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

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Introduction

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 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. The least-squares and ridge regression models also took into account all possible two-way interaction terms between the variables.

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~

Results

Table 1: Test Metrics

Response	Least.Regression.Test.MSE	Ridge.Regression.Test.MSE	Regression.Tree.Test.MSE
bodyDiff	32.45	21.61	20.60
letDiff	24.45	14.20	15.41
formDiff	23.19	12.83	14.92
numbDiff	28.24	14.63	15.91
relatDiff	23.64	19.86	19.89
clasfDiff	65.41	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.

Conclusion

Appendix

```
##
## 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
```

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

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

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

```
##
## 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
```

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

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

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

```
##
## 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
```

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

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

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

```
##
## 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
```

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

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

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

```
##
## 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
```

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

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

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

```
##
## 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
```

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

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

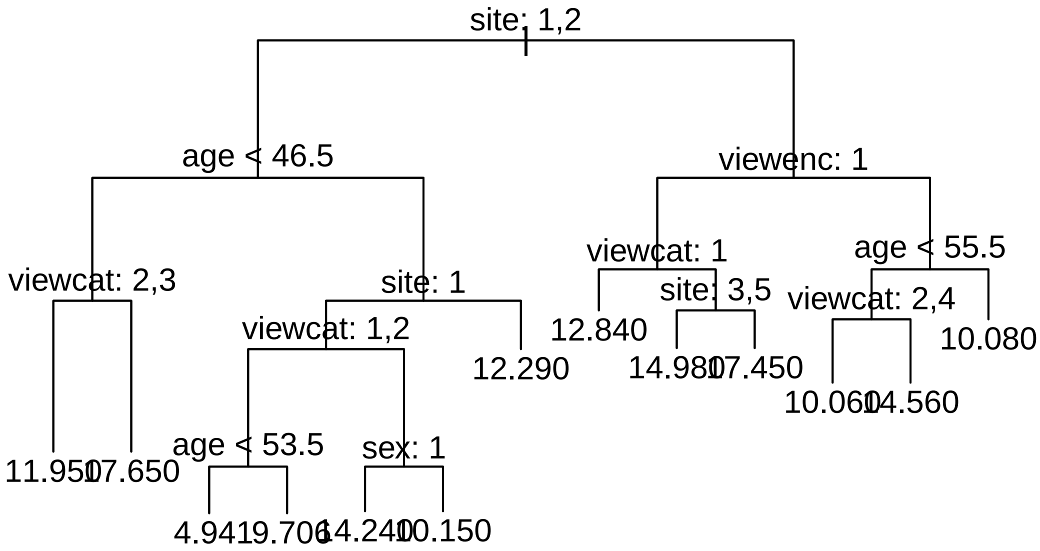
```
## [1] 44.26185
```

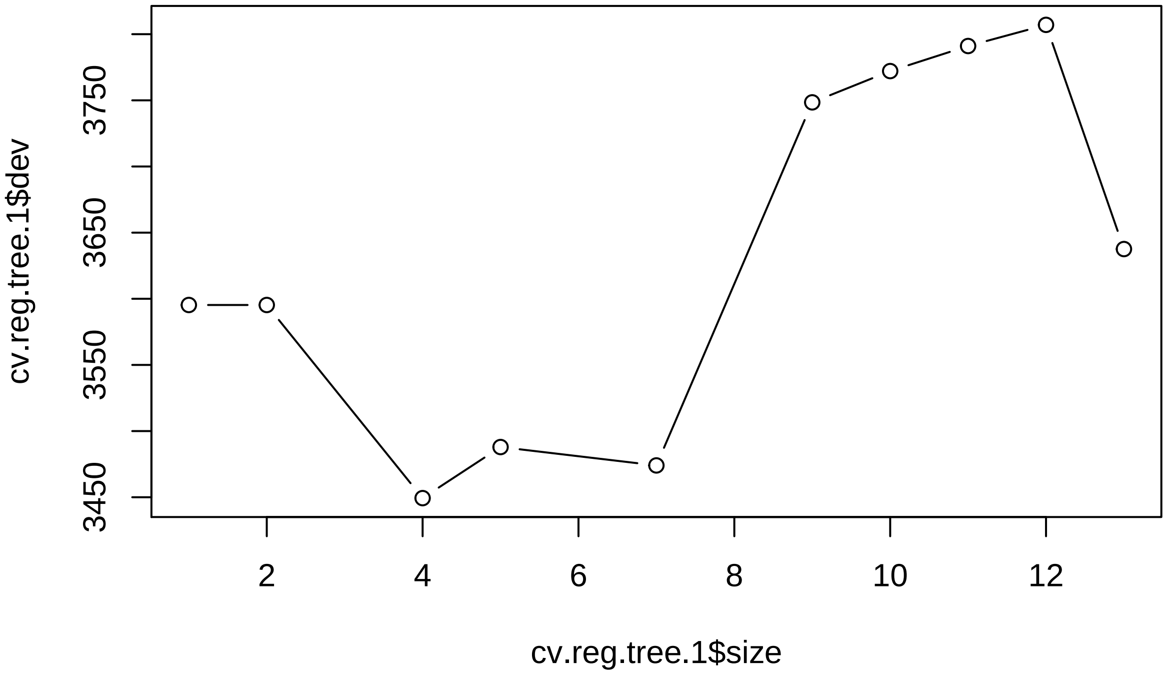
Regression Tree Models

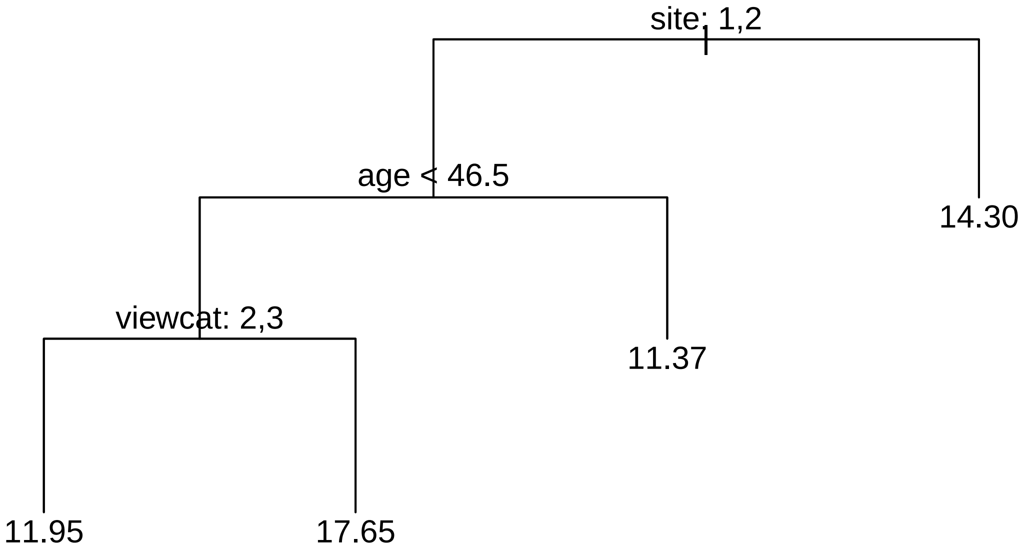
In the context of a regression tree, the deviance is simply the sum of the squared errors.

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
```



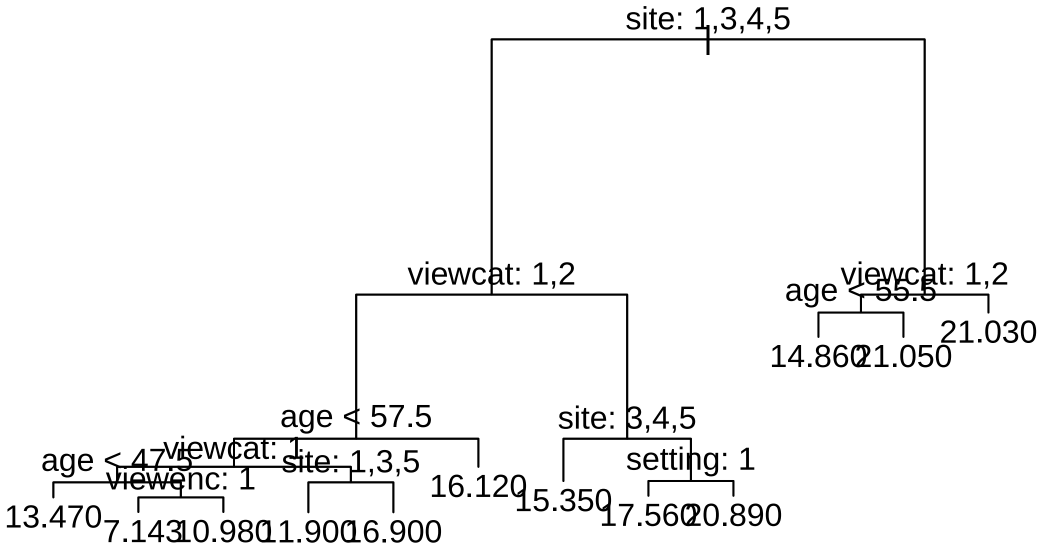

cv.reg.tree.1$dev
3450
3550
3650
3750
2
4
6
8
10
12
cv.reg.tree.1$size

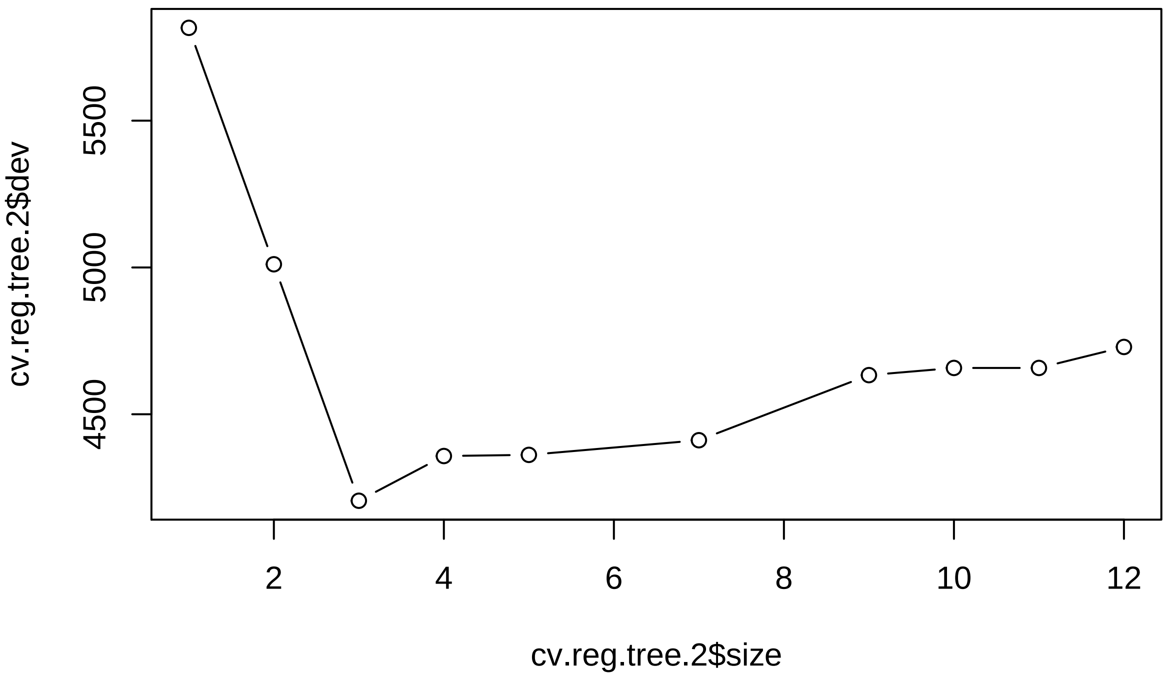


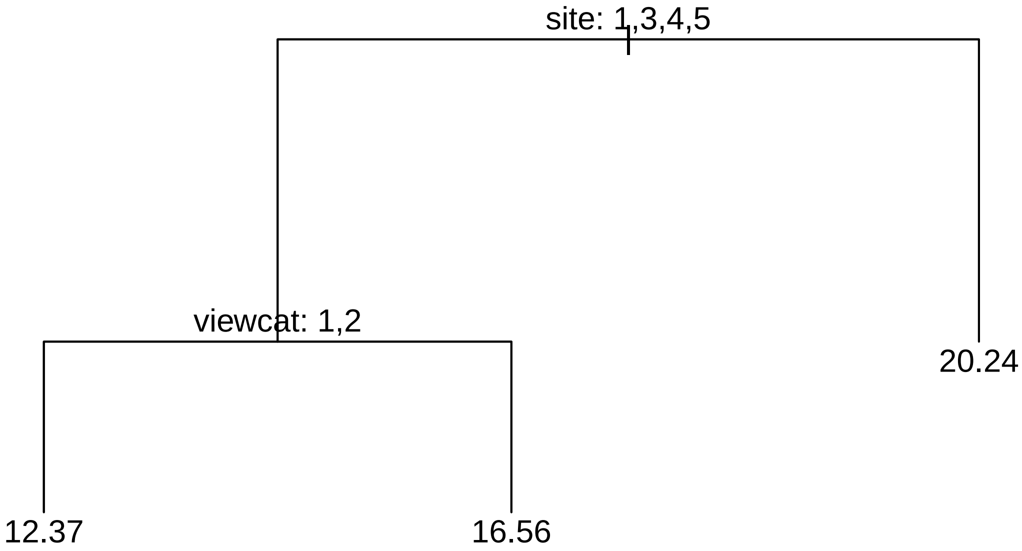
```
## [1] 20.60159
```

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
viewenc: 1
site: 1,3,5
setting: 1
16.120
15.350
13.470
7.143
10.980
11.900
16.900
17.560
20.890

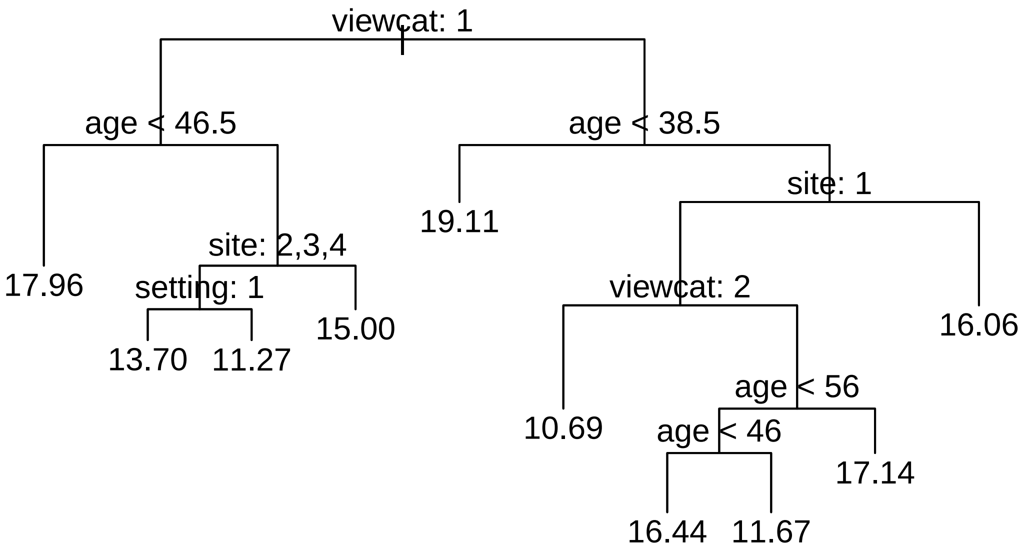

cv.reg.tree.2$dev
5500
5000
4500
2
4
6
8
10
12
cv.reg.tree.2$size

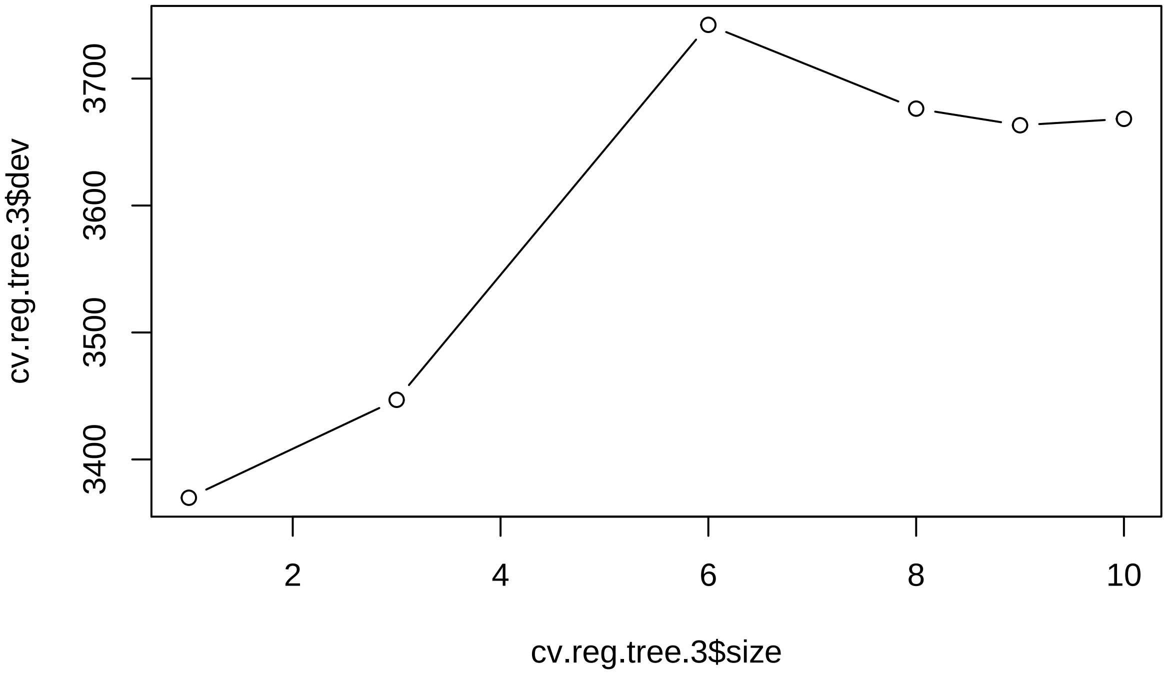


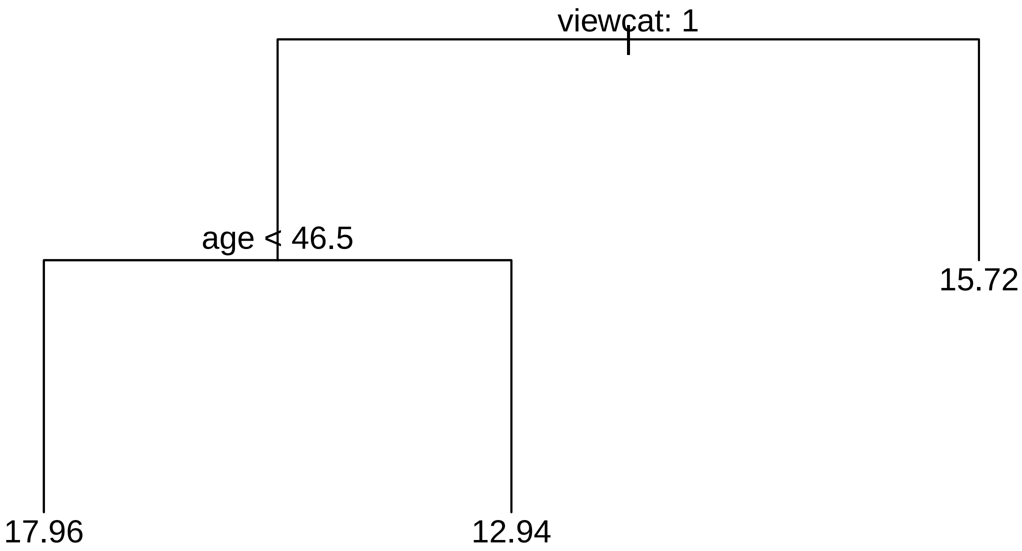
```
## [1] 15.4124
```

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

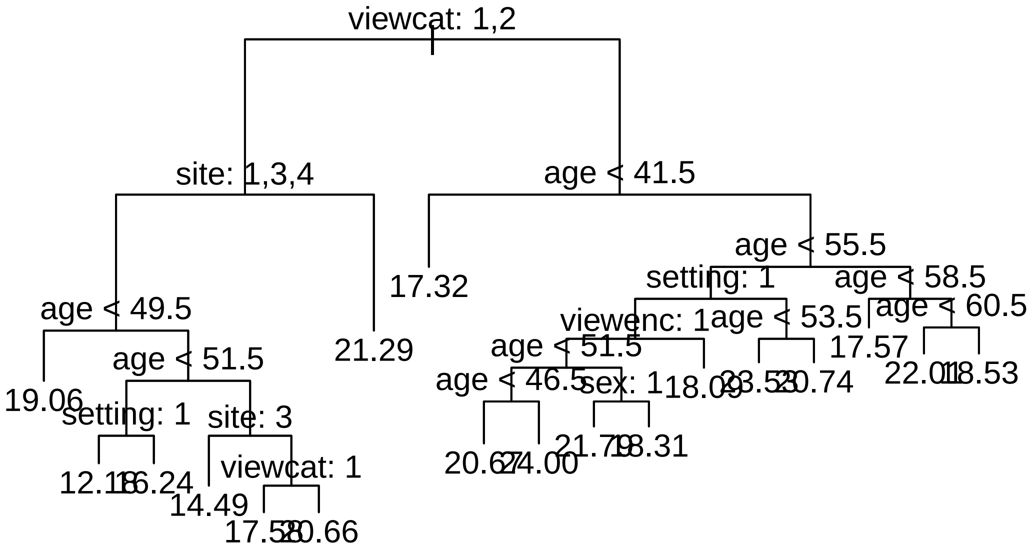

3400
3500
3600
3700
cv.reg.tree.3$dev
2
4
6
8
10
cv.reg.tree.3$size

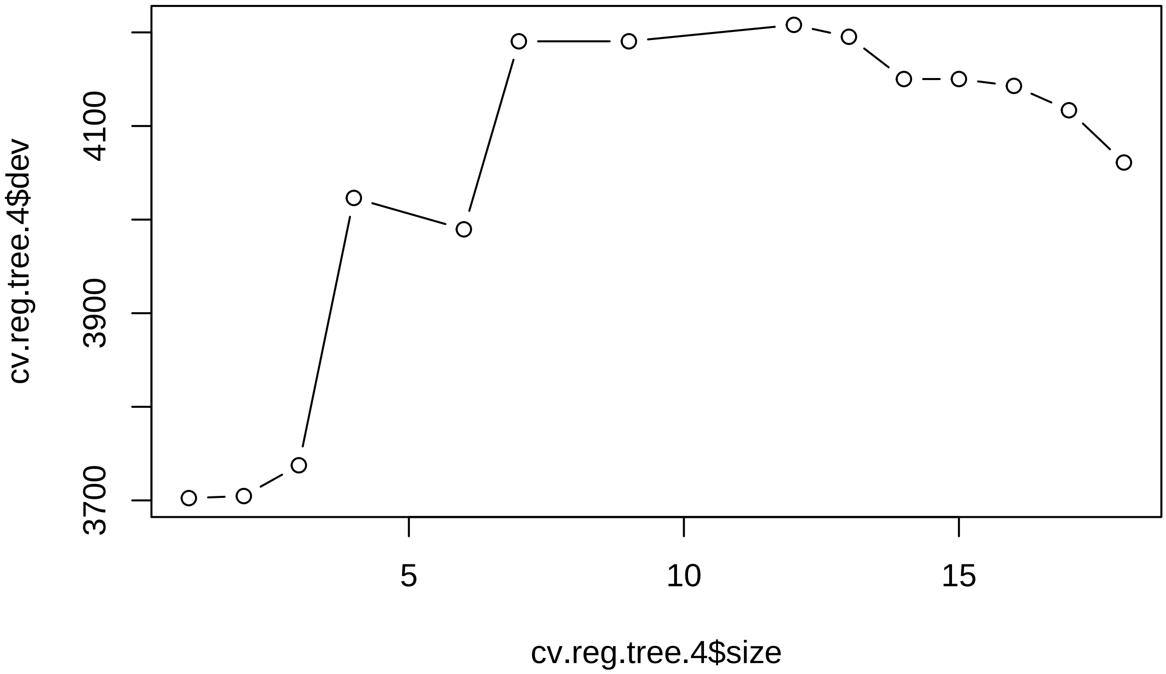


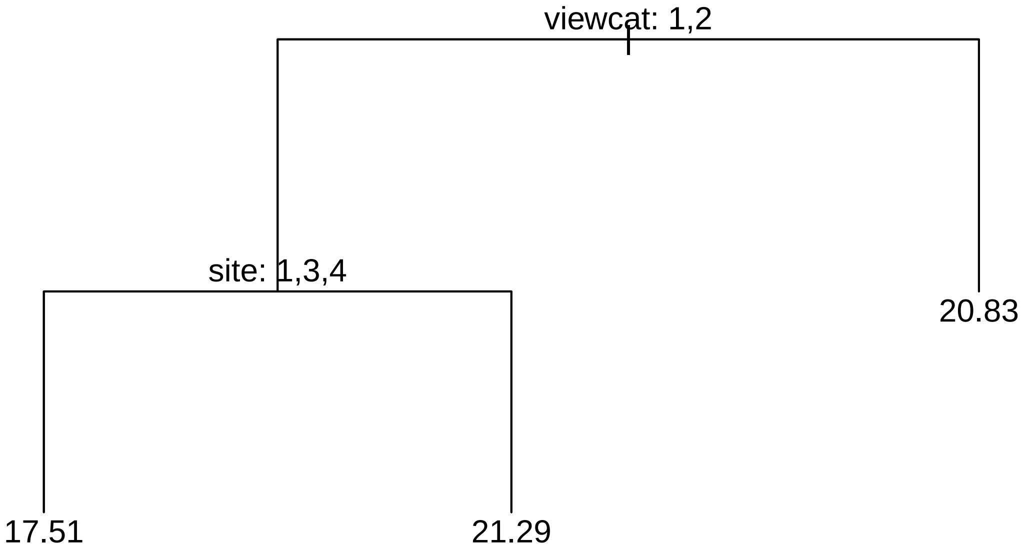
```
## [1] 14.92273
```

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 < 55.5
setting: 1
age < 58.5
17.32
age < 60.5
age < 49.5
viewenc: 1
age < 53.5
age < 51.5
21.29
17.57
age < 51.5
age < 46.5
sex: 1
18.09
23.52
20.74
22.01
18.53
19.06
setting: 1
site: 3
21.79
18.31
20.67
24.00
viewcat: 1
12.18
16.24
14.49
17.58
20.66

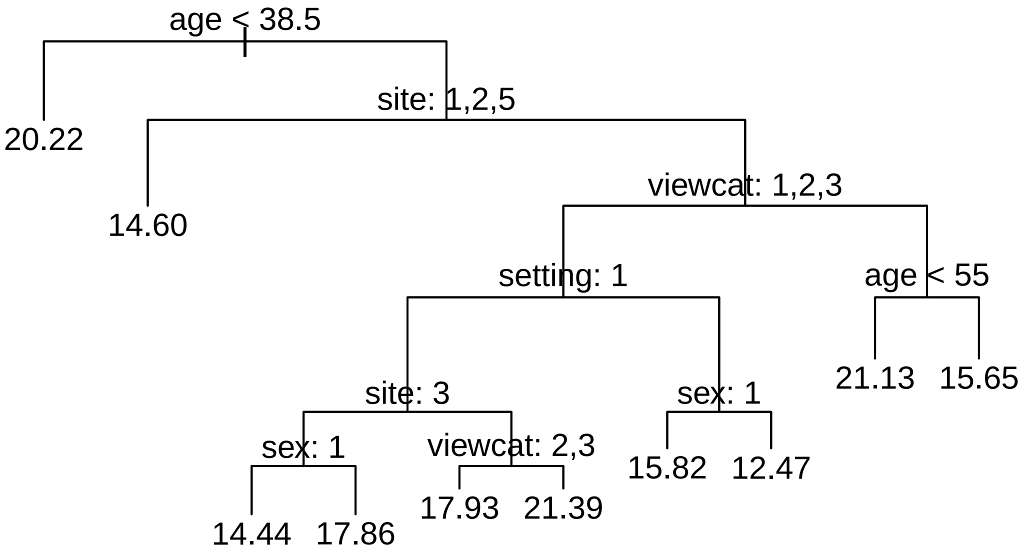

cv.reg.tree.4$dev
3700
3900
4100
5
10
15
cv.reg.tree.4$size

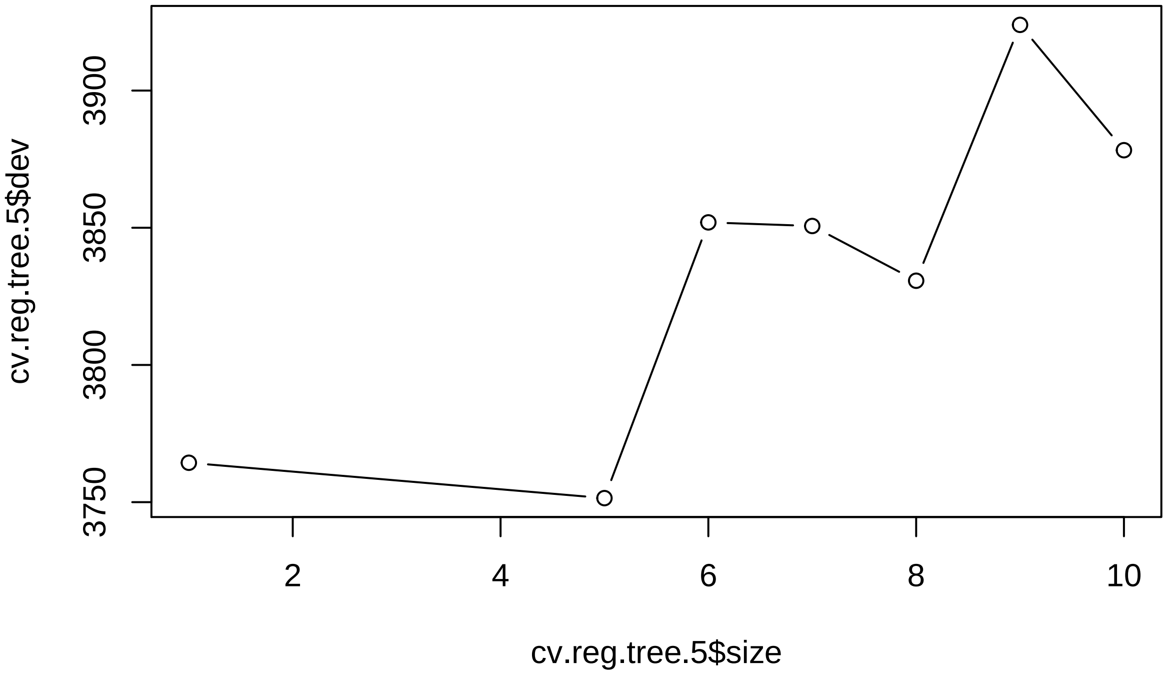


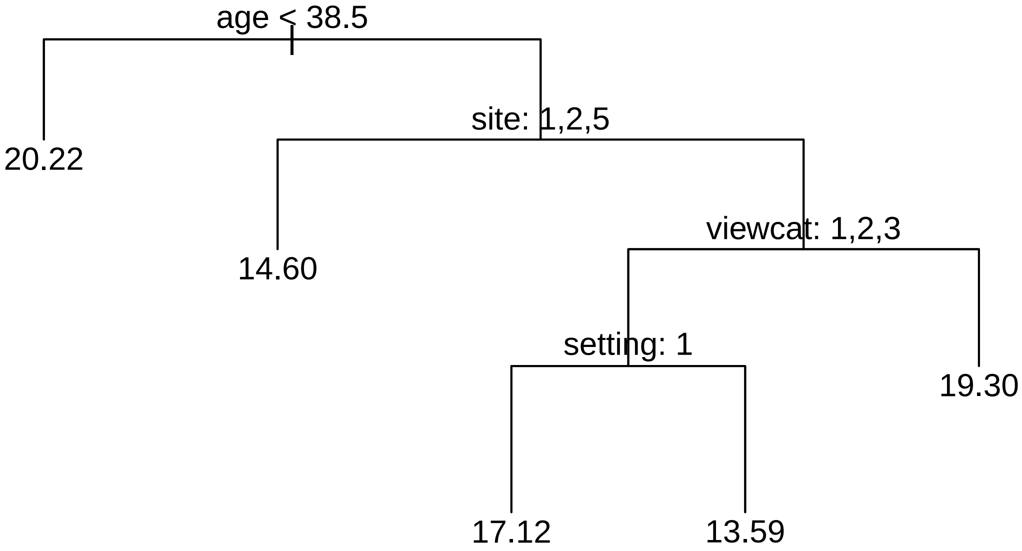
```
## [1] 15.90771
```

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
sex: 1
viewcat: 2,3
15.82
12.47
17.93
21.39
14.44
17.86

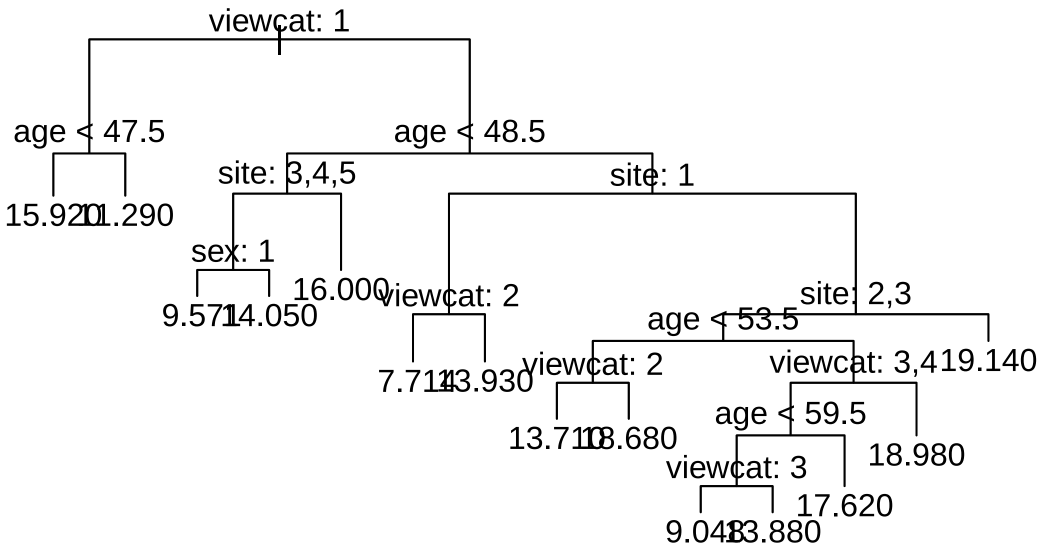

3750
3800
3850
3900
cv.reg.tree.5$dev
2
4
6
8
10
cv.reg.tree.5$size

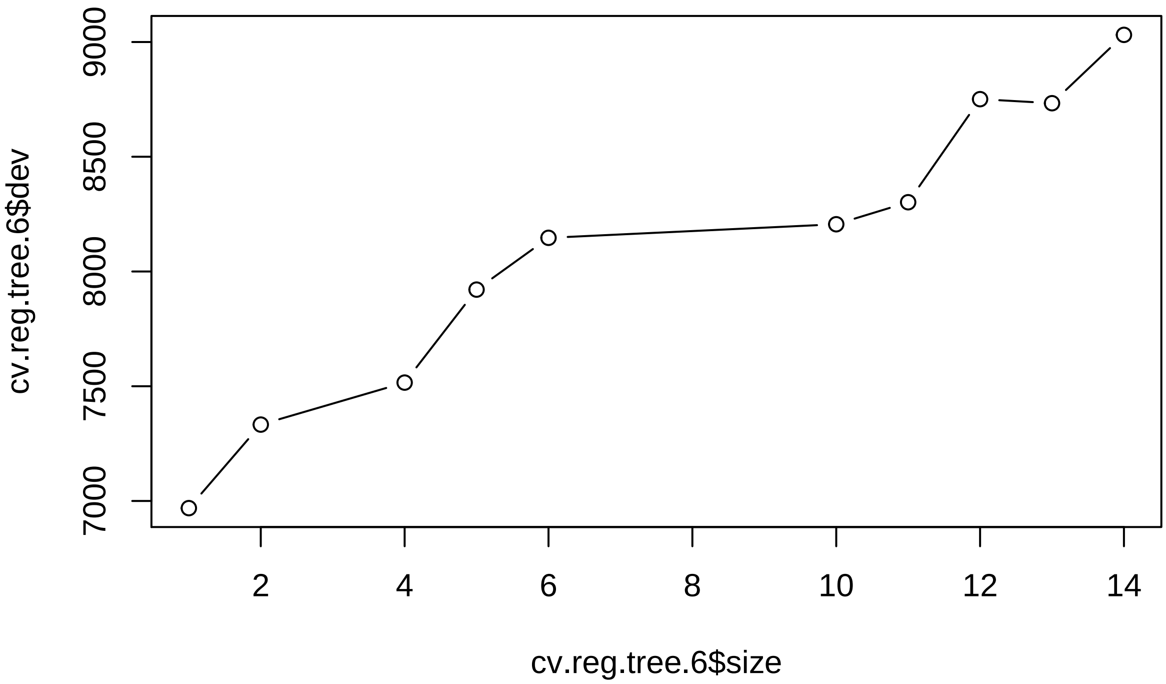


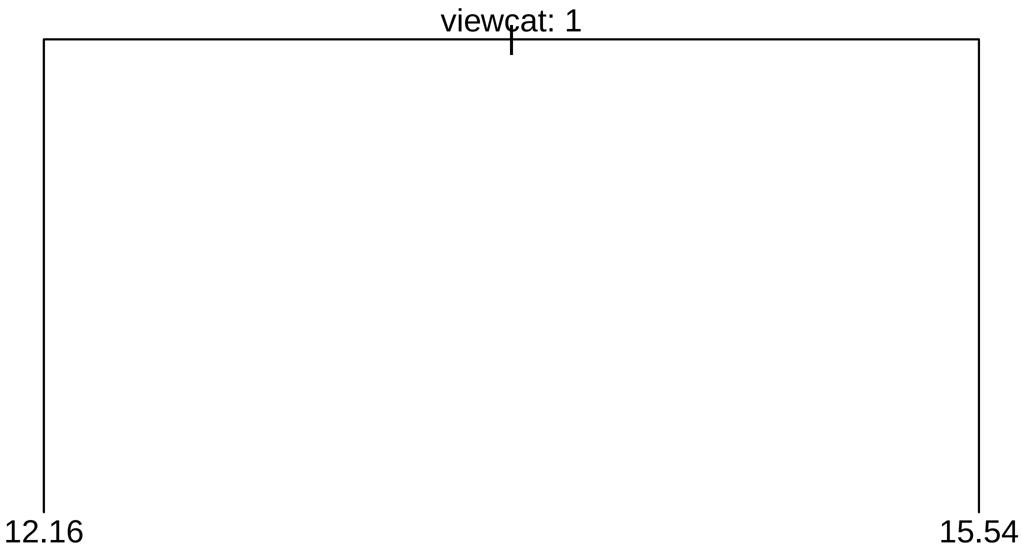
```
## [1] 19.88506
```

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
site: 3,4,5
site: 1
15.920
11.290
sex: 1
16.000
9.571
14.050
viewcat: 2
site: 2,3
age < 53.5
7.714
13.930
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$dev
7000
7500
8000
8500
9000
2
4
6
8
10
12
14
cv.reg.tree.6$size



```
## [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.