(chosen$sig.terms)
```

```
[[1]]
[1] "Cadavers:Ladybird"
```

```
[[2]]
[1] "Host"
```

The `chooseModel` function produces a list with components `sig.terms`, a list with the terms in the marginality-compliant model, and `choose.summary`, a data.frame that details the tests performed in choosing the model. Note that `chooseModel` does not test the main effects for Cadavers or Ladybird, because these are marginal to the significant two-factor interaction Cadavers:Ladybird.

Form formula for selected model

```
chosen.mod <- paste(unlist(chosen$sig.terms), collapse = " + ")
(chosen.mod <- as.formula(paste("~", chosen.mod)))
```

```
~Cadavers:Ladybird + Host
```

Form predictions that conform to the chosen model

Use `emmeans` to get the predictions and associated statistics for the full model.

```
HCL.emm <- emmeans::emmeans(m1.lmer, specs = ~ Host:Cadavers:Ladybird)
HCL.preds <- summary(HCL.emm)
den.df <- min(HCL.preds$df)
HCL.vcov <- vcov(HCL.emm)
```

Setting the `specs` argument to `Host:Ladybird:Cadavers` requests predictions for all combinations of the three factors.

Modify HCL.preds to be compatible with a predictions.frame

Basically, this is an exercise in renaming the columns in the `data.frame` containing the predictions.

```
names(HCL.preds)
```

```
[1] "Host"      "Cadavers" "Ladybird" "emmmean"   "SE"        "df"        "lower.CL"  "upper.CL"

HCL.preds <- as.predictions.frame(HCL.preds, predictions = "emmmean",
                                    se = "SE", interval.type = "CI",
                                    interval.names = c("lower.CL", "upper.CL"))
names(HCL.preds)

[1] "Host"                  "Cadavers"            "Ladybird"
[4] "predicted.value"       "standard.error"      "df"
[7] "lower.Confidence.limit" "upper.Confidence.limit" "est.status"
```

Form an alldiffs object with predictions obtained with emmeans

```
HCL.diffs <- allDifferences(predictions = HCL.preds, classify = "Host:Ladybird:Cadavers",
                               vcov = HCL.vcov, tdf = den.df)
```

The functions `allDifferences` is used to form the `alldiffs.obj` that contains a `predictions` component, along with components related to pairwise comparisons. The `predictions` component contains upper and lower confidence limits produced by `emmeans`. The `tdf` is supplied so that it can be used to get the degrees of freedom for the *t*-value to be used in calculating the error intervals.

Transform the prediction to conform to chosen model

The `linTransform` function is used to obtain estimated marginal means (emm) that conform to the chosen model. Because we would prefer error intervals based on $\pm 0.5LSD$, the `error.intervals` argument has been set to `"halfLeast"`, the `LSDtype` argument to `"factor.combination"` and the `LSDby` argument to `"Host"` so that the average LSD will be calculated for each Host. This necessary because, under the chosen model, the LSDs differ between Hosts. It results in `lower.halfLeastSignificant.limit` and `upper.halfLeastSignificant.limit` replacing the limits based on the confidence intervals in the `predictions` component of the resulting `alldiffs` object.

```
diffs <- linTransform(HCL.diffs, linear.transformation = ~ Cadavers:Ladybird + Host,
                      error.intervals = "halfLeast",
                      LSDtype = "factor.combination", LSDby = "Host",
                      tables = "predictions")
```

```
#### Predictions for transform(s) from Host:Ladybird:Cadavers
```

The original predictions, obtained as described below, have been linearly transformed to form estimated marginal means.

	Host	Ladybird	Cadavers	predicted.value	standard.error	df
1	bean	-	5	-1.6038338	0.1485977	47.2
2	bean	-	10	-1.1454308	0.1485977	47.2
3	bean	-	20	-0.7448097	0.1485977	47.2
4	bean	+	5	-1.0195475	0.1485977	47.2
5	bean	+	10	-0.5983440	0.1485977	47.2
6	bean	+	20	0.4786704	0.1485977	47.2
7	trefoil	-	5	-2.4730339	0.1485977	47.2
8	trefoil	-	10	-2.0146309	0.1485977	47.2
9	trefoil	-	20	-1.6140098	0.1485977	47.2
10	trefoil	+	5	-1.8887476	0.1485977	47.2
11	trefoil	+	10	-1.4675441	0.1485977	47.2
12	trefoil	+	20	-0.3905297	0.1485977	47.2
				upper.halfLeastSignificant.limit	lower.halfLeastSignificant.limit	est.status
1				-1.4081535		-1.7995140 Estimable
2				-0.9497506		-1.3411111 Estimable
3				-0.5491295		-0.9404900 Estimable
4				-0.8238673		-1.2152278 Estimable
5				-0.4026637		-0.7940242 Estimable
6				0.6743507		0.2829901 Estimable
7				-2.2773537		-2.6687142 Estimable
8				-1.8189507		-2.2103112 Estimable
9				-1.4183296		-1.8096901 Estimable
10				-1.6930674		-2.0844279 Estimable
11				-1.2718638		-1.6632243 Estimable
12				-0.1948495		-0.5862100 Estimable

LSD values

```
minimum LSD = 0.3913605 0.3913605  
mean LSD = 0.3913605 0.3913605  
maximum LSD = 0.3913605 0.3913605  
(sed range / mean sed = 3.49e-14 3.45e-14 )
```

Plot the predictions

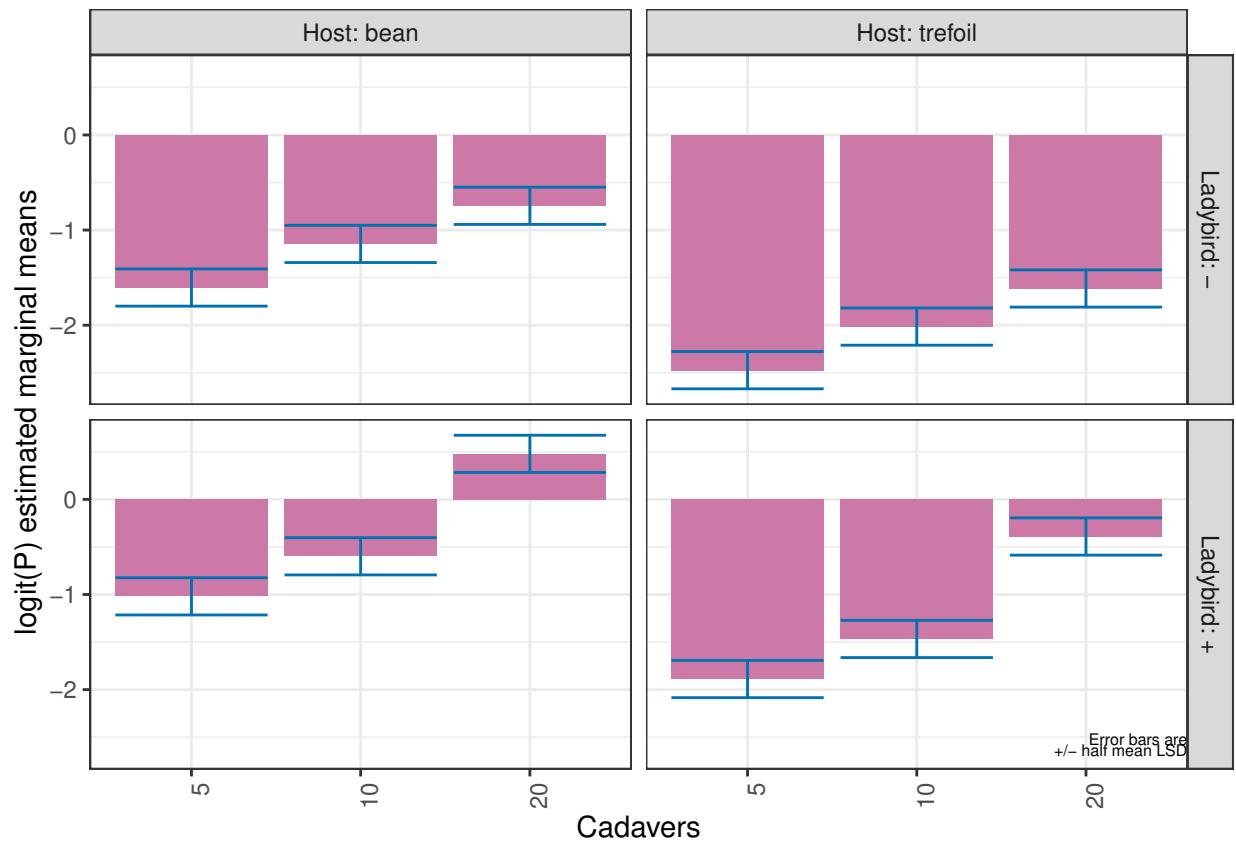
The function `plotPredictions` uses `ggplot` to produce the plot and the `ggplotFuncs` argument allows the addition of `ggplot` functions to modify the plot. In this case, the `facet.grid` function is respecified to include `prepper` functions that modify the labels of the facets to include the factor names. Note the the error bars in the plots are of $\pm 0.5LSD$ so that pairs of prediction with nonoverlapping bars are significantly different (Snee, 1981).

```
plotPredictions(diffs$predictions, y ="predicted.value",  
y.title = "logit(P) estimated marginal means",
```

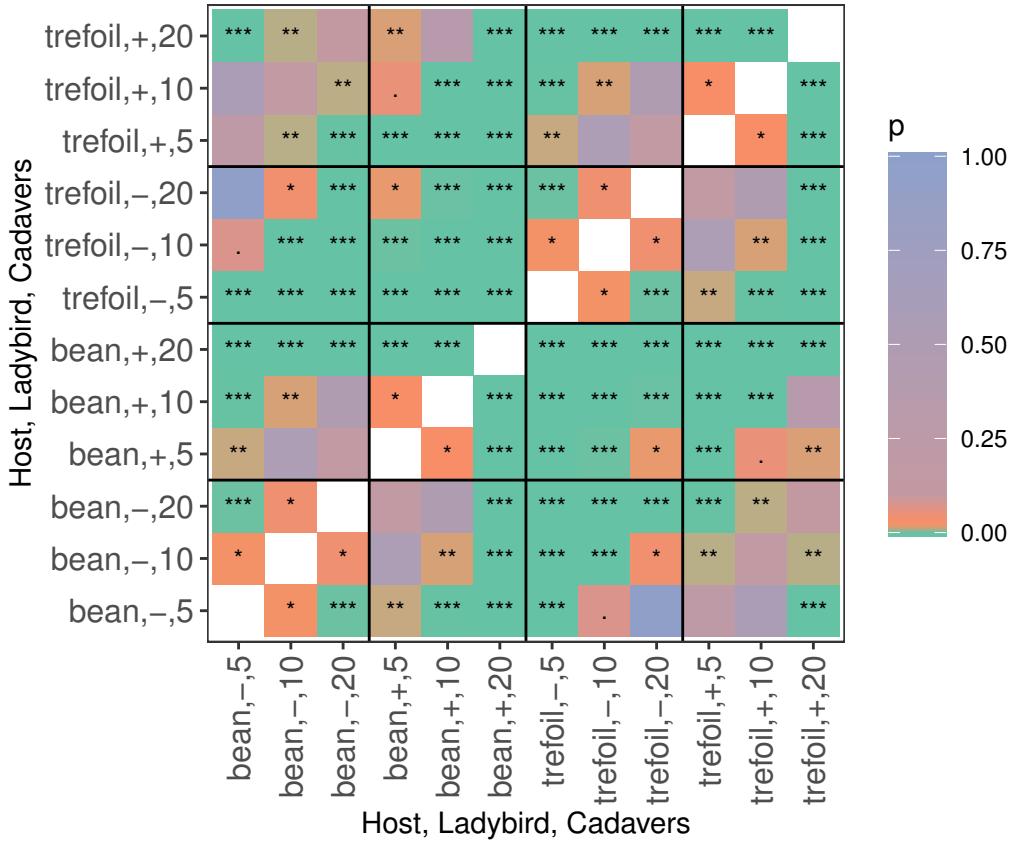
```

classify = "Host:Ladybird:Cadavers",
error.intervals = "halfLeast",
ggplotFuncs = list(facet_grid(Ladybird ~ Host,
                             labeller = label_both)))

```



```
plotPvalues(diffs, factors.per.grid = 1, show.sig = TRUE)
```



```
options(width = 90)
print(diffs$sed)
```

	bean,-,5	bean,-,10	bean,-,20	bean,+5	bean,+10	bean,+20	trefoil,-5	trefoil,-10	trefoil,-20	trefoil,+5	trefoil,+10	trefoil,+20
bean,-,5	NA	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1123293
bean,-,10	0.1945600	NA	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.2246586
bean,-,20	0.1945600	0.1945600	NA	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.2246586
bean,+5	0.1945600	0.1945600	0.1945600	NA	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.2246586
bean,+10	0.1945600	0.1945600	0.1945600	0.1945600	NA	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.2246586
bean,+20	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	NA	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.2246586
trefoil,-5	0.1123293	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	NA	
trefoil,-10	0.2246586	0.1123293	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.1945600	
trefoil,-20	0.2246586	0.2246586	0.1123293	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.1945600	
trefoil,+5	0.2246586	0.2246586	0.2246586	0.1123293	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.1945600	
trefoil,+10	0.2246586	0.2246586	0.2246586	0.2246586	0.1123293	0.2246586	0.2246586	0.2246586	0.2246586	0.1945600	0.1945600	
trefoil,+20	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.1123293	0.2246586	0.2246586	0.1123293	0.1945600	0.1945600	
trefoil,-,10	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	
trefoil,-,20	NA	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	

trefoil,-,20	0.1945600	NA	0.1945600	0.1945600	0.1945600
trefoil,+,5	0.1945600	0.1945600	NA	0.1945600	0.1945600
trefoil,+,10	0.1945600	0.1945600	0.1945600	NA	0.1945600
trefoil,+,20	0.1945600	0.1945600	0.1945600	0.1945600	NA

Perform the analysis with just the selected model fitted

The model with nonsignificant fixed terms dropped is obtained in order to compare it with the fit when they are retained and the estimated marginal means for the chosen model are obtained.

```
m.sig.lm <- lm(logitP ~ Run + Cadavers*Ladybird + Host,
                  data=Ladybird.dat)
(aov.tab <- anova(m.sig.lm))
```

Analysis of Variance Table

```
Response: logitP
          Df  Sum Sq Mean Sq F value    Pr(>F)
Run           1  0.0677  0.0677  0.3029   0.58398
Cadavers      2 17.0274  8.5137 38.1160 1.255e-11
Ladybird       1 11.0907 11.0907 49.6531 1.542e-09
Host           1 13.5992 13.5992 60.8836 7.179e-11
Cadavers:Ladybird 2  1.7349  0.8675  3.8836   0.02559
Residuals     64 14.2952  0.2234
```

```
HCL.emm <- emmeans::emmeans(m.sig.lm, specs = ~ Host:Cadavers:Ladybird)
HCL.preds <- summary(HCL.emm)
den.df <- min(HCL.preds$df)
HCL.vcov <- vcov(HCL.emm)
HCL.preds <- as.predictions.frame(HCL.preds, predictions = "emmmean",
                                    se = "SE", interval.type = "CI",
                                    interval.names = c("lower.CL", "upper.CL"))
diffs.red <- allDifferences(predictions = HCL.preds, classify = "Host:Ladybird:Cadavers",
                               vcov = HCL.vcov, tdf = den.df)
diffs.red <- redoErrorIntervals(diffs, error.intervals = "halfLeast",
                                 LSDtype = "factor.combination", LSDby = "Host")

options(width = 90)
print(diffs.red$sed)
```

bean,-,5	bean,-,10	bean,-,20	bean,+,5	bean,+,10	bean,+,20	trefoil,-,5
bean,-,5	NA	0.1945600	0.1945600	0.1945600	0.1945600	0.1123293
bean,-,10	0.1945600	NA	0.1945600	0.1945600	0.1945600	0.2246586
bean,-,20	0.1945600	0.1945600	NA	0.1945600	0.1945600	0.2246586
bean,+,5	0.1945600	0.1945600	0.1945600	NA	0.1945600	0.2246586
bean,+,10	0.1945600	0.1945600	0.1945600	0.1945600	NA	0.2246586
bean,+,20	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	NA
trefoil,-,5	0.1123293	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586
trefoil,-,10	0.2246586	0.1123293	0.2246586	0.2246586	0.2246586	0.1945600
trefoil,-,20	0.2246586	0.2246586	0.1123293	0.2246586	0.2246586	0.1945600
trefoil,+,5	0.2246586	0.2246586	0.2246586	0.1123293	0.2246586	0.2246586
trefoil,+,10	0.2246586	0.2246586	0.2246586	0.2246586	0.1123293	0.2246586

trefoil,+,20	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.1123293	0.1945600
trefoil,-,10	trefoil,-,20	trefoil,+,5	trefoil,+,10	trefoil,+,20			
bean,-,5	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	
bean,-,10	0.1123293	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	
bean,-,20	0.2246586	0.1123293	0.2246586	0.2246586	0.2246586	0.2246586	
bean,+,5	0.2246586	0.2246586	0.1123293	0.2246586	0.2246586	0.2246586	
bean,+,10	0.2246586	0.2246586	0.2246586	0.1123293	0.2246586	0.2246586	
bean,+,20	0.2246586	0.2246586	0.2246586	0.2246586	0.2246586	0.1123293	
trefoil,-,5	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	
trefoil,-,10	NA	0.1945600	0.1945600	0.1945600	0.1945600	0.1945600	
trefoil,-,20	0.1945600	NA	0.1945600	0.1945600	0.1945600	0.1945600	
trefoil,+,5	0.1945600	0.1945600	NA	0.1945600	0.1945600	0.1945600	
trefoil,+,10	0.1945600	0.1945600	0.1945600	NA	0.1945600	0.1945600	
trefoil,+,20	0.1945600	0.1945600	0.1945600	0.1945600	NA		

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