Read Data

11/23/2021

```
library(foreign)
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --
```

```
## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.4     v dplyr   1.0.7
## v tidyr   1.1.3     v stringr 1.4.0
## v readr   2.0.1     v forcats 0.5.1
```

```
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(e1071)
library(tree)
```

```
## Registered S3 method overwritten by 'tree':
##   method     from
##   print.tree cli
```

```
library(nnet)
library(gbm)
```

```
## Loaded gbm 2.1.8
```

```
library(randomForest)
```

```
## randomForest 4.6-14
```

```
## Type rfNews() to see new features/changes/bug fixes.
```

```
##
## Attaching package: 'randomForest'
```

```
## The following object is masked from 'package:dplyr':
##
##     combine
```

```
## The following object is masked from 'package:ggplot2':
##
##     margin
```

```
library(caret)
```

```
## Loading required package: lattice
```

```
##
## Attaching package: 'caret'
```

```
## The following object is masked from 'package:purrr':
##
```

```
##     lift
```

```
library(ggplot2)
library(dplyr)
library(tidyr)
library(tidyverse)
library(patchwork)
library(UBL)
```

```
## Loading required package: MBA
```

```
## Loading required package: gstat
```

```
## Loading required package: automap
```

```
## Loading required package: sp
```

```
library(scales)
```

```
##
## Attaching package: 'scales'
```

```
## The following object is masked from 'package:purrr':
##
##     discard
```

```
## The following object is masked from 'package:readr':
##
##     col_factor
```

```
sesame <- read.dta("sesame.dta")
sesame <- sesame %>%
  mutate(site=factor(site)) %>%
  mutate(bodyDiff = postbody - prebody,
         letDiff = postlet - prelet,
         formDiff = postform - preform,
         numbDiff = postnumb - prenumb,
         relatDiff = postrelat - prerelat,
         clasfDiff = postclasf - preclasf)
sesame.sd <- sesame%>%
  mutate(sd_pBod = scale(prebody, center = TRUE, scale = TRUE),
         sd_plet = scale(prelet, center = TRUE, scale = TRUE),
         sd_pform = scale(preform, center = TRUE, scale = TRUE),
         sd_pnumb = scale(prenumb, center = TRUE, scale = TRUE),
         sd_prelat = scale(prerelat, center = TRUE, scale = TRUE),
         sd_pclasf = scale(preclasf, center = TRUE, scale = TRUE),
         sd_peabody = scale(peabody, center = TRUE, scale = TRUE),
         sd_age = scale(age, center =TRUE, scale = TRUE),
         male=if_else(sex==1, 1, 0),
         female=if_else(sex==2, 1, 0))
```

Exploratory Data Analysis

```
head(sesame)
```

```
##   rownames id site sex age viewcat setting viewenc prebody prelet preform
## 1        1  1    1   1  66       1       2       1      16     23      12
## 2        2  2    1   2  67       3       2       1      30     26       9
```

```
## 3        3  3    1   1  56       3       2       2      22     14       9
## 4        4  4    1   1  49       1       2       2      23     11      10
## 5        5  5    1   1  69       4       2       2      32     47      15
## 6        6  6    1   2  54       3       2       2      29     26      10
##   prenumb prerelat preclasf postbody postlet postform postnumb postrelat
## 1      40       14       20       18      30       14       44        14
## 2      39       16       22       30      37       17       39        14
## 3       9        9        8       21      46       15       40         9
## 4      14        9       13       21      14       13       19         8
## 5      51       17       22       32      63       18       54        14
## 6      33       14       14       27      36       14       39        16
##   postclasf peabody agecat encour _Isite_2 _Isite_3 _Isite_4 _Isite_5 regular
## 1        23      62      1      1        0        0        0        0       0
## 2        22       8      1      1        0        0        0        0       1
## 3        19      32      1      0        0        0        0        0       1
## 4        15      27      0      0        0        0        0        0       0
## 5        21      71      1      0        0        0        0        0       1
## 6        24      32      1      0        0        0        0        0       1
##   bodyDiff letDiff formDiff numbDiff relatDiff clasfDiff
## 1        2       7        2        4         0         3
## 2        0      11        8        0        -2         0
## 3       -1      32        6       31         0        11
## 4       -2       3        3        5        -1         2
## 5        0      16        3        3        -3        -1
## 6       -2      10        4        6         2        10
```

Variables:

The ID refers to a subject's identification number. The site refers to the age and background information of the child. A site value of 1 indicates a 3-5 year old disadvantaged child from the inner city. A site value of 2 represents a 4 year old advantaged child from the suburbs. A value of 3 represents an advantaged rural child. A site value of 4 indicates a disadvantaged rural child. Lastly, a value of 5 represents a disadvantaged Spanish speaking child. For the sex, a value of 1 indicates male, and a value of 2 indicates female. The age category is the child's age in months. The viewcat column is the frequency of viewing Sesame Street (1 = rarely, 2 = once/twice per week, 3 = 3-5 times a week, 4 = more than 5 times per week). The setting is where Sesame Street was viewed; a value of 1 indicates home and a value of 2 indicates school. The viewenc column refers to if the child was encouraged to watch or not (1 = child not encouraged, 2 = child encouraged). Encour is the same variable but with values 0 and 1, respectively. Regular is an indicator variable representing if a child is a regular viewer (0 = rarely watched, 1 = watched once per week or greater).

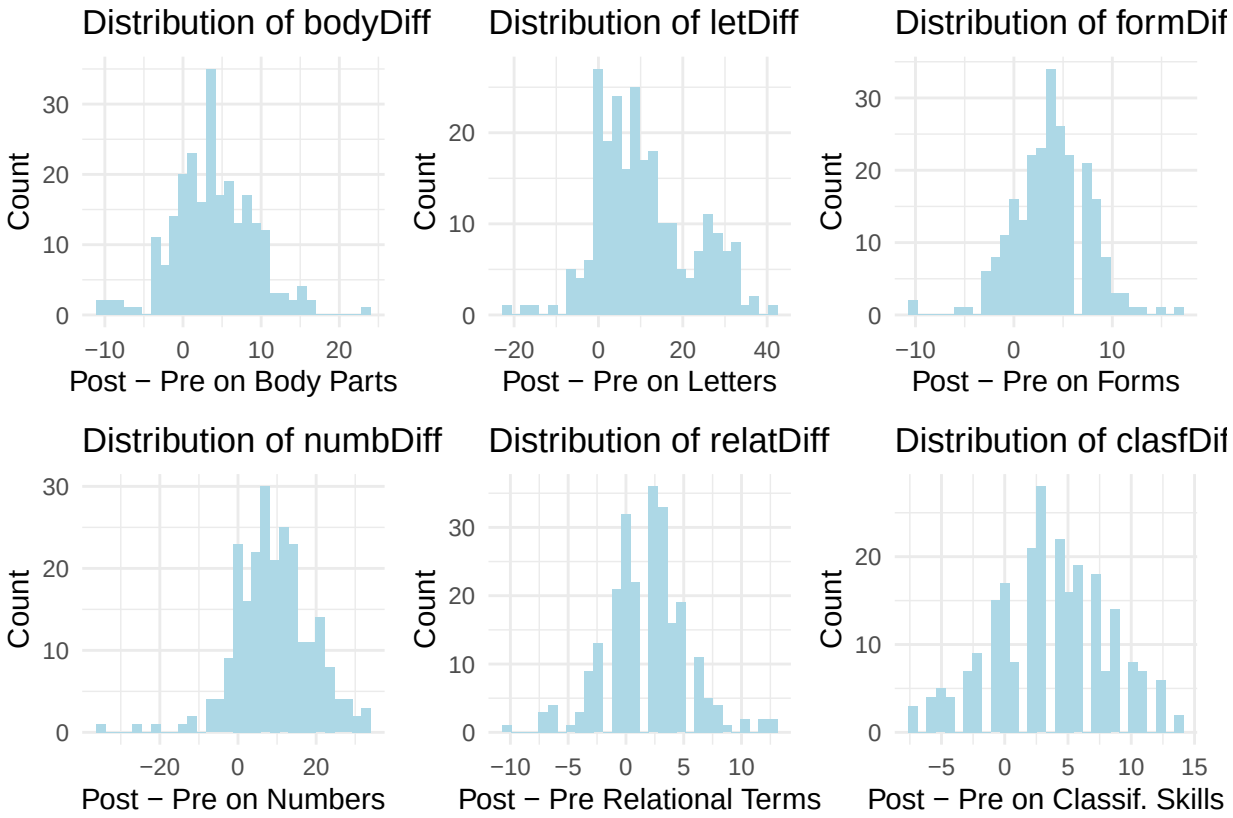
The prebody, prelet, preform, prenumb, prerelat, and preclasf columns all decribe pretest scores on varying types of assessments (body parts, letters, forms, numbers, relational terms, and classification skills, respectively). The columns labelled postbody, postlet, postform, postnumb, postrelat, and postclasf are the children's respective posttest scores. Above, we created the following variables - bodydiff, letDiff, formDiff, numbDiff, relatDiff, clasfDiff - to represent the difference in posttest scores and pretest scores for each child. Lastly, peabody represents a score of "mental age" for vocabulary maturity from the Peabody Picture Vocabulary Test.

Our main focus will be on the new variables we created (bodyDiff, letDiff, formDiff, numbDiff, relatDiff, clasfDiff) and variables related to how often the children watch Sesame Street (namely, viewcat and regular). Lastly, we will look into the backgrounds of the children, including site, sex, and age.

Distributions:

For the purposes of our analysis, we will first look at the distributions of bodyDiff, letDiff, formDiff, numbDiff, relatDiff, and clasfDiff.

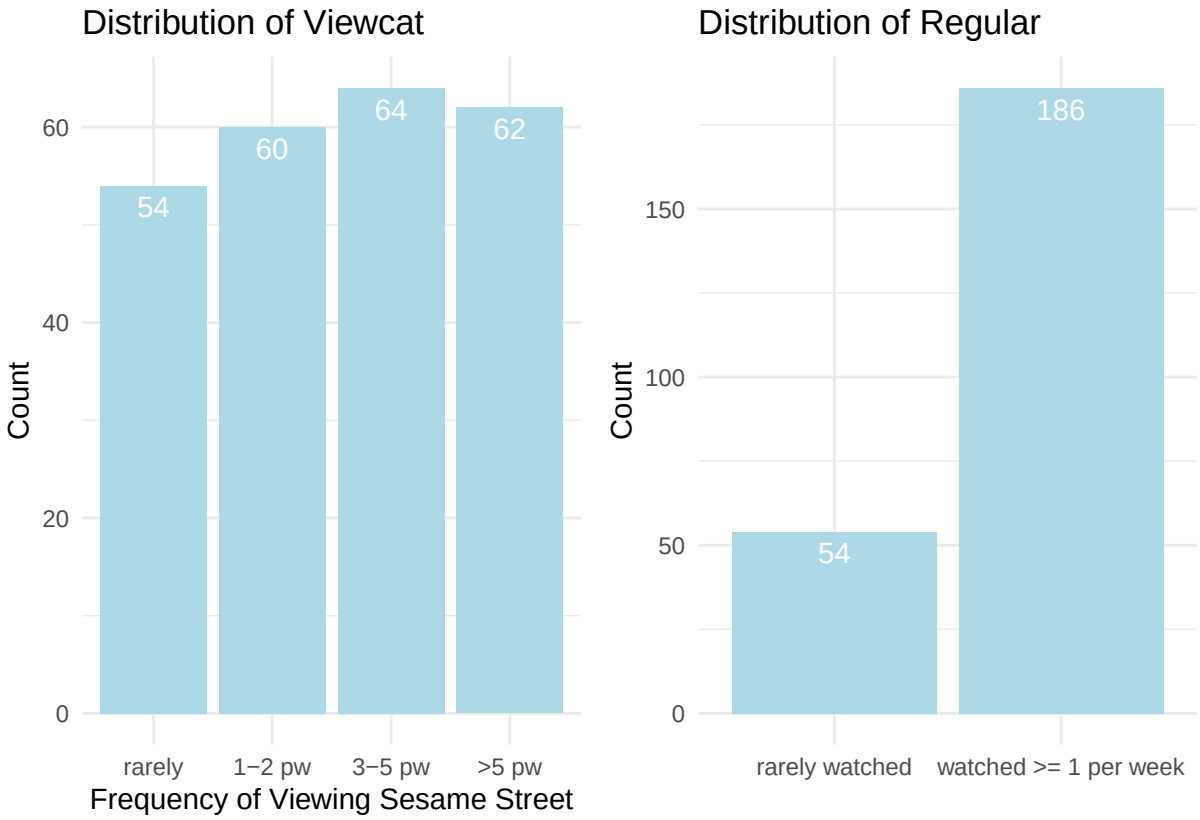
```r
#want to visualize distributions of bodyDiff, letDiff, formDiff, numbDiff, relatDiff, clasfDiff

bodyDiffplot <- ggplot(sesame, aes(x = bodyDiff)) +
  geom_histogram(fill = "lightblue") +
  labs(title = "Distribution of bodyDiff", x = "Post - Pre on Body Parts", y = "Count") +
  theme_minimal()

letDiffplot <- ggplot(sesame, aes(x = letDiff)) +
  geom_histogram(fill = "lightblue") +
  labs(title = "Distribution of letDiff", x = "Post - Pre on Letters", y = "Count") +
  theme_minimal()

formDiffplot <- ggplot(sesame, aes(x = formDiff)) +
  geom_histogram(fill = "lightblue") +
  labs(title = "Distribution of formDiff", x = "Post - Pre on Forms", y = "Count") +
  theme_minimal()

numbDiffplot <- ggplot(sesame, aes(x = numbDiff)) +
  geom_histogram(fill = "lightblue") +
  labs(title = "Distribution of numbDiff", x = "Post - Pre on Numbers", y = "Count") +
  theme_minimal()

relatDiffplot <- ggplot(sesame, aes(x = relatDiff)) +
  geom_histogram(fill = "lightblue") +
  labs(title = "Distribution of relatDiff", x = "Post - Pre Relational Terms", y = "Count") +
  theme_minimal()

clasfDiffplot <- ggplot(sesame, aes(x = clasfDiff)) +
  geom_histogram(fill = "lightblue") +
  labs(title = "Distribution of clasfDiff", x = "Post - Pre on Classif. Skills", y = "Count") +
  theme_minimal()


bodyDiffplot + letDiffplot + formDiffplot + numbDiffplot + relatDiffplot + clasfDiffplot
```



The six variables above were calculated by subtracting pre-test scores from post-test scores, so they are all numerical. The distributions of these six variables (bodyDiff, letDiff, formDiff, numbDiff, relatDiff, and clasfDiff) all appear to be roughly normal and unimodal. BodyDiff, letDiff, formDiff, relatDiff, and classDiff do not appear to have any obvious extreme outliers. Numbdiff, however, seems to be slightly left-skewed with outliers to the left -20. All of the six variables appear to have centers between 2 and 4.

We will now examine the distrubtions of the variables related to how often children watch Sesame Street (namely, viewcat and regular).

```
# want to visualize distributions of viewcat and regular

viewcatplot <- ggplot(sesame, aes(x = factor(viewcat))) +
  geom_bar(fill = "lightblue") +
  labs(title = "Distribution of Viewcat", x = "Frequency of viewing Sesame Street", y = "Count") +
  scale_x_discrete("Frequency of Viewing Sesame Street", labels=c("rarely", "1-2 pw", "3-5 pw", ">5 pw"
  theme_minimal() +
  geom_text(aes(label = ..count..), stat = "count", vjust = 1.5, colour = "white")


regularplot <- ggplot(sesame, aes(x = factor(regular))) +
  geom_bar(fill = "lightblue") +
  labs(title = "Distribution of Regular", y = "Count") +
  scale_x_discrete(labels=c("rarely watched", "watched >= 1 per week")) +
  theme_minimal() +
  theme(axis.title.x = element_blank()) +
  geom_text(aes(label = ..count..), stat = "count", vjust = 1.5, colour = "white")

viewcatplot + regularplot
```

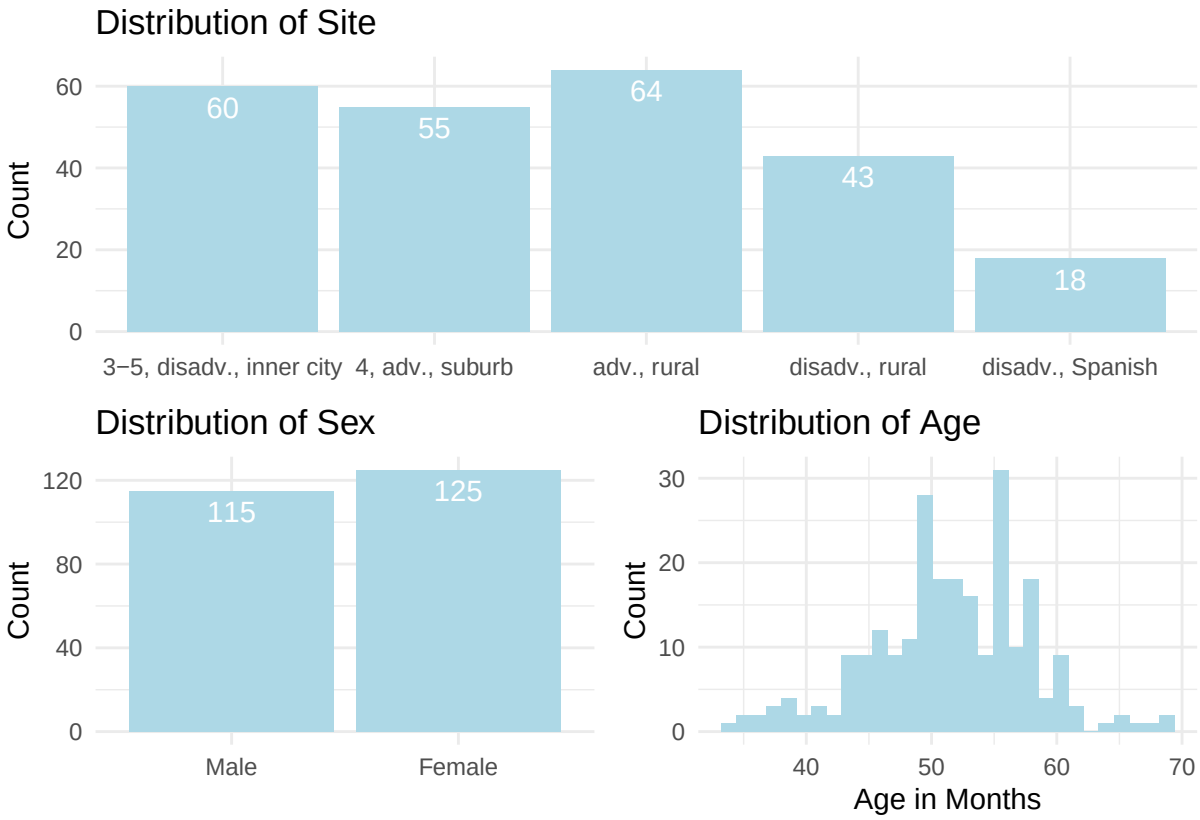


Both of these variables are categorical. On the left, viewcat appears to have a roughly uniform distribution, with "rarely" having the least amount of children and 3-5 times per week having the most (the range is only 10 children, so all of the bars are relatively close in height). For the variable regular, the category "watched once per week or greater" has far more observations than "rarely watched." The former category has more than triple the amount of the latter. We will be aware of this disparity in our analysis and continue with caution towards potential bias.

Lastly, we want to examine the distributions of site, sex, and age, all variables that relate to a child's background.

```
# want to visualize distributions of site, sex, and age

siteplot <- ggplot(sesame, aes(x = factor(site))) +
  geom_bar(fill = "lightblue") +
  labs(title = "Distribution of Site", y = "Count") +
  scale_x_discrete(labels=c("3-5, disadv., inner city", "4, adv., suburb", "adv., rural", "disadv., rura
  theme_minimal() +
  theme(axis.title.x = element_blank()) +
  geom_text(aes(label = ..count..), stat = "count", vjust = 1.5, colour = "white")

sexplot <- ggplot(sesame, aes(x = factor(sex))) +
  geom_bar(fill = "lightblue") +
  labs(title = "Distribution of Sex", y = "Count") +
  scale_x_discrete(labels=c("Male", "Female")) +
  theme_minimal() +
  theme(axis.title.x = element_blank()) +
  geom_text(aes(label = ..count..), stat = "count", vjust = 1.5, colour = "white")

ageplot <- ggplot(sesame, aes(x = age)) +
```

```
  geom_histogram(fill = "lightblue") +
  labs(title = "Distribution of Age", x = "Age in Months", y = "Count") +
  theme_minimal()

siteplot / (sexplot + ageplot)
```



Site and Sex are both categorical variables. Distribution of Site has four categories with roughly the same amount of children (ranging from 43 to 64), but one category with far fewer observations (disadvantaged Spanish-speaking). This category has less than half of the observations as the next smallest category, which is a relatively large disparity. We will continue our analysis with caution towards this bias in the data. The distribution of sex is very even - the male category has 115 observations, while the female category has 125 observations. Age is a numerical variable that appears to be normal and bimodal, with two peaks around 50 and 56. There do not appear to be any extreme outliers in the distribution of age.

Q.1 Prediction Question: Can we use linear regression to predict the change in a child's test scores that occur after watching Sesame street (or in some instances, not watching Seasame street)?

Linear Regression Models

Here, I am fitting 6 linear regression models. Each of the models predicts a different difference in test score.

```
sesame.q1 <- sesame

sesame.q1$site <- as.factor(sesame.q1$site)
sesame.q1$sex <- as.factor(sesame.q1$sex)
sesame.q1$viewcat <- as.factor(sesame.q1$viewcat)
sesame.q1$setting <- as.factor(sesame.q1$setting)
```

```r
sesame.q1$viewenc <- as.factor(sesame.q1$viewenc)
```

```r
# Scaling Variables

sesame.q1$bodyDiff <- rescale(sesame.q1$bodyDiff, to = c(0, 30))
sesame.q1$letDiff <- rescale(sesame.q1$letDiff, to = c(0, 30))
sesame.q1$formDiff <- rescale(sesame.q1$formDiff, to = c(0, 30))
sesame.q1$numbDiff <- rescale(sesame.q1$numbDiff, to = c(0, 30))
sesame.q1$relatDiff <- rescale(sesame.q1$relatDiff, to = c(0, 30))
sesame.q1$clasfDiff <- rescale(sesame.q1$clasfDiff, to = c(0, 30))
```

```r
# Test-Train Split

set.seed(1)
train <- sample(1:nrow(sesame.q1), nrow(sesame.q1)*0.7)

training = sesame.q1[train,]
testing = sesame.q1[-train, ]
```

Firstly, we factored the following variables to encode them as categoricals: `site`, `sex`, `viewcat`, `setting`, `viewenc`.

One problem that we envisioned when evaluating the and comparing the different models is that the tests are scored on different scales. For example, the scores for the test on knowledge of body parts (noted by `bodyDiff`) range from 0-32, while those of the test on letters (noted by `letDiff`) range from 0-58. To be able to aptly compare the mean squared error (MSE) between models, we also decided to convert each response variable to the same range. More specifically, we scaled each variable to the arbitrary range [0, 30].

Lastly, we randomly split the data between testing and training, using 70% of the data for training and 30% of the data for testing.

```r
lin.mod1.full <- lm(bodyDiff ~ (site + sex + age + viewcat + setting + viewenc)^2, data = training)
summary(lin.mod1.full)
```

```
##
## Call:
## lm(formula = bodyDiff ~ (site + sex + age + viewcat + setting +
##     viewenc)^2, data = training)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -8.0419 -2.3623 -0.0666  2.0079  9.9599
##
## Coefficients: (2 not defined because of singularities)
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)       -5.21460   14.63930  -0.356   0.7224
## site2             -1.67860   13.72456  -0.122   0.9029
## site3              1.18809    9.13599   0.130   0.8968
## site4             36.76705   16.49603   2.229   0.0278 *
## site5              2.51268   17.41166   0.144   0.8855
## sex2               2.67852    6.79950   0.394   0.6944
## age                0.30634    0.26777   1.144   0.2551
## viewcat2          11.62045   14.78702   0.786   0.4336
## viewcat3          12.46797   13.36691   0.933   0.3530
## viewcat4          29.95220   14.54421   2.059   0.0418 *
## setting2          -9.74959    9.11761  -1.069   0.2872
```

```
## viewenc2          19.16298   10.20959   1.877   0.0631 .
## site2:sex2         3.01414    2.22656   1.354   0.1786
## site3:sex2         2.32383    2.17020   1.071   0.2866
## site4:sex2         0.53119    2.63525   0.202   0.8406
## site5:sex2         0.32139    3.71691   0.086   0.9312
## site2:age          0.04657    0.24040   0.194   0.8467
## site3:age          0.03300    0.17150   0.192   0.8477
## site4:age         -0.59988    0.30613  -1.960   0.0525 .
## site5:age          0.01087    0.33703   0.032   0.9743
## site2:viewcat2     3.94606    5.50815   0.716   0.4752
## site3:viewcat2     2.11625    3.88814   0.544   0.5873
## site4:viewcat2     2.33983    3.90246   0.600   0.5500
## site5:viewcat2     5.15446    6.28877   0.820   0.4142
## site2:viewcat3    -4.60122    5.15701  -0.892   0.3742
## site3:viewcat3    -2.61690    3.66597  -0.714   0.4768
## site4:viewcat3    -4.29765    4.15537  -1.034   0.3033
## site5:viewcat3          NA         NA      NA       NA
## site2:viewcat4    -2.76550    5.23768  -0.528   0.5985
## site3:viewcat4    -2.14835    3.84372  -0.559   0.5773
## site4:viewcat4    -6.19787    4.85958  -1.275   0.2048
## site5:viewcat4    -3.85743    6.63742  -0.581   0.5623
## site2:setting2     0.63008    2.76440   0.228   0.8201
## site3:setting2     0.14259    3.16610   0.045   0.9642
## site4:setting2     5.09348    3.25326   1.566   0.1203
## site5:setting2          NA         NA      NA       NA
## site2:viewenc2     0.89088    2.60475   0.342   0.7330
## site3:viewenc2    -1.79090    3.30478  -0.542   0.5890
## site4:viewenc2    -5.97857    3.03298  -1.971   0.0512 .
## site5:viewenc2    -2.07853    7.09228  -0.293   0.7700
## sex2:age          -0.10641    0.12653  -0.841   0.4022
## sex2:viewcat2      1.49879    2.64935   0.566   0.5727
## sex2:viewcat3      0.58754    2.51057   0.234   0.8154
## sex2:viewcat4     -1.20166    2.68241  -0.448   0.6550
## sex2:setting2     -1.53778    1.70350  -0.903   0.3686
## sex2:viewenc2      1.20679    1.93998   0.622   0.5352
## age:viewcat2      -0.27426    0.26179  -1.048   0.2971
## age:viewcat3      -0.15379    0.23654  -0.650   0.5169
## age:viewcat4      -0.46253    0.26054  -1.775   0.0786 .
## age:setting2       0.05401    0.15397   0.351   0.7264
## age:viewenc2      -0.27988    0.18128  -1.544   0.1254
## viewcat2:setting2  5.64914    3.31141   1.706   0.0908 .
## viewcat3:setting2  6.07677    3.20554   1.896   0.0606 .
## viewcat4:setting2  6.21301    3.52866   1.761   0.0810 .
## viewcat2:viewenc2 -7.71647    3.54437  -2.177   0.0316 *
## viewcat3:viewenc2 -6.24879    3.34488  -1.868   0.0644 .
## viewcat4:viewenc2 -7.65623    3.62444  -2.112   0.0369 *
## setting2:viewenc2  1.97122    2.32061   0.849   0.3974
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.226 on 112 degrees of freedom
## Multiple R-squared:  0.4033, Adjusted R-squared:  0.1103
## F-statistic: 1.377 on 55 and 112 DF,  p-value: 0.07819
```

```r
AIC(lin.mod1.full)
```

```
## [1] 1006.935
```

```r
yhat <- predict(lin.mod1.full, newdata = testing)
```

```
## Warning in predict.lm(lin.mod1.full, newdata = testing): prediction from a rank-
## deficient fit may be misleading
```

```r
y.test <- testing[, "bodyDiff"]

# Test MSE
mean((yhat-y.test)^2)
```

```
## [1] 32.44637
```

```r
lin.mod2.full <- lm(letDiff ~ (site + sex + age + viewcat + setting + viewenc)^2, data = training)
summary(lin.mod2.full)
```

```
##
## Call:
## lm(formula = letDiff ~ (site + sex + age + viewcat + setting +
##     viewenc)^2, data = training)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12.7462  -2.3134   0.0386   2.3986  10.2234
##
## Coefficients: (2 not defined because of singularities)
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         19.20505   15.54400   1.236   0.2192
## site2               -7.55435   14.57273  -0.518   0.6052
## site3                7.76205    9.70058   0.800   0.4253
## site4              -12.82246   17.51547  -0.732   0.4657
## site5                1.39944   18.48769   0.076   0.9398
## sex2                -7.03111    7.21970  -0.974   0.3322
## age                 -0.13633    0.28432  -0.480   0.6325
## viewcat2           -20.28956   15.70085  -1.292   0.1989
## viewcat3            -0.74326   14.19298  -0.052   0.9583
## viewcat4             5.71015   15.44303   0.370   0.7123
## setting2            -0.93795    9.68107  -0.097   0.9230
## viewenc2            -5.41528   10.84054  -0.500   0.6184
## site2:sex2           1.20390    2.36416   0.509   0.6116
## site3:sex2          -0.63445    2.30431  -0.275   0.7836
## site4:sex2          -3.21100    2.79810  -1.148   0.2536
## site5:sex2          -1.80949    3.94661  -0.458   0.6475
## site2:age            0.27245    0.25526   1.067   0.2881
## site3:age           -0.17713    0.18209  -0.973   0.3328
## site4:age            0.32387    0.32505   0.996   0.3212
## site5:age           -0.06901    0.35786  -0.193   0.8474
## site2:viewcat2      -1.69100    5.84855  -0.289   0.7730
## site3:viewcat2       0.28314    4.12842   0.069   0.9454
## site4:viewcat2       3.57460    4.14363   0.863   0.3902
## site5:viewcat2       4.79038    6.67741   0.717   0.4746
## site2:viewcat3      -5.13072    5.47571  -0.937   0.3508
## site3:viewcat3      -1.48691    3.89252  -0.382   0.7032
```

```
## site4:viewcat3     -5.03691    4.41217  -1.142   0.2561
## site5:viewcat3           NA         NA      NA       NA
## site2:viewcat4     -3.19663    5.56136  -0.575   0.5666
## site3:viewcat4     -0.93894    4.08126  -0.230   0.8185
## site4:viewcat4     -5.99748    5.15990  -1.162   0.2476
## site5:viewcat4     -0.21046    7.04760  -0.030   0.9762
## site2:setting2     -1.36444    2.93524  -0.465   0.6429
## site3:setting2     -1.30832    3.36176  -0.389   0.6979
## site4:setting2     -4.68028    3.45430  -1.355   0.1782
## site5:setting2           NA         NA      NA       NA
## site2:viewenc2     -2.65415    2.76572  -0.960   0.3393
## site3:viewenc2      0.03940    3.50901   0.011   0.9911
## site4:viewenc2     -0.05966    3.22042  -0.019   0.9853
## site5:viewenc2      7.97522    7.53058   1.059   0.2919
## sex2:age            0.15410    0.13435   1.147   0.2538
## sex2:viewcat2       2.86176    2.81308   1.017   0.3112
## sex2:viewcat3      -0.20025    2.66573  -0.075   0.9403
## sex2:viewcat4      -0.45238    2.84818  -0.159   0.8741
## sex2:setting2      -1.93840    1.80878  -1.072   0.2862
## sex2:viewenc2       3.18303    2.05987   1.545   0.1251
## age:viewcat2        0.38696    0.27796   1.392   0.1666
## age:viewcat3        0.14608    0.25116   0.582   0.5620
## age:viewcat4        0.01779    0.27664   0.064   0.9488
## age:setting2        0.01359    0.16348   0.083   0.9339
## age:viewenc2        0.02087    0.19248   0.108   0.9139
## viewcat2:setting2   2.59739    3.51606   0.739   0.4616
## viewcat3:setting2   4.02713    3.40364   1.183   0.2392
## viewcat4:setting2  -0.78643    3.74673  -0.210   0.8341
## viewcat2:viewenc2  -3.47489    3.76341  -0.923   0.3578
## viewcat3:viewenc2  -1.80040    3.55159  -0.507   0.6132
## viewcat4:viewenc2   1.81492    3.84842   0.472   0.6381
## setting2:viewenc2   4.70866    2.46403   1.911   0.0586 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.488 on 112 degrees of freedom
## Multiple R-squared:  0.5727, Adjusted R-squared:  0.3628
## F-statistic: 2.729 on 55 and 112 DF,  p-value: 3.56e-06
```

```
AIC(lin.mod2.full)
```

```
## [1] 1027.083
```

```
yhat <- predict(lin.mod2.full, newdata = testing)
```

```
## Warning in predict.lm(lin.mod2.full, newdata = testing): prediction from a rank-
## deficient fit may be misleading
```

```
y.test <- testing[, "letDiff"]

# Test MSE
mean((yhat-y.test)^2)
```

```
## [1] 24.44647
```

```
lin.mod3.full <- lm(formDiff ~ (site + sex + age + viewcat + setting + viewenc)^2, data = training)
summary(lin.mod3.full)
```

```
##
## Call:
## lm(formula = formDiff ~ (site + sex + age + viewcat + setting +
##     viewenc)^2, data = training)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -8.9228 -1.8652 -0.0169  1.8737 12.7649
##
## Coefficients: (2 not defined because of singularities)
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)        29.944763  14.480042   2.068   0.0409 *
## site2              12.327359  13.575252   0.908   0.3658
## site3              -1.058753   9.036594  -0.117   0.9069
## site4               4.392580  16.316566   0.269   0.7883
## site5               4.356217  17.222238   0.253   0.8008
## sex2                3.675853   6.725528   0.547   0.5858
## age                -0.296259   0.264860  -1.119   0.2657
## viewcat2          -24.508158  14.626151  -1.676   0.0966 .
## viewcat3          -15.832596  13.221492  -1.197   0.2336
## viewcat4           -2.141958  14.385978  -0.149   0.8819
## setting2            7.516078   9.018414   0.833   0.4064
## viewenc2          -15.197856  10.098523  -1.505   0.1351
## site2:sex2         -3.772624   2.202334  -1.713   0.0895 .
## site3:sex2         -4.100876   2.146588  -1.910   0.0586 .
## site4:sex2         -5.714483   2.606577  -2.192   0.0304 *
## site5:sex2         -4.513182   3.676472  -1.228   0.2222
## site2:age          -0.271127   0.237788  -1.140   0.2566
## site3:age           0.001186   0.169630   0.007   0.9944
## site4:age          -0.031048   0.302804  -0.103   0.9185
## site5:age          -0.082011   0.333365  -0.246   0.8061
## site2:viewcat2      6.777720   5.448230   1.244   0.2161
## site3:viewcat2      6.728359   3.845840   1.750   0.0829 .
## site4:viewcat2      5.866619   3.860003   1.520   0.1314
## site5:viewcat2      7.030391   6.220350   1.130   0.2608
## site2:viewcat3      2.122722   5.100911   0.416   0.6781
## site3:viewcat3      4.363483   3.626088   1.203   0.2314
## site4:viewcat3      0.418813   4.110165   0.102   0.9190
## site5:viewcat3            NA         NA      NA       NA
## site2:viewcat4      1.747657   5.180694   0.337   0.7365
## site3:viewcat4      5.788361   3.801908   1.522   0.1307
## site4:viewcat4     -0.137820   4.806713  -0.029   0.9772
## site5:viewcat4      1.851415   6.565206   0.282   0.7785
## site2:setting2      1.586718   2.734325   0.580   0.5629
## site3:setting2     -6.267179   3.131653  -2.001   0.0478 *
## site4:setting2      1.393469   3.217863   0.433   0.6658
## site5:setting2            NA         NA      NA       NA
## site2:viewenc2     -0.253451   2.576413  -0.098   0.9218
## site3:viewenc2      4.996265   3.268825   1.528   0.1292
## site4:viewenc2     -4.076868   2.999986  -1.359   0.1769
## site5:viewenc2      0.542663   7.015121   0.077   0.9385
## sex2:age            0.040381   0.125154   0.323   0.7476
```

```
## sex2:viewcat2      -2.039436   2.620528  -0.778   0.4381
## sex2:viewcat3       0.317803   2.483262   0.128   0.8984
## sex2:viewcat4      -0.544298   2.653230  -0.205   0.8378
## sex2:setting2      -2.642309   1.684970  -1.568   0.1197
## sex2:viewenc2      -2.157924   1.918879  -1.125   0.2632
## age:viewcat2        0.364615   0.258937   1.408   0.1619
## age:viewcat3        0.253258   0.233965   1.082   0.2814
## age:viewcat4        0.017013   0.257708   0.066   0.9475
## age:setting2       -0.094395   0.152294  -0.620   0.5366
## age:viewenc2        0.288927   0.179305   1.611   0.1099
## viewcat2:setting2   0.045540   3.275387   0.014   0.9889
## viewcat3:setting2  -0.916800   3.170671  -0.289   0.7730
## viewcat4:setting2   2.713885   3.490273   0.778   0.4385
## viewcat2:viewenc2   7.112277   3.505815   2.029   0.0449 *
## viewcat3:viewenc2   2.220835   3.308488   0.671   0.5034
## viewcat4:viewenc2   0.718803   3.585006   0.201   0.8415
## setting2:viewenc2  -1.590335   2.295369  -0.693   0.4898
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.18 on 112 degrees of freedom
## Multiple R-squared:  0.3905, Adjusted R-squared:  0.09115
## F-statistic: 1.305 on 55 and 112 DF,  p-value: 0.1189
```

```
AIC(lin.mod3.full)
```

```
## [1] 1003.259
```

```
yhat <- predict(lin.mod3.full, newdata = testing)
```

```
## Warning in predict.lm(lin.mod3.full, newdata = testing): prediction from a rank-
## deficient fit may be misleading
```

```
y.test <- testing[, "formDiff"]

# Test MSE
mean((yhat-y.test)^2)
```

```
## [1] 23.18844
```

```
lin.mod4.full <- lm(numbDiff ~ (site + sex + age + viewcat + setting + viewenc)^2, data = training)
summary(lin.mod4.full)
```

```
##
## Call:
## lm(formula = numbDiff ~ (site + sex + age + viewcat + setting +
##     viewenc)^2, data = training)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -14.9731  -2.2530  -0.0413   2.4864   9.4788
##
## Coefficients: (2 not defined because of singularities)
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)        16.70541   15.13888   1.103   0.2722
## site2              15.96399   14.19292   1.125   0.2631
## site3               6.64629    9.44776   0.703   0.4832
```

```
## site4              -4.69062   17.05897  -0.275   0.7838
## site5               1.27560   18.00585   0.071   0.9436
## sex2                9.80788    7.03154   1.395   0.1658
## age                -0.08799    0.27691  -0.318   0.7513
## viewcat2          -12.34222   15.29164  -0.807   0.4213
## viewcat3          -11.17277   13.82307  -0.808   0.4206
## viewcat4            3.28623   15.04054   0.218   0.8274
## setting2           17.35032    9.42875   1.840   0.0684 .
## viewenc2           -7.37000   10.55800  -0.698   0.4866
## site2:sex2         -3.34924    2.30254  -1.455   0.1486
## site3:sex2         -2.90207    2.24426  -1.293   0.1986
## site4:sex2         -3.42395    2.72518  -1.256   0.2116
## site5:sex2         -0.25383    3.84375  -0.066   0.9475
## site2:age          -0.06976    0.24861  -0.281   0.7795
## site3:age          -0.05208    0.17735  -0.294   0.7696
## site4:age           0.27163    0.31658   0.858   0.3927
## site5:age           0.05536    0.34853   0.159   0.8741
## site2:viewcat2     -6.50669    5.69612  -1.142   0.2558
## site3:viewcat2     -1.86918    4.02083  -0.465   0.6429
## site4:viewcat2     -4.52539    4.03563  -1.121   0.2645
## site5:viewcat2     -0.06176    6.50337  -0.009   0.9924
## site2:viewcat3     -6.54853    5.33300  -1.228   0.2220
## site3:viewcat3      0.37710    3.79107   0.099   0.9209
## site4:viewcat3     -2.80346    4.29718  -0.652   0.5155
## site5:viewcat3           NA         NA      NA       NA
## site2:viewcat4    -10.05730    5.41641  -1.857   0.0660 .
## site3:viewcat4      0.44685    3.97489   0.112   0.9107
## site4:viewcat4     -6.50503    5.02542  -1.294   0.1982
## site5:viewcat4     -5.38827    6.86392  -0.785   0.4341
## site2:setting2     -2.14597    2.85874  -0.751   0.4544
## site3:setting2     -4.76023    3.27414  -1.454   0.1488
## site4:setting2     -7.31658    3.36428  -2.175   0.0317 *
## site5:setting2           NA         NA      NA       NA
## site2:viewenc2     -2.72744    2.69364  -1.013   0.3135
## site3:viewenc2     -1.35549    3.41756  -0.397   0.6924
## site4:viewenc2     -1.50418    3.13649  -0.480   0.6325
## site5:viewenc2      6.83681    7.33431   0.932   0.3533
## sex2:age           -0.16226    0.13085  -1.240   0.2176
## sex2:viewcat2       2.21351    2.73976   0.808   0.4208
## sex2:viewcat3       2.04053    2.59625   0.786   0.4336
## sex2:viewcat4      -0.65653    2.77395  -0.237   0.8133
## sex2:setting2      -0.04353    1.76164  -0.025   0.9803
## sex2:viewenc2       1.03717    2.00619   0.517   0.6062
## age:viewcat2        0.29579    0.27072   1.093   0.2769
## age:viewcat3        0.28309    0.24461   1.157   0.2496
## age:viewcat4        0.08420    0.26943   0.312   0.7552
## age:setting2       -0.22758    0.15922  -1.429   0.1557
## age:viewenc2        0.12555    0.18746   0.670   0.5044
## viewcat2:setting2  -2.23219    3.42442  -0.652   0.5158
## viewcat3:setting2  -0.89840    3.31494  -0.271   0.7869
## viewcat4:setting2  -1.33874    3.64908  -0.367   0.7144
## viewcat2:viewenc2   3.29199    3.66533   0.898   0.3710
## viewcat3:viewenc2   1.09871    3.45902   0.318   0.7514
## viewcat4:viewenc2   2.49482    3.74812   0.666   0.5070
```

```
## setting2:viewenc2   0.59013    2.39981   0.246   0.8062
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.371 on 112 degrees of freedom
## Multiple R-squared:  0.3558, Adjusted R-squared:  0.03945
## F-statistic: 1.125 on 55 and 112 DF,  p-value: 0.2971
```

```
AIC(lin.mod4.full)
```

```
## [1] 1018.209
```

```
yhat <- predict(lin.mod4.full, newdata = testing)
```

```
## Warning in predict.lm(lin.mod4.full, newdata = testing): prediction from a rank-
## deficient fit may be misleading
```

```
y.test <- testing[, "numbDiff"]

# Test MSE
mean((yhat-y.test)^2)
```

```
## [1] 28.23554
```

```
lin.mod5.full <- lm(relatDiff ~ (site + sex + age + viewcat + setting + viewenc)^2, data = training)
summary(lin.mod5.full)
```

```
##
## Call:
## lm(formula = relatDiff ~ (site + sex + age + viewcat + setting +
##     viewenc)^2, data = training)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -10.1381  -2.1057  -0.0037   1.9658  11.4625
##
## Coefficients: (2 not defined because of singularities)
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)        17.06032   14.42797   1.182   0.2395
## site2              -4.32400   13.52644  -0.320   0.7498
## site3               0.09709    9.00410   0.011   0.9914
## site4               8.82232   16.25789   0.543   0.5885
## site5              10.23066   17.16031   0.596   0.5523
## sex2               11.05162    6.70134   1.649   0.1019
## age                -0.19817    0.26391  -0.751   0.4543
## viewcat2          -12.06564   14.57356  -0.828   0.4095
## viewcat3           -1.76765   13.17395  -0.134   0.8935
## viewcat4           12.95777   14.33425   0.904   0.3679
## setting2            5.49314    8.98598   0.611   0.5422
## viewenc2            1.41758   10.06221   0.141   0.8882
## site2:sex2         -2.89712    2.19441  -1.320   0.1895
## site3:sex2         -1.50609    2.13887  -0.704   0.4828
## site4:sex2         -5.48305    2.59720  -2.111   0.0370 *
## site5:sex2         -2.72621    3.66325  -0.744   0.4583
## site2:age           0.14657    0.23693   0.619   0.5374
## site3:age           0.09339    0.16902   0.553   0.5817
## site4:age           0.11553    0.30171   0.383   0.7025
```

```
## site5:age          -0.12613    0.33217  -0.380   0.7049
## site2:viewcat2      1.39325    5.42864   0.257   0.7979
## site3:viewcat2      0.58876    3.83201   0.154   0.8782
## site4:viewcat2     -3.40928    3.84612  -0.886   0.3773
## site5:viewcat2     -0.56097    6.19798  -0.091   0.9280
## site2:viewcat3     -0.72033    5.08257  -0.142   0.8876
## site3:viewcat3     -0.90613    3.61305  -0.251   0.8024
## site4:viewcat3     -7.73848    4.09539  -1.890   0.0614 .
## site5:viewcat3           NA         NA      NA       NA
## site2:viewcat4     -3.95053    5.16206  -0.765   0.4457
## site3:viewcat4     -1.08877    3.78824  -0.287   0.7743
## site4:viewcat4     -3.82113    4.78943  -0.798   0.4267
## site5:viewcat4     -1.25414    6.54160  -0.192   0.8483
## site2:setting2     -0.87824    2.72449  -0.322   0.7478
## site3:setting2     -3.25960    3.12039  -1.045   0.2985
## site4:setting2     -6.71576    3.20629  -2.095   0.0385 *
## site5:setting2           NA         NA      NA       NA
## site2:viewenc2      0.09165    2.56715   0.036   0.9716
## site3:viewenc2      0.08926    3.25707   0.027   0.9782
## site4:viewenc2     -5.67745    2.98920  -1.899   0.0601 .
## site5:viewenc2     -1.58031    6.98990  -0.226   0.8215
## sex2:age           -0.10161    0.12470  -0.815   0.4169
## sex2:viewcat2      -0.32485    2.61110  -0.124   0.9012
## sex2:viewcat3      -0.81092    2.47433  -0.328   0.7437
## sex2:viewcat4      -2.75732    2.64369  -1.043   0.2992
## sex2:setting2      -3.19781    1.67891  -1.905   0.0594 .
## sex2:viewenc2      -0.94590    1.91198  -0.495   0.6218
## age:viewcat2        0.29068    0.25801   1.127   0.2623
## age:viewcat3        0.09494    0.23312   0.407   0.6846
## age:viewcat4       -0.11889    0.25678  -0.463   0.6443
## age:setting2       -0.01405    0.15175  -0.093   0.9264
## age:viewenc2        0.06598    0.17866   0.369   0.7126
## viewcat2:setting2  -2.52471    3.26361  -0.774   0.4408
## viewcat3:setting2  -0.09666    3.15927  -0.031   0.9756
## viewcat4:setting2   2.70973    3.47772   0.779   0.4375
## viewcat2:viewenc2  -2.40402    3.49321  -0.688   0.4928
## viewcat3:viewenc2  -1.85347    3.29659  -0.562   0.5751
## viewcat4:viewenc2  -2.73805    3.57212  -0.767   0.4450
## setting2:viewenc2  -3.01217    2.28711  -1.317   0.1905
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.165 on 112 degrees of freedom
## Multiple R-squared:  0.4263, Adjusted R-squared:  0.1446
## F-statistic: 1.513 on 55 and 112 DF,  p-value: 0.03312
```

```
AIC(lin.mod5.full)
```

```
## [1] 1002.049
```

```
yhat <- predict(lin.mod5.full, newdata = testing)
```

```
## Warning in predict.lm(lin.mod5.full, newdata = testing): prediction from a rank-
## deficient fit may be misleading
```

```r
y.test <- testing[, "relatDiff"]

# Test MSE
mean((yhat-y.test)^2)
```

```
## [1] 23.63526
```

```r
lin.mod6.full <- lm(clasfDiff ~ (site + sex + age + viewcat + setting + viewenc)^2, data = training)
summary(lin.mod6.full)
```

```
##
## Call:
## lm(formula = clasfDiff ~ (site + sex + age + viewcat + setting +
##     viewenc)^2, data = training)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11.6108  -3.1873   0.0668   3.0854  10.7635
##
## Coefficients: (2 not defined because of singularities)
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         31.86932   20.13470   1.583   0.1163
## site2                5.71113   18.87658   0.303   0.7628
## site3              -11.78957   12.56551  -0.938   0.3501
## site4              -35.64786   22.68842  -1.571   0.1190
## site5              -56.84008   23.94777  -2.374   0.0193 *
## sex2                16.72781    9.35194   1.789   0.0764 .
## age                 -0.37531    0.36829  -1.019   0.3104
## viewcat2           -33.62976   20.33787  -1.654   0.1010
## viewcat3           -33.98623   18.38467  -1.849   0.0672 .
## viewcat4           -12.80847   20.00391  -0.640   0.5233
## setting2            25.39476   12.54023   2.025   0.0452 *
## viewenc2            -9.74311   14.04214  -0.694   0.4892
## site2:sex2          -0.52039    3.06238  -0.170   0.8654
## site3:sex2           2.53032    2.98486   0.848   0.3984
## site4:sex2          -3.37095    3.62448  -0.930   0.3543
## site5:sex2          -4.87172    5.11219  -0.953   0.3427
## site2:age            0.08205    0.33065   0.248   0.8045
## site3:age            0.16320    0.23587   0.692   0.4904
## site4:age            0.80312    0.42105   1.907   0.0590 .
## site5:age            1.15008    0.46355   2.481   0.0146 *
## site2:viewcat2      -2.93114    7.57584  -0.387   0.6996
## site3:viewcat2       5.06294    5.34770   0.947   0.3458
## site4:viewcat2       3.68884    5.36739   0.687   0.4933
## site5:viewcat2       5.58665    8.64949   0.646   0.5197
## site2:viewcat3      -8.51958    7.09289  -1.201   0.2322
## site3:viewcat3       0.53577    5.04213   0.106   0.9156
## site4:viewcat3       1.94832    5.71524   0.341   0.7338
## site5:viewcat3            NA         NA      NA       NA
## site2:viewcat4     -11.97418    7.20383  -1.662   0.0993 .
## site3:viewcat4       6.67420    5.28661   1.262   0.2094
## site4:viewcat4      -7.87519    6.68380  -1.178   0.2412
## site5:viewcat4      -2.47008    9.12901  -0.271   0.7872
## site2:setting2       3.68492    3.80212   0.969   0.3345
```

```
## site3:setting2     -6.53049    4.35461  -1.500   0.1365
## site4:setting2     -3.60393    4.47448  -0.805   0.4223
## site5:setting2           NA         NA      NA       NA
## site2:viewenc2     -3.02265    3.58254  -0.844   0.4006
## site3:viewenc2      3.51672    4.54535   0.774   0.4407
## site4:viewenc2      1.12474    4.17152   0.270   0.7879
## site5:viewenc2     12.00787    9.75463   1.231   0.2209
## sex2:age           -0.28474    0.17403  -1.636   0.1046
## sex2:viewcat2       1.58139    3.64388   0.434   0.6651
## sex2:viewcat3       1.22311    3.45301   0.354   0.7238
## sex2:viewcat4      -3.07878    3.68935  -0.835   0.4058
## sex2:setting2      -3.66101    2.34297  -1.563   0.1210
## sex2:viewenc2       1.89995    2.66823   0.712   0.4779
## age:viewcat2        0.59861    0.36006   1.663   0.0992 .
## age:viewcat3        0.67510    0.32533   2.075   0.0403 *
## age:viewcat4        0.32333    0.35835   0.902   0.3688
## age:setting2       -0.32330    0.21177  -1.527   0.1297
## age:viewenc2       -0.03592    0.24933  -0.144   0.8857
## viewcat2:setting2  -9.02471    4.55447  -1.982   0.0500 *
## viewcat3:setting2  -7.57750    4.40886  -1.719   0.0884 .
## viewcat4:setting2  -1.82366    4.85327  -0.376   0.7078
## viewcat2:viewenc2  10.57132    4.87489   2.169   0.0322 *
## viewcat3:viewenc2  11.25111    4.60050   2.446   0.0160 *
## viewcat4:viewenc2   6.93655    4.98500   1.391   0.1668
## setting2:viewenc2   1.22748    3.19174   0.385   0.7013
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.813 on 112 degrees of freedom
## Multiple R-squared:  0.4256, Adjusted R-squared:  0.1436
## F-statistic: 1.509 on 55 and 112 DF,  p-value: 0.03404
```

```
AIC(lin.mod6.full)
```

```
## [1] 1114.029
```

```
yhat <- predict(lin.mod6.full, newdata = testing)
```

```
## Warning in predict.lm(lin.mod6.full, newdata = testing): prediction from a rank-
## deficient fit may be misleading
```

```
y.test <- testing[, "clasfDiff"]

# Test MSE
mean((yhat-y.test)^2)
```

```
## [1] 65.41
```

Regression Tree Models

In the context of a regression tree, the deviance is simply the sum of the squared errors.

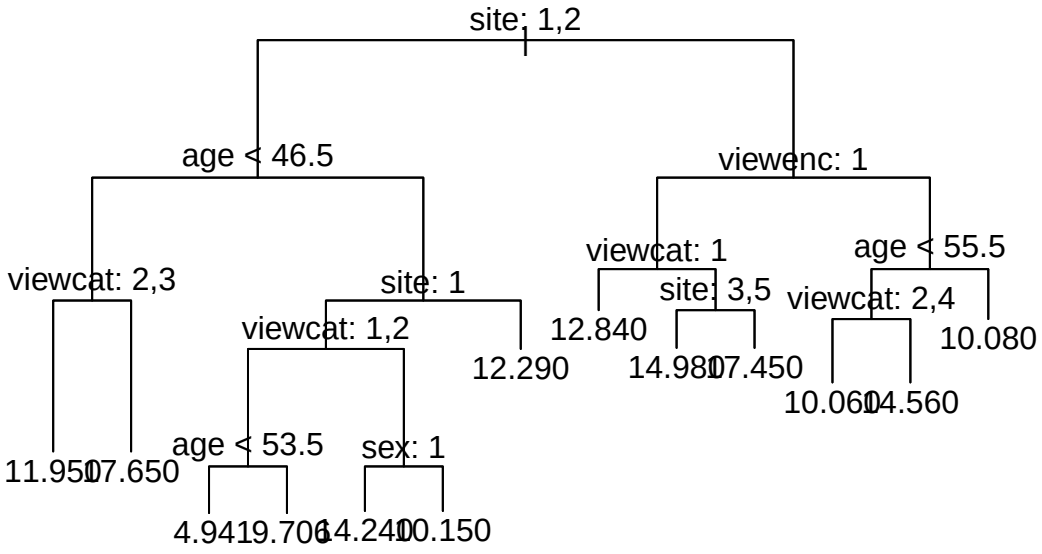
Model 1

```
set.seed(1)
```

```
reg.tree.1 <- tree(bodyDiff ~ site + sex + age + viewcat + setting + viewenc, sesame.q1, subset = train)
summary(reg.tree.1)
```

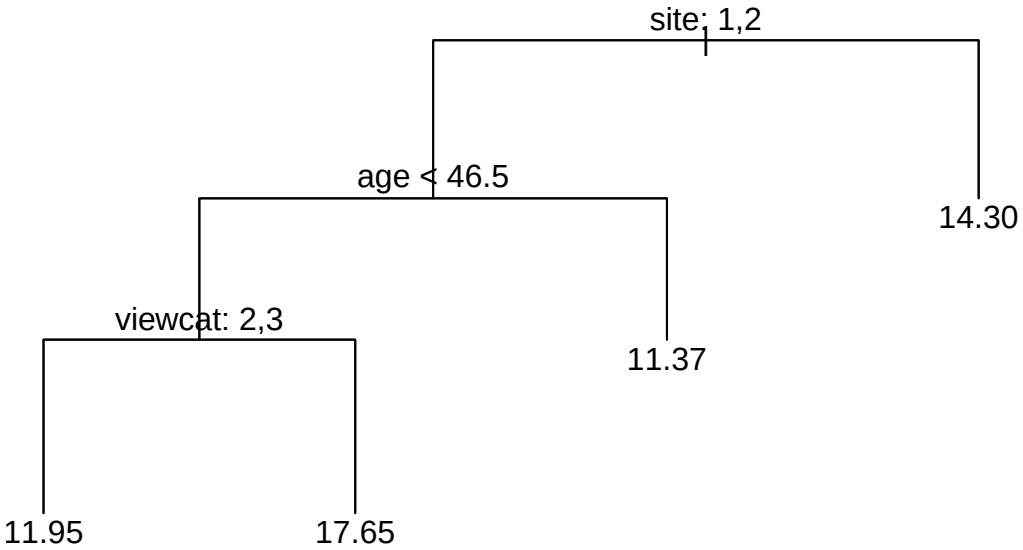
```
##
## Regression tree:
## tree(formula = bodyDiff ~ site + sex + age + viewcat + setting +
##     viewenc, data = sesame.q1, subset = train)
## Variables actually used in tree construction:
## [1] "site"    "age"     "viewcat" "sex"     "viewenc"
## Number of terminal nodes:  13
## Residual mean deviance:  14.16 = 2194 / 155
## Distribution of residuals:
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## -11.08000  -2.45100  -0.06303   0.00000   2.16900  12.55000
```

```
plot(reg.tree.1)
text(reg.tree.1, pretty = 0)
```




```
cv.reg.tree.1  <- cv.tree(reg.tree.1)
plot(cv.reg.tree.1$size, cv.reg.tree.1$dev, type = "b")
```


```
prune.reg.tree.1  <- prune.tree(reg.tree.1, best = 4)
plot(prune.reg.tree.1)
text(prune.reg.tree.1, pretty = 0)
```




```
yhat <- predict(prune.reg.tree.1, newdata = testing)
y.test <- testing[, "bodyDiff"]

# Test MSE
mean((yhat-y.test)^2)
```

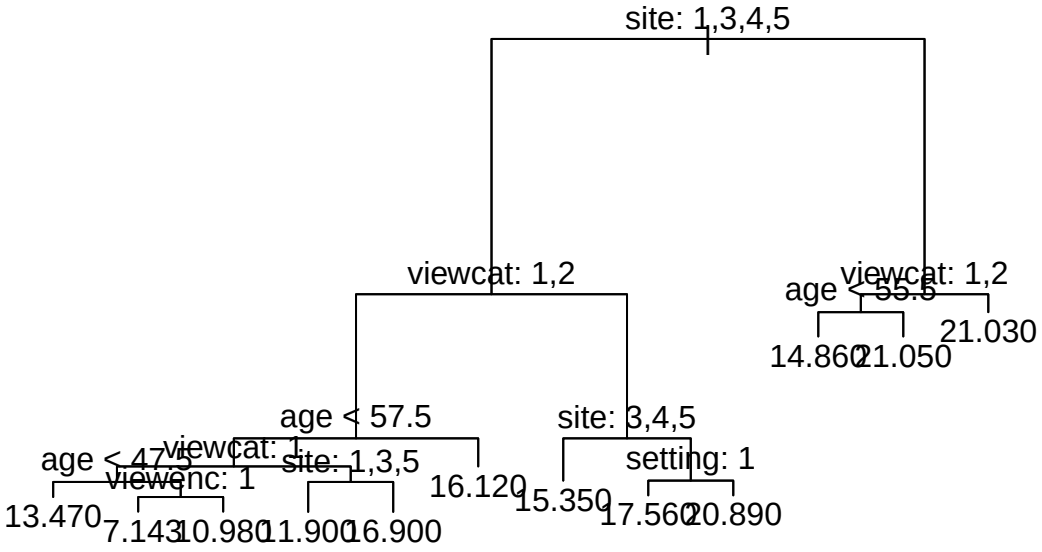
```
## [1] 20.60159
```

Model 2

```
set.seed(1)

reg.tree.2 <- tree(letDiff ~ site + sex + age + viewcat + setting + viewenc, sesame.q1, subset = train)
summary(reg.tree.2)
```

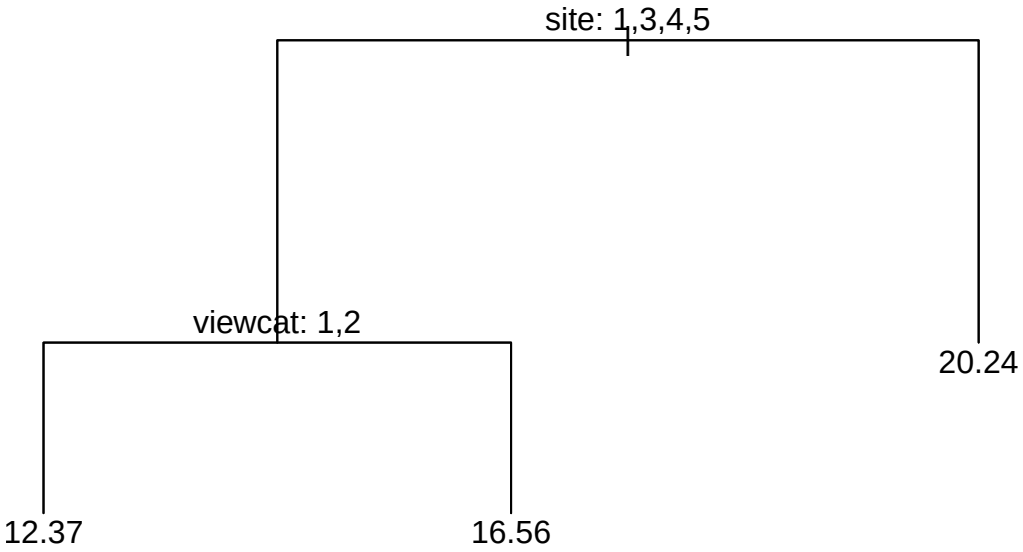
```
##
## Regression tree:
## tree(formula = letDiff ~ site + sex + age + viewcat + setting +
##     viewenc, data = sesame.q1, subset = train)
## Variables actually used in tree construction:
## [1] "site"    "viewcat" "age"     "viewenc" "setting"
## Number of terminal nodes:  12
## Residual mean deviance:  18.63 = 2906 / 156
## Distribution of residuals:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -17.560  -2.430   0.000   0.000   2.765   9.587
```

```
plot(reg.tree.2)
text(reg.tree.2, pretty = 0)
```




```
cv.reg.tree.2  <- cv.tree(reg.tree.2)
plot(cv.reg.tree.2$size, cv.reg.tree.2$dev, type = "b")
```


```
prune.reg.tree.2  <- prune.tree(reg.tree.2, best = 3)
plot(prune.reg.tree.2)
text(prune.reg.tree.2, pretty = 0)
```




```
yhat <- predict(prune.reg.tree.2, newdata = testing)
y.test <- testing[, "letDiff"]

# Test MSE
mean((yhat-y.test)^2)
```

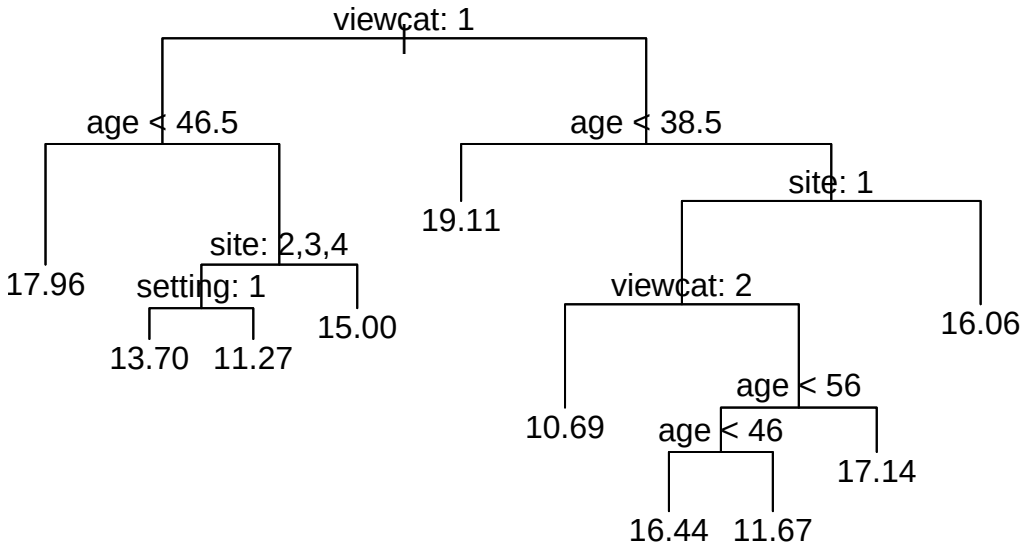
```
## [1] 15.4124
```

Model 3

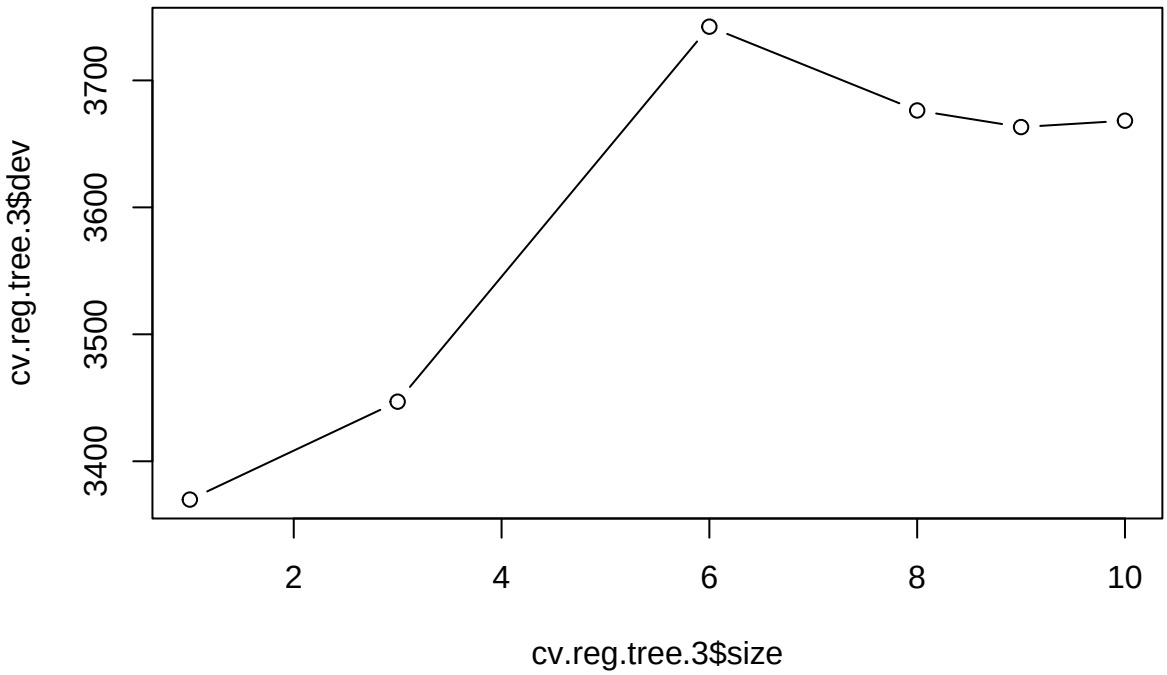
```
set.seed(1)

reg.tree.3 <- tree(formDiff ~ site + sex + age + viewcat + setting + viewenc, sesame.q1, subset = train)
summary(reg.tree.3)
```

```
##
## Regression tree:
## tree(formula = formDiff ~ site + sex + age + viewcat + setting +
##     viewenc, data = sesame.q1, subset = train)
## Variables actually used in tree construction:
## [1] "viewcat" "age"     "site"    "setting"
## Number of terminal nodes:  10
## Residual mean deviance:  15.88 = 2509 / 158
## Distribution of residuals:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -11.610  -1.667   0.129   0.000   2.159  13.940
```

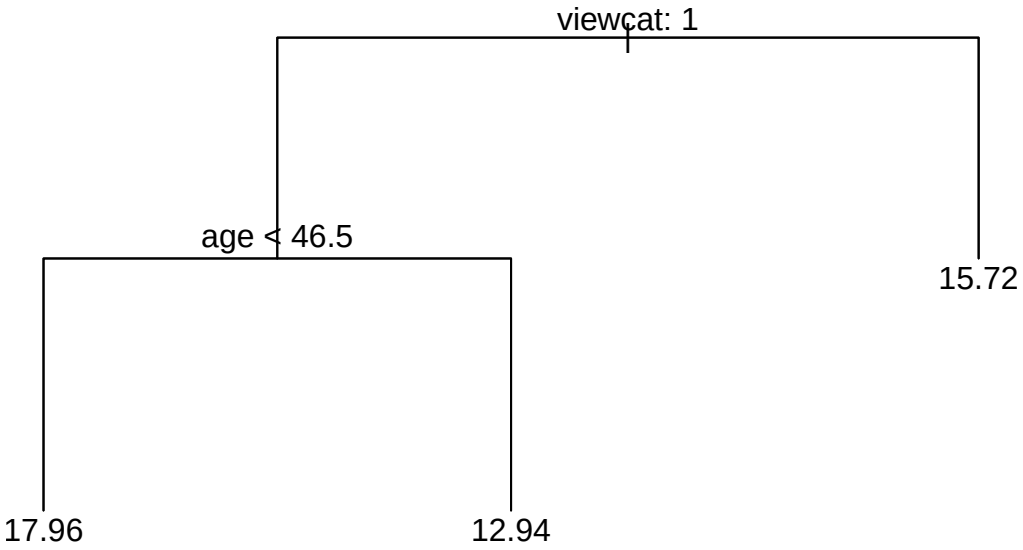
```
plot(reg.tree.3)
text(reg.tree.3, pretty = 0)
```




```
cv.reg.tree.3  <- cv.tree(reg.tree.3)
plot(cv.reg.tree.3$size, cv.reg.tree.3$dev, type = "b")
```




```
prune.reg.tree.3  <- prune.tree(reg.tree.3, best = 2)
plot(prune.reg.tree.3)
text(prune.reg.tree.3, pretty = 0)
```




```
yhat <- predict(prune.reg.tree.3, newdata = testing)
y.test <- testing[, "formDiff"]

# Test MSE
mean((yhat-y.test)^2)
```

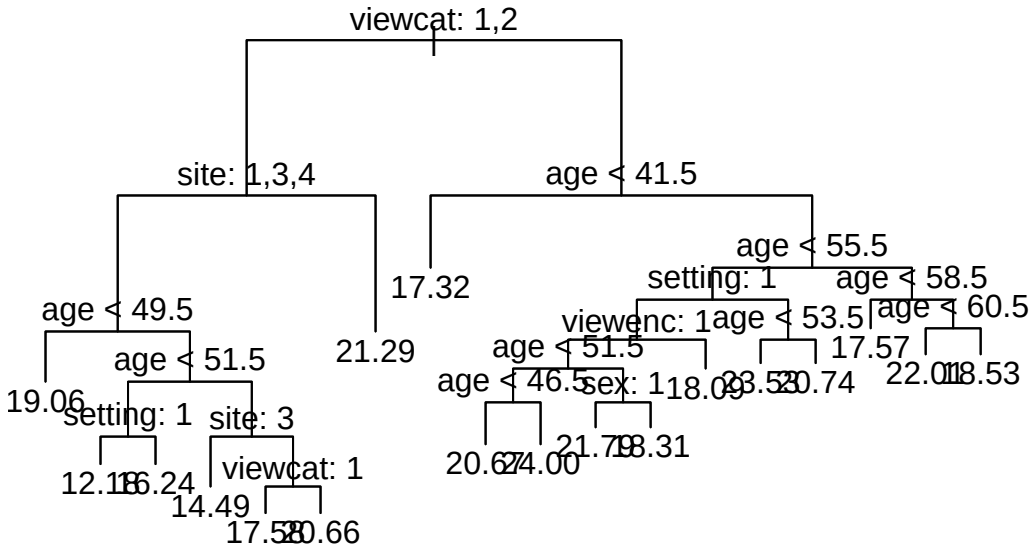
```
## [1] 14.92273
```

Model 4

```
set.seed(1)

reg.tree.4 <- tree(numbDiff ~ site + sex + age + viewcat + setting + viewenc, sesame.q1, subset = train)
summary(reg.tree.4)
```

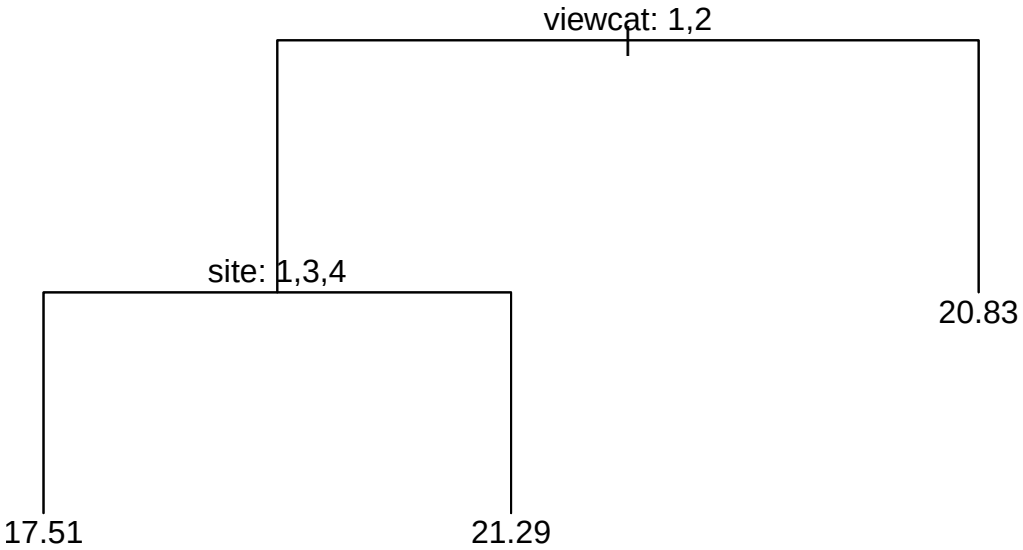
```
##
## Regression tree:
## tree(formula = numbDiff ~ site + sex + age + viewcat + setting +
##     viewenc, data = sesame.q1, subset = train)
## Number of terminal nodes:  18
## Residual mean deviance:  13.64 = 2046 / 150
## Distribution of residuals:
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -18.0900  -2.1210   0.2647   0.0000   2.1180  11.4700
```

```
plot(reg.tree.4)
text(reg.tree.4, pretty = 0)
```




```
cv.reg.tree.4  <- cv.tree(reg.tree.4)
plot(cv.reg.tree.4$size, cv.reg.tree.4$dev, type = "b")
```


```
prune.reg.tree.4  <- prune.tree(reg.tree.4, best = 3)
plot(prune.reg.tree.4)
text(prune.reg.tree.4, pretty = 0)
```




```
yhat <- predict(prune.reg.tree.4, newdata = testing)
y.test <- testing[, "numbDiff"]

# Test MSE
mean((yhat-y.test)^2)
```

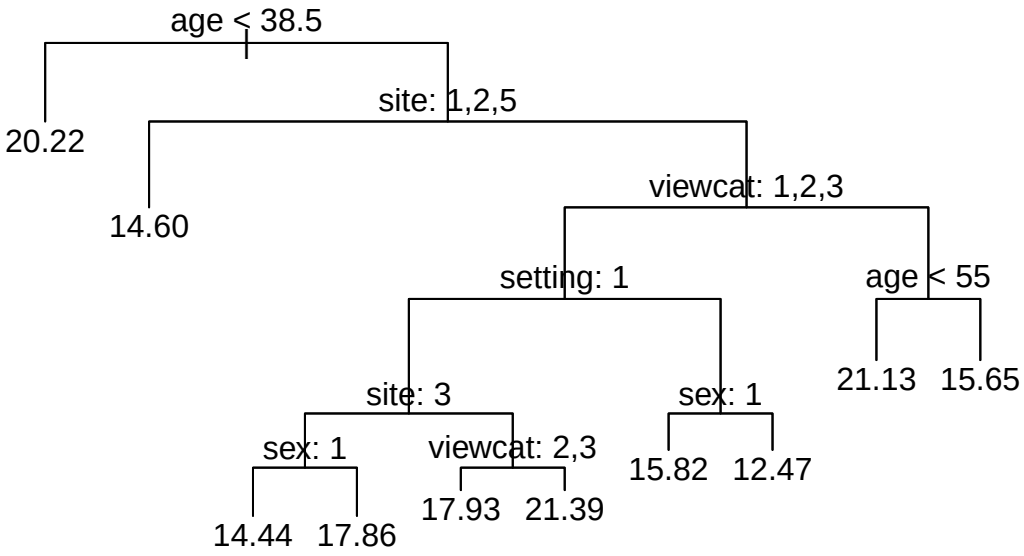
```
## [1] 15.90771
```

Model 5

```
set.seed(1)

reg.tree.5 <- tree(relatDiff ~ site + sex + age + viewcat + setting + viewenc, sesame.q1, subset = train
summary(reg.tree.5)
```

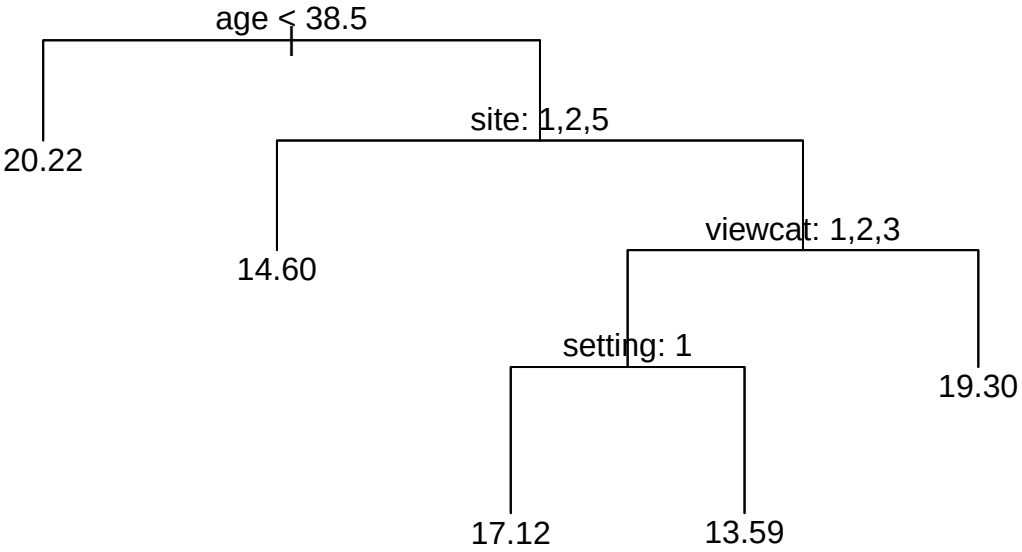
```
##
## Regression tree:
## tree(formula = relatDiff ~ site + sex + age + viewcat + setting +
##     viewenc, data = sesame.q1, subset = train)
## Variables actually used in tree construction:
## [1] "age"     "site"    "viewcat" "setting" "sex"
## Number of terminal nodes:  10
## Residual mean deviance:  15.3 = 2418 / 158
## Distribution of residuals:
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -10.6900  -1.5650  -0.2514   0.0000   1.8950  11.4900
```

```
plot(reg.tree.5)
text(reg.tree.5, pretty = 0)
```




```
cv.reg.tree.5  <- cv.tree(reg.tree.5)
plot(cv.reg.tree.5$size, cv.reg.tree.5$dev, type = "b")
```


```
prune.reg.tree.5  <- prune.tree(reg.tree.5, best = 5)
plot(prune.reg.tree.5)
text(prune.reg.tree.5, pretty = 0)
```




```
yhat <- predict(prune.reg.tree.5, newdata = testing)
y.test <- testing[, "relatDiff"]

# Test MSE
mean((yhat-y.test)^2)
```

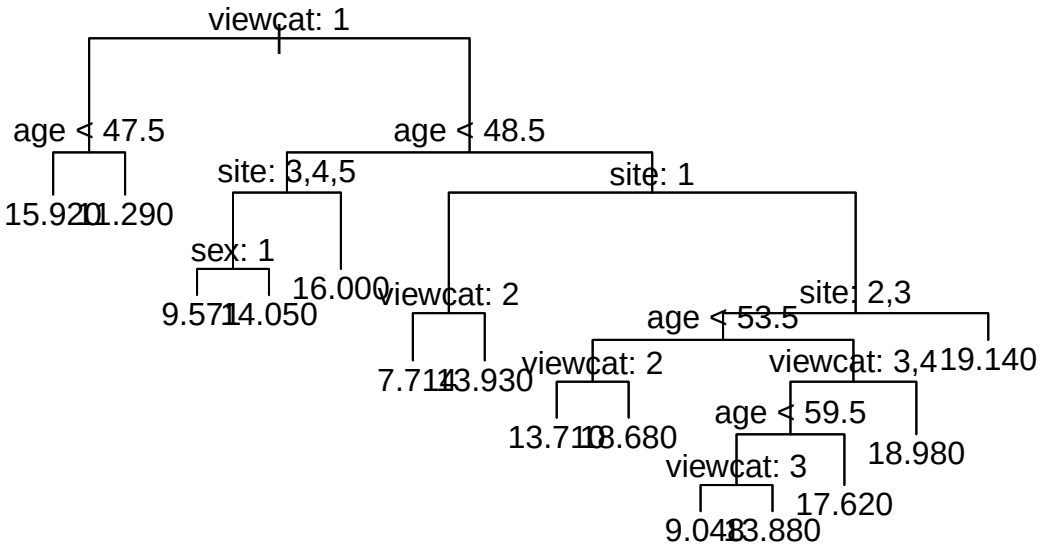
```
## [1] 19.88506
```

Model 6

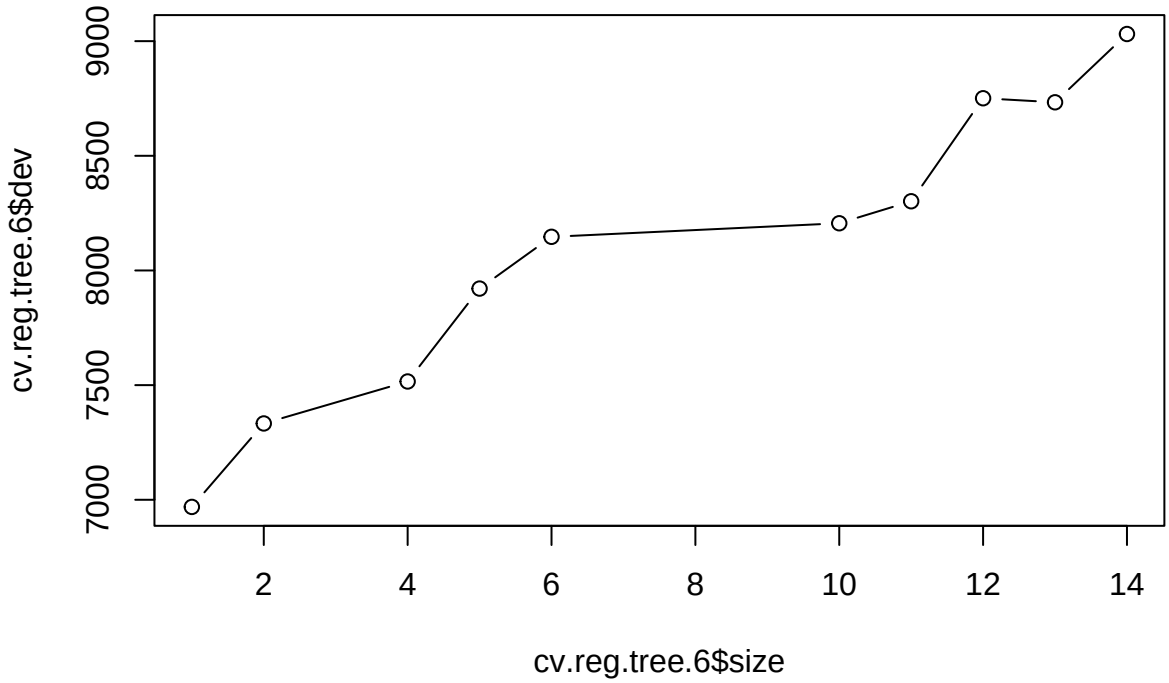
```
set.seed(1)

reg.tree.6 <- tree(clasfDiff ~ site + sex + age + viewcat + setting + viewenc, sesame.q1, subset = train
summary(reg.tree.6)
```

```
##
## Regression tree:
## tree(formula = clasfDiff ~ site + sex + age + viewcat + setting +
##     viewenc, data = sesame.q1, subset = train)
## Variables actually used in tree construction:
## [1] "viewcat" "age"     "site"    "sex"
## Number of terminal nodes:  14
## Residual mean deviance:  29.66 = 4568 / 154
## Distribution of residuals:
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
## -16.00000  -3.17300   0.01852   0.00000   3.71400  13.10000
```

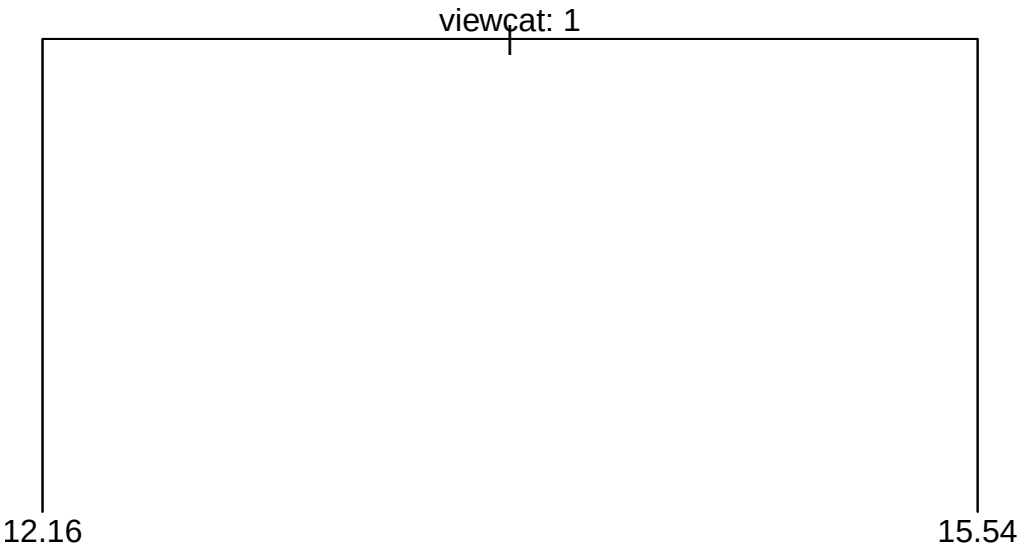
```
plot(reg.tree.6)
text(reg.tree.6, pretty = 0)
```




```
cv.reg.tree.6  <- cv.tree(reg.tree.6)
plot(cv.reg.tree.6$size, cv.reg.tree.6$dev, type = "b")
```




```
prune.reg.tree.6  <- prune.tree(reg.tree.6, best = 2)
plot(prune.reg.tree.6)
text(prune.reg.tree.6, pretty = 0)
```

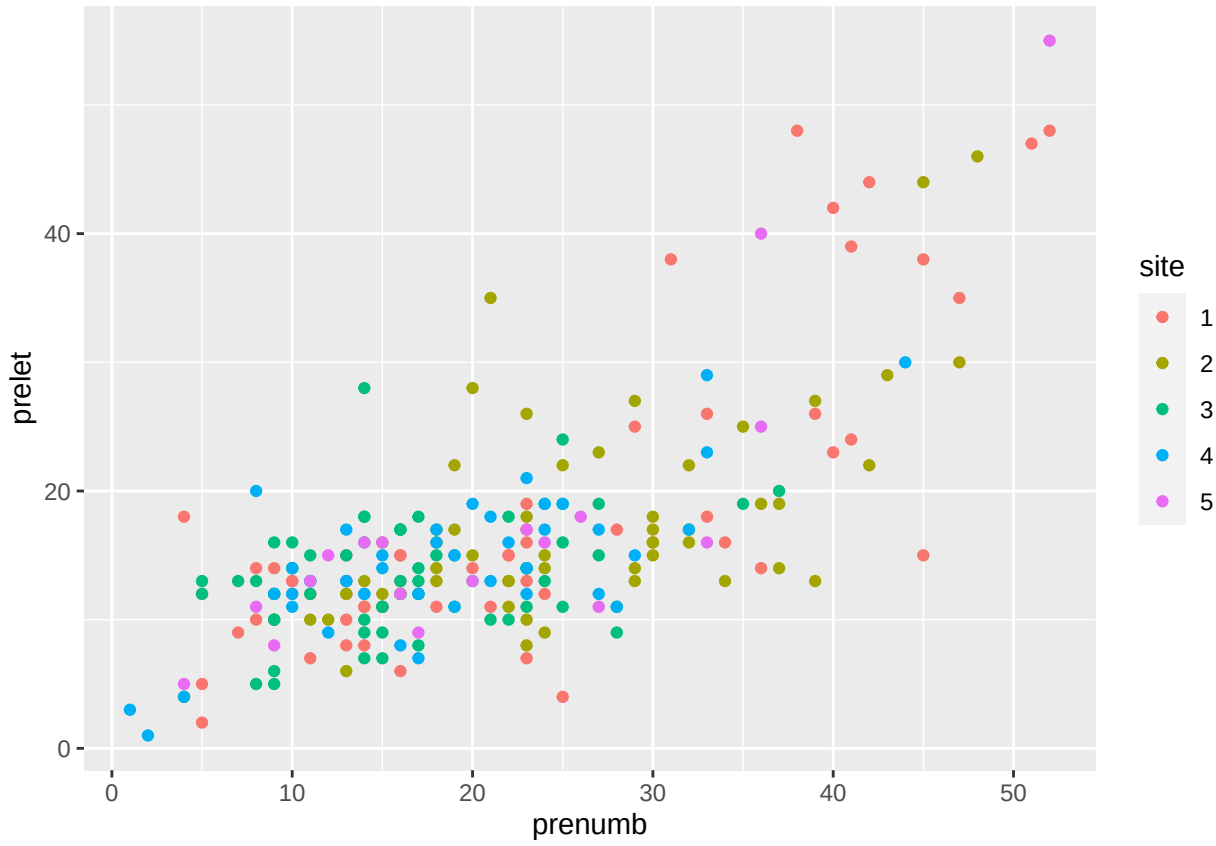



```
yhat <- predict(prune.reg.tree.6, newdata = testing)
y.test <- testing[, "clasfDiff"]

# Test MSE
mean((yhat-y.test)^2)
```

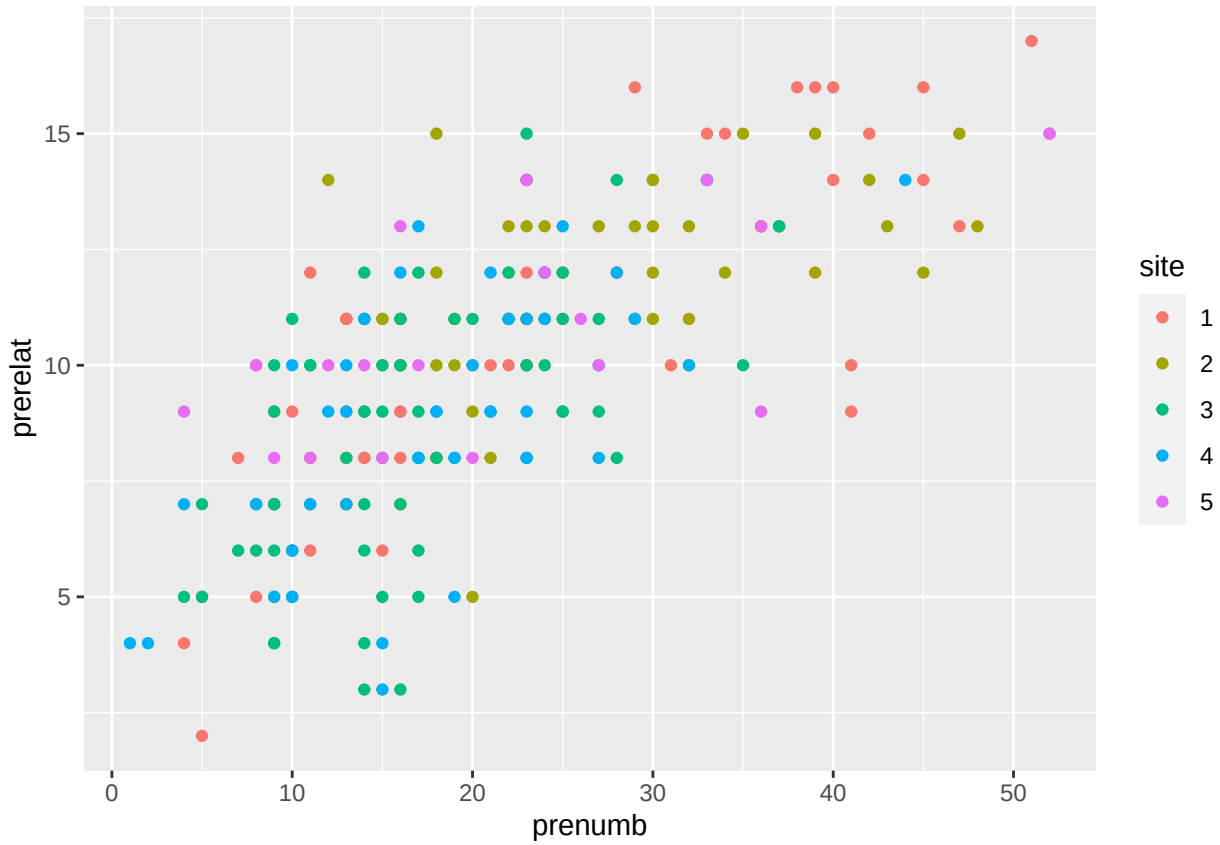
```
## [1] 45.52784
```

Q.2 Classification Question: Can we use the pre-test scores and other demographic variables to predict which region the children came from?

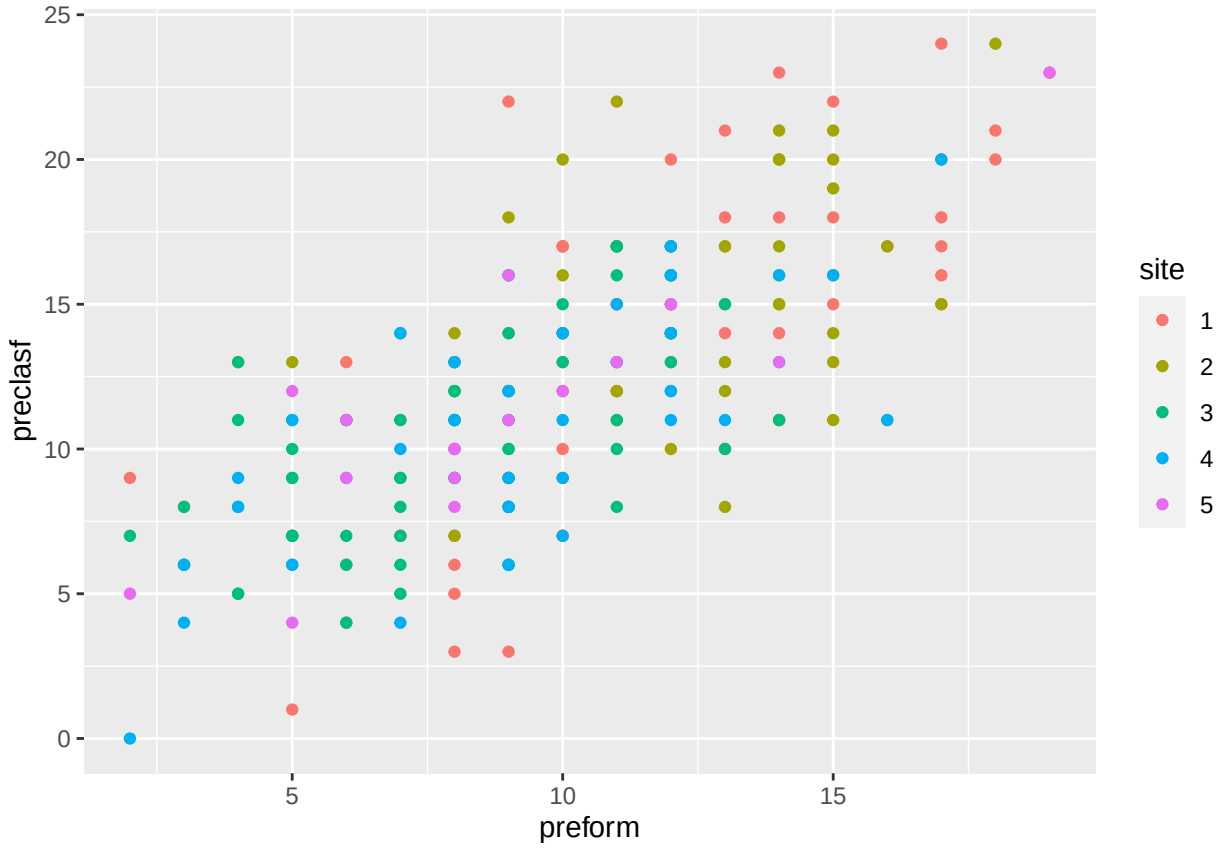
```
ggplot(data=sesame, aes(x=prenumb, y=prelet, color=site))+
  geom_point()
```



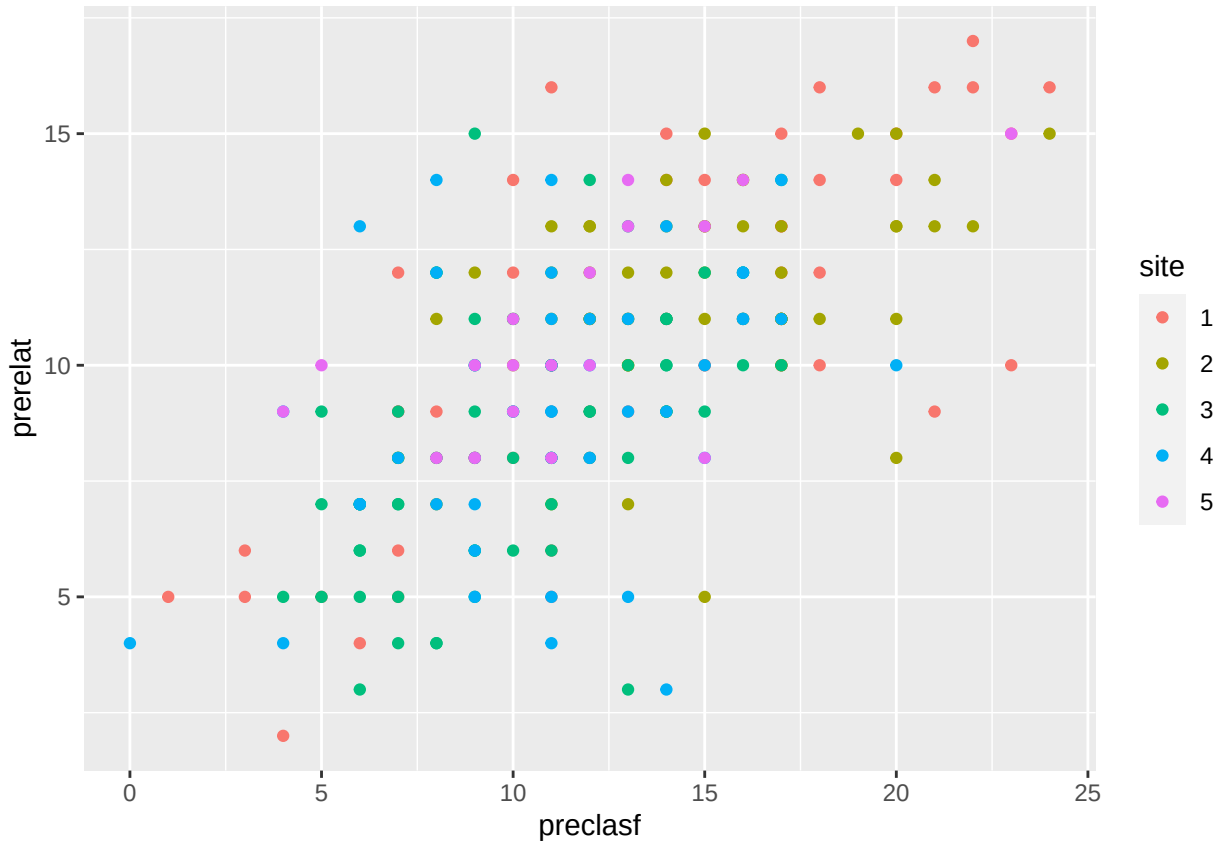

```
ggplot(data=sesame, aes(x=prenumb, y=prerelat, color=site))+
  geom_point()
```




```
ggplot(data=sesame, aes(x=preform, y=preclasf, color=site))+
  geom_point()
```




```
ggplot(data=sesame, aes(x=preclasf, y=prerelat, color=site))+
  geom_point()
```



SVM

```
set.seed(3241)

n <- nrow(sesame)
train.index <- sample(1:n, size = floor(0.7*n), replace=FALSE)
train.data <- sesame.sd[train.index,]
test.data <- sesame.sd[-train.index,]

train.data %>%
  count(site)
```

```
##   site  n
## 1    1 40
## 2    2 42
## 3    3 48
## 4    4 25
## 5    5 13
```

```
#1  60
#2  55
#3  64
#4  43
#5  18

total.weight <- 60+55+64+43+18
weight.1 <- total.weight/(5*60)
```

```r
weight.2 <- total.weight/(5*55)
weight.3 <- total.weight/(5*64)
weight.4 <- total.weight/(5*43)
weight.5 <- total.weight/(5*18)


weight.4 <- 1.5
weight.5 <- 3
# Response: site (categorical)
set.seed(315)
costs <- c(0.001, 0.01, 0.1, 1, 5, 10, 100)
# c(0.1, 0.2, 0.5, 0.7, 1, 2, 3, 4)
gammas <- seq(0, 4, by=0.1)

linear.tune <- tune(svm, site~female+ male + sd_age+sd_pBod+sd_plet+sd_pform + sd_pnumb+sd_prelat+sd_pc
                    data=train.data, kernel="linear",
                    ranges=list(cost=costs),
                    class.weights=c("1"=weight.1,
                                    "2"=weight.2,
                                    "3"=weight.3,
                                    "4"=weight.4,
                                    "5"=weight.5),
                    class.type="one.versus.one")

radial.tune <- tune(svm, site~female + male + sd_age+sd_pBod+sd_plet+sd_pform + sd_pnumb+sd_prelat+sd_p
                    data=train.data, kernel="radial",
                    ranges=list(cost=costs,
                                gamma=gammas),
                    class.weights=c("1"=weight.1,
                                    "2"=weight.2,
                                    "3"=weight.3,
                                    "4"=weight.4,
                                    "5"=weight.5))
#radial.tune <- tune(svm, site~sex+age+prebody+prelet+preform+prenumb+prerelat+preclasf,
#                    data=train.data, kernel="radial",
#                    ranges=list(cost=costs,
#                                gamma=gammas))

sigmoid.tune <- tune(svm, site~female + male + sd_age+sd_pBod+sd_plet+sd_pform + sd_pnumb+sd_prelat+sd_
                    data=train.data, kernel="sigmoid",
                    ranges=list(cost=costs,
                                gamma=gammas),
                    class.weights=c("1"=weight.1,
                                    "2"=weight.2,
                                    "3"=weight.3,
                                    "4"=weight.4,
                                    "5"=weight.5))
```

```r
linear.conMatrix <- table(true=test.data[, "site"],
                          pred=predict(linear.tune$best.model, newdata=test.data))

radial.conMatrix <- table(true=test.data[, "site"],
                          pred=predict(radial.tune$best.model, newdata=test.data))
```

```
sigmoid.conMatrix <- table(true=test.data[, "site"],
                           pred=predict(sigmoid.tune$best.model, newdata=test.data))

confusionMatrix(linear.conMatrix)
```

```
## Confusion Matrix and Statistics
##
##     pred
## true  1  2  3  4  5
##    1  6  1  6  2  5
##    2  1  7  1  1  3
##    3  0  1 11  1  3
##    4  3  3  9  3  0
##    5  0  1  1  1  2
##
## Overall Statistics
##
##                Accuracy : 0.4028
##                  95% CI : (0.2888, 0.525)
##     No Information Rate : 0.3889
##     P-Value [Acc > NIR] : 0.44844
##
##                   Kappa : 0.2554
##
##  Mcnemar's Test P-Value : 0.01728
##
## Statistics by Class:
##
##                      Class: 1 Class: 2 Class: 3 Class: 4 Class: 5
## Sensitivity           0.60000  0.53846   0.3929  0.37500  0.15385
## Specificity           0.77419  0.89831   0.8864  0.76562  0.94915
## Pos Pred Value        0.30000  0.53846   0.6875  0.16667  0.40000
## Neg Pred Value        0.92308  0.89831   0.6964  0.90741  0.83582
## Prevalence            0.13889  0.18056   0.3889  0.11111  0.18056
## Detection Rate        0.08333  0.09722   0.1528  0.04167  0.02778
## Detection Prevalence  0.27778  0.18056   0.2222  0.25000  0.06944
## Balanced Accuracy     0.68710  0.71838   0.6396  0.57031  0.55150
```

```
confusionMatrix(radial.conMatrix)
```

```
## Confusion Matrix and Statistics
##
##     pred
## true  1  2  3  4  5
##    1  6  2  7  4  1
##    2  4  4  3  0  2
##    3  1  1 11  3  0
##    4  2  2  9  4  1
##    5  0  2  1  1  1
##
## Overall Statistics
##
##                Accuracy : 0.3611
##                  95% CI : (0.2512, 0.4829)
##     No Information Rate : 0.4306
```

```
##     P-Value [Acc > NIR] : 0.9056
##
##                   Kappa : 0.181
##
##  Mcnemar's Test P-Value : 0.1807
##
## Statistics by Class:
##
##                      Class: 1 Class: 2 Class: 3 Class: 4 Class: 5
## Sensitivity           0.46154  0.36364   0.3548  0.33333  0.20000
## Specificity           0.76271  0.85246   0.8780  0.76667  0.94030
## Pos Pred Value        0.30000  0.30769   0.6875  0.22222  0.20000
## Neg Pred Value        0.86538  0.88136   0.6429  0.85185  0.94030
## Prevalence            0.18056  0.15278   0.4306  0.16667  0.06944
## Detection Rate        0.08333  0.05556   0.1528  0.05556  0.01389
## Detection Prevalence  0.27778  0.18056   0.2222  0.25000  0.06944
## Balanced Accuracy     0.61213  0.60805   0.6164  0.55000  0.57015
```

```
confusionMatrix(sigmoid.conMatrix)
```

```
## Confusion Matrix and Statistics
##
##     pred
## true  1  2  3  4  5
##    1  1  1  6  9  3
##    2  1  3  4  5  0
##    3  1  0  4 11  0
##    4  0  0  7 11  0
##    5  0  0  3  2  0
##
## Overall Statistics
##
##                Accuracy : 0.2639
##                  95% CI : (0.167, 0.381)
##     No Information Rate : 0.5278
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.0434
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: 1 Class: 2 Class: 3 Class: 4 Class: 5
## Sensitivity           0.33333  0.75000  0.16667   0.2895  0.00000
## Specificity           0.72464  0.85294  0.75000   0.7941  0.92754
## Pos Pred Value        0.05000  0.23077  0.25000   0.6111  0.00000
## Neg Pred Value        0.96154  0.98305  0.64286   0.5000  0.95522
## Prevalence            0.04167  0.05556  0.33333   0.5278  0.04167
## Detection Rate        0.01389  0.04167  0.05556   0.1528  0.00000
## Detection Prevalence  0.27778  0.18056  0.22222   0.2500  0.06944
## Balanced Accuracy     0.52899  0.80147  0.45833   0.5418  0.46377
```

```
predict(linear.tune$best.model, newdata=test.data)
```

```
##   6   7   8   9  12  16  19  22  24  25  29  38  42  43  46  48  54  56  57  59
##   1   4   1   1   5   1   1   2   5   5   5   3   1   4   3   3   3   5   3   3
##  64  82  84  88  92  93  94  98  99 100 104 106 113 116 118 120 125 127 128 137
##   5   1   4   2   2   2   2   2   5   3   5   2   2   4   3   3   3   5   3   3
## 139 143 145 152 156 162 164 172 176 180 181 182 183 187 188 189 190 191 192 193
##   3   2   3   3   5   3   3   3   5   3   3   4   1   2   3   3   4   3   3   2
## 196 202 207 208 212 221 222 225 226 227 234 235
##   1   2   3   3   4   3   1   5   3   4   5   2
## Levels: 1 2 3 4 5
```

```
predict(radial.tune$best.model, newdata=test.data)
```

```
##   6   7   8   9  12  16  19  22  24  25  29  38  42  43  46  48  54  56  57  59
##   3   3   1   1   2   4   4   4   3   3   3   1   2   1   5   3   4   1   1   3
##  64  82  84  88  92  93  94  98  99 100 104 106 113 116 118 120 125 127 128 137
##   3   1   1   2   1   2   5   2   5   3   3   2   1   1   4   3   3   3   4   3
## 139 143 145 152 156 162 164 172 176 180 181 182 183 187 188 189 190 191 192 193
##   3   4   3   3   3   3   3   3   2   3   3   3   3   2   3   3   3   3   4   2
## 196 202 207 208 212 221 222 225 226 227 234 235
##   4   1   1   4   5   3   4   2   3   4   5   2
## Levels: 1 2 3 4 5
```

```
predict(sigmoid.tune$best.model, newdata=test.data)
```

```
##   6   7   8   9  12  16  19  22  24  25  29  38  42  43  46  48  54  56  57  59
##   5   3   3   3   4   1   4   2   3   4   5   4   4   4   3   4   4   5   3   4
##  64  82  84  88  92  93  94  98  99 100 104 106 113 116 118 120 125 127 128 137
##   4   3   4   3   3   2   1   2   4   4   4   3   2   4   4   3   4   4   3   4
## 139 143 145 152 156 162 164 172 176 180 181 182 183 187 188 189 190 191 192 193
##   4   3   4   4   1   4   3   4   4   4   4   4   4   3   4   4   4   3   3   4
## 196 202 207 208 212 221 222 225 226 227 234 235
##   3   4   4   3   3   4   3   3   4   3   4   3
## Levels: 1 2 3 4 5
```

```
test.data$site
```

```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 3 3 3 3 3
## [39] 3 3 3 3 3 3 3 3 3 3 3 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 5 5 5 5 5
## Levels: 1 2 3 4 5
```

Radial kernel improves prediction on class 1.

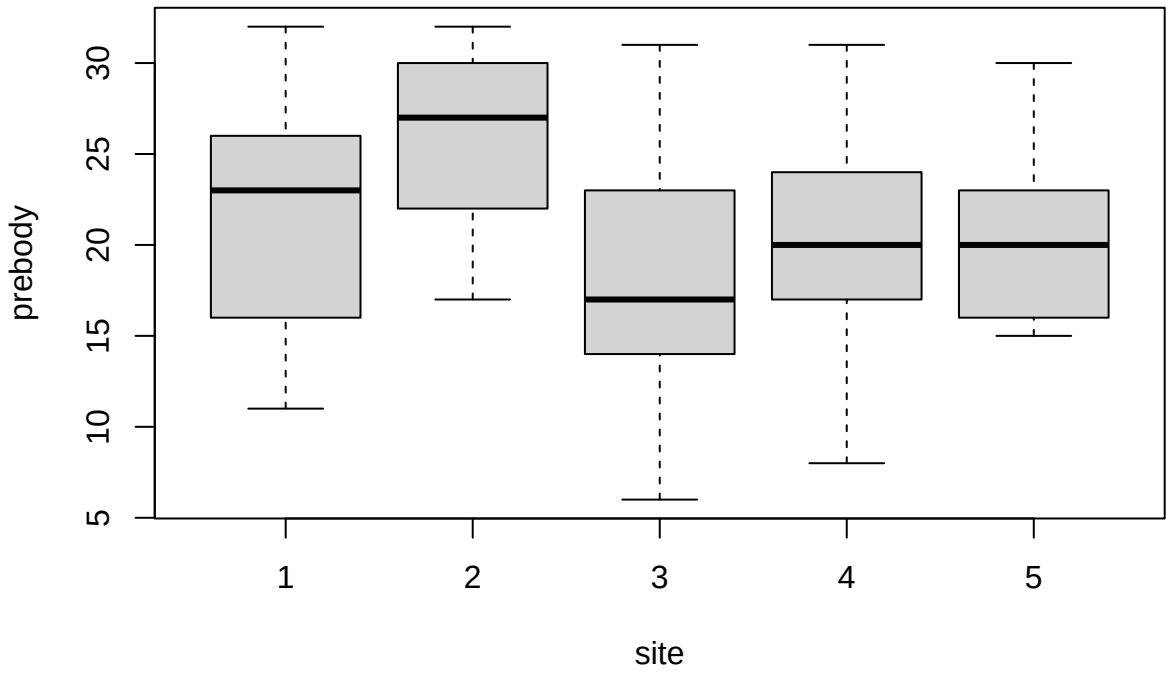
RBF slightly improved after standardizing? (it seems slightly more likely to predict on class 1.) thought, simpler models still retain the same performance (arguably better) sd_age+sd_pBod+sd_plet. But we are still not getting any prediction on class 4 & 5.

After assign class weights using this formula:

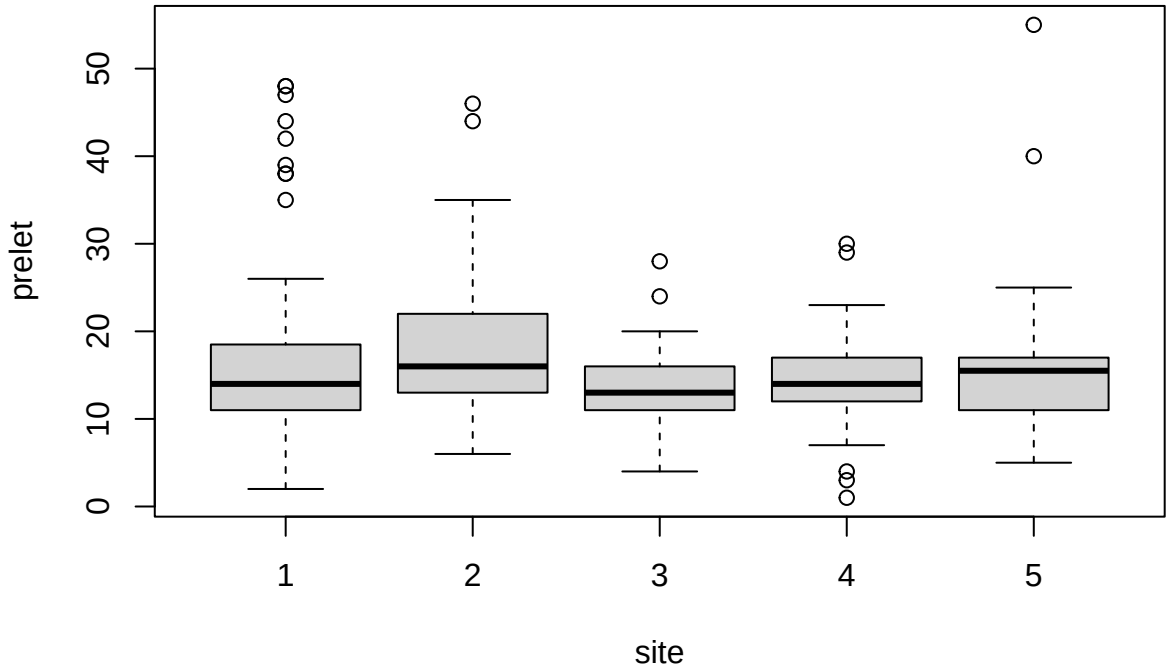
$$w_j = \frac{n}{kn_j}, \text{ n is total number of data points, k is number of classes}$$

Our model begins to make predictions on class 4 & class 5, though at the cost of overall accuracy. If we increase the weight for 4 & 5 to 1.5 and 3 respectively the performance of Radial SVM decreases but that of linear SVM increases to be comparable to Radial SVM's recorded highest accuracy (a little bit over 0.40).

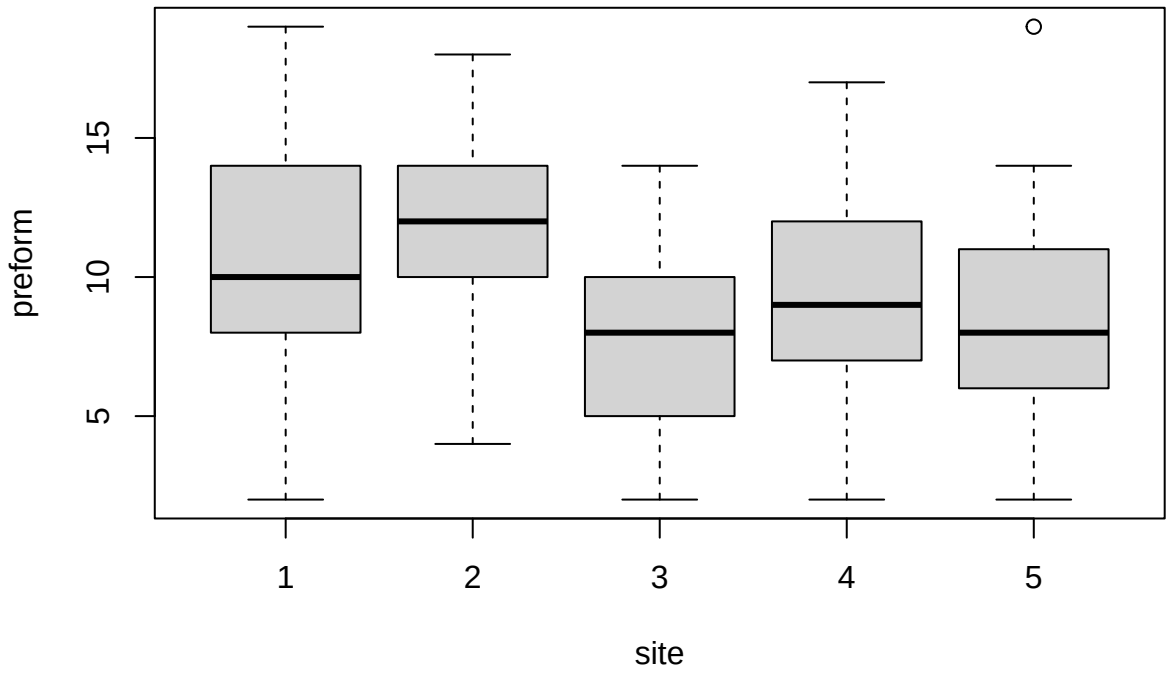
```
# trying to do more EDA to see if anything explains why the data is not linearly separable
boxplot(prebody~site, data=sesame)
```



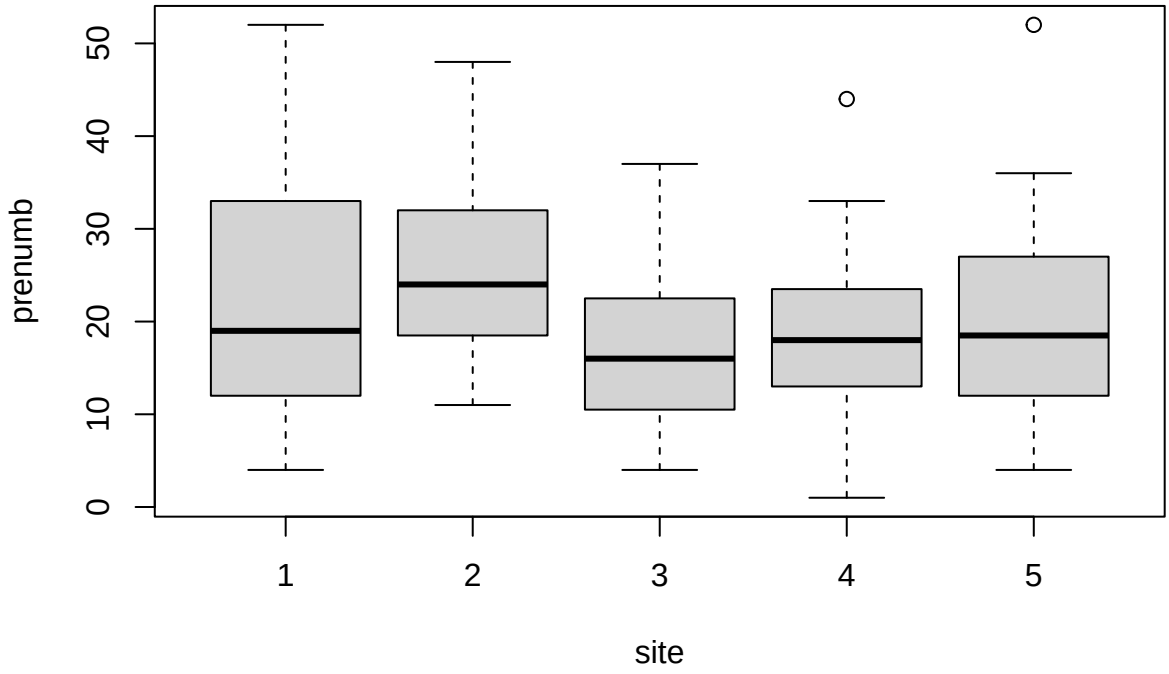

```
boxplot(prelet~site, data=sesame)
```



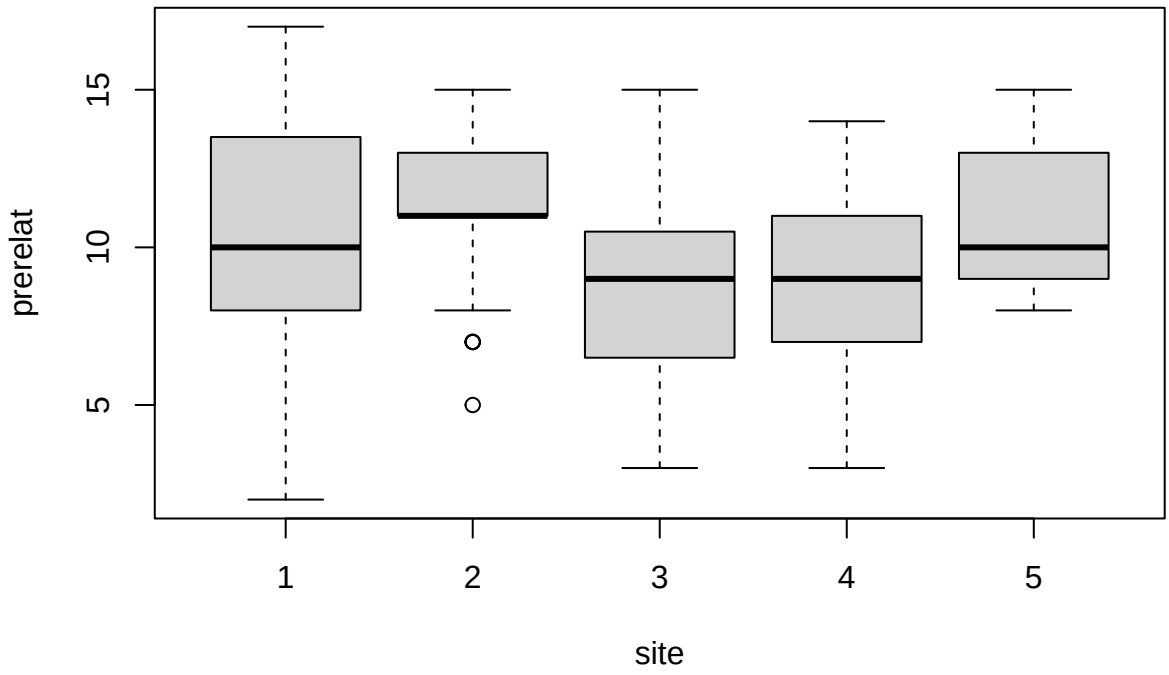

```
boxplot(preform~site, data=sesame)
```



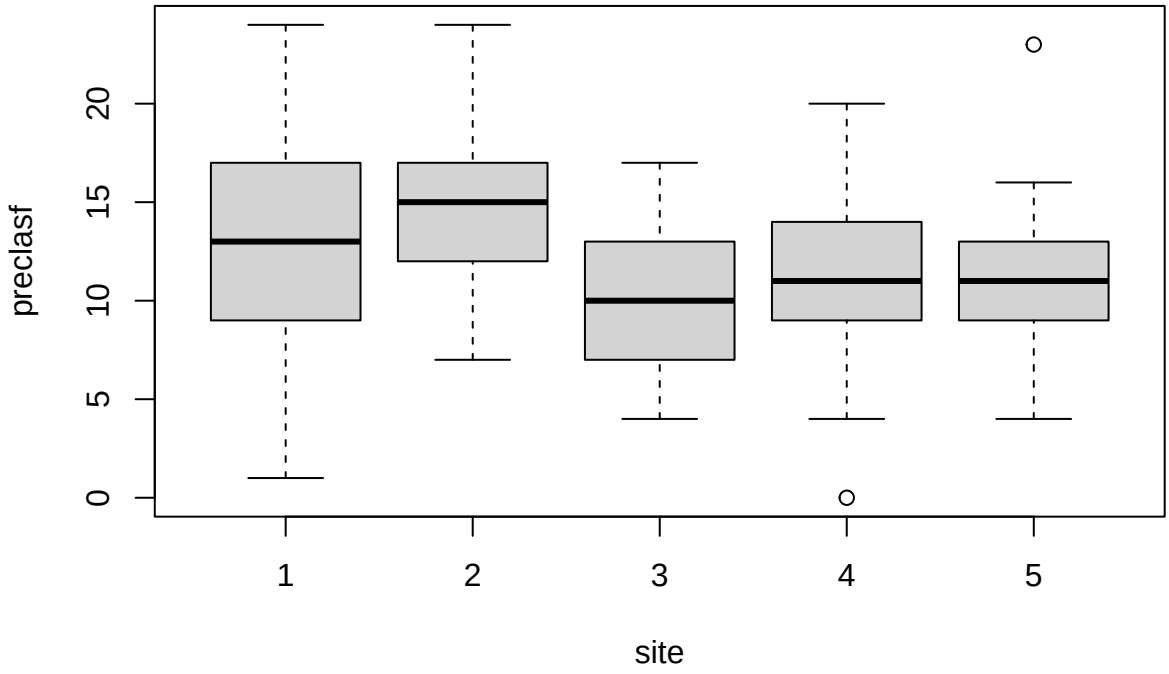

```
boxplot(prenumb~site, data=sesame)
```



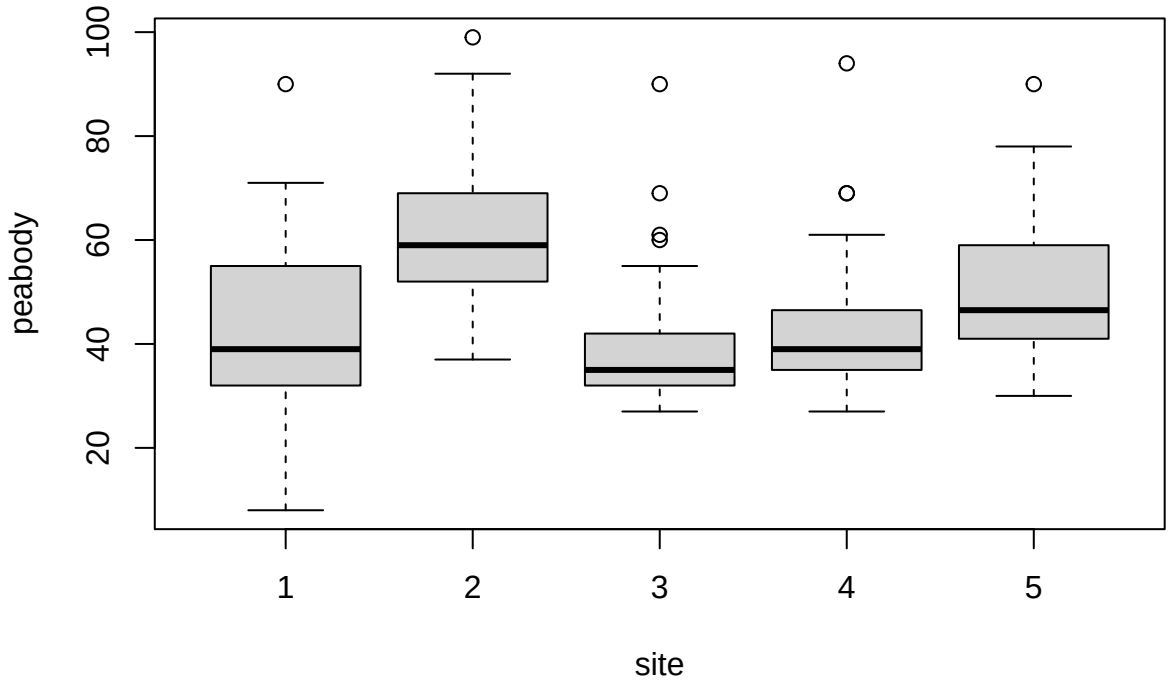

```
boxplot(prerelat~site, data=sesame)
```




```
boxplot(preclasf~site, data=sesame)
```




```
boxplot(peabody~site, data=sesame)
```



Trees

```
set.seed(3215)
#tree.data <- sesame %>%
#  select(site, sex, age, viewcat, setting, viewenc, prebody, prelet, preform,
#         prenumb, prerelat, preclasf)

n <- nrow(sesame)
train.index <- sample(1:n, size = floor(0.7*n), replace=FALSE)
#train.tree <- tree.data[train.index,]
#test.tree <- tree.data[-train.index,]
# "viewcat", "setting", "viewenc",

# ,"prebody", "prelet","preform", "prenumb", "prerelat", "preclasf", "postbody", "postlet", "postform",

tree.features <- c("site", "age", "viewcat", "setting", "viewenc")

tree.data <- sesame[, tree.features]
train.data <- tree.data[train.index,]
test.data <- tree.data[-train.index,]
```

```
rf.tree<- randomForest(site~., data=tree.data, subset=train.index,
                       mtry=4, importance=TRUE)

importance(rf.tree)
```

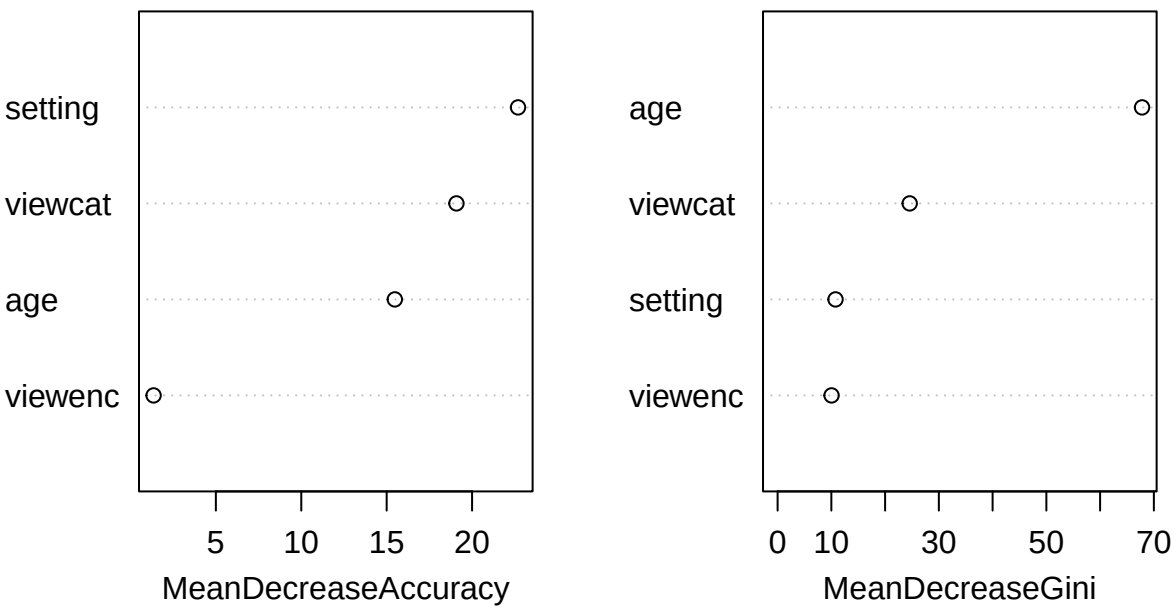
```
##                1          2         3        4          5 MeanDecreaseAccuracy
## age     16.071180 11.5639655  1.533526 10.24956 -12.646482             15.477245
## viewcat  1.412544  8.8509648  4.714890 26.85440  -5.674656             19.084980
## setting  9.950184  0.7116516 11.570042 20.04012   6.879913             22.690481
## viewenc  1.061428 -1.4942151  6.283556 -2.36010  -3.154027              1.353554
##         MeanDecreaseGini
```

```
## age             67.80480
## viewcat         24.57478
## setting         10.77912
## viewenc         10.03605
```

```
rf.pred <- predict(rf.tree, newdata=test.data)

tree.conMatrix <- table(true=test.data[,"site"],
                        pred=rf.pred)
confusionMatrix(tree.conMatrix)
```

```
## Confusion Matrix and Statistics
##
##     pred
## true  1  2  3  4  5
##    1 10  2  3  3  0
##    2  4 10  1  1  2
##    3  2  3 11  3  0
##    4  1  1  3  5  2
##    5  0  1  3  0  1
##
## Overall Statistics
##
##                Accuracy : 0.5139
##                  95% CI : (0.3931, 0.6335)
##     No Information Rate : 0.2917
##     P-Value [Acc > NIR] : 6.203e-05
##
##                   Kappa : 0.3706
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: 1 Class: 2 Class: 3 Class: 4 Class: 5
## Sensitivity            0.5882   0.5882   0.5238  0.41667  0.20000
## Specificity            0.8545   0.8545   0.8431  0.88333  0.94030
## Pos Pred Value         0.5556   0.5556   0.5789  0.41667  0.20000
## Neg Pred Value         0.8704   0.8704   0.8113  0.88333  0.94030
## Prevalence             0.2361   0.2361   0.2917  0.16667  0.06944
## Detection Rate         0.1389   0.1389   0.1528  0.06944  0.01389
## Detection Prevalence   0.2500   0.2500   0.2639  0.16667  0.06944
## Balanced Accuracy      0.7214   0.7214   0.6835  0.65000  0.57015
```

```
varImpPlot(rf.tree)
```



0.42 – 0.5139 (but not including the test scores.) around 0.45-0.48, when including the pretest scores.

As seen in the table above, there is a notable discrepancy in the number of observations that lay in classes 4 and 5 for the variable `site`. More specifically, in the training data, there are just 25 observations with a value of 4 for the variable `site` and just 13 observations with a value of 5 for the variable `site`. In other words, there are less disadvantaged rural children and disadvantaged Spanish speaking children.

Consequently, when we initially ran our random forest model, our model was performing worse for test observations that take on the values 4 or 5 for the variable `site`.

To remedy this problem, we decided to use Synthetic Minority Oversampling Technique (SMOTE). SMOTE works by generating new samples in the classes of the response variable that are less represented. These new samples are generated using linear combinations of the "k" nearest neighbors in a given class. In this instance, we set $k = 5$.

```
train.data$age <- as.numeric(train.data$age)
train.data$viewcat <- as.numeric(train.data$viewcat)
train.data$setting <- as.numeric(train.data$setting)
train.data$viewenc <- as.factor(train.data$viewenc)

test.data$age <- as.numeric(test.data$age)
test.data$viewcat <- as.numeric(test.data$viewcat)
test.data$setting <- as.numeric(test.data$setting)
test.data$viewenc <- as.factor(test.data$viewenc)

balanced.train.data <- SmoteClassif(site ~ ., train.data, k = 5, repl = FALSE, dist = "HEOM")
  # k --> represents the number of nearest neighbors (5) used to generate new examples of the minority
  # repl = FALSE --> cannot have repetition of examples when performing under-sampling by selecting amo

balanced.train.data %>%
  count(site)
```

```
##   site  n
## 1    1 34
## 2    2 34
## 3    3 34
## 4    4 33
## 5    5 34
```

```
rf.tree<- randomForest(site~., data=balanced.train.data,
                       mtry=4, importance=TRUE)

importance(rf.tree)
```

```
##                 1          2        3          4        5 MeanDecreaseAccuracy
## age     15.112165 11.5044815 2.831522 12.2530454 12.35896             24.534350
## viewcat  2.482319 12.5671060 5.114628 28.5410065 19.94849             32.088862
## setting 14.672536  0.4233347 5.467389 22.8438707 32.97928             34.377861
## viewenc  5.604315 -2.5081007 6.322412  0.1078161 12.91417              9.960821
##         MeanDecreaseGini
## age            73.124641
## viewcat        29.595993
## setting         9.359814
## viewenc         9.254742
```

```
rf.pred <- predict(rf.tree, newdata=test.data)

tree.conMatrix <- table(true=test.data[,"site"],
                        pred=rf.pred)
confusionMatrix(tree.conMatrix)
```

```
## Confusion Matrix and Statistics
##
##     pred
## true 1 2 3 4 5
##    1 7 4 3 2 2
##    2 4 8 1 2 3
##    3 3 4 9 2 1
##    4 0 2 3 5 2
##    5 0 2 2 0 1
##
## Overall Statistics
##
##                Accuracy : 0.4167
##                  95% CI : (0.3015, 0.5389)
##     No Information Rate : 0.2778
##     P-Value [Acc > NIR] : 0.007741
##
##                   Kappa : 0.2539
##
##  Mcnemar's Test P-Value : 0.576888
##
## Statistics by Class:
##
##                      Class: 1 Class: 2 Class: 3 Class: 4 Class: 5
## Sensitivity           0.50000   0.4000   0.5000  0.45455  0.11111
## Specificity           0.81034   0.8077   0.8148  0.88525  0.93651
```

```
## Pos Pred Value         0.38889   0.4444   0.4737  0.41667  0.20000
## Neg Pred Value         0.87037   0.7778   0.8302  0.90000  0.88060
## Prevalence             0.19444   0.2778   0.2500  0.15278  0.12500
## Detection Rate         0.09722   0.1111   0.1250  0.06944  0.01389
## Detection Prevalence   0.25000   0.2500   0.2639  0.16667  0.06944
## Balanced Accuracy      0.65517   0.6038   0.6574  0.66990  0.52381
```

While the `SmoteClassif()` function certainly did its job by balancing out the number of observations for each value of `site` in the training data, the new random forest model (fitted to this new data set) is less accurate and sees little improvement in the detection of `site` values of 4 and 5.

```
# set.seed(3215)
#
# # ,"prebody", "prelet","preform", "prenumb", "prerelat", "preclasf", "postbody", "postlet", "postform
#
#
#
# features <- c("site", "age", "viewcat", "setting", "viewenc","prebody", "prelet","preform", "prenumb"
#
# tree.2 <- sesame[, features]
# train.2 <- tree.2[train.index,]
# test.2 <- tree.2[-train.index,]
#
# boost.tree <- gbm(site ~., data=train.2,
#                   distribution="multinomial", n.trees=5000,
#                   interaction.depth=1)
#
# #y.boost <- table(true=test.2[,"site"],
# #                  pred=predict(boost.tree, newdata=test.2))
#
# boost.conMatrix <- table(true=test.2$site,
#                          pred=predict(boost.tree, newdata=test.2))
# confusionMatrix(boost.conMatrix)
```

Logistic Regression

```
# ,"prebody", "prelet","preform", "prenumb", "prerelat", "preclasf", "postbody", "postlet", "postform",

tree.features <- c("site", "age", "viewcat", "setting", "viewenc","prebody", "prelet","preform", "prenu

tree.log <- sesame[, tree.features]
train.log <- tree.log[train.index,]
test.log <- tree.log[-train.index,]

multinom.log <- multinom(factor(site)~., data=train.log)
```

```
## # weights:  60 (44 variable)
## initial  value 270.385569
## iter  10 value 224.661284
## iter  20 value 205.001057
## iter  30 value 193.994082
## iter  40 value 186.948903
## iter  50 value 186.213534
## iter  60 value 186.148958
## iter  70 value 186.146812
```

```
## iter  70 value 186.146811
## iter  70 value 186.146811
## final  value 186.146811
## converged
```

```
summary(multinom.log)
```

```
## Call:
## multinom(formula = factor(site) ~ ., data = train.log)
##
## Coefficients:
##   (Intercept)         age    viewcat     setting    viewenc     prebody
## 2 -2.33155723 -0.02851059  0.1671689  -0.1723663 -0.4205104  0.18169812
## 3  0.05755516  0.20107446  0.0726002  -1.4396594 -1.5937567 -0.10132305
## 4  0.52070488  0.14041265 -1.1560807  -0.2744569 -1.3458286 -0.08902983
## 5 10.77382380  0.20246633 -0.1290428 -16.3009311 -1.5011369 -0.09094212
##         prelet     preform       prenumb    prerelat    preclasf
## 2 -0.021574850 -0.12985947 -0.0781747329  0.16740257  0.10875790
## 3 -0.009618286 -0.32080214 -0.0307718697  0.05942666 -0.08062801
## 4 -0.023880439  0.05801188 -0.0008763081 -0.11001706 -0.01601207
## 5  0.149877507 -0.31580541 -0.1020246788  0.34854595 -0.12639855
##
## Std. Errors:
##   (Intercept)        age   viewcat   setting   viewenc    prebody     prelet
## 2    2.539808 0.05877122 0.2735599 0.6038785 0.6013929 0.07166225 0.03755288
## 3    2.552263 0.06296057 0.2800905 0.6392345 0.6272709 0.07157933 0.05105309
## 4    2.743404 0.06311748 0.3228949 0.6489907 0.6712331 0.07501958 0.04404500
## 5    2.206224 0.08353394 0.4579698 2.2063318 0.9368912 0.09992158 0.07033801
##     preform    prenumb  prerelat   preclasf
## 2 0.1144522 0.05108224 0.1361291 0.08630272
## 3 0.1256428 0.05602075 0.1440701 0.09338212
## 4 0.1173569 0.05356710 0.1389164 0.09183664
## 5 0.1771026 0.08446858 0.2087433 0.14707062
##
## Residual Deviance: 372.2936
## AIC: 460.2936
```

```
tabs <- table(true=test.log[, "site"],
              pred=predict(multinom.log,newdata=test.log))
confusionMatrix(tabs)
```

```
## Confusion Matrix and Statistics
##
##     pred
## true  1  2  3  4  5
##    1  3  4  8  3  0
##    2  8  7  2  1  0
##    3  2  3 12  2  0
##    4  0  1  4  6  1
##    5  0  0  2  1  2
##
## Overall Statistics
##
##                Accuracy : 0.4167
##                  95% CI : (0.3015, 0.5389)
```

```
##     No Information Rate : 0.3889
##     P-Value [Acc > NIR] : 0.3557
##
##                   Kappa : 0.2396
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: 1 Class: 2 Class: 3 Class: 4 Class: 5
## Sensitivity           0.23077  0.46667   0.4286  0.46154  0.66667
## Specificity           0.74576  0.80702   0.8409  0.89831  0.95652
## Pos Pred Value        0.16667  0.38889   0.6316  0.50000  0.40000
## Neg Pred Value        0.81481  0.85185   0.6981  0.88333  0.98507
## Prevalence            0.18056  0.20833   0.3889  0.18056  0.04167
## Detection Rate        0.04167  0.09722   0.1667  0.08333  0.02778
## Detection Prevalence  0.25000  0.25000   0.2639  0.16667  0.06944
## Balanced Accuracy     0.48827  0.63684   0.6347  0.67992  0.81159
```

```
##forward selection
log.tune <- train(site~(.)^2, data=train.log, method="multinom", direction="forward",
                  k=log(3562))
```

```
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 223.009710
## iter  20 value 185.817438
## iter  30 value 164.746276
## iter  40 value 142.208692
## iter  50 value 114.120976
## iter  60 value 105.061057
## iter  70 value 96.136366
## iter  80 value 86.279565
## iter  90 value 68.226344
## iter 100 value 56.986576
## final  value 56.986576
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 223.009765
## iter  20 value 185.818463
## iter  30 value 164.749701
## iter  40 value 142.227179
## iter  50 value 114.217355
## iter  60 value 105.233432
## iter  70 value 96.390732
## iter  80 value 85.327276
## iter  90 value 70.002063
## iter 100 value 59.270525
## final  value 59.270525
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 223.009710
## iter  20 value 185.817439
```

```
## iter  30 value 164.746280
## iter  40 value 142.208711
## iter  50 value 114.121072
## iter  60 value 105.061229
## iter  70 value 96.136613
## iter  80 value 86.280792
## iter  90 value 68.229713
## iter 100 value 56.993283
## final  value 56.993283
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 173.938475
## iter  20 value 138.721492
## iter  30 value 121.837401
## iter  40 value 102.694977
## iter  50 value 87.793408
## iter  60 value 78.834826
## iter  70 value 69.705169
## iter  80 value 60.078338
## iter  90 value 49.433061
## iter 100 value 30.412960
## final  value 30.412960
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 173.938525
## iter  20 value 138.722238
## iter  30 value 121.840535
## iter  40 value 102.713762
## iter  50 value 87.856776
## iter  60 value 78.916581
## iter  70 value 71.245467
## iter  80 value 61.578500
## iter  90 value 49.020816
## iter 100 value 35.855958
## final  value 35.855958
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 173.938475
## iter  20 value 138.721493
## iter  30 value 121.837404
## iter  40 value 102.694996
## iter  50 value 87.793471
## iter  60 value 78.834899
## iter  70 value 69.705169
## iter  80 value 60.081440
## iter  90 value 49.429589
## iter 100 value 30.613095
## final  value 30.613095
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
```

```
## iter  10 value 196.128288
## iter  20 value 152.338821
## iter  30 value 134.098144
## iter  40 value 120.528256
## iter  50 value 107.006267
## iter  60 value 97.433053
## iter  70 value 91.319595
## iter  80 value 80.124846
## iter  90 value 66.699682
## iter 100 value 51.368028
## final  value 51.368028
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 196.128329
## iter  20 value 152.339603
## iter  30 value 134.101185
## iter  40 value 120.542755
## iter  50 value 107.075877
## iter  60 value 97.622659
## iter  70 value 90.390179
## iter  80 value 79.683704
## iter  90 value 68.002823
## iter 100 value 53.884570
## final  value 53.884570
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 196.128288
## iter  20 value 152.338822
## iter  30 value 134.098147
## iter  40 value 120.528271
## iter  50 value 107.006336
## iter  60 value 97.433244
## iter  70 value 91.320015
## iter  80 value 80.124455
## iter  90 value 66.695323
## iter 100 value 52.559315
## final  value 52.559315
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 189.587833
## iter  20 value 163.400377
## iter  30 value 149.397008
## iter  40 value 130.865745
## iter  50 value 118.037225
## iter  60 value 102.868952
## iter  70 value 92.450294
## iter  80 value 81.333564
## iter  90 value 66.847399
## iter 100 value 54.770259
## final  value 54.770259
## stopped after 100 iterations
```

```
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 189.587869
## iter  20 value 163.400999
## iter  30 value 149.399651
## iter  40 value 130.879708
## iter  50 value 118.074280
## iter  60 value 103.060569
## iter  70 value 92.686823
## iter  80 value 82.398605
## iter  90 value 70.243125
## iter 100 value 56.884732
## final  value 56.884732
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 189.587833
## iter  20 value 163.400378
## iter  30 value 149.397010
## iter  40 value 130.865759
## iter  50 value 118.037262
## iter  60 value 102.869143
## iter  70 value 92.450438
## iter  80 value 81.335289
## iter  90 value 66.849983
## iter 100 value 54.773938
## final  value 54.773938
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 218.066994
## iter  20 value 166.160778
## iter  30 value 147.813821
## iter  40 value 126.512571
## iter  50 value 105.678336
## iter  60 value 92.005056
## iter  70 value 76.732392
## iter  80 value 65.655736
## iter  90 value 52.831643
## iter 100 value 41.316977
## final  value 41.316977
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 218.067049
## iter  20 value 166.161877
## iter  30 value 147.817302
## iter  40 value 126.532313
## iter  50 value 106.035090
## iter  60 value 92.573822
## iter  70 value 77.440839
## iter  80 value 66.671660
## iter  90 value 57.517909
## iter 100 value 46.862520
```

```
## final  value 46.862520
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 218.066994
## iter  20 value 166.160780
## iter  30 value 147.813825
## iter  40 value 126.512591
## iter  50 value 105.678677
## iter  60 value 92.005568
## iter  70 value 76.732185
## iter  80 value 65.656811
## iter  90 value 52.829713
## iter 100 value 41.436199
## final  value 41.436199
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 187.347617
## iter  20 value 167.486745
## iter  30 value 154.146359
## iter  40 value 139.480057
## iter  50 value 122.619656
## iter  60 value 110.529375
## iter  70 value 102.625116
## iter  80 value 90.421158
## iter  90 value 74.054788
## iter 100 value 57.909803
## final  value 57.909803
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 187.347643
## iter  20 value 167.487082
## iter  30 value 154.148036
## iter  40 value 139.492855
## iter  50 value 122.826896
## iter  60 value 110.867861
## iter  70 value 102.854835
## iter  80 value 92.576101
## iter  90 value 77.396820
## iter 100 value 64.941930
## final  value 64.941930
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 187.347617
## iter  20 value 167.486745
## iter  30 value 154.146360
## iter  40 value 139.480070
## iter  50 value 122.619857
## iter  60 value 110.529704
## iter  70 value 102.625311
## iter  80 value 90.422822
```

```
## iter  90 value 74.054983
## iter 100 value 57.934475
## final  value 57.934475
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 208.590047
## iter  20 value 174.245490
## iter  30 value 157.555386
## iter  40 value 129.021489
## iter  50 value 109.837072
## iter  60 value 93.512606
## iter  70 value 81.991673
## iter  80 value 74.052179
## iter  90 value 60.298671
## iter 100 value 48.252392
## final  value 48.252392
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 208.590094
## iter  20 value 174.246094
## iter  30 value 157.557920
## iter  40 value 129.041017
## iter  50 value 110.099794
## iter  60 value 95.257380
## iter  70 value 84.712232
## iter  80 value 76.674761
## iter  90 value 63.088355
## iter 100 value 48.790899
## final  value 48.790899
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 208.590047
## iter  20 value 174.245490
## iter  30 value 157.555389
## iter  40 value 129.021509
## iter  50 value 109.837330
## iter  60 value 93.513161
## iter  70 value 81.992850
## iter  80 value 74.053951
## iter  90 value 60.302615
## iter 100 value 48.251118
## final  value 48.251118
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 198.318184
## iter  20 value 175.950870
## iter  30 value 165.501135
## iter  40 value 147.679228
## iter  50 value 135.519155
## iter  60 value 124.002190
```

```
## iter  70 value 113.636452
## iter  80 value 99.187196
## iter  90 value 80.973452
## iter 100 value 67.940819
## final  value 67.940819
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 198.318211
## iter  20 value 175.951353
## iter  30 value 165.503279
## iter  40 value 147.694380
## iter  50 value 135.553180
## iter  60 value 124.189654
## iter  70 value 114.073441
## iter  80 value 100.694573
## iter  90 value 84.427530
## iter 100 value 69.210273
## final  value 69.210273
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 198.318184
## iter  20 value 175.950870
## iter  30 value 165.501137
## iter  40 value 147.679243
## iter  50 value 135.519189
## iter  60 value 124.002378
## iter  70 value 113.636894
## iter  80 value 99.188748
## iter  90 value 80.977323
## iter 100 value 67.968767
## final  value 67.968767
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 195.878402
## iter  20 value 160.411948
## iter  30 value 146.293438
## iter  40 value 132.445684
## iter  50 value 121.735515
## iter  60 value 110.913748
## iter  70 value 101.797034
## iter  80 value 89.943451
## iter  90 value 76.345444
## iter 100 value 66.319285
## final  value 66.319285
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 195.878435
## iter  20 value 160.412633
## iter  30 value 146.295768
## iter  40 value 132.456699
```

```
## iter  50 value 121.753991
## iter  60 value 111.068167
## iter  70 value 101.725838
## iter  80 value 91.901527
## iter  90 value 79.790681
## iter 100 value 67.956986
## final  value 67.956986
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 195.878402
## iter  20 value 160.411948
## iter  30 value 146.293441
## iter  40 value 132.445695
## iter  50 value 121.735534
## iter  60 value 110.913903
## iter  70 value 101.797552
## iter  80 value 89.944796
## iter  90 value 76.348390
## iter 100 value 66.328651
## final  value 66.328651
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 195.507155
## iter  20 value 168.008151
## iter  30 value 154.351529
## iter  40 value 139.161429
## iter  50 value 126.127147
## iter  60 value 115.398471
## iter  70 value 107.554452
## iter  80 value 97.821720
## iter  90 value 79.668626
## iter 100 value 66.257381
## final  value 66.257381
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 195.507174
## iter  20 value 168.008683
## iter  30 value 154.353641
## iter  40 value 139.169359
## iter  50 value 126.120865
## iter  60 value 115.561001
## iter  70 value 107.881745
## iter  80 value 98.577837
## iter  90 value 81.756531
## iter 100 value 68.196680
## final  value 68.196680
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 195.507155
## iter  20 value 168.008152
```

```
## iter  30 value 154.351531
## iter  40 value 139.161437
## iter  50 value 126.127140
## iter  60 value 115.398638
## iter  70 value 107.554789
## iter  80 value 97.822265
## iter  90 value 79.670619
## iter 100 value 66.258275
## final  value 66.258275
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 216.166446
## iter  20 value 185.522611
## iter  30 value 173.564102
## iter  40 value 155.099978
## iter  50 value 139.144040
## iter  60 value 129.027054
## iter  70 value 119.722624
## iter  80 value 107.450564
## iter  90 value 91.208985
## iter 100 value 78.111012
## final  value 78.111012
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 216.166467
## iter  20 value 185.523132
## iter  30 value 173.566575
## iter  40 value 155.113493
## iter  50 value 139.192277
## iter  60 value 128.900937
## iter  70 value 119.118226
## iter  80 value 107.573476
## iter  90 value 94.029691
## iter 100 value 82.140576
## final  value 82.140576
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 216.166446
## iter  20 value 185.522611
## iter  30 value 173.564105
## iter  40 value 155.099991
## iter  50 value 139.144087
## iter  60 value 129.026928
## iter  70 value 119.723323
## iter  80 value 107.451068
## iter  90 value 91.210481
## iter 100 value 78.142450
## final  value 78.142450
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
```

```
## iter  10 value 205.902789
## iter  20 value 154.466750
## iter  30 value 139.653249
## iter  40 value 119.238914
## iter  50 value 105.406380
## iter  60 value 88.117632
## iter  70 value 81.629122
## iter  80 value 67.715729
## iter  90 value 50.488608
## iter 100 value 41.579569
## final  value 41.579569
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 205.902819
## iter  20 value 154.467845
## iter  30 value 139.654432
## iter  40 value 119.255897
## iter  50 value 105.473859
## iter  60 value 88.376053
## iter  70 value 81.017059
## iter  80 value 67.879342
## iter  90 value 53.401341
## iter 100 value 44.545720
## final  value 44.545720
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 205.902789
## iter  20 value 154.466751
## iter  30 value 139.653250
## iter  40 value 119.238931
## iter  50 value 105.406448
## iter  60 value 88.117893
## iter  70 value 81.629666
## iter  80 value 67.717719
## iter  90 value 50.492750
## iter 100 value 41.591961
## final  value 41.591961
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 207.828724
## iter  20 value 176.130978
## iter  30 value 150.697453
## iter  40 value 133.751248
## iter  50 value 116.398121
## iter  60 value 103.381280
## iter  70 value 93.375389
## iter  80 value 83.585598
## iter  90 value 68.466643
## iter 100 value 57.109246
## final  value 57.109246
## stopped after 100 iterations
```

```
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 207.828758
## iter  20 value 176.131477
## iter  30 value 150.702178
## iter  40 value 133.771356
## iter  50 value 116.447071
## iter  60 value 103.577894
## iter  70 value 94.171941
## iter  80 value 84.466346
## iter  90 value 69.755066
## iter 100 value 59.272430
## final  value 59.272430
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 207.828724
## iter  20 value 176.130978
## iter  30 value 150.697458
## iter  40 value 133.751268
## iter  50 value 116.398170
## iter  60 value 103.381476
## iter  70 value 93.376113
## iter  80 value 83.586754
## iter  90 value 68.469243
## iter 100 value 57.171046
## final  value 57.171046
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 197.459887
## iter  20 value 171.807460
## iter  30 value 162.216908
## iter  40 value 145.682362
## iter  50 value 131.191764
## iter  60 value 116.528722
## iter  70 value 99.801864
## iter  80 value 87.048354
## iter  90 value 71.433299
## iter 100 value 62.605663
## final  value 62.605663
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 197.459939
## iter  20 value 171.808111
## iter  30 value 162.218561
## iter  40 value 145.695424
## iter  50 value 131.200207
## iter  60 value 117.099548
## iter  70 value 100.169194
## iter  80 value 87.031378
## iter  90 value 72.315875
## iter 100 value 65.278252
```

```
## final  value 65.278252
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 197.459888
## iter  20 value 171.807461
## iter  30 value 162.216910
## iter  40 value 145.682375
## iter  50 value 131.191771
## iter  60 value 116.529329
## iter  70 value 99.791086
## iter  80 value 87.059637
## iter  90 value 71.418633
## iter 100 value 61.334669
## final  value 61.334669
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 202.702743
## iter  20 value 159.830659
## iter  30 value 139.978162
## iter  40 value 118.274196
## iter  50 value 100.017759
## iter  60 value 88.746993
## iter  70 value 83.800188
## iter  80 value 71.801326
## iter  90 value 59.118625
## iter 100 value 44.540729
## final  value 44.540729
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 202.702828
## iter  20 value 159.831649
## iter  30 value 139.981279
## iter  40 value 118.291279
## iter  50 value 100.096491
## iter  60 value 88.961493
## iter  70 value 84.107769
## iter  80 value 73.071035
## iter  90 value 62.452530
## iter 100 value 50.377832
## final  value 50.377832
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 202.702743
## iter  20 value 159.830660
## iter  30 value 139.978165
## iter  40 value 118.274213
## iter  50 value 100.017838
## iter  60 value 88.747209
## iter  70 value 83.800488
## iter  80 value 71.802620
```

```
## iter  90 value 59.120887
## iter 100 value 44.563505
## final  value 44.563505
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 202.431157
## iter  20 value 175.359213
## iter  30 value 160.382800
## iter  40 value 140.003843
## iter  50 value 124.504878
## iter  60 value 111.647835
## iter  70 value 99.352902
## iter  80 value 87.131942
## iter  90 value 70.093546
## iter 100 value 56.313191
## final  value 56.313191
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 202.431192
## iter  20 value 175.359877
## iter  30 value 160.385404
## iter  40 value 140.021855
## iter  50 value 124.572136
## iter  60 value 111.845314
## iter  70 value 99.830156
## iter  80 value 86.696368
## iter  90 value 71.285501
## iter 100 value 59.652946
## final  value 59.652946
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 202.431157
## iter  20 value 175.359214
## iter  30 value 160.382803
## iter  40 value 140.003861
## iter  50 value 124.504945
## iter  60 value 111.648030
## iter  70 value 99.353384
## iter  80 value 87.135619
## iter  90 value 70.097516
## iter 100 value 56.327647
## final  value 56.327647
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 201.371805
## iter  20 value 166.031971
## iter  30 value 150.075932
## iter  40 value 135.132305
## iter  50 value 120.592996
## iter  60 value 104.861049
```

```
## iter  70 value 94.760756
## iter  80 value 86.209075
## iter  90 value 70.479690
## iter 100 value 59.293584
## final  value 59.293584
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 201.371834
## iter  20 value 166.032587
## iter  30 value 150.078439
## iter  40 value 135.145979
## iter  50 value 120.647244
## iter  60 value 105.100395
## iter  70 value 95.630193
## iter  80 value 86.629358
## iter  90 value 73.769241
## iter 100 value 62.418038
## final  value 62.418038
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 201.371805
## iter  20 value 166.031971
## iter  30 value 150.075934
## iter  40 value 135.132319
## iter  50 value 120.593051
## iter  60 value 104.861290
## iter  70 value 94.761635
## iter  80 value 86.204322
## iter  90 value 70.477907
## iter 100 value 59.380211
## final  value 59.380211
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 193.758552
## iter  20 value 161.466052
## iter  30 value 143.149426
## iter  40 value 119.906737
## iter  50 value 105.972213
## iter  60 value 94.038716
## iter  70 value 86.611103
## iter  80 value 76.999325
## iter  90 value 64.304604
## iter 100 value 49.108594
## final  value 49.108594
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 193.758575
## iter  20 value 161.466759
## iter  30 value 143.152818
## iter  40 value 119.925067
```

```
## iter  50 value 106.063601
## iter  60 value 94.476557
## iter  70 value 88.125313
## iter  80 value 79.353741
## iter  90 value 68.383917
## iter 100 value 55.778427
## final  value 55.778427
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 193.758552
## iter  20 value 161.466053
## iter  30 value 143.149429
## iter  40 value 119.906755
## iter  50 value 105.972298
## iter  60 value 94.039119
## iter  70 value 86.612063
## iter  80 value 77.024634
## iter  90 value 64.294496
## iter 100 value 48.946694
## final  value 48.946694
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 205.700241
## iter  20 value 172.245031
## iter  30 value 161.350362
## iter  40 value 145.949562
## iter  50 value 134.646862
## iter  60 value 123.431117
## iter  70 value 115.427646
## iter  80 value 107.575646
## iter  90 value 93.359323
## iter 100 value 78.496595
## final  value 78.496595
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 205.700275
## iter  20 value 172.245662
## iter  30 value 161.352088
## iter  40 value 145.960485
## iter  50 value 134.688955
## iter  60 value 123.574379
## iter  70 value 115.743901
## iter  80 value 108.252481
## iter  90 value 95.287892
## iter 100 value 84.379872
## final  value 84.379872
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 205.700241
## iter  20 value 172.245032
```

```
## iter  30 value 161.350363
## iter  40 value 145.949573
## iter  50 value 134.646905
## iter  60 value 123.431261
## iter  70 value 115.427971
## iter  80 value 107.576296
## iter  90 value 93.361320
## iter 100 value 78.502007
## final  value 78.502007
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 219.760490
## iter  20 value 187.124426
## iter  30 value 169.999087
## iter  40 value 150.988583
## iter  50 value 138.413835
## iter  60 value 123.009829
## iter  70 value 109.478001
## iter  80 value 93.806014
## iter  90 value 75.758745
## iter 100 value 58.395941
## final  value 58.395941
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 219.760529
## iter  20 value 187.125144
## iter  30 value 170.001985
## iter  40 value 151.002233
## iter  50 value 138.477224
## iter  60 value 123.272620
## iter  70 value 111.151892
## iter  80 value 92.955032
## iter  90 value 77.276762
## iter 100 value 64.227998
## final  value 64.227998
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 219.760490
## iter  20 value 187.124427
## iter  30 value 169.999090
## iter  40 value 150.988596
## iter  50 value 138.413899
## iter  60 value 123.010094
## iter  70 value 109.478646
## iter  80 value 93.807518
## iter  90 value 75.762081
## iter 100 value 58.410349
## final  value 58.410349
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
```

```
## iter  10 value 202.083849
## iter  20 value 171.218444
## iter  30 value 148.002738
## iter  40 value 131.483341
## iter  50 value 119.899625
## iter  60 value 101.885103
## iter  70 value 88.167837
## iter  80 value 77.579263
## iter  90 value 67.403824
## iter 100 value 54.845992
## final  value 54.845992
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 202.083917
## iter  20 value 171.219158
## iter  30 value 148.006594
## iter  40 value 131.494731
## iter  50 value 119.947547
## iter  60 value 102.164080
## iter  70 value 88.909884
## iter  80 value 80.246572
## iter  90 value 70.884610
## iter 100 value 62.437067
## final  value 62.437067
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 202.083849
## iter  20 value 171.218445
## iter  30 value 148.002742
## iter  40 value 131.483352
## iter  50 value 119.899672
## iter  60 value 101.885379
## iter  70 value 88.168693
## iter  80 value 77.580997
## iter  90 value 67.407609
## iter 100 value 54.896169
## final  value 54.896169
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 210.893574
## iter  20 value 176.968481
## iter  30 value 157.621487
## iter  40 value 142.056823
## iter  50 value 121.819529
## iter  60 value 111.531475
## iter  70 value 100.966866
## iter  80 value 88.183437
## iter  90 value 73.319758
## iter 100 value 58.907600
## final  value 58.907600
## stopped after 100 iterations
```

```
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 210.893616
## iter  20 value 176.969104
## iter  30 value 157.624217
## iter  40 value 142.070829
## iter  50 value 121.894347
## iter  60 value 111.706223
## iter  70 value 101.934582
## iter  80 value 88.907037
## iter  90 value 74.853558
## iter 100 value 62.676623
## final  value 62.676623
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 210.893574
## iter  20 value 176.968482
## iter  30 value 157.621490
## iter  40 value 142.056837
## iter  50 value 121.819604
## iter  60 value 111.531651
## iter  70 value 100.967339
## iter  80 value 88.182492
## iter  90 value 73.321790
## iter 100 value 58.923957
## final  value 58.923957
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 215.234341
## iter  20 value 187.495648
## iter  30 value 156.884090
## iter  40 value 126.627495
## iter  50 value 108.092316
## iter  60 value 93.655427
## iter  70 value 82.956918
## iter  80 value 70.727103
## iter  90 value 54.497157
## iter 100 value 38.707756
## final  value 38.707756
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 215.234405
## iter  20 value 187.496165
## iter  30 value 156.890467
## iter  40 value 126.670853
## iter  50 value 108.136155
## iter  60 value 93.903580
## iter  70 value 82.571252
## iter  80 value 71.747868
## iter  90 value 60.863267
## iter 100 value 46.666754
```

```
## final  value 46.666754
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 215.234341
## iter  20 value 187.495649
## iter  30 value 156.884096
## iter  40 value 126.627538
## iter  50 value 108.092360
## iter  60 value 93.655673
## iter  70 value 82.958070
## iter  80 value 70.733975
## iter  90 value 54.499717
## iter 100 value 38.186024
## final  value 38.186024
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 206.360036
## iter  20 value 172.487861
## iter  30 value 155.021658
## iter  40 value 136.335948
## iter  50 value 119.177256
## iter  60 value 110.476952
## iter  70 value 103.090165
## iter  80 value 95.068108
## iter  90 value 79.645467
## iter 100 value 66.656328
## final  value 66.656328
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 206.360068
## iter  20 value 172.488629
## iter  30 value 155.023441
## iter  40 value 136.350067
## iter  50 value 119.240533
## iter  60 value 110.611543
## iter  70 value 103.346467
## iter  80 value 95.453720
## iter  90 value 81.089286
## iter 100 value 71.797990
## final  value 71.797990
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 206.360036
## iter  20 value 172.487862
## iter  30 value 155.021660
## iter  40 value 136.335963
## iter  50 value 119.177320
## iter  60 value 110.477087
## iter  70 value 103.090422
## iter  80 value 95.067651
```

```
## iter  90 value 79.646829
## iter 100 value 66.657618
## final  value 66.657618
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 220.183939
## iter  20 value 185.813346
## iter  30 value 166.002072
## iter  40 value 145.689793
## iter  50 value 129.203808
## iter  60 value 112.779371
## iter  70 value 101.156987
## iter  80 value 89.181144
## iter  90 value 71.341174
## iter 100 value 60.270997
## final  value 60.270997
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 220.183976
## iter  20 value 185.813893
## iter  30 value 166.005036
## iter  40 value 145.706838
## iter  50 value 129.260881
## iter  60 value 113.034823
## iter  70 value 101.614811
## iter  80 value 90.462165
## iter  90 value 74.152421
## iter 100 value 64.434659
## final  value 64.434659
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 220.183939
## iter  20 value 185.813346
## iter  30 value 166.002075
## iter  40 value 145.689810
## iter  50 value 129.203865
## iter  60 value 112.779628
## iter  70 value 101.157452
## iter  80 value 89.182589
## iter  90 value 71.344062
## iter 100 value 60.255059
## final  value 60.255059
## stopped after 100 iterations
## # weights:  285 (224 variable)
## initial  value 270.385569
## iter  10 value 213.786480
## iter  20 value 183.820116
## iter  30 value 175.610350
## iter  40 value 166.416809
## iter  50 value 156.687239
## iter  60 value 150.770066
```

```
## iter  70 value 141.604223
## iter  80 value 132.373761
## iter  90 value 117.371155
## iter 100 value 107.188847
## final  value 107.188847
## stopped after 100 iterations
```

```
summary(log.tune)
```

```
## Call:
## nnet::multinom(formula = .outcome ~ ., data = dat, decay = param$decay,
##     direction = "forward", k = ..2)
##
## Coefficients:
##   (Intercept)       age     viewcat     setting     viewenc    prebody
## 2 -0.10430024 0.2129859 -0.34982789  0.04138759 -0.09653652 -0.3325268
## 3  0.06293638 0.5017950 -0.86594527  0.17242433  0.34030478 -1.5850149
## 4 -0.11348294 0.1084882 -0.09580164 -0.05144057 -0.28198446 -0.2926012
## 5 -0.04232544 0.1268965 -0.00157604 -0.04201233 -0.16079544  0.2624026
##        prelet     preform    prenumb    prerelat   preclasf `age:viewcat`
## 2  1.07548218 -1.19154198 -0.1355582  0.01218500 -0.8281805    0.01101840
## 3 -0.09390197 -0.31628259  0.9186298  0.31343738 -0.5633445   -0.02328669
## 4 -0.30935254  0.01800312 -0.2184987 -0.26198492  0.9754936    0.08728599
## 5  0.02435272  0.22175132 -0.6841873  0.08376244  0.2796019    0.01044005
##   `age:setting` `age:viewenc` `age:prebody` `age:prelet` `age:preform`
## 2    -0.1950952    0.15083709  -0.015740783  0.003796499    0.03454772
## 3    -0.2402140    0.05406668   0.006006701  0.002664593    0.04427898
## 4     0.0370847    0.03283911  -0.013181506  0.011476032    0.01067502
## 5    -0.1834337    0.06846291  -0.011654324  0.010500400    0.00502330
##   `age:prenumb` `age:prerelat` `age:preclasf` `viewcat:setting`
## 2   0.002748548    0.017421552    -0.03449594        -0.7157048
## 3  -0.021179041    0.006862094    -0.02046393         1.9296577
## 4   0.005381244    0.002834208    -0.03462003        -1.3304799
## 5   0.004025159    0.021167701    -0.01529625        -0.6193439
##   `viewcat:viewenc` `viewcat:prebody` `viewcat:prelet` `viewcat:preform`
## 2        -0.6267928        0.14158801      -0.18278208       -0.33356833
## 3        -0.6451057        0.15032040      -0.19113344       -0.19616855
## 4        -0.7600318        0.02100516      -0.06168443       -0.09204344
## 5        -0.7298604       -0.01705615      -0.08760215       -0.00448432
##   `viewcat:prenumb` `viewcat:prerelat` `viewcat:preclasf` `setting:viewenc`
## 2       0.036088877         0.14586964         0.23145567        0.07630395
## 3       0.021174552         0.31836093        -0.07370337        0.86832568
## 4       0.003855981         0.07887976        -0.10100460       -0.63499806
## 5       0.087689197         0.24193609        -0.07174626        0.37153187
##   `setting:prebody` `setting:prelet` `setting:preform` `setting:prenumb`
## 2       0.469099240       -0.4122878       -0.13051934        0.05284150
## 3       0.135607010       -0.1971371        0.01884259        0.05295298
## 4      -0.006161835       -0.2960129       -0.10589631        0.26263062
## 5       0.421579113       -0.2513299        0.15172993        0.04497442
##   `setting:prerelat` `setting:preclasf` `viewenc:prebody` `viewenc:prelet`
## 2          0.9158782        -0.20327566     -0.1732281310      -0.15753436
## 3         -0.6874554         0.77873656     -0.1003194116       0.22031347
## 4          0.2901539        -0.09297208      0.0008472878       0.10954771
## 5          0.1997050        -0.02496983     -0.4660637394       0.08286859
##   `viewenc:preform` `viewenc:prenumb` `viewenc:prerelat` `viewenc:preclasf`
```

```
## 2       -0.56985394        0.03247080         -1.3095372          1.4372910
## 3       -0.78356022        0.06169254         -0.8061659          0.8328746
## 4       -0.01496193       -0.09635533         -0.2666694          0.3122020
## 5       -0.17168716        0.20628325         -0.4768000          0.5294078
##   `prebody:prelet` `prebody:preform` `prebody:prenumb` `prebody:prerelat`
## 2    -0.026728574        0.02310599      -0.004690487         0.06567582
## 3     0.008919958       -0.07757222       0.004168160         0.08221147
## 4     0.002594866       -0.06621870      -0.005876983         0.08031019
## 5    -0.018649963       -0.05937411      -0.031267621         0.12347594
##   `prebody:preclasf` `prelet:preform` `prelet:prenumb` `prelet:prerelat`
## 2         0.01621294      0.053767578     -0.024222497       0.010990911
## 3         0.04294225      0.037711752     -0.028066953       0.054014235
## 4         0.07572520      0.003193047     -0.011355172      -0.003240511
## 5         0.04845629      0.023606964      0.002600023      -0.039934799
##   `prelet:preclasf` `preform:prenumb` `preform:prerelat` `preform:preclasf`
## 2       0.040880193       -0.06146975       0.0001794691        0.072813219
## 3      -0.006339726        0.02589022      -0.0338563962       -0.005385365
## 4       0.029870629        0.01796772       0.0091114656        0.046634386
## 5       0.028841972        0.03215846      -0.0931836916        0.036711837
##   `prenumb:prerelat` `prenumb:preclasf` `prerelat:preclasf`
## 2       0.0347272942        0.034704048          -0.2159680
## 3      -0.0023133262        0.006896269          -0.1384417
## 4      -0.0002585178       -0.019663447          -0.1506193
## 5       0.0255919064       -0.001445600          -0.2108050
##
## Std. Errors:
##   (Intercept)       age    viewcat     setting    viewenc   prebody    prelet
## 2  0.01769491 0.2281321 0.04463296 0.017978327 0.02743229 0.2795415 0.2451148
## 3  0.02272730 0.1783334 0.06424362 0.029933348 0.03521339 0.2644438 0.4033421
## 4  0.02199825 0.1887900 0.06092779 0.024090342 0.03376304 0.3572217 0.4088392
## 5  0.01018045 0.2010834 0.03038656 0.009964914 0.01420608 0.1814051 0.2567150
##      preform   prenumb   prerelat   preclasf `age:viewcat` `age:setting`
## 2 0.11178013 0.3364181 0.09881117 0.13663278    0.05635717    0.09530280
## 3 0.13921911 0.3950844 0.09883397 0.14861756    0.05043176    0.09138367
## 4 0.13220239 0.3274458 0.11556801 0.14712060    0.04885287    0.08840051
## 5 0.09857628 0.1968719 0.07393768 0.09452461    0.06297351    0.11500433
##   `age:viewenc` `age:prebody` `age:prelet` `age:preform` `age:prenumb`
## 2    0.11304152    0.01433104   0.01356935    0.02786496    0.01497572
## 3    0.09915620    0.01349342   0.01315086    0.02339626    0.01438330
## 4    0.09331245    0.01429374   0.01221907    0.02392057    0.01476449
## 5    0.13061367    0.01728838   0.01324726    0.02935786    0.01581603
##   `age:prerelat` `age:preclasf` `viewcat:setting` `viewcat:viewenc`
## 2     0.02584354     0.02741556         0.2490771         0.3332642
## 3     0.02480077     0.02372367         0.2847775         0.2908848
## 4     0.02586148     0.02541847         0.3029041         0.4216808
## 5     0.02754718     0.02878072         0.1607059         0.1494858
##   `viewcat:prebody` `viewcat:prelet` `viewcat:preform` `viewcat:prenumb`
## 2         0.1108576       0.11755013         0.2010431        0.09697412
## 3         0.1219053       0.11054466         0.1733514        0.09255908
## 4         0.1107068       0.09731512         0.1698175        0.08853306
## 5         0.1380371       0.12158710         0.2223183        0.11578095
##   `viewcat:prerelat` `viewcat:preclasf` `setting:viewenc` `setting:prebody`
## 2          0.2751360          0.1629227        0.08493856         0.2330639
## 3          0.2601977          0.1541121        0.07712831         0.2437100
```

```
## 4          0.2304470          0.1370595        0.13297704         0.2560144
## 5          0.2974449          0.2124611        0.06689098         0.3039591
##   `setting:prelet` `setting:preform` `setting:prenumb` `setting:prerelat`
## 2        0.2149093         0.3573498         0.2038061          0.3706735
## 3        0.2632529         0.3247801         0.2250007          0.3562895
## 4        0.2180408         0.3425432         0.2068494          0.3963333
## 5        0.2570749         0.3889281         0.2517049          0.2415947
##   `setting:preclasf` `viewenc:prebody` `viewenc:prelet` `viewenc:preform`
## 2          0.3342676         0.2457295        0.1839863         0.3807850
## 3          0.3125047         0.2560498        0.1967347         0.3360116
## 4          0.3433573         0.2228863        0.1694260         0.3106407
## 5          0.3701965         0.3151663        0.2098595         0.4171969
##   `viewenc:prenumb` `viewenc:prerelat` `viewenc:preclasf` `prebody:prelet`
## 2         0.1837119          0.4035093          0.3503429       0.02038602
## 3         0.2189024          0.3392222          0.3549874       0.02341377
## 4         0.1679850          0.4089991          0.3004770       0.01934844
## 5         0.2426103          0.3200753          0.3722014       0.02845440
##   `prebody:preform` `prebody:prenumb` `prebody:prerelat` `prebody:preclasf`
## 2        0.05337533        0.02326317         0.06436399         0.05175746
## 3        0.05680423        0.02309044         0.06277950         0.04906464
## 4        0.05059798        0.02129793         0.06010049         0.04585516
## 5        0.06802325        0.02925413         0.07559607         0.05945588
##   `prelet:preform` `prelet:prenumb` `prelet:prerelat` `prelet:preclasf`
## 2       0.04333995       0.01443954        0.04451862        0.03412912
## 3       0.04561577       0.01585042        0.04955802        0.03562827
## 4       0.04016587       0.01239328        0.04068016        0.02845603
## 5       0.04602906       0.01454398        0.05396960        0.03432086
##   `preform:prenumb` `preform:prerelat` `preform:preclasf` `prenumb:prerelat`
## 2        0.04078930         0.10960277         0.07055708         0.04544892
## 3        0.04170952         0.10147248         0.06993119         0.04374414
## 4        0.03378745         0.08337231         0.05951540         0.04023916
## 5        0.04886538         0.11943772         0.08905010         0.05140125
##   `prenumb:preclasf` `prerelat:preclasf`
## 2         0.03153069          0.10242770
## 3         0.02978874          0.09538739
## 4         0.03086232          0.09338443
## 5         0.04096462          0.11263783
##
## Residual Deviance: 214.3777
## AIC: 662.3777
```

```
tabs2 <- table(true=test.log[, "site"],
               pred=predict(log.tune,newdata=test.log))
confusionMatrix(tabs2)
```

```
## Confusion Matrix and Statistics
##
##     pred
## true  1  2  3  4  5
##    1  4  1  5  4  4
##    2  3  6  7  1  1
##    3  3  0 16  0  0
##    4  0  1  6  4  1
##    5  1  1  3  0  0
##
```

```
## Overall Statistics
##
##                Accuracy : 0.4167
##                  95% CI : (0.3015, 0.5389)
##     No Information Rate : 0.5139
##     P-Value [Acc > NIR] : 0.961676
##
##                   Kappa : 0.2408
##
##  Mcnemar's Test P-Value : 0.006843
##
## Statistics by Class:
##
##                      Class: 1 Class: 2 Class: 3 Class: 4 Class: 5
## Sensitivity           0.36364  0.66667   0.4324  0.44444  0.00000
## Specificity           0.77049  0.80952   0.9143  0.87302  0.92424
## Pos Pred Value        0.22222  0.33333   0.8421  0.33333  0.00000
## Neg Pred Value        0.87037  0.94444   0.6038  0.91667  0.91045
## Prevalence            0.15278  0.12500   0.5139  0.12500  0.08333
## Detection Rate        0.05556  0.08333   0.2222  0.05556  0.00000
## Detection Prevalence  0.25000  0.25000   0.2639  0.16667  0.06944
## Balanced Accuracy     0.56706  0.73810   0.6734  0.65873  0.46212
```

Questions for OH:

should we transform regular?

Both linear and radial kernels never output predictions for 4 & 5?

polynomial kernel? Which variables to give polynomial terms

use PCA to perform feature selection?

feature selections for SVM in general?

how to interpret the confusion matrix tables for SVM & Trees

How to interpret the imporatnce variance for multiclass classification

interpretations about the dataset, using the bad performance of the classifiers