Investigating Alternate Models

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Workspace Setup

Loading the Data

Load the raw data and verify its dimensions and structure.

```
df <- readRDS('../data/tidy.Rds')
dim(df)
```

```
## [1] 1023   35
```

```
summary(df)
```

```
##  acq_12_wo_or_less    age_yrs        neutered       train_6mo_or_less
##  Mode :logical     Min.   : 1.000   Mode :logical   Mode :logical
##  FALSE:449         1st Qu.: 4.000   FALSE:132       FALSE:529
##  TRUE :557         Median : 7.000   TRUE :891       TRUE :494
##  NA's :17          Mean   : 7.131
##                    3rd Qu.:10.000
##                    Max.   :19.000
##
##  train_class_count train_technique aggression      fear_anxiety
##  1-3  : 49         punish: 54      Mode :logical   Mode :logical
##  4-6  :120         reward:440      FALSE:474       FALSE:310
##  7-9  : 72         NA's  :529      TRUE :549       TRUE :713
##  10+  :242
##  NA's:540
##
##
##   jumping          barking          coprophagia      compulsion
##  Mode :logical    Mode :logical    Mode :logical    Mode :logical
##  FALSE:793        FALSE:806        FALSE:642        FALSE:769
##  TRUE :230        TRUE :217        TRUE :381        TRUE :254
##
##
##
##
##  rep_materials    hyperactive      destructive       escape
##  Mode :logical    Mode :logical    Mode :logical    Mode :logical
##  FALSE:595        FALSE:907        FALSE:892        FALSE:793
##  TRUE :428        TRUE :116        TRUE :131        TRUE :230
##
##
##
```

```
##
##   mounting                                   owner_id   train_1_3_mo
##  Mode :logical   3ea182741999dd54cb902c478ba2704c:  8   FALSE:248
##  FALSE:833       1b9b35f5434de88ff7f3ff4b0e371d48:  7   TRUE :234
##  TRUE :190       796cf2f6f66cf06329ecc6067d7419f0:  6   NA's :541
##                  a5069b3d48cbac2d77080428c7d8d315:  6
##                  f9968086714b82f1c1c87019d1187507:  6
##                  0d29a6dde9e38788ba6a480bf902fb53:  4
##                  (Other)                         :986
##  train_4_mo   train_5_6_mo train_start_age    male          device_used
##  FALSE:267    FALSE:256    1-3 mo:234      Mode :logical   Mode :logical
##  TRUE :215    TRUE :226    4 mo  :130      FALSE:526       FALSE:62
##  NA's :541    NA's :541    5-6 mo:118      TRUE :497       TRUE :432
##                            NA's  :541                      NA's :529
##
##
##
##  buckle_collar   martingale      slip_collar     shock_collar
##  Mode :logical   Mode :logical   Mode :logical   Mode :logical
##  FALSE:259       FALSE:404       FALSE:449       FALSE:485
##  TRUE :235       TRUE :90        TRUE :45        TRUE :9
##  NA's :529       NA's :529       NA's :529       NA's :529
##
##
##
##   harness        head_halter     choke_collar    prong_collar
##  Mode :logical   Mode :logical   Mode :logical   Mode :logical
##  FALSE:345       FALSE:468       FALSE:467       FALSE:461
##  TRUE :149       TRUE :26        TRUE :27        TRUE :33
##  NA's :529       NA's :529       NA's :529       NA's :529
##
##
##
##  house_soiling   adj_train_technique punish_device
##  Mode :logical   punish:178          FALSE:316
##  FALSE:225       reward:316          TRUE :178
##  TRUE :798       NA's  :529          NA's :529
##
##
##
##
```

Preparing Common Variables and Functions

```
outcomes <- c(
  'aggression',
  'fear_anxiety',
  'jumping',
  'barking',
  'coprophagia',
  'compulsion',
  'house_soiling',
  'rep_materials',
```

```r
  'hyperactive',
  'destructive',
  'escape',
  'mounting'
)
outcomes <- sort(outcomes)
```

```r
apply_min_xtab <- function(df, outcome, cutoff=10)
{
  drops <- NULL
  for (col in names(df)) {
    if (col == outcome) next
    if (is.integer(df[,col])) next

    xtab <- table(df[,col], df[,outcome])
    if (min(xtab) < cutoff) {
      drops <- c(drops, col)
      break
    }
  }

  if (length(drops) > 0) {
    cat('\nDropped from model due to insufficient responses:\n')
    cat(drops)
    cat('\n')
  }

  return(df[, !(names(df) %in% drops)])
}
```

```r
df_exp <- df %>%
  filter(train_6mo_or_less == TRUE)
summary(df_exp)
```

```
##  acq_12_wo_or_less    age_yrs        neutered       train_6mo_or_less
##  Mode :logical     Min.   : 1.000   Mode :logical   Mode:logical
##  FALSE:78          1st Qu.: 3.000   FALSE:103       TRUE:494
##  TRUE :410         Median : 6.000   TRUE :391
##  NA's :6           Mean   : 6.368
##                    3rd Qu.: 9.000
##                    Max.   :16.000
##
##  train_class_count train_technique aggression      fear_anxiety
##  1-3 : 49          punish: 54      Mode :logical   Mode :logical
##  4-6 :120          reward:440      FALSE:267       FALSE:186
##  7-9 : 72                          TRUE :227       TRUE :308
##  10+ :242
##  NA's: 11
##
##
##   jumping          barking         coprophagia     compulsion
##  Mode :logical   Mode :logical   Mode :logical   Mode :logical
##  FALSE:382       FALSE:412       FALSE:308       FALSE:394
##  TRUE :112       TRUE :82        TRUE :186       TRUE :100
```

```
##
##
##
##
##  rep_materials   hyperactive     destructive       escape
##  Mode :logical   Mode :logical   Mode :logical   Mode :logical
##  FALSE:278       FALSE:442       FALSE:455       FALSE:407
##  TRUE :216       TRUE :52        TRUE :39        TRUE :87
##
##
##
##
##   mounting                                   owner_id   train_1_3_mo
##  Mode :logical   3ea182741999dd54cb902c478ba2704c:  8   FALSE:248
##  FALSE:405       249e300dbb0ad0fe1be2fee5d1a3eadd:  4   TRUE :234
##  TRUE :89        30f24317ad30eb964fd7d4c0b9053a5f:  4   NA's : 12
##                  465f724d7f9d1903ffe9ef1230a2054b:  4
##                  7dd1f8eacb783aa0ec257424f46a3361:  4
##                  84155e784cae7d62097ef477c17422c9:  4
##                  (Other)                         :466
##  train_4_mo  train_5_6_mo train_start_age    male         device_used
##  FALSE:267   FALSE:256    1-3 mo:234      Mode :logical   Mode :logical
##  TRUE :215   TRUE :226    4 mo  :130      FALSE:248       FALSE:62
##  NA's : 12   NA's : 12    5-6 mo:118      TRUE :246       TRUE :432
##                           NA's  : 12
##
##
##
##  buckle_collar   martingale      slip_collar     shock_collar
##  Mode :logical   Mode :logical   Mode :logical   Mode :logical
##  FALSE:259       FALSE:404       FALSE:449       FALSE:485
##  TRUE :235       TRUE :90        TRUE :45        TRUE :9
##
##
##
##
##   harness        head_halter     choke_collar    prong_collar
##  Mode :logical   Mode :logical   Mode :logical   Mode :logical
##  FALSE:345       FALSE:468       FALSE:467       FALSE:461
##  TRUE :149       TRUE :26        TRUE :27        TRUE :33
##
##
##
##
##  house_soiling   adj_train_technique punish_device
##  Mode :logical   punish:178          FALSE:316
##  FALSE:81        reward:316          TRUE :178
##  TRUE :413
##
##
##
##
```

Alternate Models

Exploring Training Methods and Equipment

With regard to training methods, the following question was presented to participants.

> At puppy training classes, what training techniques were used? - Rewarding techniques (e.g., treats, praise, pets) - Tough love techniques (e.g., yelling, bopping on the nose, swatting on the rump, alpha rolls (pinning on back until dog submits), use of aversive collars (e.g., shock, prong, choke), jerking on the leash, water spraying, scruffing) - A combination of rewarding and tough love techniques

However, after discussing with clinicians, the unanimous decision was that all training methods that involved some form of punishment could be considered punishment-based. This modification can be seen in the first notebook for this study (`0_tidy.Rmd`) and the result can be seen by looking at the `train_technique` column.

```r
summary(df_exp$train_technique)
```

```
## punish reward
##     54    440
```

In addition, we also presented the following questions to participants:

> What restraining/training devices were employed? - Nylon slip collar - Buckle collar - Head halter (with nose band) - Harness (around chest) - Metal "choke" collar - Prong collar - Martingale collar - Electric shock collar - No devices were employed

We exclude the "Other" response from the list above for simplicity since the only actionable submissions were for harnesses. The harness count was updated accordingly.

These devices generally fall into two caregories: punishing and non-punishing.

> Punishing: - Metal "choke" collar - Prong collar - Martingale collar - Electric shock collar - Nylon slip collar Non-punishing: - Buckle collar - Head halter (with nose band) - Harness (around chest)

We calculated the number of dogs exposed to these punishing devices in our initial notebook.

```r
summary(df_exp$punish_device)
```

```
## FALSE  TRUE
##   316   178
```

Analysis of Grouped Devices

The `punish_device` variable is not enough for our "grouped" analysis since it does not account for dogs being exposed to no devices. Therefore, we create a device group (`device_group`) column with three values: punish, non-punish, none.

```r
df_exp <- df_exp %>%
  mutate(device_group = as.factor(ifelse(
    device_used == FALSE, 'none', ifelse(
      punish_device == TRUE, 'punish', 'non_punish'))))

summary(df_exp$device_group)
```

```
## non_punish       none     punish
##        254         62        178
```

```r
df_exp <- df_exp %>%
  mutate(reward = ifelse(
    is.na(train_technique), NA, ifelse(
```

```r
      train_technique == 'reward', TRUE, FALSE)))

common_params <- c(
  'age_yrs',
  'male',
  'neutered',
  'acq_12_wo_or_less',
  'train_1_3_mo',
  'train_4_mo',
  'train_5_6_mo',
  'train_class_count'
)

glm_attribs <- c(
  common_params,
  'reward',
  'device_group'
)

print(glm_attribs)
```

```
##  [1] "age_yrs"           "male"              "neutered"
##  [4] "acq_12_wo_or_less" "train_1_3_mo"      "train_4_mo"
##  [7] "train_5_6_mo"      "train_class_count" "reward"
## [10] "device_group"
```

```r
set.seed(1)
for (outcome in outcomes) {
  cat(paste(replicate(80, '-'), collapse=''))
  cat(paste0('\n', outcome, '\n'))
  f <- as.formula(paste0(outcome, '~', '.'))

  df_tmp <- df_exp[,c(outcome, glm_attribs)]
  df_tmp <- apply_min_xtab(df_tmp, outcome)

  glm_fit <- glm(f, data=df_tmp, family='binomial')
  print(summary(glm_fit))
  print(exp(cbind(OR=coef(glm_fit), suppressMessages(confint(glm_fit)))))
  cat('\nVIF:\n')
  print(car::vif(glm_fit))
  cat('\n')
}
```

```
## --------------------------------------------------------------------------------
## aggression
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.6491  -1.0805  -0.9321   1.2243   1.5174
##
## Coefficients:
```

```
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)           0.662045   0.529245   1.251   0.2110
## age_yrs               0.001667   0.029154   0.057   0.9544
## maleTRUE             -0.357088   0.189379  -1.886   0.0594 .
## neuteredTRUE          0.173252   0.253248   0.684   0.4939
## acq_12_wo_or_lessTRUE -0.191276   0.287739  -0.665   0.5062
## train_1_3_moTRUE     -0.103380   0.222223  -0.465   0.6418
## train_4_moTRUE        0.058224   0.196751   0.296   0.7673
## train_5_6_moTRUE     -0.146981   0.201272  -0.730   0.4652
## train_class_count.L  -0.191487   0.233760  -0.819   0.4127
## train_class_count.Q   0.029409   0.233525   0.126   0.8998
## train_class_count.C  -0.022075   0.221326  -0.100   0.9206
## rewardTRUE           -0.635660   0.330730  -1.922   0.0546 .
## device_groupnone      0.340893   0.304020   1.121   0.2622
## device_grouppunish    0.060116   0.217794   0.276   0.7825
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 646.58  on 468  degrees of freedom
## Residual deviance: 633.92  on 455  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 661.92
##
## Number of Fisher Scoring iterations: 4
##
##                             OR     2.5 %   97.5 %
## (Intercept)           1.9387527 0.6902845 5.518775
## age_yrs               1.0016679 0.9458653 1.060599
## maleTRUE              0.6997110 0.4819850 1.013201
## neuteredTRUE          1.1891660 0.7250187 1.960105
## acq_12_wo_or_lessTRUE 0.8259049 0.4688716 1.452383
## train_1_3_moTRUE      0.9017844 0.5829438 1.394538
## train_4_moTRUE        1.0599521 0.7204511 1.559183
## train_5_6_moTRUE      0.8633102 0.5810055 1.279984
## train_class_count.L   0.8257301 0.5210198 1.307568
## train_class_count.Q   1.0298457 0.6515241 1.630294
## train_class_count.C   0.9781672 0.6339058 1.511779
## rewardTRUE            0.5295860 0.2737084 1.006546
## device_groupnone      1.4062021 0.7747649 2.562848
## device_grouppunish    1.0619593 0.6920111 1.626969
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.227368  1        1.107866
## male              1.014429  1        1.007189
## neutered          1.230288  1        1.109183
## acq_12_wo_or_less 1.289052  1        1.135364
## train_1_3_mo      1.397023  1        1.181957
## train_4_mo        1.083349  1        1.040840
## train_5_6_mo      1.141546  1        1.068432
## train_class_count 1.142509  3        1.022453
## reward            1.155812  1        1.075087
```

```
## device_group      1.158436  2       1.037452
##
## --------------------------------------------------------------------------------
## barking
##
## Dropped from model due to insufficient responses:
## train_class_count
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.8329  -0.6299  -0.5423  -0.4552   2.3308
##
## Coefficients:
##                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -2.877706   0.732251  -3.930  8.5e-05 ***
## age_yrs               -0.001639   0.039068  -0.042    0.967
## maleTRUE              -0.226369   0.256213  -0.884    0.377
## neuteredTRUE           0.571209   0.365875   1.561    0.118
## acq_12_wo_or_lessTRUE  0.464094   0.417115   1.113    0.266
## train_1_3_moTRUE      -0.125049   0.281488  -0.444    0.657
## train_4_moTRUE         0.343104   0.261729   1.311    0.190
## train_5_6_moTRUE      -0.023065   0.263286  -0.088    0.930
## rewardTRUE             0.139414   0.417861   0.334    0.739
## device_groupnone       0.486046   0.391957   1.240    0.215
## device_grouppunish     0.470446   0.292286   1.610    0.107
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 414.70  on 475  degrees of freedom
## Residual deviance: 404.93  on 465  degrees of freedom
##   (18 observations deleted due to missingness)
## AIC: 426.93
##
## Number of Fisher Scoring iterations: 4
##
##                               OR      2.5 %    97.5 %
## (Intercept)           0.05626366 0.01277376 0.2275589
## age_yrs               0.99836242 0.92424574 1.0776350
## maleTRUE              0.79742394 0.48047836 1.3158186
## neuteredTRUE          1.77040670 0.88701503 3.7609636
## acq_12_wo_or_lessTRUE 1.59057200 0.72640713 3.7882113
## train_1_3_moTRUE      0.88245374 0.50734367 1.5350448
## train_4_moTRUE        1.40931590 0.84311020 2.3597016
## train_5_6_moTRUE      0.97719862 0.58108938 1.6361958
## rewardTRUE            1.14959983 0.52482570 2.7435123
## device_groupnone      1.62587428 0.72801569 3.4268326
## device_grouppunish    1.60070770 0.89961700 2.8404938
##
## VIF:
```

```
##                      GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.171233  1        1.082235
## male              1.009685  1        1.004831
## neutered          1.164681  1        1.079204
## acq_12_wo_or_less 1.192504  1        1.092018
## train_1_3_mo      1.221899  1        1.105395
## train_4_mo        1.059753  1        1.029443
## train_5_6_mo      1.067965  1        1.033424
## reward            1.131143  1        1.063552
## device_group      1.149645  2        1.035478
##
## -----------------------------------------------------------------------------
## compulsion
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.1064  -0.7188  -0.5772  -0.4510   2.1611
##
## Coefficients:
##                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)          -1.2028850  0.6493493  -1.852  0.06396 .
## age_yrs               0.0006222  0.0364592   0.017  0.98639
## maleTRUE             -0.6972279  0.2422033  -2.879  0.00399 **
## neuteredTRUE          0.0932819  0.3171278   0.294  0.76865
## acq_12_wo_or_lessTRUE  0.0506946  0.3516555   0.144  0.88537
## train_1_3_moTRUE     -0.1311433  0.2760606  -0.475  0.63475
## train_4_moTRUE       -0.0835458  0.2452993  -0.341  0.73341
## train_5_6_moTRUE      0.3238097  0.2527520   1.281  0.20015
## train_class_count.L  -0.3853995  0.2795752  -1.379  0.16804
## train_class_count.Q  -0.1191250  0.2814364  -0.423  0.67209
## train_class_count.C   0.0213234  0.2676382   0.080  0.93650
## rewardTRUE           -0.0395590  0.3994990  -0.099  0.92112
## device_groupnone      0.4093585  0.3596968   1.138  0.25509
## device_grouppunish    0.0747779  0.2758916   0.271  0.78636
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 469.93  on 468  degrees of freedom
## Residual deviance: 454.24  on 455  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 482.24
##
## Number of Fisher Scoring iterations: 4
##
##                             OR      2.5 %    97.5 %
## (Intercept)          0.3003265 0.08222718 1.0565816
## age_yrs              1.0006224 0.93123278 1.0746535
## maleTRUE             0.4979638 0.30722703 0.7959053
## neuteredTRUE         1.0977712 0.59615936 2.0779141
```

```
## acq_12_wo_or_lessTRUE 1.0520016 0.53441596 2.1338581
## train_1_3_moTRUE      0.8770921 0.50969393 1.5087557
## train_4_moTRUE        0.9198490 0.56631679 1.4848294
## train_5_6_moTRUE      1.3823842 0.84211735 2.2742106
## train_class_count.L   0.6801789 0.39819681 1.2006847
## train_class_count.Q   0.8876969 0.50857397 1.5398078
## train_class_count.C   1.0215523 0.60867074 1.7458757
## rewardTRUE            0.9612133 0.44971561 2.1788123
## device_groupnone      1.5058514 0.72603440 2.9996821
## device_grouppunish    1.0776448 0.62307576 1.8433050
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.194699  1        1.093023
## male              1.016477  1        1.008205
## neutered          1.200395  1        1.095625
## acq_12_wo_or_less 1.298926  1        1.139704
## train_1_3_mo      1.370529  1        1.170696
## train_4_mo        1.077359  1        1.037959
## train_5_6_mo      1.158869  1        1.076508
## train_class_count 1.157865  3        1.024731
## reward            1.169691  1        1.081523
## device_group      1.181515  2        1.042581
##
## ----------------------------------------------------------------------------
## coprophagia
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.5405  -0.9789  -0.7252   1.2314   2.0333
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -0.17479    0.55657  -0.314 0.753482
## age_yrs               -0.03741    0.03026  -1.236 0.216403
## maleTRUE               0.01050    0.19785   0.053 0.957659
## neuteredTRUE           1.01025    0.28958   3.489 0.000486 ***
## acq_12_wo_or_lessTRUE -0.55920    0.29356  -1.905 0.056793 .
## train_1_3_moTRUE       0.19104    0.23796   0.803 0.422075
## train_4_moTRUE        -0.36901    0.20651  -1.787 0.073962 .
## train_5_6_moTRUE      -0.06189    0.21394  -0.289 0.772351
## train_class_count.L   -0.08051    0.24193  -0.333 0.739300
## train_class_count.Q    0.03193    0.24193   0.132 0.895012
## train_class_count.C   -0.35167    0.23018  -1.528 0.126561
## rewardTRUE            -0.30942    0.34136  -0.906 0.364702
## device_groupnone       0.42183    0.31338   1.346 0.178275
## device_grouppunish    -0.19114    0.23119  -0.827 0.408372
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
```

```
##
##     Null deviance: 620.67  on 468  degrees of freedom
## Residual deviance: 589.35  on 455  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 617.35
##
## Number of Fisher Scoring iterations: 4
##
##                            OR     2.5 %   97.5 %
## (Intercept)           0.8396330 0.2803900 2.496027
## age_yrs               0.9632816 0.9073953 1.021916
## maleTRUE              1.0105594 0.6852901 1.489472
## neuteredTRUE          2.7462896 1.5782525 4.929733
## acq_12_wo_or_lessTRUE 0.5716659 0.3205721 1.015915
## train_1_3_moTRUE      1.2105092 0.7595552 1.933615
## train_4_moTRUE        0.6914213 0.4601240 1.034902
## train_5_6_moTRUE      0.9399825 0.6168418 1.428723
## train_class_count.L   0.9226460 0.5754077 1.491274
## train_class_count.Q   1.0324409 0.6417735 1.659958
## train_class_count.C   0.7035090 0.4474086 1.104936
## rewardTRUE            0.7338720 0.3766590 1.444339
## device_groupnone      1.5247537 0.8228652 2.823779
## device_grouppunish    0.8260201 0.5230575 1.296560
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.205829  1        1.098103
## male              1.006595  1        1.003292
## neutered          1.190301  1        1.091009
## acq_12_wo_or_less 1.300505  1        1.140397
## train_1_3_mo      1.455736  1        1.206539
## train_4_mo        1.066394  1        1.032664
## train_5_6_mo      1.171561  1        1.082387
## train_class_count 1.147159  3        1.023145
## reward            1.171826  1        1.082509
## device_group      1.166210  2        1.039188
##
## --------------------------------------------------------------------------------
## destructive
##
## Dropped from model due to insufficient responses:
## neutered
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.7562  -0.4161  -0.3491  -0.2936   2.6283
##
## Coefficients:
##                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -1.564037   0.936847  -1.669   0.0950 .
## age_yrs               -0.003068   0.051805  -0.059   0.9528
```

```
## maleTRUE               0.063610   0.366274   0.174   0.8621
## acq_12_wo_or_lessTRUE -0.886757   0.499063  -1.777   0.0756 .
## train_1_3_moTRUE       0.038729   0.483986   0.080   0.9362
## train_4_moTRUE        -0.150639   0.408985  -0.368   0.7126
## train_5_6_moTRUE      -0.494597   0.414856  -1.192   0.2332
## train_class_count.L    0.040542   0.466131   0.087   0.9307
## train_class_count.Q   -0.325586   0.439243  -0.741   0.4585
## train_class_count.C   -0.293596   0.390052  -0.753   0.4516
## rewardTRUE            -0.151061   0.606089  -0.249   0.8032
## device_groupnone      -0.227976   0.656765  -0.347   0.7285
## device_grouppunish     0.343054   0.407534   0.842   0.3999
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 238.79  on 468  degrees of freedom
## Residual deviance: 231.36  on 456  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 257.36
##
## Number of Fisher Scoring iterations: 5
##
##                              OR     2.5 %   97.5 %
## (Intercept)           0.2092894 0.0312115 1.267814
## age_yrs               0.9969371 0.8990162 1.102619
## maleTRUE              1.0656763 0.5177376 2.201997
## acq_12_wo_or_lessTRUE 0.4119896 0.1548171 1.118732
## train_1_3_moTRUE      1.0394888 0.3929630 2.697218
## train_4_moTRUE        0.8601581 0.3697657 1.881275
## train_5_6_moTRUE      0.6098165 0.2585226 1.345508
## train_class_count.L   1.0413755 0.4487344 2.951419
## train_class_count.Q   0.7221042 0.2884675 1.670625
## train_class_count.C   0.7455779 0.3456983 1.626150
## rewardTRUE            0.8597955 0.2831138 3.223913
## device_groupnone      0.7961431 0.1780337 2.551683
## device_grouppunish    1.4092444 0.6239473 3.125956
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.083327  1        1.040830
## male              1.010079  1        1.005027
## acq_12_wo_or_less 1.441104  1        1.200460
## train_1_3_mo      1.753478  1        1.324190
## train_4_mo        1.205254  1        1.097841
## train_5_6_mo      1.242713  1        1.114770
## train_class_count 1.159102  3        1.024913
## reward            1.176724  1        1.084769
## device_group      1.147685  2        1.035037
##
## ---------------------------------------------------------------------------------
## escape
##
## Dropped from model due to insufficient responses:
```

```
## device_group
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.9320  -0.6633  -0.5821  -0.4419   2.2772
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -1.62776    0.65864  -2.471   0.0135 *
## age_yrs               -0.01783    0.03776  -0.472   0.6368
## maleTRUE              -0.31111    0.24842  -1.252   0.2104
## neuteredTRUE           0.80211    0.37315   2.150   0.0316 *
## acq_12_wo_or_lessTRUE -0.14593    0.37706  -0.387   0.6987
## train_1_3_moTRUE       0.36707    0.29754   1.234   0.2173
## train_4_moTRUE        -0.13110    0.25840  -0.507   0.6119
## train_5_6_moTRUE       0.02242    0.26725   0.084   0.9331
## train_class_count.L   -0.45493    0.28297  -1.608   0.1079
## train_class_count.Q    0.14882    0.29756   0.500   0.6170
## train_class_count.C    0.16352    0.29630   0.552   0.5810
## rewardTRUE            -0.31187    0.38035  -0.820   0.4122
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 434.74  on 468  degrees of freedom
## Residual deviance: 422.49  on 457  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 446.49
##
## Number of Fisher Scoring iterations: 4
##
##                              OR      2.5 %   97.5 %
## (Intercept)           0.1963690 0.05221906 0.696829
## age_yrs               0.9823240 0.91172475 1.057577
## maleTRUE              0.7326316 0.44806986 1.189625
## neuteredTRUE          2.2302345 1.10702004 4.836291
## acq_12_wo_or_lessTRUE 0.8642163 0.41785344 1.848714
## train_1_3_moTRUE      1.4435023 0.80841602 2.606490
## train_4_moTRUE        0.8771289 0.52564406 1.451738
## train_5_6_moTRUE      1.0226753 0.60422347 1.728553
## train_class_count.L   0.6344901 0.36881678 1.126851
## train_class_count.Q   1.1604672 0.64733029 2.090906
## train_class_count.C   1.1776465 0.66818262 2.153457
## rewardTRUE            0.7320770 0.35674518 1.604438
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.166875  1        1.080220
## male              1.007592  1        1.003789
## neutered          1.154333  1        1.074399
```

```
## acq_12_wo_or_less 1.323295  1        1.150346
## train_1_3_mo      1.454823  1        1.206160
## train_4_mo        1.065630  1        1.032294
## train_5_6_mo      1.171427  1        1.082325
## train_class_count 1.139802  3        1.022049
## reward            1.053533  1        1.026417
##
## --------------------------------------------------------------------------------
## fear_anxiety
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9609  -1.1563   0.7058   0.9429   1.7349
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -0.07420    0.56494  -0.131    0.896
## age_yrs               -0.01428    0.03117  -0.458    0.647
## maleTRUE              -0.14580    0.20135  -0.724    0.469
## neuteredTRUE           1.16104    0.26250   4.423 9.73e-06 ***
## acq_12_wo_or_lessTRUE -0.40836    0.32800  -1.245    0.213
## train_1_3_moTRUE      -0.15452    0.23204  -0.666    0.505
## train_4_moTRUE         0.22003    0.20984   1.049    0.294
## train_5_6_moTRUE       0.26785    0.21421   1.250    0.211
## train_class_count.L   -0.33912    0.25079  -1.352    0.176
## train_class_count.Q   -0.30709    0.25242  -1.217    0.224
## train_class_count.C   -0.08023    0.24439  -0.328    0.743
## rewardTRUE             0.11563    0.34485   0.335    0.737
## device_groupnone       0.53849    0.34808   1.547    0.122
## device_grouppunish    -0.05911    0.22906  -0.258    0.796
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 627.37  on 468  degrees of freedom
## Residual deviance: 578.36  on 455  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 606.36
##
## Number of Fisher Scoring iterations: 4
##
##                              OR     2.5 %   97.5 %
## (Intercept)           0.9284829 0.3073494 2.828111
## age_yrs               0.9858239 0.9271601 1.047926
## maleTRUE              0.8643314 0.5817170 1.281988
## neuteredTRUE          3.1932642 1.9185843 5.379138
## acq_12_wo_or_lessTRUE 0.6647370 0.3433668 1.249232
## train_1_3_moTRUE      0.8568291 0.5433633 1.351178
## train_4_moTRUE        1.2461093 0.8267532 1.884018
## train_5_6_moTRUE      1.3071481 0.8593370 1.992225
```

```
## train_class_count.L   0.7123990 0.4305718 1.156050
## train_class_count.Q   0.7355834 0.4486256 1.209822
## train_class_count.C   0.9229073 0.5691145 1.487170
## rewardTRUE            1.1225757 0.5662776 2.200210
## device_groupnone      1.7134260 0.8819065 3.477275
## device_grouppunish    0.9425993 0.6021934 1.480048
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.247138  1        1.116753
## male              1.015256  1        1.007599
## neutered          1.236368  1        1.111921
## acq_12_wo_or_less 1.228692  1        1.108464
## train_1_3_mo      1.346451  1        1.160367
## train_4_mo        1.088911  1        1.043509
## train_5_6_mo      1.138780  1        1.067136
## train_class_count 1.125096  3        1.019839
## reward            1.168988  1        1.081198
## device_group      1.161084  2        1.038044
##
## --------------------------------------------------------------------------------
## house_soiling
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4592   0.3957   0.5126   0.6552   1.0871
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)            0.11347    0.69088   0.164    0.870
## age_yrs                0.03607    0.04038   0.893    0.372
## maleTRUE              -0.03585    0.25720  -0.139    0.889
## neuteredTRUE           0.41490    0.33178   1.251    0.211
## acq_12_wo_or_lessTRUE  0.27419    0.38347   0.715    0.475
## train_1_3_moTRUE       0.25188    0.32255   0.781    0.435
## train_4_moTRUE         0.29540    0.28453   1.038    0.299
## train_5_6_moTRUE       0.46587    0.28948   1.609    0.108
## train_class_count.L    0.49916    0.30411   1.641    0.101
## train_class_count.Q    0.25185    0.30306   0.831    0.406
## train_class_count.C   -0.27017    0.28672  -0.942    0.346
## rewardTRUE             0.46925    0.40213   1.167    0.243
## device_groupnone      -0.53544    0.38654  -1.385    0.166
## device_grouppunish    -0.24960    0.30205  -0.826    0.409
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 418.85  on 468  degrees of freedom
## Residual deviance: 398.99  on 455  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 426.99
##
```

```
## Number of Fisher Scoring iterations: 5
##
##                              OR     2.5 %   97.5 %
## (Intercept)           1.1201624 0.2893673 4.381624
## age_yrs               1.0367331 0.9583246 1.123171
## maleTRUE              0.9647859 0.5818166 1.599322
## neuteredTRUE          1.5142172 0.7829157 2.889483
## acq_12_wo_or_lessTRUE 1.3154586 0.6076918 2.756638
## train_1_3_moTRUE      1.2864436 0.6869364 2.449997
## train_4_moTRUE        1.3436658 0.7761317 2.381817
## train_5_6_moTRUE      1.5933953 0.9124125 2.855118
## train_class_count.L   1.6473291 0.8829695 2.938830
## train_class_count.Q   1.2864081 0.7108653 2.348094
## train_class_count.C   0.7632528 0.4261591 1.320573
## rewardTRUE            1.5987902 0.7075860 3.460013
## device_groupnone      0.5854089 0.2796532 1.286679
## device_grouppunish    0.7791131 0.4320035 1.417896
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.263140  1        1.123895
## male              1.017442  1        1.008684
## neutered          1.304797  1        1.142277
## acq_12_wo_or_less 1.328148  1        1.152453
## train_1_3_mo      1.589479  1        1.260745
## train_4_mo        1.203899  1        1.097223
## train_5_6_mo      1.239831  1        1.113477
## train_class_count 1.144269  3        1.022715
## reward            1.198694  1        1.094849
## device_group      1.213353  2        1.049535
##
## --------------------------------------------------------------------------------
## hyperactive
##
## Dropped from model due to insufficient responses:
## acq_12_wo_or_less
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.0622  -0.5008  -0.3966  -0.3092   2.4931
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)         -1.20973    0.69727  -1.735   0.0827 .
## age_yrs             -0.06699    0.04976  -1.346   0.1782
## maleTRUE            -0.50765    0.31801  -1.596   0.1104
## neuteredTRUE        -0.13018    0.39115  -0.333   0.7393
## train_1_3_moTRUE     0.08179    0.34187   0.239   0.8109
## train_4_moTRUE      -0.06734    0.31891  -0.211   0.8328
## train_5_6_moTRUE     0.13740    0.32861   0.418   0.6759
## train_class_count.L -0.58734    0.36459  -1.611   0.1072
```

```
## train_class_count.Q -0.33046    0.37232  -0.888   0.3748
## train_class_count.C  0.35041    0.35882   0.977   0.3288
## rewardTRUE          -0.50517    0.45524  -1.110   0.2671
## device_groupnone    -0.17999    0.58009  -0.310   0.7563
## device_grouppunish   0.52775    0.35435   1.489   0.1364
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 315.37  on 474  degrees of freedom
## Residual deviance: 296.89  on 462  degrees of freedom
##   (19 observations deleted due to missingness)
## AIC: 322.89
##
## Number of Fisher Scoring iterations: 5
##
##                            OR     2.5 %   97.5 %
## (Intercept)         0.2982767 0.0740279 1.152658
## age_yrs             0.9352034 0.8468022 1.029891
## maleTRUE            0.6019111 0.3179781 1.113703
## neuteredTRUE        0.8779358 0.4137200 1.936285
## train_1_3_moTRUE    1.0852241 0.5511984 2.121492
## train_4_moTRUE      0.9348735 0.4954878 1.741263
## train_5_6_moTRUE    1.1472838 0.6000719 2.191749
## train_class_count.L 0.5558028 0.2789723 1.188326
## train_class_count.Q 0.7185942 0.3427885 1.499165
## train_class_count.C 1.4196546 0.7246200 3.013700
## rewardTRUE          0.6034059 0.2533199 1.533480
## device_groupnone    0.8352781 0.2314426 2.379706
## device_grouppunish  1.6951181 0.8417278 3.403362
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.224101  1        1.106391
## male              1.022174  1        1.011026
## neutered          1.235113  1        1.111356
## train_1_3_mo      1.227913  1        1.108113
## train_4_mo        1.050158  1        1.024772
## train_5_6_mo      1.134355  1        1.065061
## train_class_count 1.163513  3        1.025562
## reward            1.204964  1        1.097708
## device_group      1.233185  2        1.053797
##
## ---------------------------------------------------------------------------------
## jumping
##
## Dropped from model due to insufficient responses:
## train_class_count
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
```

```
##     Min       1Q   Median       3Q      Max
## -1.3219  -0.7520  -0.5342  -0.2836   2.4958
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)            0.10363    0.66844   0.155   0.8768
## age_yrs               -0.22794    0.04044  -5.637 1.73e-08 ***
## maleTRUE              -0.47264    0.23629  -2.000   0.0455 *
## neuteredTRUE           0.28232    0.29301   0.963   0.3353
## acq_12_wo_or_lessTRUE -0.32583    0.34170  -0.954   0.3403
## train_1_3_moTRUE      -0.37100    0.26995  -1.374   0.1693
## train_4_moTRUE        -0.11561    0.24176  -0.478   0.6325
## train_5_6_moTRUE       0.09698    0.24549   0.395   0.6928
## rewardTRUE             0.42192    0.45174   0.934   0.3503
## device_groupnone       0.09188    0.38026   0.242   0.8091
## device_grouppunish    -0.02294    0.27048  -0.085   0.9324
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 504.84  on 475  degrees of freedom
## Residual deviance: 457.84  on 465  degrees of freedom
##   (18 observations deleted due to missingness)
## AIC: 479.84
##
## Number of Fisher Scoring iterations: 5
##
##                              OR     2.5 %    97.5 %
## (Intercept)           1.1091888 0.2923386 4.0638715
## age_yrs               0.7961756 0.7336920 0.8599924
## maleTRUE              0.6233559 0.3901962 0.9871157
## neuteredTRUE          1.3261998 0.7532185 2.3826831
## acq_12_wo_or_lessTRUE 0.7219264 0.3712146 1.4235956
## train_1_3_moTRUE      0.6900458 0.4050673 1.1702388
## train_4_moTRUE        0.8908225 0.5524727 1.4281263
## train_5_6_moTRUE      1.1018436 0.6797139 1.7833688
## rewardTRUE            1.5248930 0.6558544 3.9233831
## device_groupnone      1.0962338 0.5040596 2.2622946
## device_grouppunish    0.9773259 0.5714903 1.6546417
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.172815  1        1.082966
## male              1.024943  1        1.012395
## neutered          1.192498  1        1.092016
## acq_12_wo_or_less 1.312668  1        1.145717
## train_1_3_mo      1.345753  1        1.160066
## train_4_mo        1.070974  1        1.034879
## train_5_6_mo      1.120643  1        1.058604
## reward            1.138326  1        1.066924
## device_group      1.157167  2        1.037168
##
## ---------------------------------------------------------------------------------
```

```
## mounting
##
## Dropped from model due to insufficient responses:
## train_class_count
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.0425  -0.7381  -0.4911  -0.3791   2.3701
##
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)          -1.50015    0.69988  -2.143   0.0321 *
## age_yrs               0.01347    0.03780   0.356   0.7215
## maleTRUE             -1.25120    0.26707  -4.685  2.8e-06 ***
## neuteredTRUE          0.42082    0.34097   1.234   0.2171
## acq_12_wo_or_lessTRUE -0.21384    0.36058  -0.593   0.5531
## train_1_3_moTRUE     -0.10405    0.28050  -0.371   0.7107
## train_4_moTRUE        0.37674    0.25467   1.479   0.1391
## train_5_6_moTRUE     -0.02977    0.25393  -0.117   0.9067
## rewardTRUE            0.18553    0.44334   0.418   0.6756
## device_groupnone      0.04292    0.38909   0.110   0.9122
## device_grouppunish   -0.08928    0.28768  -0.310   0.7563
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 452.75  on 475  degrees of freedom
## Residual deviance: 422.89  on 465  degrees of freedom
##   (18 observations deleted due to missingness)
## AIC: 444.89
##
## Number of Fisher Scoring iterations: 5
##
##                              OR      2.5 %    97.5 %
## (Intercept)          0.2230974 0.05460988 0.8576473
## age_yrs              1.0135652 0.94086957 1.0915416
## maleTRUE             0.2861621 0.16660413 0.4765306
## neuteredTRUE         1.5232040 0.79545939 3.0497763
## acq_12_wo_or_lessTRUE 0.8074769 0.40146337 1.6610404
## train_1_3_moTRUE     0.9011759 0.51935875 1.5647123
## train_4_moTRUE       1.4575250 0.88442521 2.4064455
## train_5_6_moTRUE     0.9706655 0.58819215 1.5955624
## rewardTRUE           1.2038619 0.52513760 3.0426266
## device_groupnone     1.0438584 0.46892287 2.1811711
## device_grouppunish   0.9145862 0.51545878 1.5977129
##
## VIF:
##                      GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.161989  1        1.077956
## male              1.014883  1        1.007414
```

```
## neutered          1.157526  1        1.075884
## acq_12_wo_or_less 1.303935  1        1.141900
## train_1_3_mo      1.298720  1        1.139614
## train_4_mo        1.081470  1        1.039938
## train_5_6_mo      1.073744  1        1.036216
## reward            1.150079  1        1.072417
## device_group      1.166223  2        1.039191
##
## --------------------------------------------------------------------------------
## rep_materials
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.5962  -1.0571  -0.7343   1.1730   1.9575
##
## Coefficients:
##                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -1.135498   0.548800  -2.069 0.038541 *
## age_yrs                0.101102   0.030377   3.328 0.000874 ***
## maleTRUE               0.302501   0.194749   1.553 0.120355
## neuteredTRUE           0.551375   0.273300   2.017 0.043646 *
## acq_12_wo_or_lessTRUE -0.323277   0.293550  -1.101 0.270780
## train_1_3_moTRUE       0.174771   0.229335   0.762 0.446013
## train_4_moTRUE        -0.014177   0.202295  -0.070 0.944130
## train_5_6_moTRUE       0.064326   0.207716   0.310 0.756804
## train_class_count.L   -0.120614   0.240111  -0.502 0.615440
## train_class_count.Q   -0.112163   0.239695  -0.468 0.639826
## train_class_count.C   -0.004488   0.227861  -0.020 0.984285
## rewardTRUE            -0.028944   0.340853  -0.085 0.932327
## device_groupnone       0.084434   0.311295   0.271 0.786211
## device_grouppunish    -0.406877   0.226507  -1.796 0.072445 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 642.22  on 468  degrees of freedom
## Residual deviance: 605.38  on 455  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 633.38
##
## Number of Fisher Scoring iterations: 4
##
##                              OR     2.5 %    97.5 %
## (Intercept)           0.3212620 0.1083695 0.9354734
## age_yrs               1.1063891 1.0430879 1.1752400
## maleTRUE              1.3532392 0.9242851 1.9845419
## neuteredTRUE          1.7356382 1.0234074 2.9969893
## acq_12_wo_or_lessTRUE 0.7237736 0.4057003 1.2857213
## train_1_3_moTRUE      1.1909734 0.7604288 1.8708121
## train_4_moTRUE        0.9859232 0.6628815 1.4662836
```

```
## train_5_6_moTRUE      1.0664396 0.7096052 1.6035367
## train_class_count.L   0.8863763 0.5540139 1.4255088
## train_class_count.Q   0.8938984 0.5578260 1.4301679
## train_class_count.C   0.9955218 0.6370801 1.5589392
## rewardTRUE            0.9714705 0.4989072 1.9085979
## device_groupnone      1.0881007 0.5901103 2.0085286
## device_grouppunish    0.6657262 0.4253871 1.0350909
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.208362  1        1.099255
## male              1.009799  1        1.004888
## neutered          1.192537  1        1.092033
## acq_12_wo_or_less 1.284520  1        1.133367
## train_1_3_mo      1.399138  1        1.182852
## train_4_mo        1.074999  1        1.036822
## train_5_6_mo      1.144115  1        1.069633
## train_class_count 1.142482  3        1.022449
## reward            1.158612  1        1.076388
## device_group      1.158440  2        1.037453
```

Considering only Punishing Devices

However, since harnesses, buckle collars, and head halters are neither punishment nor reward is it worth looking at this "non-punishment" device group? We don't expect any of these devices to "help" and that is confirmed above. By including them we are just diluting our models. Instead, we just want to know if punishing devices were used and what their impacts were.

```r
glm_attribs <- c(
  common_params,
  'reward',
  'punish_device'
)

set.seed(1)
for (outcome in outcomes) {
  cat(paste(replicate(80, '-'), collapse=''))
  cat(paste0('\n', outcome, '\n'))
  f <- as.formula(paste0(outcome, '~', '.'))

  df_tmp <- df_exp[,c(outcome, glm_attribs)]
  df_tmp <- apply_min_xtab(df_tmp, outcome)

  glm_fit <- glm(f, data=df_tmp, family='binomial')
  print(summary(glm_fit))
  print(exp(cbind(OR=coef(glm_fit), suppressMessages(confint(glm_fit)))))
  cat('\nVIF:\n')
  print(car::vif(glm_fit))
  cat('\n')
}
```

```
## --------------------------------------------------------------------------------
## aggression
##
## Call:
```

```
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.5761  -1.0832  -0.9403   1.2389   1.5236
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)            0.727251   0.525146   1.385   0.1661
## age_yrs                0.004334   0.029010   0.149   0.8812
## maleTRUE              -0.354072   0.189084  -1.873   0.0611 .
## neuteredTRUE           0.166040   0.252831   0.657   0.5114
## acq_12_wo_or_lessTRUE -0.189801   0.287434  -0.660   0.5090
## train_1_3_moTRUE      -0.112354   0.221749  -0.507   0.6124
## train_4_moTRUE         0.065421   0.196342   0.333   0.7390
## train_5_6_moTRUE      -0.151942   0.200963  -0.756   0.4496
## train_class_count.L   -0.192232   0.233361  -0.824   0.4101
## train_class_count.Q    0.028889   0.233132   0.124   0.9014
## train_class_count.C   -0.021411   0.221026  -0.097   0.9228
## rewardTRUE            -0.648751   0.329851  -1.967   0.0492 *
## punish_deviceTRUE     -0.005563   0.209547  -0.027   0.9788
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 646.58  on 468  degrees of freedom
## Residual deviance: 635.18  on 456  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 661.18
##
## Number of Fisher Scoring iterations: 4
##
##                              OR     2.5 %    97.5 %
## (Intercept)           2.0693843 0.7430963 5.8464682
## age_yrs               1.0043438 0.9486929 1.0631641
## maleTRUE              0.7018242 0.4837384 1.0157031
## neuteredTRUE          1.1806199 0.7203719 1.9443586
## acq_12_wo_or_lessTRUE 0.8271240 0.4698082 1.4535470
## train_1_3_moTRUE      0.8937282 0.5782660 1.3807758
## train_4_moTRUE        1.0676083 0.7262817 1.5692752
## train_5_6_moTRUE      0.8590384 0.5784637 1.2728328
## train_class_count.L   0.8251154 0.5210512 1.3056122
## train_class_count.Q   1.0293100 0.6516941 1.6281971
## train_class_count.C   0.9788165 0.6346875 1.5118551
## rewardTRUE            0.5226981 0.2706109 0.9918046
## punish_deviceTRUE     0.9944522 0.6583074 1.4985027
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.218851  1        1.104016
## male              1.014021  1        1.006986
## neutered          1.229033  1        1.108618
## acq_12_wo_or_less 1.288196  1        1.134987
```

```
## train_1_3_mo      1.394793  1        1.181014
## train_4_mo        1.081875  1        1.040132
## train_5_6_mo      1.141148  1        1.068245
## train_class_count 1.142882  3        1.022508
## reward            1.152806  1        1.073688
## punish_device     1.141919  1        1.068606
##
## ----------------------------------------------------------------------------
## barking
##
## Dropped from model due to insufficient responses:
## train_class_count
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.8298  -0.6338  -0.5462  -0.4553   2.2900
##
## Coefficients:
##                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -2.752133   0.722682  -3.808  0.00014 ***
## age_yrs                0.001993   0.038764   0.051  0.95899
## maleTRUE              -0.225938   0.255872  -0.883  0.37723
## neuteredTRUE           0.556533   0.365073   1.524  0.12740
## acq_12_wo_or_lessTRUE  0.468111   0.416476   1.124  0.26102
## train_1_3_moTRUE      -0.138692   0.280610  -0.494  0.62113
## train_4_moTRUE         0.348697   0.261336   1.334  0.18211
## train_5_6_moTRUE      -0.029897   0.262550  -0.114  0.90934
## rewardTRUE             0.108599   0.418014   0.260  0.79502
## punish_deviceTRUE      0.359150   0.274983   1.306  0.19153
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 414.7  on 475  degrees of freedom
## Residual deviance: 406.4  on 466  degrees of freedom
##   (18 observations deleted due to missingness)
## AIC: 426.4
##
## Number of Fisher Scoring iterations: 4
##
##                               OR      2.5 %    97.5 %
## (Intercept)           0.06379162 0.01476011 0.2533239
## age_yrs               1.00199520 0.92821895 1.0809768
## maleTRUE              0.79776758 0.48098923 1.3154609
## neuteredTRUE          1.74461287 0.87548966 3.7006084
## acq_12_wo_or_lessTRUE 1.59697471 0.73038299 3.7994261
## train_1_3_moTRUE      0.87049630 0.50126258 1.5114205
## train_4_moTRUE        1.41722029 0.84854805 2.3712710
## train_5_6_moTRUE      0.97054519 0.57793970 1.6225898
## rewardTRUE            1.11471560 0.50897547 2.6618532
```

```
## punish_deviceTRUE     1.43211103 0.82981895 2.4467726
##
## VIF:
##           age_yrs              male          neutered acq_12_wo_or_less
##          1.169010          1.010017          1.163274          1.191644
##      train_1_3_mo        train_4_mo      train_5_6_mo            reward
##          1.218140          1.059877          1.065298          1.133306
##     punish_device
##          1.137983
##
## ------------------------------------------------------------------------------
## compulsion
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.9769  -0.7151  -0.5912  -0.4662   2.1393
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)          -1.119207   0.643868  -1.738   0.0822 .
## age_yrs               0.004235   0.036154   0.117   0.9067
## maleTRUE             -0.689802   0.241567  -2.856   0.0043 **
## neuteredTRUE          0.088464   0.316960   0.279   0.7802
## acq_12_wo_or_lessTRUE  0.058376   0.350894   0.166   0.8679
## train_1_3_moTRUE     -0.145000   0.275225  -0.527   0.5983
## train_4_moTRUE       -0.074463   0.244635  -0.304   0.7608
## train_5_6_moTRUE      0.317010   0.252208   1.257   0.2088
## train_class_count.L  -0.388644   0.278543  -1.395   0.1629
## train_class_count.Q  -0.115387   0.280505  -0.411   0.6808
## train_class_count.C   0.020240   0.267369   0.076   0.9397
## rewardTRUE           -0.064117   0.398856  -0.161   0.8723
## punish_deviceTRUE    -0.013165   0.263212  -0.050   0.9601
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 469.93  on 468  degrees of freedom
## Residual deviance: 455.49  on 456  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 481.49
##
## Number of Fisher Scoring iterations: 4
##
##                             OR      2.5 %    97.5 %
## (Intercept)           0.3265386 0.09038219 1.1368341
## age_yrs               1.0042444 0.93522945 1.0779697
## maleTRUE              0.5016755 0.30994751 0.8009396
## neuteredTRUE          1.0924952 0.59348399 2.0672407
## acq_12_wo_or_lessTRUE 1.0601131 0.53941101 2.1473691
## train_1_3_moTRUE      0.8650223 0.50342313 1.4852911
```

```
## train_4_moTRUE        0.9282420 0.57230244 1.4965966
## train_5_6_moTRUE      1.3730164 0.83726666 2.2562626
## train_class_count.L   0.6779756 0.39773049 1.1944530
## train_class_count.Q   0.8910214 0.51148649 1.5429585
## train_class_count.C   1.0204466 0.60833392 1.7430889
## rewardTRUE            0.9378949 0.43954265 2.1241538
## punish_deviceTRUE     0.9869215 0.58373936 1.6428056
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.187801  1        1.089863
## male              1.014278  1        1.007114
## neutered          1.200051  1        1.095469
## acq_12_wo_or_less 1.295386  1        1.138150
## train_1_3_mo      1.365949  1        1.168738
## train_4_mo        1.074730  1        1.036692
## train_5_6_mo      1.157225  1        1.075744
## train_class_count 1.156217  3        1.024487
## reward            1.170812  1        1.082041
## punish_device     1.161031  1        1.077512
##
## ----------------------------------------------------------------------------------
## coprophagia
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.3914  -0.9869  -0.7265   1.2365   2.0338
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -0.09235    0.55196  -0.167 0.867125
## age_yrs               -0.03436    0.03013  -1.140 0.254087
## maleTRUE               0.01334    0.19740   0.068 0.946110
## neuteredTRUE           1.00411    0.28958   3.467 0.000525 ***
## acq_12_wo_or_lessTRUE -0.55427    0.29258  -1.894 0.058165 .
## train_1_3_moTRUE       0.17797    0.23737   0.750 0.453399
## train_4_moTRUE        -0.35966    0.20588  -1.747 0.080652 .
## train_5_6_moTRUE      -0.06697    0.21358  -0.314 0.753849
## train_class_count.L   -0.08383    0.24167  -0.347 0.728693
## train_class_count.Q    0.02796    0.24131   0.116 0.907761
## train_class_count.C   -0.35061    0.22935  -1.529 0.126333
## rewardTRUE            -0.32840    0.34050  -0.964 0.334818
## punish_deviceTRUE     -0.27335    0.22254  -1.228 0.219324
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 620.67  on 468  degrees of freedom
## Residual deviance: 591.16  on 456  degrees of freedom
##   (25 observations deleted due to missingness)
```

```
## AIC: 617.16
##
## Number of Fisher Scoring iterations: 4
##
##                              OR     2.5 %   97.5 %
## (Intercept)           0.9117875 0.3073735 2.687424
## age_yrs               0.9662247 0.9104421 1.024797
## maleTRUE              1.0134322 0.6878685 1.492438
## neuteredTRUE          2.7294753 1.5686907 4.899797
## acq_12_wo_or_lessTRUE 0.5744905 0.3227793 1.018956
## train_1_3_moTRUE      1.1947946 0.7505101 1.906185
## train_4_moTRUE        0.6979153 0.4650685 1.043425
## train_5_6_moTRUE      0.9352212 0.6141477 1.420448
## train_class_count.L   0.9195896 0.5738071 1.485646
## train_class_count.Q   1.0283536 0.6399514 1.651235
## train_class_count.C   0.7042599 0.4486267 1.104289
## rewardTRUE            0.7200747 0.3702384 1.415035
## punish_deviceTRUE     0.7608265 0.4896499 1.173289
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.201286  1        1.096032
## male              1.006290  1        1.003140
## neutered          1.190526  1        1.091112
## acq_12_wo_or_less 1.299501  1        1.139956
## train_1_3_mo      1.454613  1        1.206073
## train_4_mo        1.064390  1        1.031693
## train_5_6_mo      1.172591  1        1.082862
## train_class_count 1.147460  3        1.023190
## reward            1.170904  1        1.082083
## punish_device     1.149034  1        1.071930
##
## ------------------------------------------------------------------------------
## destructive
##
## Dropped from model due to insufficient responses:
## neutered
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.7542  -0.4161  -0.3476  -0.2974   2.6401
##
## Coefficients:
##                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -1.600131   0.930906  -1.719   0.0856 .
## age_yrs               -0.004368   0.051831  -0.084   0.9328
## maleTRUE               0.058172   0.365904   0.159   0.8737
## acq_12_wo_or_lessTRUE -0.886088   0.499229  -1.775   0.0759 .
## train_1_3_moTRUE       0.041718   0.484055   0.086   0.9313
## train_4_moTRUE        -0.155416   0.408803  -0.380   0.7038
## train_5_6_moTRUE      -0.493956   0.415115  -1.190   0.2341
```

```
## train_class_count.L    0.037779   0.465922   0.081   0.9354
## train_class_count.Q   -0.319714   0.439008  -0.728   0.4665
## train_class_count.C   -0.294890   0.390049  -0.756   0.4496
## rewardTRUE            -0.142102   0.604629  -0.235   0.8142
## punish_deviceTRUE      0.383553   0.392690   0.977   0.3287
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 238.79  on 468  degrees of freedom
## Residual deviance: 231.48  on 457  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 255.48
##
## Number of Fisher Scoring iterations: 5
##
##                              OR      2.5 %   97.5 %
## (Intercept)           0.2018700 0.03041508 1.207229
## age_yrs               0.9956413 0.89790802 1.101352
## maleTRUE              1.0598975 0.51525570 2.188264
## acq_12_wo_or_lessTRUE 0.4122655 0.15485347 1.119732
## train_1_3_moTRUE      1.0426001 0.39410438 2.705882
## train_4_moTRUE        0.8560586 0.36810468 1.871513
## train_5_6_moTRUE      0.6102073 0.25850035 1.346864
## train_class_count.L   1.0385016 0.44768547 2.942270
## train_class_count.Q   0.7263569 0.29028755 1.679663
## train_class_count.C   0.7446135 0.34524913 1.624035
## rewardTRUE            0.8675332 0.28682186 3.246484
## punish_deviceTRUE     1.4674896 0.66627983 3.144821
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.077094  1        1.037831
## male              1.008294  1        1.004138
## acq_12_wo_or_less 1.442358  1        1.200982
## train_1_3_mo      1.754387  1        1.324533
## train_4_mo        1.204487  1        1.097491
## train_5_6_mo      1.244529  1        1.115585
## train_class_count 1.158552  3        1.024832
## reward            1.171517  1        1.082366
## punish_device     1.130588  1        1.063291
##
## --------------------------------------------------------------------------------
## escape
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.9262  -0.6631  -0.5834  -0.4422   2.2790
##
## Coefficients:
```

```
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -1.58669    0.68612  -2.313   0.0207 *
## age_yrs               -0.01746    0.03779  -0.462   0.6441
## maleTRUE              -0.31265    0.24856  -1.258   0.2084
## neuteredTRUE           0.79694    0.37389   2.131   0.0331 *
## acq_12_wo_or_lessTRUE -0.13873    0.37864  -0.366   0.7141
## train_1_3_moTRUE       0.36904    0.29769   1.240   0.2151
## train_4_moTRUE        -0.13178    0.25845  -0.510   0.6101
## train_5_6_moTRUE       0.02755    0.26841   0.103   0.9183
## train_class_count.L   -0.45402    0.28297  -1.605   0.1086
## train_class_count.Q    0.14823    0.29756   0.498   0.6184
## train_class_count.C    0.15952    0.29690   0.537   0.5911
## rewardTRUE            -0.34122    0.40447  -0.844   0.3989
## punish_deviceTRUE     -0.05973    0.27918  -0.214   0.8306
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 434.74  on 468  degrees of freedom
## Residual deviance: 422.44  on 456  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 448.44
##
## Number of Fisher Scoring iterations: 4
##
##                              OR      2.5 %    97.5 %
## (Intercept)           0.2046015 0.05172472 0.7687831
## age_yrs               0.9826963 0.91202069 1.0580108
## maleTRUE              0.7315075 0.44724530 1.1880894
## neuteredTRUE          2.2187355 1.09957602 4.8177033
## acq_12_wo_or_lessTRUE 0.8704646 0.41959820 1.8677698
## train_1_3_moTRUE      1.4463489 0.80975792 2.6124088
## train_4_moTRUE        0.8765346 0.52523623 1.4508830
## train_5_6_moTRUE      1.0279281 0.60605355 1.7417603
## train_class_count.L   0.6350686 0.36914857 1.1278666
## train_class_count.Q   1.1597807 0.64693812 2.0896353
## train_class_count.C   1.1729421 0.66467355 2.1471295
## rewardTRUE            0.7109003 0.32870436 1.6246774
## punish_deviceTRUE     0.9420220 0.53850093 1.6148089
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.169581  1        1.081472
## male              1.008580  1        1.004281
## neutered          1.158780  1        1.076466
## acq_12_wo_or_less 1.334417  1        1.155170
## train_1_3_mo      1.456258  1        1.206755
## train_4_mo        1.065967  1        1.032457
## train_5_6_mo      1.181585  1        1.087007
## train_class_count 1.144462  3        1.022744
## reward            1.191794  1        1.091693
## punish_device     1.172949  1        1.083028
##
```

```
## ------------------------------------------------------------------------------------
## fear_anxiety
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.8808  -1.1701   0.7264   0.9371   1.7285
##
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)           0.01948    0.55948   0.035    0.972
## age_yrs              -0.01038    0.03105  -0.334    0.738
## maleTRUE             -0.14664    0.20078  -0.730    0.465
## neuteredTRUE          1.14656    0.26191   4.378  1.2e-05 ***
## acq_12_wo_or_lessTRUE -0.40227    0.32673  -1.231    0.218
## train_1_3_moTRUE     -0.16664    0.23181  -0.719    0.472
## train_4_moTRUE        0.23252    0.20910   1.112    0.266
## train_5_6_moTRUE      0.25479    0.21374   1.192    0.233
## train_class_count.L  -0.33565    0.24950  -1.345    0.179
## train_class_count.Q  -0.30534    0.25123  -1.215    0.224
## train_class_count.C  -0.07693    0.24314  -0.316    0.752
## rewardTRUE            0.09897    0.34237   0.289    0.773
## punish_deviceTRUE    -0.15414    0.22109  -0.697    0.486
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 627.37  on 468  degrees of freedom
## Residual deviance: 580.87  on 456  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 606.87
##
## Number of Fisher Scoring iterations: 4
##
##                              OR     2.5 %   97.5 %
## (Intercept)           1.0196664 0.3415407 3.076031
## age_yrs               0.9896748 0.9310391 1.051795
## maleTRUE              0.8636039 0.5818569 1.279430
## neuteredTRUE          3.1473411 1.8931232 5.295420
## acq_12_wo_or_lessTRUE 0.6688015 0.3462988 1.253611
## train_1_3_moTRUE      0.8465054 0.5370726 1.334309
## train_4_moTRUE        1.2617706 0.8384564 1.905144
## train_5_6_moTRUE      1.2901915 0.8488928 1.964421
## train_class_count.L   0.7148725 0.4331581 1.157164
## train_class_count.Q   0.7368752 0.4505155 1.209233
## train_class_count.C   0.9259591 0.5724210 1.488456
## rewardTRUE            1.1040287 0.5593812 2.152413
## punish_deviceTRUE     0.8571554 0.5561759 1.324887
##
## VIF:
##                        GVIF Df GVIF^(1/(2*Df))
```

```
## age_yrs           1.238853  1        1.113038
## male              1.014714  1        1.007330
## neutered          1.234005  1        1.110858
## acq_12_wo_or_less 1.229263  1        1.108721
## train_1_3_mo      1.350520  1        1.162119
## train_4_mo        1.085881  1        1.042056
## train_5_6_mo      1.139881  1        1.067652
## train_class_count 1.124413  3        1.019736
## reward            1.163664  1        1.078733
## punish_device     1.141375  1        1.068352
##
## ----------------------------------------------------------------------------
## house_soiling
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.4125   0.4018   0.5185   0.6416   1.0445
##
## Coefficients:
##                         Estimate Std. Error z value Pr(>|z|)
## (Intercept)            0.0001824  0.6825834   0.000    1.000
## age_yrs                0.0310768  0.0399153   0.779    0.436
## maleTRUE              -0.0454739  0.2564390  -0.177    0.859
## neuteredTRUE           0.4191867  0.3314063   1.265    0.206
## acq_12_wo_or_lessTRUE  0.2747757  0.3817531   0.720    0.472
## train_1_3_moTRUE       0.2649886  0.3217685   0.824    0.410
## train_4_moTRUE         0.2817329  0.2835040   0.994    0.320
## train_5_6_moTRUE       0.4656177  0.2884375   1.614    0.106
## train_class_count.L    0.4900975  0.3038650   1.613    0.107
## train_class_count.Q    0.2547301  0.3025635   0.842    0.400
## train_class_count.C   -0.2762900  0.2863624  -0.965    0.335
## rewardTRUE             0.5045877  0.4000695   1.261    0.207
## punish_deviceTRUE     -0.1272179  0.2855778  -0.445    0.656
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 418.85  on 468  degrees of freedom
## Residual deviance: 400.81  on 456  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 426.81
##
## Number of Fisher Scoring iterations: 5
##
##                              OR     2.5 %   97.5 %
## (Intercept)           1.0001824 0.2623601 3.846535
## age_yrs               1.0315647 0.9543270 1.116425
## maleTRUE              0.9555445 0.5770045 1.581328
## neuteredTRUE          1.5207242 0.7867459 2.899398
## acq_12_wo_or_lessTRUE 1.3162354 0.6101954 2.749403
## train_1_3_moTRUE      1.3034161 0.6971644 2.478877
## train_4_moTRUE        1.3254246 0.7670297 2.344444
```

```
## train_5_6_moTRUE      1.5929979 0.9138730 2.847817
## train_class_count.L   1.6324753 0.8752349 2.910241
## train_class_count.Q   1.2901134 0.7136079 2.352620
## train_class_count.C   0.7585929 0.4238199 1.311491
## rewardTRUE            1.6563025 0.7354879 3.568092
## punish_deviceTRUE     0.8805418 0.5062559 1.556975
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.255455  1        1.120471
## male              1.015748  1        1.007843
## neutered          1.304032  1        1.141942
## acq_12_wo_or_less 1.327105  1        1.152000
## train_1_3_mo      1.588209  1        1.260242
## train_4_mo        1.200093  1        1.095487
## train_5_6_mo      1.237047  1        1.112226
## train_class_count 1.142400  3        1.022437
## reward            1.198773  1        1.094885
## punish_device     1.188687  1        1.090269
##
## --------------------------------------------------------------------------------
## hyperactive
##
## Dropped from model due to insufficient responses:
## acq_12_wo_or_less
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.0620  -0.4995  -0.3987  -0.3081   2.5136
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)         -1.24402    0.68872  -1.806   0.0709 .
## age_yrs             -0.06836    0.04963  -1.377   0.1684
## maleTRUE            -0.51130    0.31780  -1.609   0.1077
## neuteredTRUE        -0.13076    0.39106  -0.334   0.7381
## train_1_3_moTRUE     0.08836    0.34147   0.259   0.7958
## train_4_moTRUE      -0.07155    0.31873  -0.224   0.8224
## train_5_6_moTRUE     0.14014    0.32847   0.427   0.6696
## train_class_count.L -0.58479    0.36445  -1.605   0.1086
## train_class_count.Q -0.33391    0.37224  -0.897   0.3697
## train_class_count.C  0.34926    0.35871   0.974   0.3302
## rewardTRUE          -0.49466    0.45331  -1.091   0.2752
## punish_deviceTRUE    0.56177    0.33847   1.660   0.0970 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 315.37  on 474  degrees of freedom
## Residual deviance: 296.99  on 463  degrees of freedom
```

```
##   (19 observations deleted due to missingness)
## AIC: 320.99
##
## Number of Fisher Scoring iterations: 5
##
##                             OR      2.5 %   97.5 %
## (Intercept)          0.2882223 0.07268716 1.094661
## age_yrs              0.9339249 0.84589738 1.028280
## maleTRUE             0.5997166 0.31693190 1.109143
## neuteredTRUE         0.8774326 0.41355981 1.934841
## train_1_3_moTRUE     1.0923807 0.55524250 2.133583
## train_4_moTRUE       0.9309522 0.49359287 1.733418
## train_5_6_moTRUE     1.1504355 0.60186221 2.197154
## train_class_count.L 0.5572230 0.27976179 1.191059
## train_class_count.Q 0.7161203 0.34166228 1.493737
## train_class_count.C 1.4180181 0.72394804 3.009632
## rewardTRUE           0.6097767 0.25718995 1.545077
## punish_deviceTRUE    1.7537654 0.89580063 3.399964
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.213221  1        1.101463
## male              1.021023  1        1.010457
## neutered          1.235223  1        1.111406
## train_1_3_mo      1.225307  1        1.106936
## train_4_mo        1.049272  1        1.024340
## train_5_6_mo      1.133622  1        1.064717
## train_class_count 1.162813  3        1.025459
## reward            1.194674  1        1.093012
## punish_device     1.199475  1        1.095205
##
## --------------------------------------------------------------------------------
## jumping
##
## Dropped from model due to insufficient responses:
## train_class_count
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.3273  -0.7504  -0.5261  -0.2882   2.4908
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)            0.12557    0.66215   0.190   0.8496
## age_yrs               -0.22691    0.04017  -5.649 1.62e-08 ***
## maleTRUE              -0.47053    0.23607  -1.993   0.0462 *
## neuteredTRUE           0.28107    0.29301   0.959   0.3374
## acq_12_wo_or_lessTRUE -0.32536    0.34162  -0.952   0.3409
## train_1_3_moTRUE      -0.37406    0.26959  -1.388   0.1653
## train_4_moTRUE        -0.11368    0.24158  -0.471   0.6379
## train_5_6_moTRUE       0.09542    0.24535   0.389   0.6973
```

```
## rewardTRUE             0.41120    0.44935   0.915   0.3601
## punish_deviceTRUE     -0.04038    0.26040  -0.155   0.8768
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 504.84  on 475  degrees of freedom
## Residual deviance: 457.90  on 466  degrees of freedom
##   (18 observations deleted due to missingness)
## AIC: 477.9
##
## Number of Fisher Scoring iterations: 5
##
##                              OR     2.5 %    97.5 %
## (Intercept)           1.1337890 0.3024025 4.1028023
## age_yrs               0.7969964 0.7348712 0.8604662
## maleTRUE              0.6246684 0.3911990 0.9888193
## neuteredTRUE          1.3245483 0.7522896 2.3797222
## acq_12_wo_or_lessTRUE 0.7222648 0.3714480 1.4240354
## train_1_3_moTRUE      0.6879341 0.4040846 1.1657600
## train_4_moTRUE        0.8925393 0.5537472 1.4304267
## train_5_6_moTRUE      1.1001202 0.6788192 1.7800446
## rewardTRUE            1.5086259 0.6519779 3.8654258
## punish_deviceTRUE     0.9604266 0.5721154 1.5921293
##
## VIF:
##           age_yrs              male          neutered acq_12_wo_or_less
##          1.159265          1.023201          1.192116          1.311948
##      train_1_3_mo        train_4_mo      train_5_6_mo            reward
##          1.342212          1.069428          1.119388          1.128061
##     punish_device
##          1.123371
##
## ----------------------------------------------------------------------------
## mounting
##
## Dropped from model due to insufficient responses:
## train_class_count
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.0290  -0.7383  -0.4861  -0.3793   2.3835
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -1.49155    0.69549  -2.145    0.032 *
## age_yrs                0.01384    0.03765   0.368    0.713
## maleTRUE              -1.25074    0.26703  -4.684 2.81e-06 ***
## neuteredTRUE           0.41952    0.34074   1.231    0.218
## acq_12_wo_or_lessTRUE -0.21205    0.36026  -0.589    0.556
```

```
## train_1_3_moTRUE      -0.10549    0.28017  -0.377    0.707
## train_4_moTRUE         0.37759    0.25456   1.483    0.138
## train_5_6_moTRUE      -0.03060    0.25380  -0.121    0.904
## rewardTRUE             0.18264    0.44262   0.413    0.680
## punish_deviceTRUE     -0.09809    0.27625  -0.355    0.723
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 452.75  on 475  degrees of freedom
## Residual deviance: 422.90  on 466  degrees of freedom
##   (18 observations deleted due to missingness)
## AIC: 442.9
##
## Number of Fisher Scoring iterations: 5
##
##                              OR      2.5 %    97.5 %
## (Intercept)           0.2250226 0.05553734 0.8574334
## age_yrs               1.0139349 0.94152388 1.0916377
## maleTRUE              0.2862916 0.16669273 0.4767099
## neuteredTRUE          1.5212372 0.79478222 3.0444169
## acq_12_wo_or_lessTRUE 0.8089249 0.40242807 1.6629105
## train_1_3_moTRUE      0.8998860 0.51892557 1.5613465
## train_4_moTRUE        1.4587684 0.88538447 2.4079661
## train_5_6_moTRUE      0.9698641 0.58784235 1.5937800
## rewardTRUE            1.2003878 0.52450245 3.0305084
## punish_deviceTRUE     0.9065680 0.52175902 1.5460805
##
## VIF:
##           age_yrs              male          neutered acq_12_wo_or_less
##          1.153560          1.014607          1.156144          1.300981
##       train_1_3_mo        train_4_mo      train_5_6_mo            reward
##          1.295666          1.080518          1.072637          1.146577
##     punish_device
##          1.143332
##
## ------------------------------------------------------------------------------
## rep_materials
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.6045  -1.0575  -0.7302   1.1667   1.9598
##
## Coefficients:
##                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -1.117953   0.544852  -2.052 0.040184 *
## age_yrs                0.101758   0.030294   3.359 0.000782 ***
## maleTRUE               0.302858   0.194731   1.555 0.119884
## neuteredTRUE           0.549609   0.273201   2.012 0.044248 *
## acq_12_wo_or_lessTRUE -0.322920   0.293484  -1.100 0.271203
```

```
## train_1_3_moTRUE       0.172612   0.229242   0.753 0.451469
## train_4_moTRUE        -0.012536   0.202177  -0.062 0.950559
## train_5_6_moTRUE       0.063212   0.207689   0.304 0.760854
## train_class_count.L   -0.121033   0.240183  -0.504 0.614316
## train_class_count.Q   -0.112585   0.239687  -0.470 0.638556
## train_class_count.C   -0.004396   0.227725  -0.019 0.984600
## rewardTRUE            -0.033344   0.340563  -0.098 0.922005
## punish_deviceTRUE     -0.423566   0.218047  -1.943 0.052072 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 642.22  on 468  degrees of freedom
## Residual deviance: 605.45  on 456  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 631.45
##
## Number of Fisher Scoring iterations: 4
##
##                              OR     2.5 %   97.5 %
## (Intercept)           0.3269484 0.1111482 0.944812
## age_yrs               1.1071154 1.0439367 1.175811
## maleTRUE              1.3537218 0.9246498 1.985185
## neuteredTRUE          1.7325756 1.0217977 2.991134
## acq_12_wo_or_lessTRUE 0.7240321 0.4058929 1.285999
## train_1_3_moTRUE      1.1884053 0.7589476 1.866501
## train_4_moTRUE        0.9875423 0.6641361 1.468376
## train_5_6_moTRUE      1.0652526 0.7088559 1.601672
## train_class_count.L   0.8860043 0.5537150 1.425135
## train_class_count.Q   0.8935211 0.5575945 1.429531
## train_class_count.C   0.9956140 0.6373113 1.558659
## rewardTRUE            0.9672060 0.4970570 1.899479
## punish_deviceTRUE     0.6547079 0.4253108 1.001151
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.201359  1        1.096065
## male              1.009790  1        1.004883
## neutered          1.191910  1        1.091746
## acq_12_wo_or_less 1.284595  1        1.133400
## train_1_3_mo      1.398254  1        1.182478
## train_4_mo        1.073877  1        1.036280
## train_5_6_mo      1.144037  1        1.069597
## train_class_count 1.142658  3        1.022475
## reward            1.156300  1        1.075314
## punish_device     1.142956  1        1.069091
```

Combining Training Methods and Devices

For sake of completeness, let's also consider a simplified model where the use of any punishing devices indicates the use of punishment training methods. The `adj_train_technique` columns exists to represent this.

```r
df_exp <- df_exp %>%
  mutate(adj_reward = ifelse(reward == TRUE, TRUE, FALSE))
summary(df_exp$adj_reward)
```

```
##    Mode   FALSE    TRUE
## logical      54     440
```

```r
glm_attribs <- c(
  common_params,
  'adj_reward'
)
```

Now let's build the models.

```r
set.seed(1)
for (outcome in outcomes) {
  cat(paste(replicate(80, '-'), collapse=''))
  cat(paste0('\n', outcome, '\n'))
  f <- as.formula(paste0(outcome, '~', '.'))

  df_tmp <- df_exp[,c(outcome, glm_attribs)]
  df_tmp <- apply_min_xtab(df_tmp, outcome)

  glm_fit <- glm(f, data=df_tmp, family='binomial')
  print(summary(glm_fit))
  print(exp(cbind(OR=coef(glm_fit), suppressMessages(confint(glm_fit)))))
  cat('\nVIF:\n')
  print(car::vif(glm_fit))
  cat('\n')
}
```

```
## --------------------------------------------------------------------------------
## aggression
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.5769  -1.0845  -0.9395   1.2397   1.5221
##
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)           0.72341    0.50480   1.433   0.1518
## age_yrs               0.00430    0.02898   0.148   0.8821
## maleTRUE             -0.35403    0.18908  -1.872   0.0611 .
## neuteredTRUE          0.16655    0.25211   0.661   0.5089
## acq_12_wo_or_lessTRUE -0.19040    0.28654  -0.664   0.5064
## train_1_3_moTRUE     -0.11258    0.22159  -0.508   0.6114
## train_4_moTRUE        0.06552    0.19631   0.334   0.7386
## train_5_6_moTRUE     -0.15233    0.20042  -0.760   0.4472
## train_class_count.L  -0.19240    0.23328  -0.825   0.4095
## train_class_count.Q   0.02892    0.23314   0.124   0.9013
## train_class_count.C  -0.02112    0.22076  -0.096   0.9238
## adj_rewardTRUE       -0.64605    0.31379  -2.059   0.0395 *
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 646.58  on 468  degrees of freedom
## Residual deviance: 635.18  on 457  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 659.18
##
## Number of Fisher Scoring iterations: 4
##
##                              OR     2.5 %    97.5 %
## (Intercept)           2.0614478 0.7706030 5.5981315
## age_yrs               1.0043090 0.9487156 1.0630655
## maleTRUE              0.7018524 0.4837635 1.0157319
## neuteredTRUE          1.1812177 0.7217731 1.9426344
## acq_12_wo_or_lessTRUE 0.8266262 0.4703465 1.4501009
## train_1_3_moTRUE      0.8935297 0.5783205 1.3800650
## train_4_moTRUE        1.0677143 0.7264046 1.5693212
## train_5_6_moTRUE      0.8587014 0.5788586 1.2709779
## train_class_count.L   0.8249735 0.5210639 1.3052333
## train_class_count.Q   1.0293386 0.6517030 1.6282520
## train_class_count.C   0.9790978 0.6351806 1.5114766
## adj_rewardTRUE        0.5241105 0.2798096 0.9633968
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.216367  1        1.102890
## male              1.013959  1        1.006955
## neutered          1.222049  1        1.105463
## acq_12_wo_or_less 1.280172  1        1.131447
## train_1_3_mo      1.392838  1        1.180186
## train_4_mo        1.081482  1        1.039943
## train_5_6_mo      1.134990  1        1.065359
## train_class_count 1.139035  3        1.021934
## adj_reward        1.043273  1        1.021407
##
## ------------------------------------------------------------------------------
## barking
##
## Dropped from model due to insufficient responses:
## train_class_count
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.7662  -0.6280  -0.5517  -0.4576   2.2483
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -2.50865    0.69663  -3.601 0.000317 ***
```

```
## age_yrs                0.00612    0.03839   0.159 0.873359
## maleTRUE              -0.22978    0.25539  -0.900 0.368280
## neuteredTRUE           0.51915    0.36323   1.429 0.152927
## acq_12_wo_or_lessTRUE  0.50391    0.41534   1.213 0.225030
## train_1_3_moTRUE      -0.12074    0.27993  -0.431 0.666232
## train_4_moTRUE         0.34290    0.26108   1.313 0.189050
## train_5_6_moTRUE      -0.00101    0.26099  -0.004 0.996912
## adj_rewardTRUE        -0.05982    0.39791  -0.150 0.880492
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 414.70  on 475  degrees of freedom
## Residual deviance: 408.08  on 467  degrees of freedom
##   (18 observations deleted due to missingness)
## AIC: 426.08
##
## Number of Fisher Scoring iterations: 4
##
##                              OR      2.5 %    97.5 %
## (Intercept)           0.0813780 0.01979162 0.3067389
## age_yrs               1.0061384 0.93280191 1.0847295
## maleTRUE              0.7947119 0.47958915 1.3091539
## neuteredTRUE          1.6806018 0.84637206 3.5522456
## acq_12_wo_or_lessTRUE 1.6551824 0.75896268 3.9305355
## train_1_3_moTRUE      0.8862648 0.51105938 1.5368912
## train_4_moTRUE        1.4090290 0.84402374 2.3562817
## train_5_6_moTRUE      0.9989904 0.59683856 1.6654680
## adj_rewardTRUE        0.9419304 0.44917522 2.1731485
##
## VIF:
##          age_yrs              male          neutered acq_12_wo_or_less
##         1.158362          1.010039          1.154231          1.189197
##     train_1_3_mo        train_4_mo      train_5_6_mo        adj_reward
##         1.216803          1.061825          1.056785          1.030758
##
## ---------------------------------------------------------------------------------
## compulsion
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.9801  -0.7150  -0.5902  -0.4665   2.1352
##
## Coefficients:
##                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -1.128252   0.617947  -1.826   0.0679 .
## age_yrs                0.004156   0.036123   0.115   0.9084
## maleTRUE              -0.689527   0.241499  -2.855   0.0043 **
## neuteredTRUE           0.089305   0.316502   0.282   0.7778
## acq_12_wo_or_lessTRUE  0.056930   0.349696   0.163   0.8707
```

```
## train_1_3_moTRUE      -0.145628   0.274939  -0.530   0.5963
## train_4_moTRUE        -0.074297   0.244609  -0.304   0.7613
## train_5_6_moTRUE       0.315910   0.251224   1.257   0.2086
## train_class_count.L   -0.388803   0.278536  -1.396   0.1627
## train_class_count.Q   -0.115133   0.280468  -0.411   0.6814
## train_class_count.C    0.021073   0.266861   0.079   0.9371
## adj_rewardTRUE        -0.057461   0.375987  -0.153   0.8785
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 469.93  on 468  degrees of freedom
## Residual deviance: 455.49  on 457  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 479.49
##
## Number of Fisher Scoring iterations: 4
##
##                              OR      2.5 %    97.5 %
## (Intercept)           0.3235984 0.09402383 1.0686408
## age_yrs               1.0041644 0.93522573 1.0778327
## maleTRUE              0.5018136 0.31007738 0.8010588
## neuteredTRUE          1.0934140 0.59456719 2.0673165
## acq_12_wo_or_lessTRUE 1.0585821 0.53991826 2.1393925
## train_1_3_moTRUE      0.8644794 0.50338606 1.4835442
## train_4_moTRUE        0.9283959 0.57243039 1.4967740
## train_5_6_moTRUE      1.3715065 0.83783605 2.2490613
## train_class_count.L   0.6778677 0.39767815 1.1942600
## train_class_count.Q   0.8912475 0.51165225 1.5432215
## train_class_count.C   1.0212969 0.60943912 1.7427860
## adj_rewardTRUE        0.9441584 0.46478223 2.0545732
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.185482  1        1.088798
## male              1.013709  1        1.006831
## neutered          1.196740  1        1.093956
## acq_12_wo_or_less 1.286471  1        1.134227
## train_1_3_mo      1.363112  1        1.167524
## train_4_mo        1.074493  1        1.036578
## train_5_6_mo      1.148208  1        1.071545
## train_class_count 1.151423  3        1.023778
## adj_reward        1.040309  1        1.019955
##
## ----------------------------------------------------------------------------
## coprophagia
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.3508  -0.9977  -0.7464   1.2414   1.9609
```

```
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -0.28266    0.52814  -0.535 0.592507
## age_yrs               -0.03557    0.03007  -1.183 0.236857
## maleTRUE               0.01656    0.19708   0.084 0.933051
## neuteredTRUE           1.02535    0.28885   3.550 0.000386 ***
## acq_12_wo_or_lessTRUE -0.58372    0.29140  -2.003 0.045165 *
## train_1_3_moTRUE       0.16858    0.23691   0.712 0.476723
## train_4_moTRUE        -0.35363    0.20549  -1.721 0.085270 .
## train_5_6_moTRUE      -0.08743    0.21253  -0.411 0.680791
## train_class_count.L   -0.08808    0.24160  -0.365 0.715441
## train_class_count.Q    0.02891    0.24118   0.120 0.904581
## train_class_count.C   -0.33195    0.22861  -1.452 0.146490
## adj_rewardTRUE        -0.19589    0.32148  -0.609 0.542304
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 620.67  on 468  degrees of freedom
## Residual deviance: 592.68  on 457  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 616.68
##
## Number of Fisher Scoring iterations: 4
##
##                              OR     2.5 %    97.5 %
## (Intercept)           0.7537733 0.2655506 2.1144954
## age_yrs               0.9650591 0.9094302 1.0234178
## maleTRUE              1.0166939 0.6905382 1.4963433
## neuteredTRUE          2.7880600 1.6049569 4.9986691
## acq_12_wo_or_lessTRUE 0.5578220 0.3140809 0.9869488
## train_1_3_moTRUE      1.1836199 0.7441603 1.8865727
## train_4_moTRUE        0.7021370 0.4682693 1.0489858
## train_5_6_moTRUE      0.9162813 0.6028325 1.3885117
## train_class_count.L   0.9156912 0.5714178 1.4790253
## train_class_count.Q   1.0293333 0.6408093 1.6525862
## train_class_count.C   0.7175222 0.4577978 1.1236046
## adj_rewardTRUE        0.8221041 0.4400143 1.5611287
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.199907  1        1.095402
## male              1.006314  1        1.003152
## neutered          1.187805  1        1.089865
## acq_12_wo_or_less 1.292078  1        1.136696
## train_1_3_mo      1.453689  1        1.205690
## train_4_mo        1.063523  1        1.031273
## train_5_6_mo      1.164737  1        1.079230
## train_class_count 1.141162  3        1.022252
## adj_reward        1.049821  1        1.024608
##
## ------------------------------------------------------------------------------
```

```
## destructive
##
## Dropped from model due to insufficient responses:
## neutered
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.6623  -0.4011  -0.3616  -0.2878   2.5855
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)          -1.336513   0.890093  -1.502   0.1332
## age_yrs              -0.004009   0.051493  -0.078   0.9379
## maleTRUE              0.047555   0.365223   0.130   0.8964
## acq_12_wo_or_lessTRUE -0.842154   0.497278  -1.694   0.0904 .
## train_1_3_moTRUE      0.051439   0.484595   0.106   0.9155
## train_4_moTRUE       -0.163048   0.408789  -0.399   0.6900
## train_5_6_moTRUE     -0.472463   0.415624  -1.137   0.2556
## train_class_count.L   0.049377   0.464848   0.106   0.9154
## train_class_count.Q  -0.313160   0.438365  -0.714   0.4750
## train_class_count.C  -0.325222   0.388291  -0.838   0.4023
## adj_rewardTRUE       -0.319328   0.578503  -0.552   0.5810
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 238.79  on 468  degrees of freedom
## Residual deviance: 232.42  on 458  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 254.42
##
## Number of Fisher Scoring iterations: 5
##
##                              OR      2.5 %   97.5 %
## (Intercept)           0.2627603 0.04267925 1.447154
## age_yrs               0.9959994 0.89884317 1.101028
## maleTRUE              1.0487039 0.51041653 2.161950
## acq_12_wo_or_lessTRUE 0.4307815 0.16241683 1.165782
## train_1_3_moTRUE      1.0527848 0.39729727 2.734498
## train_4_moTRUE        0.8495502 0.36517547 1.856618
## train_5_6_moTRUE      0.6234645 0.26361828 1.376757
## train_class_count.L   1.0506160 0.45407107 2.971863
## train_class_count.Q   0.7311327 0.29253439 1.688522
## train_class_count.C   0.7223668 0.33591243 1.569404
## adj_rewardTRUE        0.7266374 0.25562301 2.614440
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.078924  1        1.038713
## male              1.007171  1        1.003579
```

```
## acq_12_wo_or_less 1.437981  1        1.199158
## train_1_3_mo      1.762636  1        1.327643
## train_4_mo        1.207800  1        1.098999
## train_5_6_mo      1.250477  1        1.118247
## train_class_count 1.145304  3        1.022869
## adj_reward        1.072709  1        1.035717
##
## ----------------------------------------------------------------------------
## escape
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.9320  -0.6633  -0.5821  -0.4419   2.2772
##
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)          -1.62776    0.65864  -2.471   0.0135 *
## age_yrs              -0.01783    0.03776  -0.472   0.6368
## maleTRUE             -0.31111    0.24842  -1.252   0.2104
## neuteredTRUE          0.80211    0.37315   2.150   0.0316 *
## acq_12_wo_or_lessTRUE -0.14593    0.37706  -0.387   0.6987
## train_1_3_moTRUE      0.36707    0.29754   1.234   0.2173
## train_4_moTRUE       -0.13110    0.25840  -0.507   0.6119
## train_5_6_moTRUE      0.02242    0.26725   0.084   0.9331
## train_class_count.L  -0.45493    0.28297  -1.608   0.1079
## train_class_count.Q   0.14882    0.29756   0.500   0.6170
## train_class_count.C   0.16352    0.29630   0.552   0.5810
## adj_rewardTRUE       -0.31187    0.38035  -0.820   0.4122
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 434.74  on 468  degrees of freedom
## Residual deviance: 422.49  on 457  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 446.49
##
## Number of Fisher Scoring iterations: 4
##
##                              OR      2.5 %   97.5 %
## (Intercept)           0.1963690 0.05221906 0.696829
## age_yrs               0.9823240 0.91172475 1.057577
## maleTRUE              0.7326316 0.44806986 1.189625
## neuteredTRUE          2.2302345 1.10702004 4.836291
## acq_12_wo_or_lessTRUE 0.8642163 0.41785344 1.848714
## train_1_3_moTRUE      1.4435023 0.80841602 2.606490
## train_4_moTRUE        0.8771289 0.52564406 1.451738
## train_5_6_moTRUE      1.0226753 0.60422347 1.728553
## train_class_count.L   0.6344901 0.36881678 1.126851
## train_class_count.Q   1.1604672 0.64733029 2.090906
```

```
## train_class_count.C   1.1776465 0.66818262 2.153457
## adj_rewardTRUE        0.7320770 0.35674518 1.604438
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.166875  1        1.080220
## male              1.007592  1        1.003789
## neutered          1.154333  1        1.074399
## acq_12_wo_or_less 1.323295  1        1.150346
## train_1_3_mo      1.454823  1        1.206160
## train_4_mo        1.065630  1        1.032294
## train_5_6_mo      1.171427  1        1.082325
## train_class_count 1.139802  3        1.022049
## adj_reward        1.053533  1        1.026417
##
## ---------------------------------------------------------------------------------
## fear_anxiety
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.8665  -1.1772   0.7368   0.9401   1.6998
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -0.08524    0.53865  -0.158    0.874
## age_yrs               -0.01122    0.03100  -0.362    0.717
## maleTRUE              -0.14700    0.20069  -0.732    0.464
## neuteredTRUE           1.15835    0.26103   4.438  9.1e-06 ***
## acq_12_wo_or_lessTRUE -0.41839    0.32598  -1.283    0.199
## train_1_3_moTRUE      -0.17384    0.23156  -0.751    0.453
## train_4_moTRUE         0.23439    0.20904   1.121    0.262
## train_5_6_moTRUE       0.24404    0.21312   1.145    0.252
## train_class_count.L   -0.34181    0.24984  -1.368    0.171
## train_class_count.Q   -0.30392    0.25155  -1.208    0.227
## train_class_count.C   -0.07151    0.24324  -0.294    0.769
## adj_rewardTRUE         0.17521    0.32430   0.540    0.589
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 627.37  on 468  degrees of freedom
## Residual deviance: 581.35  on 457  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 605.35
##
## Number of Fisher Scoring iterations: 4
##
##                              OR     2.5 %   97.5 %
## (Intercept)           0.9182882 0.3203009 2.658783
## age_yrs               0.9888393 0.9303376 1.050780
```

```
## maleTRUE             0.8632921 0.5817427 1.278713
## neuteredTRUE         3.1846593 1.9191760 5.349804
## acq_12_wo_or_lessTRUE 0.6581042 0.3412241 1.231650
## train_1_3_moTRUE     0.8404278 0.5334598 1.324049
## train_4_moTRUE       1.2641410 0.8401411 1.908496
## train_5_6_moTRUE     1.2763942 0.8407914 1.940875
## train_class_count.L  0.7104846 0.4302541 1.150885
## train_class_count.Q  0.7379202 0.4508876 1.211709
## train_class_count.C  0.9309875 0.5753894 1.496765
## adj_rewardTRUE       1.1914962 0.6251650 2.241976
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.236907  1        1.112163
## male              1.014951  1        1.007448
## neutered          1.229411  1        1.108788
## acq_12_wo_or_less 1.224167  1        1.106421
## train_1_3_mo      1.349024  1        1.161475
## train_4_mo        1.086443  1        1.042326
## train_5_6_mo      1.134190  1        1.064983
## train_class_count 1.122108  3        1.019387
## adj_reward        1.045556  1        1.022525
##
## ----------------------------------------------------------------------------
## house_soiling
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.3939   0.3972   0.5175   0.6439   1.0365
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -0.08881    0.65317  -0.136    0.892
## age_yrs                0.02993    0.03977   0.753    0.452
## maleTRUE              -0.04344    0.25636  -0.169    0.865
## neuteredTRUE           0.43123    0.33016   1.306    0.192
## acq_12_wo_or_lessTRUE  0.25882    0.38023   0.681    0.496
## train_1_3_moTRUE       0.26295    0.32186   0.817    0.414
## train_4_moTRUE         0.28694    0.28333   1.013    0.311
## train_5_6_moTRUE       0.45727    0.28806   1.587    0.112
## train_class_count.L    0.48536    0.30356   1.599    0.110
## train_class_count.Q    0.25395    0.30250   0.839    0.401
## train_class_count.C   -0.26956    0.28597  -0.943    0.346
## adj_rewardTRUE         0.56653    0.37548   1.509    0.131
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 418.85  on 468  degrees of freedom
## Residual deviance: 401.01  on 457  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 425.01
```

```
##
## Number of Fisher Scoring iterations: 5
##
##                             OR     2.5 %   97.5 %
## (Intercept)           0.9150227 0.2546966 3.328567
## age_yrs               1.0303821 0.9534734 1.114771
## maleTRUE              0.9574921 0.5782841 1.584350
## neuteredTRUE          1.5391482 0.7982788 2.927620
## acq_12_wo_or_lessTRUE 1.2954018 0.6022697 2.697630
## train_1_3_moTRUE      1.3007600 0.6956800 2.474628
## train_4_moTRUE        1.3323449 0.7713460 2.356047
## train_5_6_moTRUE      1.5797592 0.9071084 2.822724
## train_class_count.L   1.6247678 0.8715547 2.894491
## train_class_count.Q   1.2891039 0.7131396 2.350489
## train_class_count.C   0.7637117 0.4269955 1.319308
## adj_rewardTRUE        1.7621465 0.8174600 3.602207
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.250532  1        1.118272
## male              1.015565  1        1.007753
## neutered          1.294682  1        1.137841
## acq_12_wo_or_less 1.316648  1        1.147453
## train_1_3_mo      1.589844  1        1.260890
## train_4_mo        1.198934  1        1.094958
## train_5_6_mo      1.234342  1        1.111009
## train_class_count 1.135463  3        1.021399
## adj_reward        1.057049  1        1.028129
##
## ---------------------------------------------------------------------------------
## hyperactive
##
## Dropped from model due to insufficient responses:
## acq_12_wo_or_less
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.0101  -0.4990  -0.4089  -0.3203   2.5997
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)         -0.80077    0.63321  -1.265   0.2060
## age_yrs             -0.06170    0.04906  -1.258   0.2085
## maleTRUE            -0.52672    0.31693  -1.662   0.0965 .
## neuteredTRUE        -0.18188    0.38816  -0.469   0.6394
## train_1_3_moTRUE     0.14004    0.33918   0.413   0.6797
## train_4_moTRUE      -0.08336    0.31718  -0.263   0.7927
## train_5_6_moTRUE     0.19314    0.32728   0.590   0.5551
## train_class_count.L -0.55875    0.36224  -1.542   0.1230
## train_class_count.Q -0.34277    0.37101  -0.924   0.3556
## train_class_count.C  0.31238    0.35692   0.875   0.3815
```

```
## adj_rewardTRUE      -0.78179    0.42124  -1.856   0.0635 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 315.37  on 474  degrees of freedom
## Residual deviance: 299.69  on 464  degrees of freedom
##   (19 observations deleted due to missingness)
## AIC: 321.69
##
## Number of Fisher Scoring iterations: 5
##
##                            OR     2.5 %   97.5 %
## (Intercept)         0.4489819 0.1259676 1.528061
## age_yrs             0.9401662 0.8525812 1.034060
## maleTRUE            0.5905388 0.3125472 1.090024
## neuteredTRUE        0.8336984 0.3950635 1.827556
## train_1_3_moTRUE    1.1503177 0.5872743 2.237068
## train_4_moTRUE      0.9200156 0.4891010 1.707247
## train_5_6_moTRUE    1.2130543 0.6361710 2.311922
## train_class_count.L 0.5719254 0.2885742 1.218056
## train_class_count.Q 0.7098048 0.3394188 1.476867
## train_class_count.C 1.3666743 0.7000436 2.890681
## adj_rewardTRUE      0.4575860 0.2067375 1.096483
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.203670  1        1.097119
## male              1.021464  1        1.010675
## neutered          1.223440  1        1.106092
## train_1_3_mo      1.217129  1        1.103236
## train_4_mo        1.045524  1        1.022509
## train_5_6_mo      1.133200  1        1.064519
## train_class_count 1.153316  3        1.024058
## adj_reward        1.041422  1        1.020501
##
## ----------------------------------------------------------------------------------
## jumping
##
## Dropped from model due to insufficient responses:
## train_class_count
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.3245  -0.7577  -0.5260  -0.2848   2.4888
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)            0.09883    0.63923   0.155   0.8771
## age_yrs               -0.22741    0.04006  -5.676 1.37e-08 ***
```

```
## maleTRUE              -0.47008    0.23604  -1.991   0.0464 *
## neuteredTRUE           0.28500    0.29192   0.976   0.3289
## acq_12_wo_or_lessTRUE -0.32893    0.34075  -0.965   0.3344
## train_1_3_moTRUE      -0.37677    0.26898  -1.401   0.1613
## train_4_moTRUE        -0.11184    0.24125  -0.464   0.6429
## train_5_6_moTRUE       0.09182    0.24422   0.376   0.7069
## adj_rewardTRUE         0.43046    0.43185   0.997   0.3189
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 504.84  on 475  degrees of freedom
## Residual deviance: 457.92  on 467  degrees of freedom
##   (18 observations deleted due to missingness)
## AIC: 475.92
##
## Number of Fisher Scoring iterations: 5
##
##                              OR     2.5 %    97.5 %
## (Intercept)           1.1038822 0.3071891 3.8117835
## age_yrs               0.7965961 0.7346791 0.8598750
## maleTRUE              0.6249551 0.3914045 0.9892198
## neuteredTRUE          1.3297609 0.7569457 2.3841761
## acq_12_wo_or_lessTRUE 0.7196963 0.3707036 1.4163349
## train_1_3_moTRUE      0.6860768 0.4034375 1.1611161
## train_4_moTRUE        0.8941866 0.5551640 1.4322096
## train_5_6_moTRUE      1.0961634 0.6778197 1.7695355
## adj_rewardTRUE        1.5379642 0.6908873 3.8253160
##
## VIF:
##           age_yrs              male          neutered acq_12_wo_or_less
##          1.152344          1.023066          1.183627          1.305562
##      train_1_3_mo        train_4_mo      train_5_6_mo        adj_reward
##          1.336241          1.066653          1.109236          1.041577
##
## --------------------------------------------------------------------------------
## mounting
##
## Dropped from model due to insufficient responses:
## train_class_count
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.0363  -0.7367  -0.4869  -0.3831   2.3976
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -1.55844    0.66946  -2.328   0.0199 *
## age_yrs                0.01285    0.03757   0.342   0.7323
## maleTRUE              -1.24880    0.26691  -4.679 2.89e-06 ***
```

```
## neuteredTRUE           0.42764    0.33990   1.258   0.2083
## acq_12_wo_or_lessTRUE -0.21926    0.35959  -0.610   0.5420
## train_1_3_moTRUE      -0.11196    0.27946  -0.401   0.6887
## train_4_moTRUE         0.37727    0.25443   1.483   0.1381
## train_5_6_moTRUE      -0.03827    0.25285  -0.151   0.8797
## adj_rewardTRUE         0.23228    0.41992   0.553   0.5802
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 452.75  on 475  degrees of freedom
## Residual deviance: 423.02  on 467  degrees of freedom
##   (18 observations deleted due to missingness)
## AIC: 441.02
##
## Number of Fisher Scoring iterations: 5
##
##                              OR      2.5 %    97.5 %
## (Intercept)           0.2104647 0.05448015 0.7598062
## age_yrs               1.0129359 0.94074984 1.0904147
## maleTRUE              0.2868477 0.16705426 0.4775364
## neuteredTRUE          1.5336309 0.80271842 3.0647613
## acq_12_wo_or_lessTRUE 0.8031108 0.40003983 1.6487352
## train_1_3_moTRUE      0.8940834 0.51623607 1.5489784
## train_4_moTRUE        1.4582931 0.88531315 2.4065321
## train_5_6_moTRUE      0.9624483 0.58438975 1.5785104
## adj_rewardTRUE        1.2614690 0.57969945 3.0662356
##
## VIF:
##           age_yrs              male          neutered acq_12_wo_or_less
##          1.147514          1.013984          1.151124          1.295795
##      train_1_3_mo        train_4_mo      train_5_6_mo        adj_reward
##          1.289556          1.079721          1.064904          1.031290
##
## --------------------------------------------------------------------------------
## rep_materials
##
## Call:
## glm(formula = f, family = "binomial", data = df_tmp)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -1.561  -1.062  -0.741   1.178   1.836
##
## Coefficients:
##                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -1.402565   0.522635  -2.684  0.00728 **
## age_yrs                0.098214   0.030049   3.269  0.00108 **
## maleTRUE               0.304508   0.193908   1.570  0.11633
## neuteredTRUE           0.584227   0.271745   2.150  0.03156 *
## acq_12_wo_or_lessTRUE -0.367845   0.291215  -1.263  0.20654
## train_1_3_moTRUE       0.158988   0.228362   0.696  0.48630
## train_4_moTRUE        -0.004247   0.201295  -0.021  0.98317
```

```
## train_5_6_moTRUE       0.033465   0.206174   0.162  0.87106
## train_class_count.L   -0.128846   0.239827  -0.537  0.59110
## train_class_count.Q   -0.110531   0.238920  -0.463  0.64363
## train_class_count.C    0.018563   0.226548   0.082  0.93470
## adj_rewardTRUE         0.170679   0.321302   0.531  0.59527
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 642.22  on 468  degrees of freedom
## Residual deviance: 609.27  on 457  degrees of freedom
##   (25 observations deleted due to missingness)
## AIC: 633.27
##
## Number of Fisher Scoring iterations: 4
##
##                              OR      2.5 %    97.5 %
## (Intercept)           0.2459653 0.08708452 0.6784791
## age_yrs               1.1031987 1.04069672 1.1710319
## maleTRUE              1.3559577 0.92768166 1.9852414
## neuteredTRUE          1.7936046 1.06109515 3.0884635
## acq_12_wo_or_lessTRUE 0.6922242 0.38963961 1.2235482
## train_1_3_moTRUE      1.1723238 0.74994813 1.8379948
## train_4_moTRUE        0.9957620 0.67088177 1.4781413
## train_5_6_moTRUE      1.0340309 0.68994681 1.5496625
## train_class_count.L   0.8791091 0.54973703 1.4129071
## train_class_count.Q   0.8953589 0.55969899 1.4306154
## train_class_count.C   1.0187361 0.65372882 1.5914248
## adj_rewardTRUE        1.1861095 0.63484836 2.2502550
##
## VIF:
##                       GVIF Df GVIF^(1/(2*Df))
## age_yrs           1.195472  1        1.093377
## male              1.009531  1        1.004754
## neutered          1.187681  1        1.089808
## acq_12_wo_or_less 1.276517  1        1.129831
## train_1_3_mo      1.399175  1        1.182867
## train_4_mo        1.072369  1        1.035552
## train_5_6_mo      1.136845  1        1.066229
## train_class_count 1.138464  3        1.021849
## adj_reward        1.044306  1        1.021913
```

Discussion

In brief, I don't think there is any benefit at looking at the non-punishing devices. Those devices are staples in the average canine household. We are more concerned with the effect of the punishing devices. I also believe that the training method and devices should stay separate to avoid over simplifying the model and the associated risk of warping the meaning of the collected data.

For these reasons, I believe the second model whihc looks only at the punishing devices, is the most logical fit for this data set.