Analyzing and Predicting the Relationships between Sesame Street Viewership and Test Scores among School Children

Angela Wang, QiHan Zhou, Matthew Murray, Michelle Mao, Sara Lemus, Sophie Dalldorf

12/9/2021

Introduction

Research Question #1

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 Sesame street)?

Methodology

Question 1

We decided to utilize three different types of models to gain inference and predict the difference in test scores that occurs after subjects watch Sesame Street: (1) least-squares regression model (2) ridge regression model and (3) regression tree model. There are six different test scores in the data set, so we fit three models for each difference in test score variable. Each model took the following variables as covariates: `site`, `sex`, `viewcat`, `setting`, `viewenc`. Before creating these models, we factored those variables to encode them as categoricals. Initially, our least-squares and ridge regression models also took into account all possible two-way interaction terms between the variables. However, we noticed that both the Akaike Information Criterion (AIC) and adjusted-R^2 values were higher for models that did not include any interaction effects. That reason, coupled with the lack of apparent interaction effects in our exploratory data analysis and the fact that we wanted our linear models to be very interpretable, is why we decided not to include any interaction effects in our final linear models.

One problem that we envisioned when evaluating 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.

We first decided to use least-squares regression models due to the fact that they provide apt inference into the relationship between the covariates and the response variable. Thereafter, we decided to use a ridge regression model due to the fact that ridge regression often provides performance improvements by shrinking slope coefficients. While shrinkage may introduce bias to a model, it decreases the variance and increases the precision of the slope coefficient estimates. The shrinkage is achieved by applying a shrinkage parameter, λ, to the Euclidean norm of a slope coefficient. Doing so slightly increases the bias of our model (as least-squares regression coefficient estimates are unbiased) but can also significantly decrease the variance (and increase the precision) of our regression coefficients. This slight increase in bias but significant decrease in variance usually decreases the MSE of a model.

We tuned our λ parameter using 10-fold cross validation. More specifically, we computed the cross-validation error rate for our model for a grid of λ values. Thereafter, we selected the λ value for which the cross-validation error is the smallest.

Initially, we were inclined to use least absolute shrinkage and selection operator (LASSO) regression. The main advantage of LASSO regression over ridge regression is that LASSO regression performs variable selection by setting the slope coefficients of inert predictors to 0. The reason why we initially thought that LASSO regression would work better than ridge regression is that in most of our linear models, only a small subset of variables are significant at a 95% significance level. However, our ridge regression models performed marginally better than our LASSO regression models, so for this reason, we decided to report the MSE's for the ridge regression models.

~Talk about why we chose regression tree models~

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

Question 2

In order to address our second research question, predicting whether a child came from an disadvantaged background or not based on their pretest scores and demographic information, we utilized a support vector machine (SVM). Our model uses the female, male, age, and all pretest score variables to predict our response variable, site. Since our response variable is a categorical variable, a SVM is a valid choice to answer our research question. We also implemented a classification Random Forest model to answer this question as well; the tree model would allow us to plot importance measures to see which feature(s) are the most 'important'.

Thus, a SVM was the most appropriate model choice for our research goals. Our full model formula is: (add formula) (Maybe present Tree as well? the tree accuracy is higher, not by much though)

We split our data into a 70% training set and 30% testing set and analyzed the performance of our model on the test set. To improve our model's predictive power, we implemented a variety of different methods. We tested our model using linear, radial, and sigmoid kernels and compared the predictive accuracy between these models. Since we are interested in high predictive power and the radial kernel had the highest prediction accuracy, we chose this kernel.

Standardizing the predictor variables in SVM and encoding categorical variables has been shown to improve performance for SVMs (https://www.csie.ntu.edu.tw/~cjlin/papers/guide/guide.pdf). Thus, we used the standardized forms of the continuous variables in our model and encoded the sex variable so that if a child was a male we would code that as 1. We did indeed observe a small improvement in prediction accuracy across all models. However, one problem that particularly piqued our interests is that we are making no predictions for sites 4 or 5. This could be due to sites 4 & 5 having a smaller number of observations than the other classes. Thus, we used the class weight formula below to assign weights to each class and specify "one versus one" comparison, which has been suggested to yield better prediction than "one versus all."

$$w_j = \frac{n}{kn_j}, \text{ n is total number of data points, k is number of classes, } n_j \text{ is the number of data in class j}$$

After the class weight assignment, the SVM models began to make prediction on class 4 & 5. However, doing so came at the cost of overall accuracy. Thus, more of the other observations are being misclassified, but the few observations of class 4&5 are correctly classified. To remedy this issue, we began to experiment with the class weights and increase the class 4 & 5 weights by roughly 0.5, which is arbitrarily chosen, and it boosted linear kernel SVM's prediction accuracy to 0.403.

Results

Linear Regression Models

$$bodyDiff = 16.43 \ + \ 2.45 \ (site3) \ + \ 2.97 \ (site4) \ + \ 3.30 \ (site5)$$

$$letDiff = 10.52 \ + \ 3.09 \ (site2) \ - \ 2.86 \ (site3) \ + 4.85 \ (viewcat3) \ + 4.77 \ (viewcat4)$$

$$formDiff = 16.04 \ + \ 2.48 \ (viewcat4)$$

$$numbDiff = 15.39 \ + \ 2.56 \ (site2) \ + \ 3.20 \ (viewcat3) \ + \ 3.64 \ (viewcat4)$$

$$relatDiff = 18.49 \ + \ 2.42 \ (site4) \ + \ 2.96 \ (viewcat4)$$

$$clasfDiff = 10.95 \ + \ 4.06 \ (viewcat4)$$

Table 1: Test Metrics

Response	Least.Squares.Regression.Test.MSE	Ridge.Regression.Test.MSE	Regression.Tree.Test.MSE
bodyDiff	24.01	21.61	20.60
letDiff	14.31	14.20	15.41
formDiff	13.26	12.83	14.92
numbDiff	15.51	14.63	15.91
relatDiff	18.94	19.86	19.89
clasfDiff	48.40	44.26	45.53

From the results of the above table, one can see that the ridge regression models have the best performance, although the performance of the regression trees are very similar . For each response variable except `bodyDiff`, the ridge regression model reports the lowest test MSE, although the difference in performance between the ridge regression and the regression tree is very marginal.

Table 2: Classification Model Accuracy Table

Model	Accuracy
Linear Kernel SVM	0.4028
Radial Kernel SVM	0.3611
Sigmoid Kernel SVM	0.2639
Polynomial Kernel SVM	0.2917
Random Forest	0.4444

Conclusion

Appendix

```
##
## Call:
## lm(formula = bodyDiff ~ (site + sex + age + viewcat + setting +
##     viewenc), data = training)
##
```

```
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11.3707  -2.7927   0.0525   2.5545  13.1411
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 16.42668    3.06383   5.361 2.92e-07 ***
## site2        0.58666    0.99737   0.588  0.55724
## site3        2.44827    0.96820   2.529  0.01244 *
## site4        2.96605    1.10488   2.685  0.00805 **
## site5        3.29854    1.45590   2.266  0.02485 *
## sex2        -1.00041    0.66732  -1.499  0.13586
## age         -0.08726    0.05558  -1.570  0.11845
## viewcat2    -0.60564    1.12908  -0.536  0.59244
## viewcat3     1.30568    1.09680   1.190  0.23568
## viewcat4     2.18215    1.12555   1.939  0.05434 .
## setting2    -1.02953    0.77713  -1.325  0.18718
## viewenc2    -0.37832    0.84111  -0.450  0.65349
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.253 on 156 degrees of freedom
## Multiple R-squared:  0.1585, Adjusted R-squared:  0.09917
## F-statistic: 2.671 on 11 and 156 DF,  p-value: 0.00362
```

```
## [1] 976.6991
```

```
## [1] 24.01045
```

```
## [1] 21.60675
```

```
##
## Call:
## lm(formula = letDiff ~ (site + sex + age + viewcat + setting +
##     viewenc), data = training)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -16.2823  -2.9776  -0.3663   2.9275  11.1426
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 10.52353    3.32595   3.164  0.00187 **
## site2        3.08586    1.08270   2.850  0.00496 **
## site3       -2.85941    1.05103  -2.721  0.00726 **
## site4       -1.07861    1.19940  -0.899  0.36989
## site5       -0.38501    1.58046  -0.244  0.80786
## sex2         0.37911    0.72441   0.523  0.60148
## age          0.05050    0.06034   0.837  0.40390
## viewcat2     1.59616    1.22568   1.302  0.19474
## viewcat3     4.85135    1.19064   4.075 7.32e-05 ***
## viewcat4     4.77123    1.22184   3.905  0.00014 ***
## setting2     0.70346    0.84362   0.834  0.40563
## viewenc2    -1.56705    0.91307  -1.716  0.08810 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.617 on 156 degrees of freedom
## Multiple R-squared:   0.37,  Adjusted R-squared:  0.3256
## F-statistic:  8.33 on 11 and 156 DF,  p-value: 2.043e-11
```

```
## [1] 1004.281
```

```
## [1] 14.31277
```

```
## [1] 14.19572
```

```
##
## Call:
## lm(formula = formDiff ~ (site + sex + age + viewcat + setting +
##     viewenc), data = training)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -14.3637  -2.5344   0.2658   2.7054  14.1942
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 16.04193    3.16388   5.070 1.11e-06 ***
## site2        0.97029    1.02994   0.942   0.3476
## site3        0.73495    0.99982   0.735   0.4634
## site4        0.92962    1.14096   0.815   0.4164
## site5        1.00499    1.50344   0.668   0.5048
## sex2         0.09439    0.68911   0.137   0.8912
## age         -0.05234    0.05740  -0.912   0.3632
## viewcat2     0.99101    1.16595   0.850   0.3966
## viewcat3     1.65614    1.13262   1.462   0.1457
## viewcat4     2.47768    1.16230   2.132   0.0346 *
## setting2    -0.08994    0.80251  -0.112   0.9109
## viewenc2    -0.42935    0.86858  -0.494   0.6218
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.392 on 156 degrees of freedom
## Multiple R-squared:  0.06302,    Adjusted R-squared:  -0.003048
## F-statistic: 0.9539 on 11 and 156 DF,  p-value: 0.4909
```

```
## [1] 987.4956
```

```
## [1] 13.25639
```

```
## [1] 12.82502
```

```
##
## Call:
```

```
## lm(formula = numbDiff ~ (site + sex + age + viewcat + setting +
##     viewenc), data = training)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -19.6433  -2.6010   0.1375   2.3541  10.3247
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 15.388591   3.084422   4.989  1.6e-06 ***
## site2        2.561427   1.004073   2.551  0.01170 *
## site3        0.768616   0.974707   0.789  0.43157
## site4        1.151651   1.112304   1.035  0.30210
## site5        1.946294   1.465685   1.328  0.18615
## sex2         0.013992   0.671801   0.021  0.98341
## age          0.009505   0.055956   0.170  0.86534
## viewcat2     1.841715   1.136668   1.620  0.10719
## viewcat3     3.199614   1.104174   2.898  0.00430 **
## viewcat4     3.636674   1.133111   3.209  0.00161 **
## setting2     0.596707   0.782354   0.763  0.44679
## viewenc2     0.589407   0.846765   0.696  0.48742
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.281 on 156 degrees of freedom
## Multiple R-squared:  0.139,  Adjusted R-squared:  0.07825
## F-statistic: 2.289 on 11 and 156 DF,  p-value: 0.01273
```

```
## [1] 978.9495
```

```
## [1] 15.5095
```

```
## [1] 14.62731
```

```
##
## Call:
## lm(formula = relatDiff ~ (site + sex + age + viewcat + setting +
##     viewenc), data = training)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12.9246  -2.7114   0.3439   2.2185  14.4415
##
## Coefficients:
##            Estimate Std. Error t value Pr(>|t|)
## (Intercept) 18.48969    3.17203   5.829  3.1e-08 ***
## site2       -0.05900    1.03259  -0.057   0.9545
## site3        1.66242    1.00239   1.658   0.0992 .
## site4        2.41955    1.14390   2.115   0.0360 *
## site5       -0.40561    1.50731  -0.269   0.7882
## sex2         0.31932    0.69088   0.462   0.6446
## age         -0.09729    0.05755  -1.691   0.0929 .
## viewcat2     1.05190    1.16895   0.900   0.3696
## viewcat3     0.96616    1.13554   0.851   0.3962
## viewcat4     2.95954    1.16529   2.540   0.0121 *
## setting2    -0.60666    0.80457  -0.754   0.4520
## viewenc2     0.19462    0.87082   0.223   0.8234
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.403 on 156 degrees of freedom
## Multiple R-squared:  0.1072, Adjusted R-squared:  0.04421
## F-statistic: 1.702 on 11 and 156 DF,  p-value: 0.07739
```

```
## [1] 988.3598
```

```
## [1] 18.94131
```

```
## [1] 19.86283
```

```
##
## Call:
## lm(formula = clasfDiff ~ (site + sex + age + viewcat + setting +
##     viewenc), data = training)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -14.1077  -4.0442   0.2665   3.8807  14.5260
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 10.951998   4.455915   2.458   0.0151 *
## site2        1.799749   1.450536   1.241   0.2166
## site3        0.420798   1.408112   0.299   0.7655
## site4        2.040728   1.606891   1.270   0.2060
## site5        1.497017   2.117404   0.707   0.4806
## sex2         1.500233   0.970519   1.546   0.1242
## age         -0.008915   0.080838  -0.110   0.9123
## viewcat2     3.041609   1.642090   1.852   0.0659 .
## viewcat3     3.072479   1.595147   1.926   0.0559 .
## viewcat4     4.060404   1.636951   2.480   0.0142 *
## setting2     0.477618   1.130229   0.423   0.6732
## viewenc2    -1.088979   1.223281  -0.890   0.3747
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.185 on 156 degrees of freedom
## Multiple R-squared:  0.09426,    Adjusted R-squared:  0.03039
## F-statistic: 1.476 on 11 and 156 DF,  p-value: 0.1455
```

```
## [1] 1102.553
```

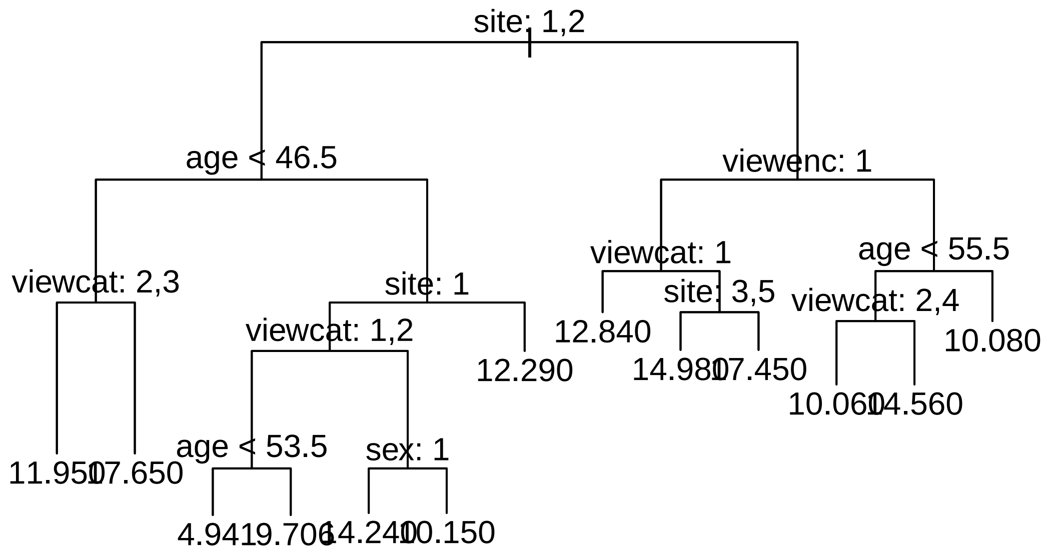
```
## [1] 48.398
```

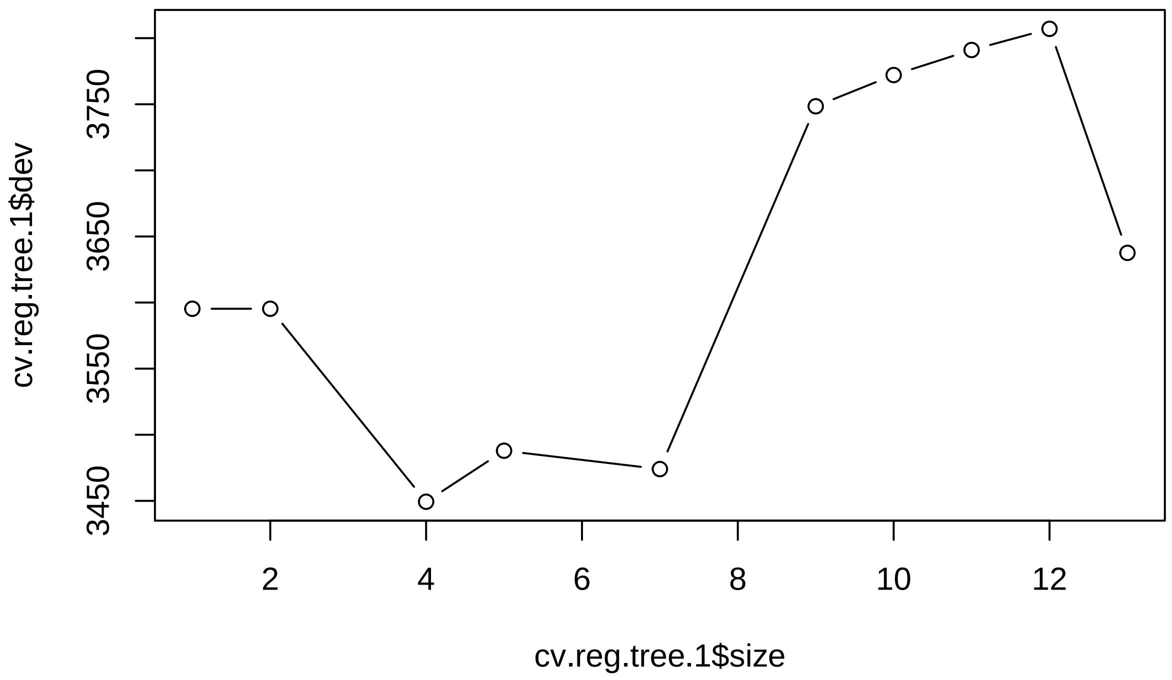
```
## [1] 44.26185
```

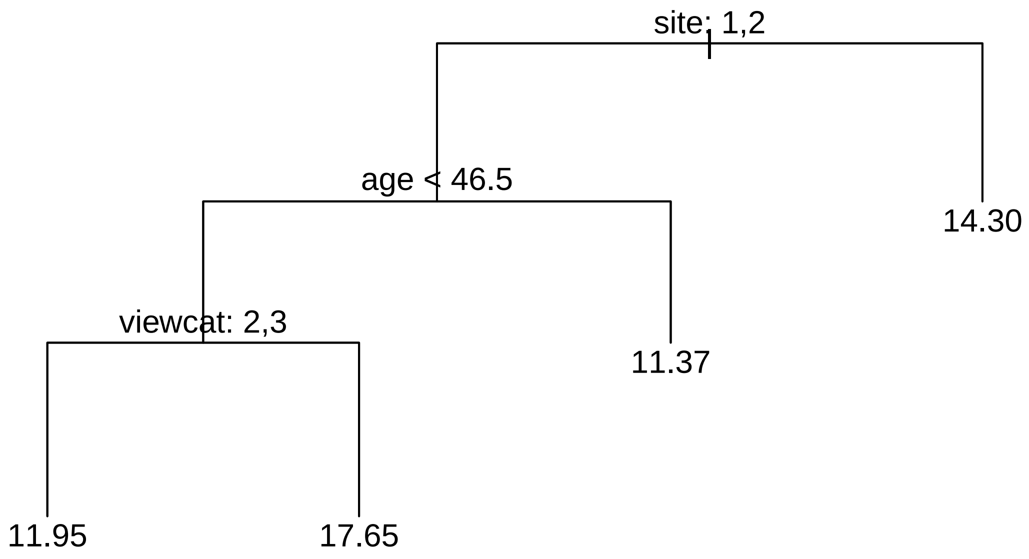
Regression Tree Models

Model 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
```



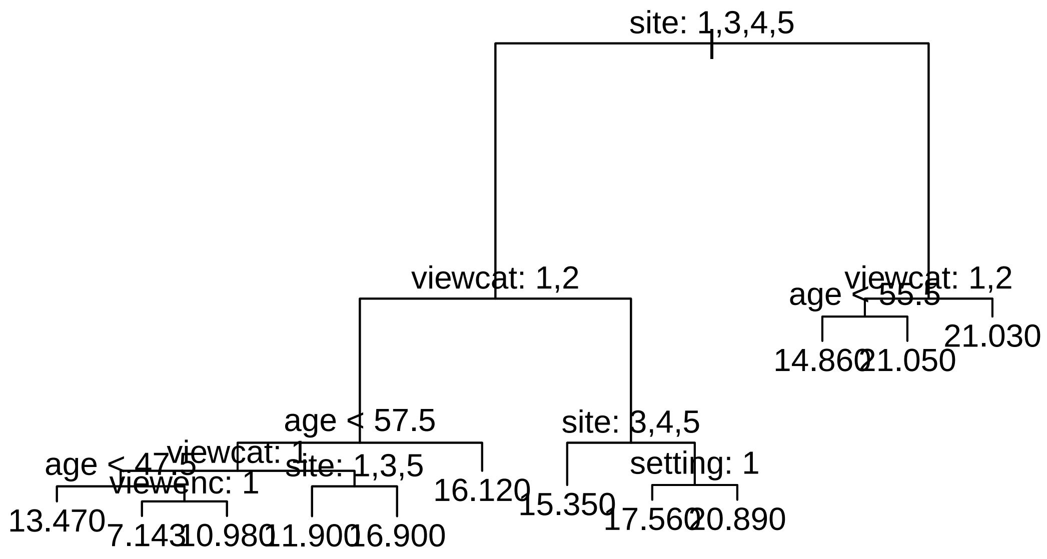

cv.reg.tree.1$dev
3450
3550
3650
3750
2
4
6
8
10
12
cv.reg.tree.1$size

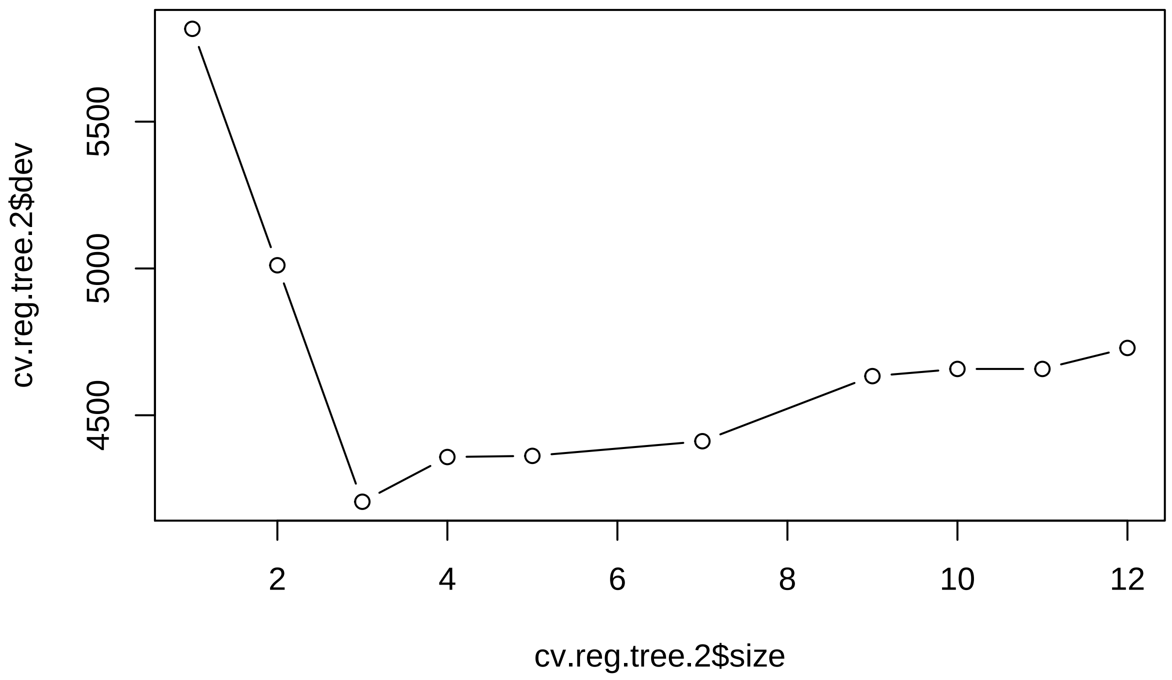


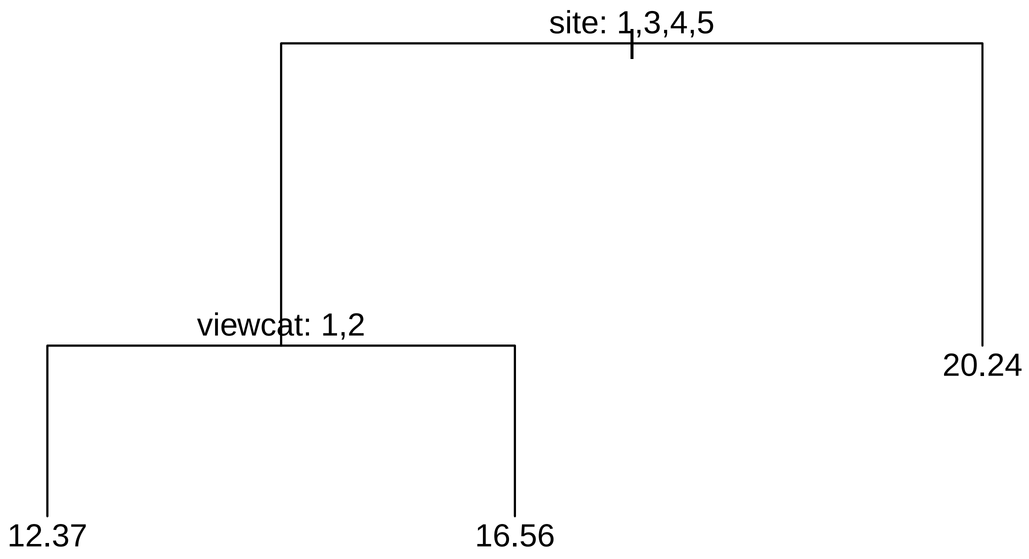
```
## [1] 20.60159
```

Model 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
```


site: 1,3,4,5
viewcat: 1,2
viewcat: 1,2
age < 55.5
21.030
14.860
21.050
age < 57.5
site: 3,4,5
viewcat: 1
age < 47.5
site: 1,3,5
setting: 1
viewenc: 1
16.120
15.350
13.470
17.560
20.890
7.143
10.980
11.900
16.900

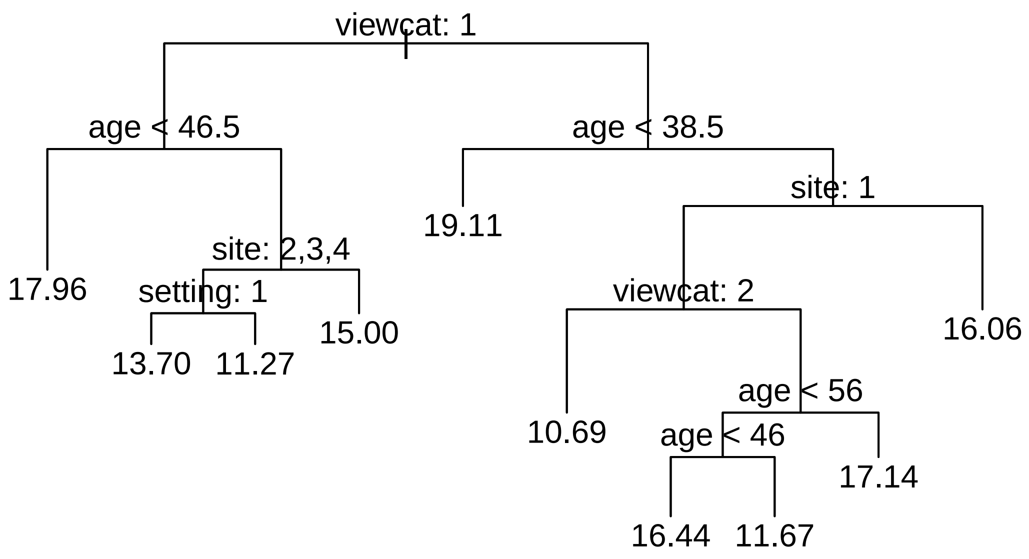

cv.reg.tree.2$dev
5500
5000
4500
2
4
6
8
10
12
cv.reg.tree.2$size

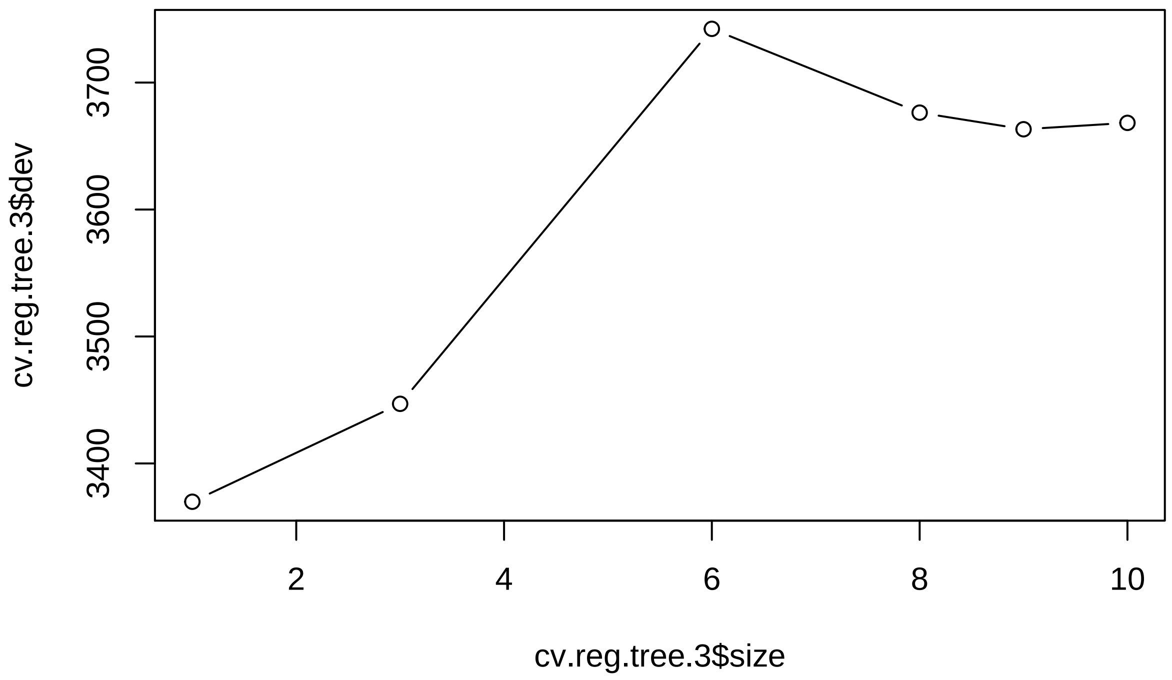


```
## [1] 15.4124
```

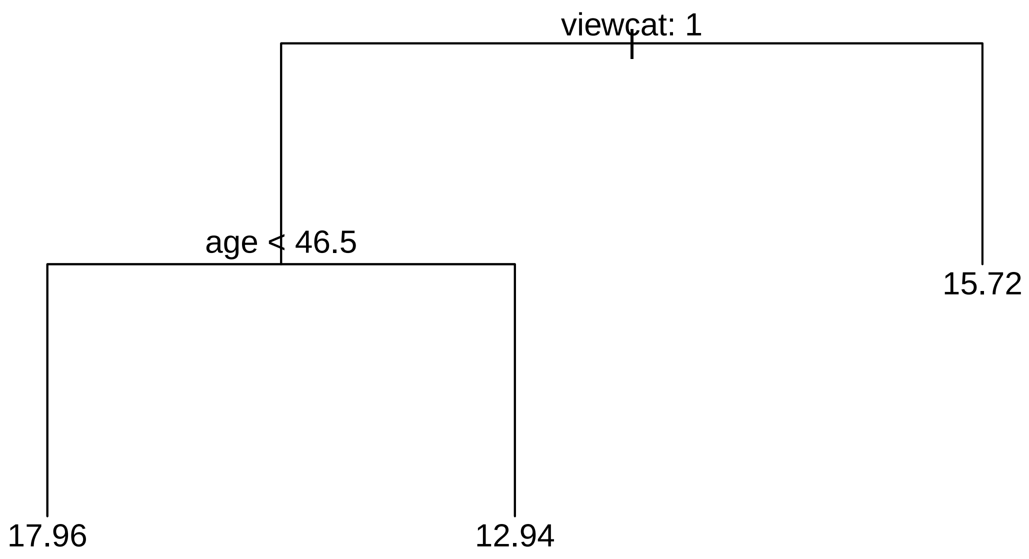
Model 3

```
##
## 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
```


viewcat: 1
age < 46.5
age < 38.5
site: 1
19.11
site: 2,3,4
17.96
setting: 1
viewcat: 2
15.00
16.06
13.70
11.27
age < 56
10.69
age < 46
17.14
16.44
11.67



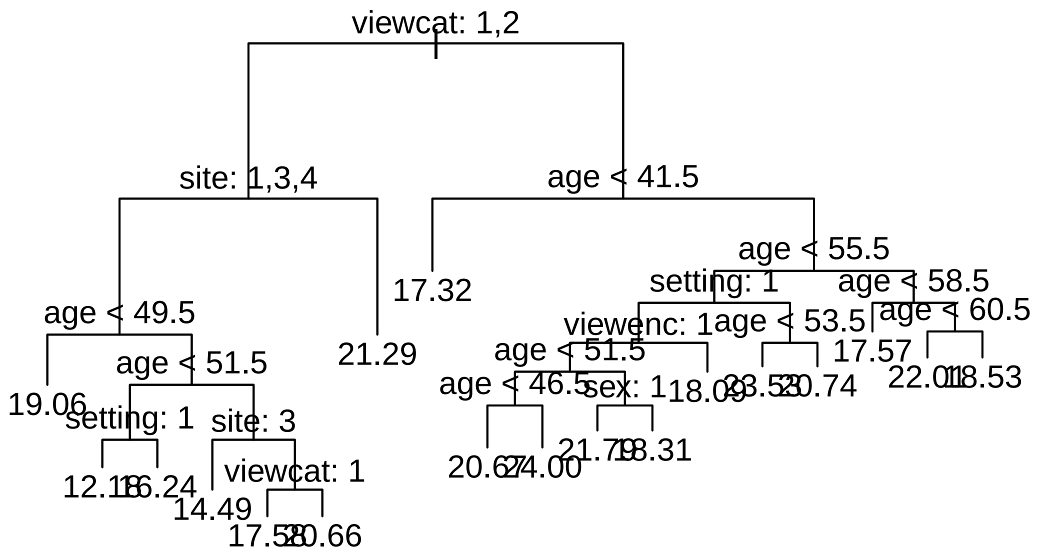
cv.reg.tree.3$dev
3400
3500
3600
3700
2
4
6
8
10
cv.reg.tree.3$size

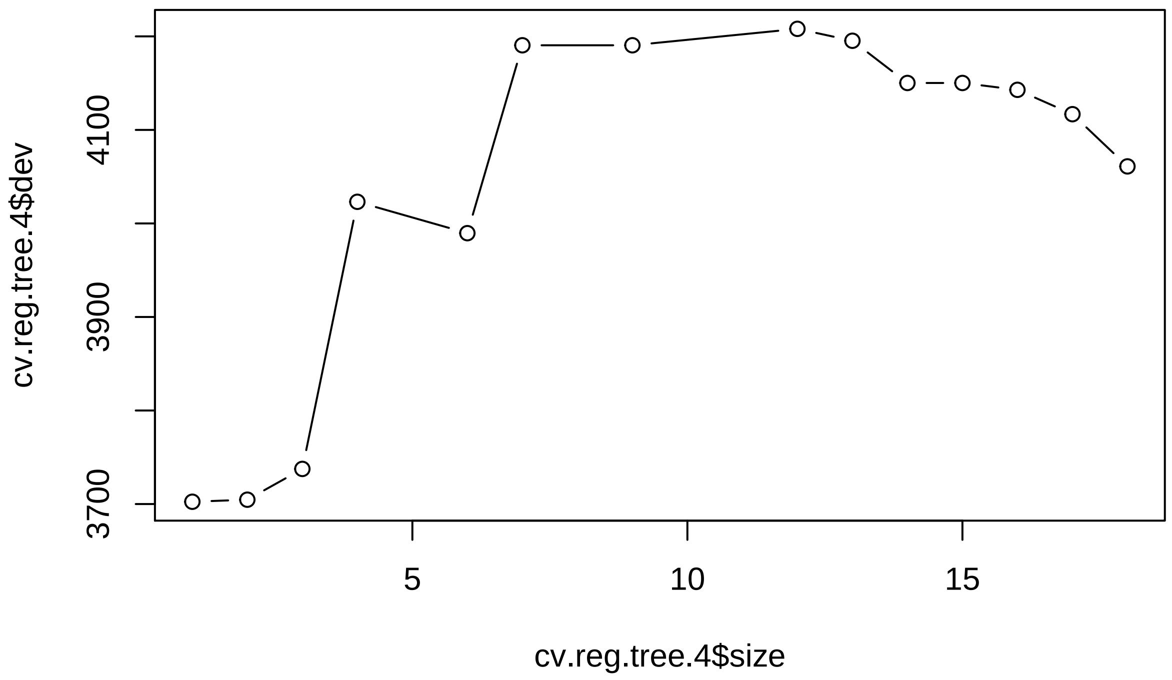


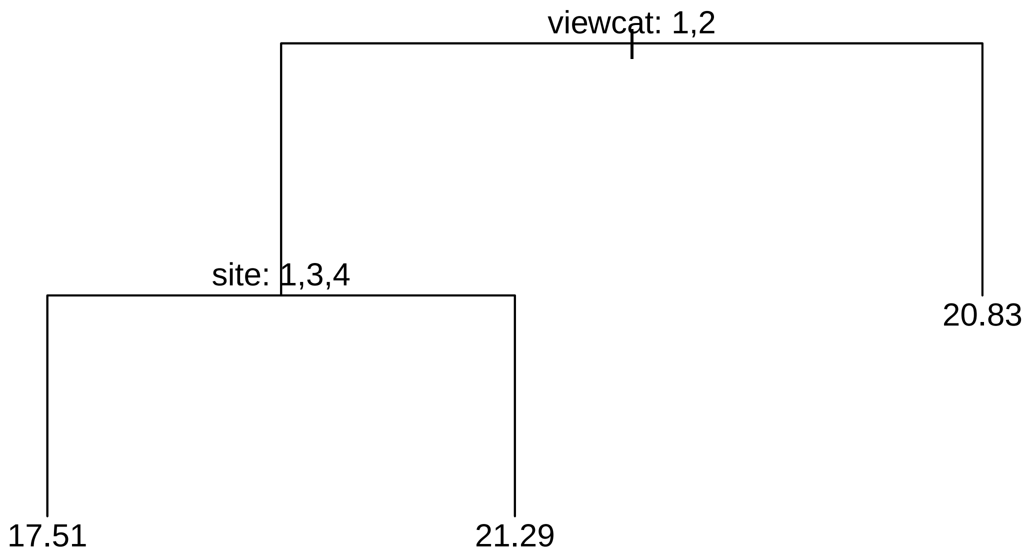
```
## [1] 14.92273
```

Model 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
```


viewcat: 1,2
site: 1,3,4
age < 41.5
age < 49.5
21.29
17.32
age < 55.5
19.06
age < 51.5
setting: 1
age < 58.5
setting: 1
site: 3
viewenc: 1
age < 53.5
age < 60.5
12.18
16.24
14.49
viewcat: 1
17.58
20.66
age < 51.5
age < 46.5
sex: 1
18.09
23.53
20.74
17.57
22.01
18.53
20.67
24.00
21.79
18.31

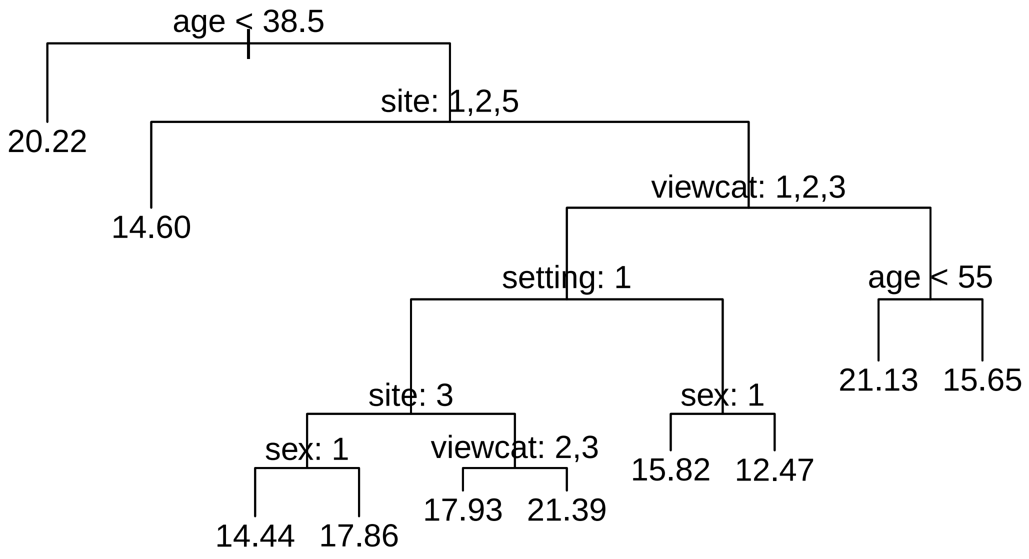

cv.reg.tree.4$dev
3700
3900
4100
5
10
15
cv.reg.tree.4$size

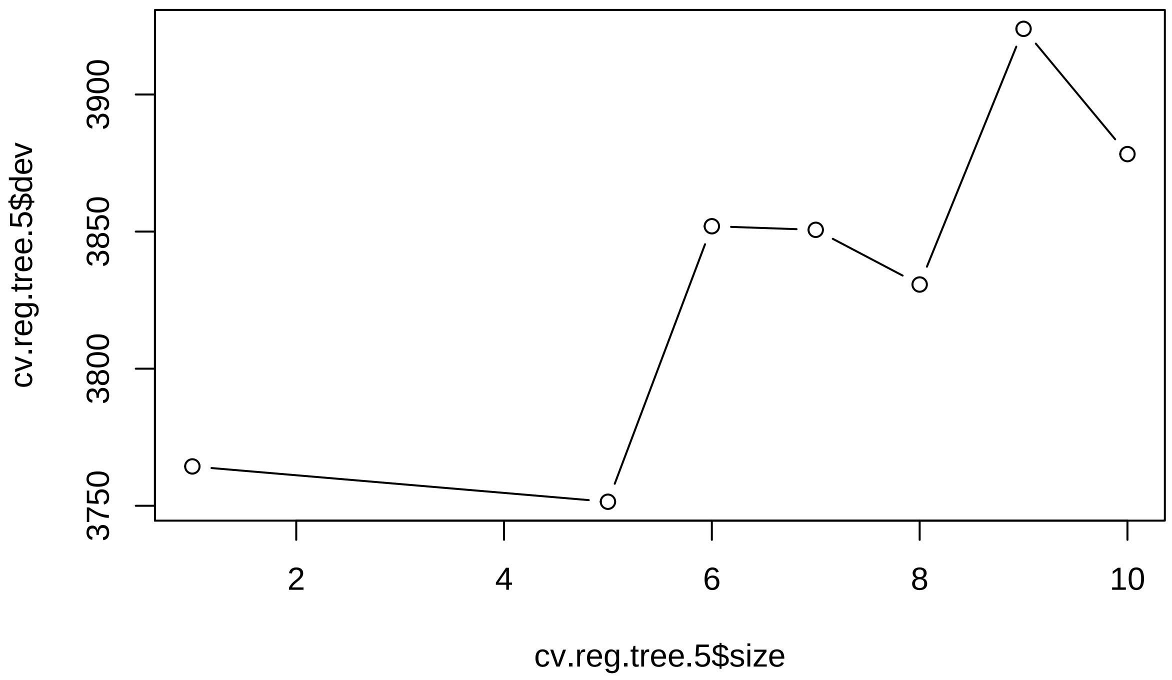


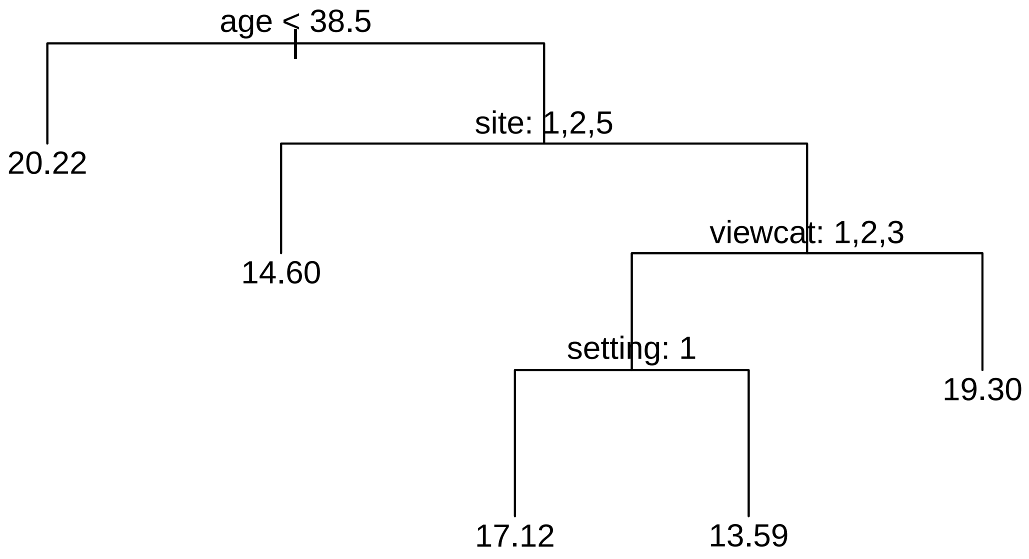
```
## [1] 15.90771
```

Model 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
```


age < 38.5
20.22
site: 1,2,5
14.60
viewcat: 1,2,3
setting: 1
age < 55
21.13
15.65
site: 3
sex: 1
15.82
12.47
sex: 1
viewcat: 2,3
14.44
17.86
17.93
21.39

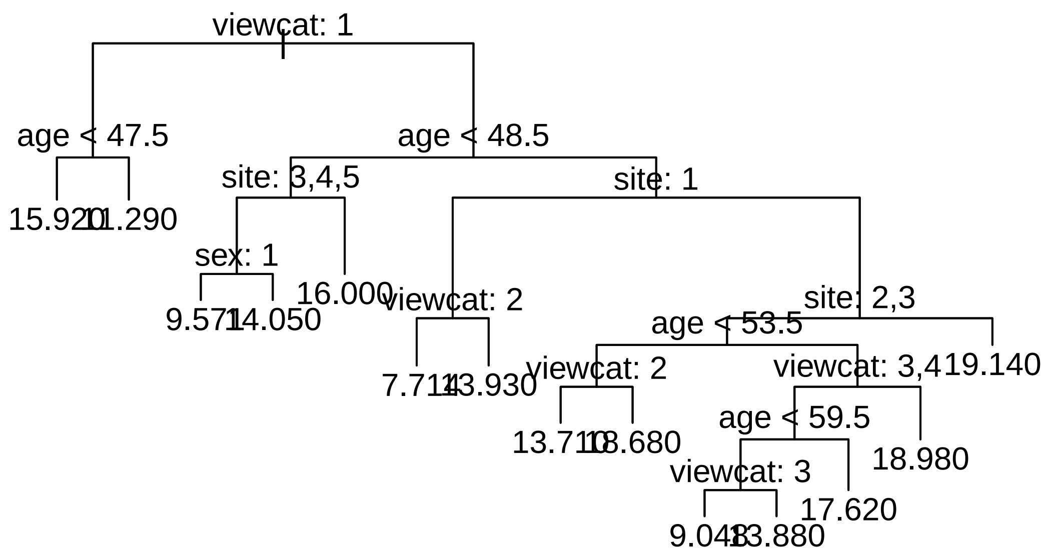

cv.reg.tree.5$dev
3750
3800
3850
3900
2
4
6
8
10
cv.reg.tree.5$size

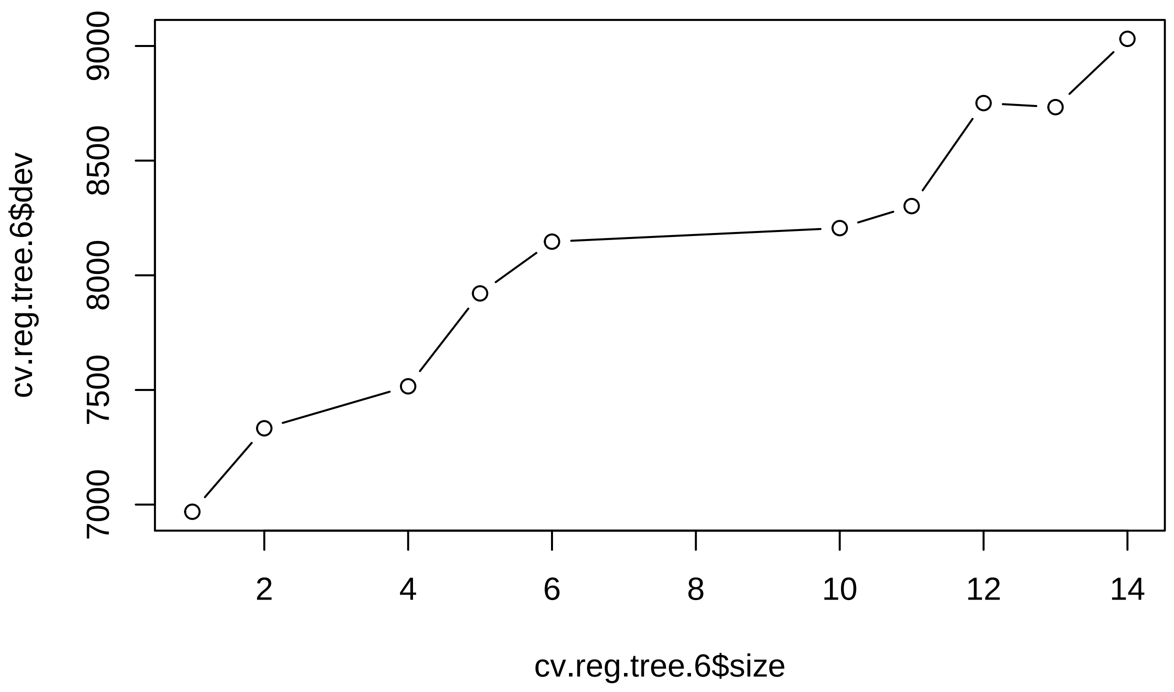


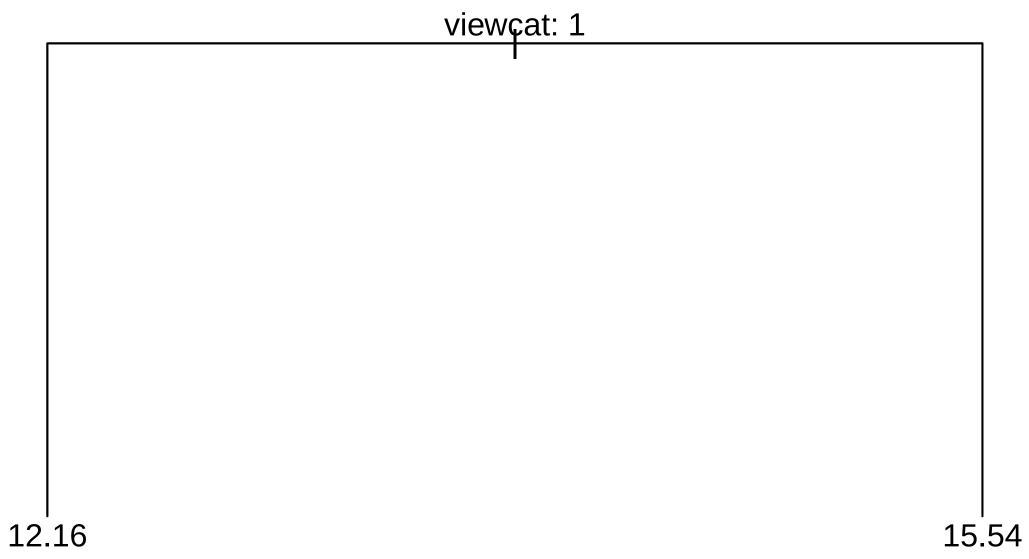
```
## [1] 19.88506
```

Model 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
```


viewcat: 1
age < 47.5
age < 48.5
15.920
11.290
site: 3,4,5
site: 1
sex: 1
16.000
9.571
14.050
viewcat: 2
site: 2,3
7.714
13.930
age < 53.5
viewcat: 2
viewcat: 3,4
19.140
13.710
18.680
age < 59.5
18.980
viewcat: 3
17.620
9.048
13.880


cv.reg.tree.6$dev
cv.reg.tree.6$size
7000
7500
8000
8500
9000
2
4
6
8
10
12
14



```
## [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?

SVM

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

```
## Confusion Matrix and Statistics
##
##     pred
## true  1  2  3  4  5
##    1  2  5 13  0  0
##    2  0  8  5  0  0
##    3  1  1 14  0  0
##    4  0  4 14  0  0
##    5  0  1  4  0  0
##
```

```
## Overall Statistics
##
##                Accuracy : 0.3333
##                  95% CI : (0.2266, 0.4543)
##     No Information Rate : 0.6944
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.1523
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: 1 Class: 2 Class: 3 Class: 4 Class: 5
## Sensitivity           0.66667   0.4211   0.2800       NA       NA
## Specificity           0.73913   0.9057   0.9091     0.75  0.93056
## Pos Pred Value        0.10000   0.6154   0.8750       NA       NA
## Neg Pred Value        0.98077   0.8136   0.3571       NA       NA
## Prevalence            0.04167   0.2639   0.6944     0.00  0.00000
## Detection Rate        0.02778   0.1111   0.1944     0.00  0.00000
## Detection Prevalence  0.27778   0.1806   0.2222     0.25  0.06944
## Balanced Accuracy     0.70290   0.6634   0.5945       NA       NA
```

```
## Confusion Matrix and Statistics
##
##     pred
## true  1  2  3  4  5
##    1  7  3 10  0  0
##    2  3  6  4  0  0
##    3  0  2 14  0  0
##    4  2  4 12  0  0
##    5  0  1  4  0  0
##
## Overall Statistics
##
##                Accuracy : 0.375
##                  95% CI : (0.2636, 0.497)
##     No Information Rate : 0.6111
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.1964
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: 1 Class: 2 Class: 3 Class: 4 Class: 5
## Sensitivity           0.58333  0.37500   0.3182       NA       NA
## Specificity           0.78333  0.87500   0.9286     0.75  0.93056
## Pos Pred Value        0.35000  0.46154   0.8750       NA       NA
## Neg Pred Value        0.90385  0.83051   0.4643       NA       NA
## Prevalence            0.16667  0.22222   0.6111     0.00  0.00000
## Detection Rate        0.09722  0.08333   0.1944     0.00  0.00000
## Detection Prevalence  0.27778  0.18056   0.2222     0.25  0.06944
## Balanced Accuracy     0.68333  0.62500   0.6234       NA       NA

## Confusion Matrix and Statistics
##
##     pred
## true  1  2  3  4  5
##    1  1  7 12  0  0
##    2  1  8  4  0  0
##    3  3  1 12  0  0
##    4  3  4 11  0  0
##    5  0  1  4  0  0
##
## Overall Statistics
##
##                Accuracy : 0.2917
##                  95% CI : (0.1905, 0.4107)
##     No Information Rate : 0.5972
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.0962
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: 1 Class: 2 Class: 3 Class: 4 Class: 5
## Sensitivity           0.12500   0.3810   0.2791       NA       NA
## Specificity           0.70312   0.9020   0.8621     0.75  0.93056
## Pos Pred Value        0.05000   0.6154   0.7500       NA       NA
## Neg Pred Value        0.86538   0.7797   0.4464       NA       NA
## Prevalence            0.11111   0.2917   0.5972     0.00  0.00000
## Detection Rate        0.01389   0.1111   0.1667     0.00  0.00000
## Detection Prevalence  0.27778   0.1806   0.2222     0.25  0.06944
## Balanced Accuracy     0.41406   0.6415   0.5706       NA       NA

## Confusion Matrix and Statistics
##
##     pred
## true  1  2  3  4  5
##    1  9  2  9  0  0
##    2  4  5  4  0  0
##    3  3  1 12  0  0
##    4  3  3 12  0  0
##    5  0  1  4  0  0
##
## Overall Statistics
##
##                Accuracy : 0.3611
##                  95% CI : (0.2512, 0.4829)
##     No Information Rate : 0.5694
##     P-Value [Acc > NIR] : 0.9999
##
##                   Kappa : 0.1703
##
```

```
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: 1 Class: 2 Class: 3 Class: 4 Class: 5
## Sensitivity            0.4737  0.41667   0.2927       NA       NA
## Specificity            0.7925  0.86667   0.8710     0.75  0.93056
## Pos Pred Value         0.4500  0.38462   0.7500       NA       NA
## Neg Pred Value         0.8077  0.88136   0.4821       NA       NA
## Prevalence             0.2639  0.16667   0.5694     0.00  0.00000
## Detection Rate         0.1250  0.06944   0.1667     0.00  0.00000
## Detection Prevalence   0.2778  0.18056   0.2222     0.25  0.06944
## Balanced Accuracy      0.6331  0.64167   0.5818       NA       NA
```

```
## 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
```

```
## 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
```

```
## 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
```

```
## Confusion Matrix and Statistics
##
##     pred
## true  1  2  3  4  5
##    1  6  2  5  1  6
##    2  4  2  3  0  4
##    3  1  0 11  1  3
##    4  3  2  8  1  4
##    5  1  1  2  0  1
##
## Overall Statistics
##
##                Accuracy : 0.2917
##                  95% CI : (0.1905, 0.4107)
##     No Information Rate : 0.4028
##     P-Value [Acc > NIR] : 0.981095
##
##                   Kappa : 0.1226
##
##  Mcnemar's Test P-Value : 0.006726
##
## Statistics by Class:
##
##                      Class: 1 Class: 2 Class: 3 Class: 4 Class: 5
## Sensitivity           0.40000  0.28571   0.3793  0.33333  0.05556
## Specificity           0.75439  0.83077   0.8837  0.75362  0.92593
## Pos Pred Value        0.30000  0.15385   0.6875  0.05556  0.20000
## Neg Pred Value        0.82692  0.91525   0.6786  0.96296  0.74627
## Prevalence            0.20833  0.09722   0.4028  0.04167  0.25000
## Detection Rate        0.08333  0.02778   0.1528  0.01389  0.01389
## Detection Prevalence  0.27778  0.18056   0.2222  0.25000  0.06944
## Balanced Accuracy     0.57719  0.55824   0.6315  0.54348  0.49074
```

In order to address our second research question, predicting whether a child came from an disadvantaged background or not based on their pretest scores and demographic information, we utilized a support vector machine (SVM). Our model uses the female, male, age, and all pretest score variables to predict our response variable, site. Since our response variable is a categorical variable, a SVM is a valid choice to answer our research question. We also implemented a classification tree to answer this question as well; however, this model performed poorly on our data. Thus, a SVM was the most appropriate model choice for our research goals. Our full model formula is: (add formula)

We split our data into a 70% training set and 30% testing set and analyzed the performance of our model on the test set. To improve our model's predictive power, we implemented a variety of different methods. We tested our model using linear, radial, and sigmoid kernels and compared the predictive accuracy between these models. Since we are interested in high predictive power and the radial kernel had the highest prediction accuracy, we chose this kernel.

Standardizing the predictor variables in SVM and encoding categorical variables has been shown to improve performance for SVMs (https://www.csie.ntu.edu.tw/~cjlin/papers/guide/guide.pdf). Thus, we used the standardized forms of the continuous variables in our model and encoded the sex variable so that if a child was a male we would code that as 1. We did indeed observe a small improvement in prediction accuracy across all models. However, one problem that particularly piqued our interests is that we are making no predictions for sites 4 or 5. This could be due to sites 4 & 5 having a smaller number of observations than the other classes. Thus, we used the class weight formula below to assign weights to each class and specify "one versus one" comparison, which has been suggested to yield better prediction than "one versus all."

$$w_j = \frac{n}{kn_j},\ \text{n is total number of data points, k is number of classes, } n_j \text{ is the number of data in class j}$$

After the class weight assignment, the SVM models began to make prediction on class 4 & 5. However, doing so came at the cost of overall accuracy. Thus, more of the other observations are being misclassified, but the few observations of class 4&5 are correctly classified. To remedy this issue, we began to experiment with the class weights and increase the class 4 & 5 weights by roughly 0.5, which is arbitrarily chosen, and it boosted linear kernel SVM's prediction accuracy to 0.403.