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

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Introduction

Sesame Street is a hallmark feature of American television that has been educating young children since 1969. The publicly-funded show was created with the goal of supplementing the learning of low-income preschoolers who did not have the access to early education that their other peers did. However, Sesame Street has had far-reaching success across all segments of the American population, regardless of background. In fact, according to one 1996 survey, 95% of all American children had watched Sesame Street by the time they turned 3. A more recent 2018 estimate suggested that about 86 million Americans had watched the show as young children. Such an impactful TV series that has influenced the childhoods of countless Americans warrants further investigation into the educational impacts of the progam itself.

This project in particular makes use of a dataset that was compiled by researchers in the early 1970s meant to assess whether or not Sesame Street was achieving its goals of educating economically disadvantaged children. The researchers tested a variety of children from different backgrounds on critical skills like numbers and letters. They then re-tested these children after they had watched Sesame Street. Through our research, we seek to answer two questions related to this dataset about childhood education:

1. Can we predict the change between pre-test and post-test scores after children watch Sesame Street?
2. Can we use information about the pre-test score and other demographic variables to predict what type of background the child is from?

The first question directly examines the relationship between Sesame Street and the knowledge of children who watch the program. Through this research goal, we hope to further understand the educational impact of the show on children of all backgrounds.

The second question investigates the relationship between various subject pre-test scores and children of different income and living situations. By understanding this, we can develop a more more nuanced understanding of how low income children may be affected by their background. The lack of education for low-income students in America has been a problem for decades, and still persists today. One statistics suggests that a mere 18% of low-income students are enrolled in high-quality pre-K. Location also plays a role: 55% of children who live in rural areas lack access to high-quality education as well. The lack of access to pre-K disproportionately affects students from disadvantaged backgrounds, as they are left less ready for kindergarten and may suffer further disadvantages from their peers as they continue their education into elementary, middle, and high school. Thus, it is critical to further understand the relationship between the background of children and how this affects their ability to learn critical subjects like learning and math.

We address our research questions using various machine modeling techniques. More specifically, we will use ______ an SVMS to classify the background that the child is from.

Methodology

Research 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 categorical. 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. The least-squares model outputs are:

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

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

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

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

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

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

Regarding model diagnostics, all models seemed to aptly satisfy the linearity condition, as the residual plots for each of the linear regression models have no discernible pattern or structure. The satisfaction of this condition ensures that there is in fact a linear relationship between the response variable and the predictors. The constant variance (homoscedasticity) condition of linear regression seems to be satisfied as well, as the vertical spread of the residuals is relatively constant across each of the plots. Lastly, the Normality assumption of linear regression seems to be aptly satisfied. For each of the models, the points fall along a straight diagonal line on the normal quantile (QQ) plot, indicating that the residuals follow a Normal Distribution.

In addition to linear regression models, we also decided to use regression tree models to predict differences in test scores. Like linear regression, regression trees are not the most competitive in terms of predictive power or accuracy, but they are easy to interpret and can provide important inferences into the relationships between covariates and the response variable.

The process of building the trees was very simple. After initially building the tree, we then performed cross validation to determine if pruning the tree would improve the deviance (the sum of the squared errors) for the tree. Using the cross validation plot that was then created, we choose the number of nodes for the tree that minimized the deviance.

Research 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 sex, 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 and a logistic model to answer this question as well; however, these models did not perform as well on our data (See Appendix for more details). Thus, a SVM was the most appropriate model choice for our research goals. Our full model formula is:

$$svm(site \sim female + male + age + bodyparts_{pretest} + letters_{pretest} + forms_{pretest} + numbers_{pretest} + relationalterms_{pretest} + class$$

We split our data into a 70% training set and 30% testing set and analyzed the performance of our model on the test set. Since we are interested in high predictive power, we implemented a variety of different methods. Standardizing the predictor variables in SVM and encoding categorical variables has been shown to improve performance for SVMs [1]. Thus, we used the standardized forms of the continuous variables in our model and encoded the female and male variables. 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 classes 4 or 5 for site. This could be due to sites 4 & 5 having a smaller number of observations than the other classes. We first tried using the Synthetic Minority Over-Sampling Technique (SMOTE) to increase observations within these classes; however, this technique had negligible effects on our accuracy. We then tried weighting the classes and used the 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" [2].

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

We tested our model using linear, radial, sigmoid, and polynomial kernels and compared the predictive accuracy between these models. 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 sites 4&5 are correctly classified. To remedy this issue, we began to experiment with the class weights and increase the sites 4&5 weights by roughly 0.5 until we reached the highest predictive power. The model with the highest accuracy was the linear kernel SVM with weights 0.8 on site 1, 0.87 on site 2, 0.75 on site 3, 1.5 on site 4, and 3 on site 5 and a cross validation selected cost parameter of 0.1. Since this model has the highest predictive accuracy of all others that we had tried, we settled on this model as our final model. There are no explicit tests for SVM model diagnostics; however, there seems to be no major issues with our model fit.

Results

Research Question 1

Table 1: Test MSE's

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: Multiple R-Squared Values for Least-Squares Regression Models

Response	R.Squared
bodyDiff	0.159
letDiff	0.370
formDiff	0.063
numbDiff	0.139
relatDiff	0.107
clasfDiff	0.094

Interpretations

Linear Regression Models

Looking at the least-squares linear models, we can note a few important features regarding predicting whether a child's test scores will increase. For `bodydiff`, or the difference between post and pre-tests scores for the recognition of body parts, we see that the intercept is 16.43, meaning the baseline difference between post score and prescore is positive. This means that the post test results are higher, however, as noted by the other predictors, this difference between post and pre gets larger as the site increases. We see if a child is `site3`, or an advantaged rural child, the difference between their scores goes up by 2.45. For a disadvantaged rural child, the difference increases even more by 2.97 and for a disadvantaged Spanish speaking child, the difference goes up by 3.30. This indicates that for children from more disadvantaged backgrounds, the difference between the scores increases as compared to the two other sites.

For differences in letter recognition scores, we note the intercept is 10.52, the baseline difference. We see for 4 year old advantaged children from the suburbs (`site2`) this difference increases by 3.09. However, interestingly enough for an advantaged rural child (`site3`), the difference in test scores decreases by 2.86. It also seems that the frequency of watching Sesame Street has an effect on letter scores with viewcat3 or watching 3-5 times a week increasing the difference by 4.85 and watching more than 5 times a week increasing the difference by 4.77.

For recognizing forms, the intercept is 16.04 and it seems that watching Sesame Street more than 5 times a week (`viewcat4`) , further increases this difference by 2.48. For numbers, the intercept is 15.39. We note that for an 4 year old advantaged child from the suburbs, the difference in number scores increases by 2.56. Watching Sesame Street 3-5 times a week (`viewcat3`) increases the difference by 3.20, and watching more than 5 times a week increases the difference by 3.64. For difference in relational term scores, the intercept is 18.49, the largest of all intercepts and the difference is further increased for a disadvantaged Spanish speaking child by 2.42. For those who watch more than 5 times a week, the difference increases by 2.96. For classification score differences, the intercept is 10.95. The only variable that increases this difference is the frequency of viewing, with those that watch Sesame Street more than 5 times a week increasing the difference by 4.06. In summary, we note that the variables that affect the difference in post and pre test scores from these linear regression models are mainly from site (demographic/background) and viewcat (frequency of viewing). It makes sense that kids who watched more Sesame street, especially those that watched more than 1-2 times a week had larger differences between their pre and post test scores.We also see that in general, the post scores are higher than the pre test scores especially for body parts, relational terms, and forms as their intercept values were the highest.

Regression Tree 1
For differences in body part recognition scores:

- We see that if a child is in site 1 and 2 (3-5 year old disadvantage child from the inner city, 4-year-old advantage child from the suburbs respectively)
  - They are younger than 46.5 months or 3.87 years old
    - They watch sesame street either once/twice per week or 3-5 times per week
      - The predicted difference is 11.95
    - They watch sesame street either rarely, or more than 5 times per week
      - The predicted difference is 17.65
  - They are older than or equal to 3.87 years old/46.5 months
    - The predicted difference is 11.37
- If the child is in site 3, 4, 5 (an advantaged rural child, a disadvantaged rural child, disadvantaged Spanish speaking child)
  - The predicted difference is 14.30

Regression Tree 2
For differences in letter recognition scores:

- If the child is in site 1, 3, 4, 5 (3-5 year old disadvantaged child from the inner city, an advantaged rural child, a disadvantaged rural child, a disadvantaged Spanish speaking child respectively)
  - They view Sesame Street either rarely or once/twice per week
    - The predicted difference is 12.37
  - They view Sesame Street either 3-5 times a week or more than 5 times a week
    - The predicted difference is 16.56
- If the child is in site 2 (4 year old advantaged child from the suburbs)
  - The predicted difference is 20.24

Regression Tree 3
For differences in form recognition scores:

- If the child rarely watches Sesame Street (`viewcat1`)
  - They are less than 46.5 months (~3.875 years old)
    - The predicted difference is 17.96
  - They are older than or equal to 46.5 months (~3.875 years old)
    - The predicted difference is 12.94
- The child watches either once/twice per week, or 3-5 times a week, or more than 5 times per week
  - The predicted differences is 15.72

Regression Tree 4
For differences in numbers testing scores:

- If the child watches Sesame Street 3-5 times a week or more (`viewcat` values of 3 and 4)

    - The predicted difference is 20.83
- If the child watches Sesame Street rarely or once/twice per week (`viewcat` values of 1 and 2)
    - If the child is a 4-year-old advantaged child from the suburbs or a disadvantaged Spanish speaking child
        * The predicted difference is 21.29
    - If the child is a 3-5 year old disadvantaged child from the inner city, an advantaged rural child, or a disadvantaged rural child
        * The predicted difference is 17.51

Regression Tree 5
For differences in relational terms scores:

- If the child is less than 38-months-old (3.16-years-old):
    - The predicted difference is 20.22
- If the child is greater than 38-months-old (3.16-years-old):
    - If the child is a 3-5 year old disadvantaged child from the inner city, a 4 year old advantaged child from the suburbs, or a disadvantaged Spanish speaking child:
        * The predicted difference is 14.60
    - If the child is an advantaged or disadvantaged rural child:
        * If the child watches Sesame Street rarely, once/twice per week, or 3-5 times per week:
            · If the child watches Sesame Street at home the predicted difference is 17.12
            · If the child watches Sesame Street at school the predicted difference is 13.59
        * If the child watches Sesame Street more than 5 times per week:
            · The predicted difference is 19.30

Regression Tree 6
For differences in classification skills scores:

- If the child rarely watches Sesame Street (`viewcat` values of 1):
    - The predicted difference is 12.16
- If the child watches Sesame Street once/twice a week or more (`viewcat` values of 2-4):
    - The predicted difference is 15.54

Overall, this tree demonstrates that children who watch Sesame Street more frequently show a greater improvement in classification skills testing than children who rarely watch Sesame Street.

Research Question 2

Table 3: 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

As evidenced in the table below, the class weighted linear kernel SVM has a prediction accuracy of 0.403 on our test data with a confidence interval of 0.289 to 0.525. From the confusion matrix, we can also see that our model predicts well for classes 2 and 3 and struggles slightly with classes 1,4, and 5. Specifically, our model has tends to predict class 3 often when the true class is 4, and it tends to predict classes 3 and 5 as commonly as class 1 when the true class is 1.

Table 4: Class Weighted Linear Kernel SVM Prediction Results

Results	Values
Accuracy	0.403
95% CI	(0.289, 0.525)

Table 5: Class Weighted Linear Kernel SVM Confusion Matrix

Truth	Class1.Prediction	Class2.Prediction	class3.Prediction	class4.Prediction	class5.Prediction
Class 1	6	1	6	2	5
Class 2	1	7	1	1	3
Class 3	0	1	11	1	3
Class 4	3	3	9	3	0
Class 5	0	1	1	1	2

Conclusion

Research Question 1

The recurring motif from the linear regression models and regression trees is that the frequency at which a child watches Sesame Street (`viewcat`) and a child's background (`site`) are the most important variables in predicting the difference in test scores for a child. In 5 of the 6 linear regression models, at least one level of `viewcat` is a significant predictor for the response variable. Additionally, `viewcat` is included in every pruned regression tree. `site` is a significant predictor in 4 of the 6 linear regression models and is also included in 4 out of the 6 pruned regression trees.

All the linear regression models indicate that children who watch Sesame Street more often are more likely to see greater improvements in test scores compared to children who rarely watch Sesame Street. More specifically, the greatest improvement is seen in children who watch Sesame Street at least 3-5 times per week. The regression tree generally corroborates the positive relationship between Sesame Street viewership frequency and test performance, but adds a few conditions.

For instance, the regression tree that predicts the difference in the numbers testing score (Tree 4) indicates that the improvement in score is greater for students who watch Sesame Street frequently than for children who watch less frequently, *depending* on the child's background. The tree predicts a higher score increase for children who either rarely watch Sesame Street or only do so once/twice a week who fall into one of these categories: (1) 4 year old advantaged child from the suburbs (2) disadvantaged Spanish speaking child. More succinctly, the tree predicts higher scores increases for certain children who watch Sesame Street less than others.

A similar scenario can be found in Tree 3 as well. In this instance, the tree predicts a higher score increase for children who rarely watch Sesame Street but are also less than 46 months (3.875 years) old than for children who watch Sesame Street at least 1-2 times per week.

Given that the test scores were scaled to the interval [0, 30], the intercept values for each of the linear regression models indicate that children, regardless of how often they watch Sesame Street, will see notable increases in test scores over the course of a year. This fact is not surprising, as the children in this study range from 3-5 years old, and children usually learn and develop intellectually very rapidly when they are in that age range. Nonetheless, the addition of frequent and regular Sesame Street viewership seems to further boost this developmental process and does so in a plethora of subject areas.

Research Question 2

Our goal for this research question was to build a model that could accurately predict the background that a child came from based on their age, sex, and pretest scores. While our model does not perform very poorly on our data, there is still room for improvement. As mentioned in the Results section, the accuracy is .403, and this is the highest accuracy of all the models we tried. This could be a flaw of the data as we have only 240 observations which is not very many. Additionally, there is some imbalance in our data set as we have less observations of children from sites 4 and 5, disadvantaged rural children and disadvantaged Spanish speaking children respectively. This may be a flaw of the data collection, and our data may not be representative of the general population. Additionally, there may have existed a clustering structure that caused the SVM model to struggle with separating the different levels of site. This phenomenon may be illustrated with the confusion matrix having some difficulty separating between certain classes. When the true site is 3, indicating an advantaged child from the inner city, the model tends to predict site 4 as well which represents an advantaged rural child. The differences between these backgrounds may be quite small, so the model does not distinguish them quite well. We may be able to improve our model and gain greater predictive accuracy with more children in our data set and more data. Including more variables into our data set, such as child attendance in preschool or daycare, may also be useful for prediction and answering this research question.

Another possible inference from these results is that pretest scores may not be predictive of background. Thus, whether a child is considered advantaged/disadvantaged or rural/suburban may not influence their pretest scores greatly. Perhaps, the difference in pretest scores between these different categories of children is not significantly different at a very young age. There also may be more factors that explain pretest scores. For example, socioeconomic status or parent education, may be a more useful response variable than a arbitrary determination of advantaged or disadvantaged. Future work may be focused on collecting information on these socioeconomic variables and performing analysis once again to see if our results differ.

Appendix

References

[1] A Practical Guide to Support Vector Machines. (2003). National Taiwan University. https://www.csie.ntu.edu.tw/~cjlin/papers/guide/guide.pdf

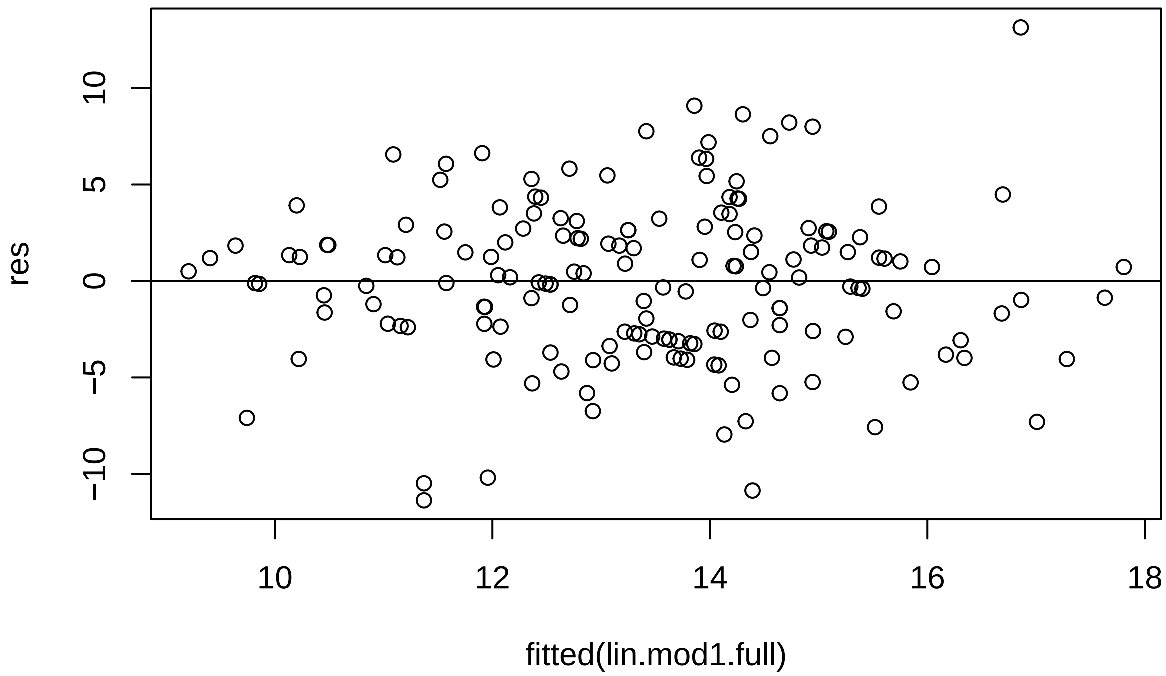
[2] One-vs-Rest and One-vs-One for Multi-Class Classification. (2020). Machine Learning Mastery. https://machinelearningmastery.com/one-vs-rest-and-one-vs-one-for-multi-class-classification/

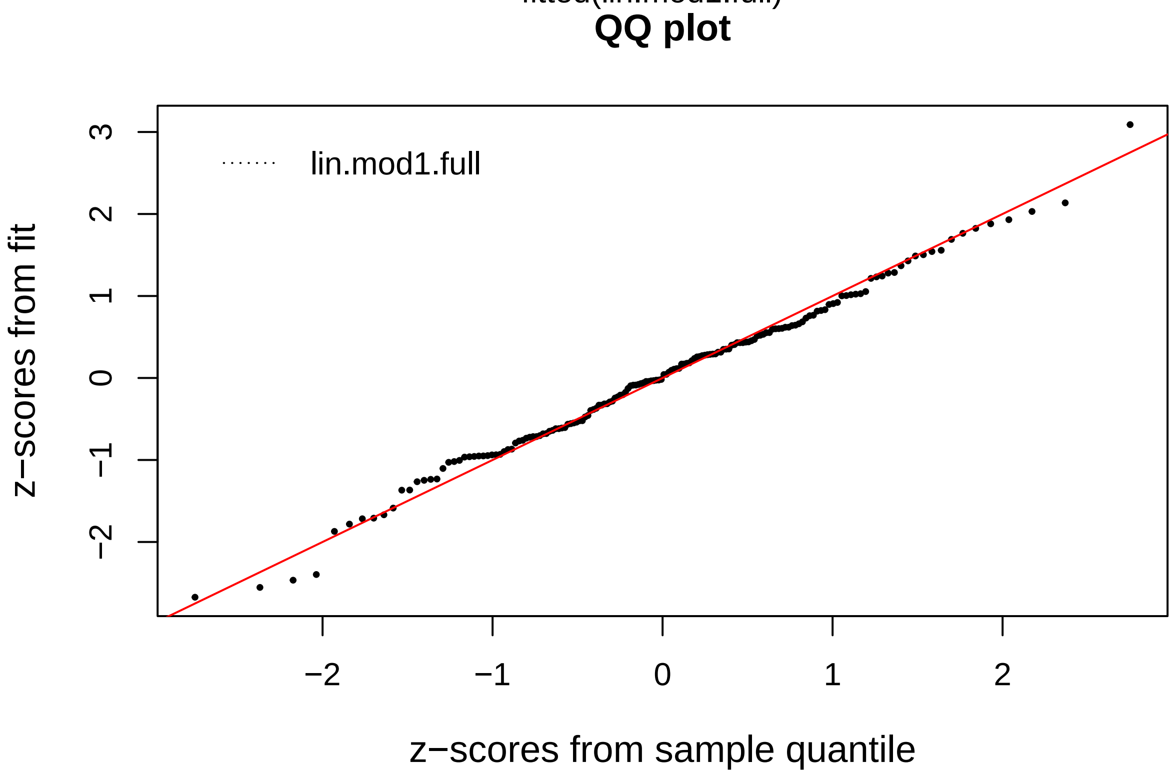
Research Question 1: Linear Models

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

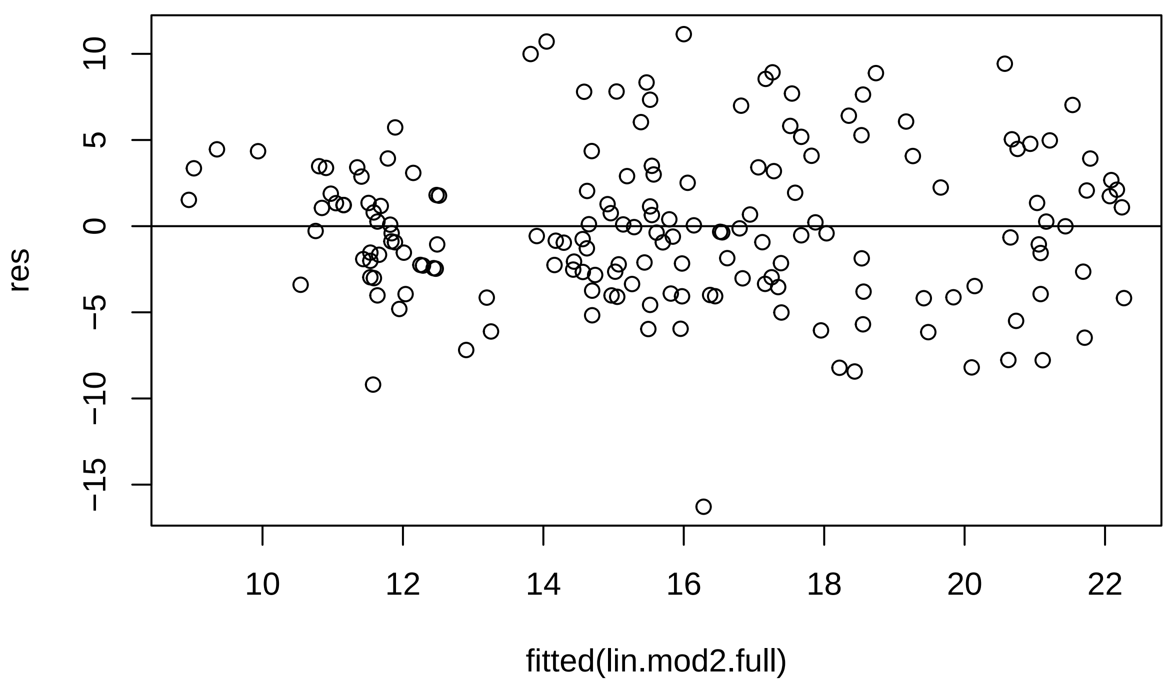
```
## [1] 24.01045
```

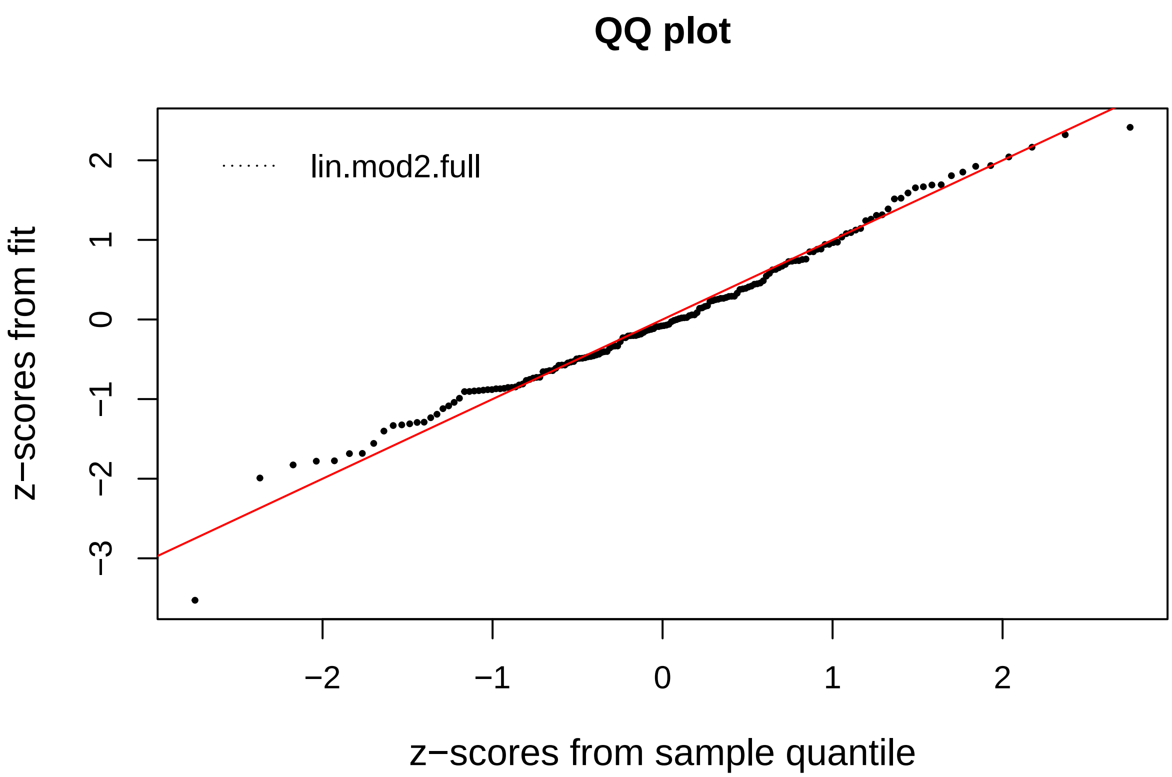





```
## [1] 21.60675

##
## Call:
## lm(formula = letDiff ~ (site + sex + age + viewcat + setting +
##     viewenc), data = training, y = TRUE)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
```

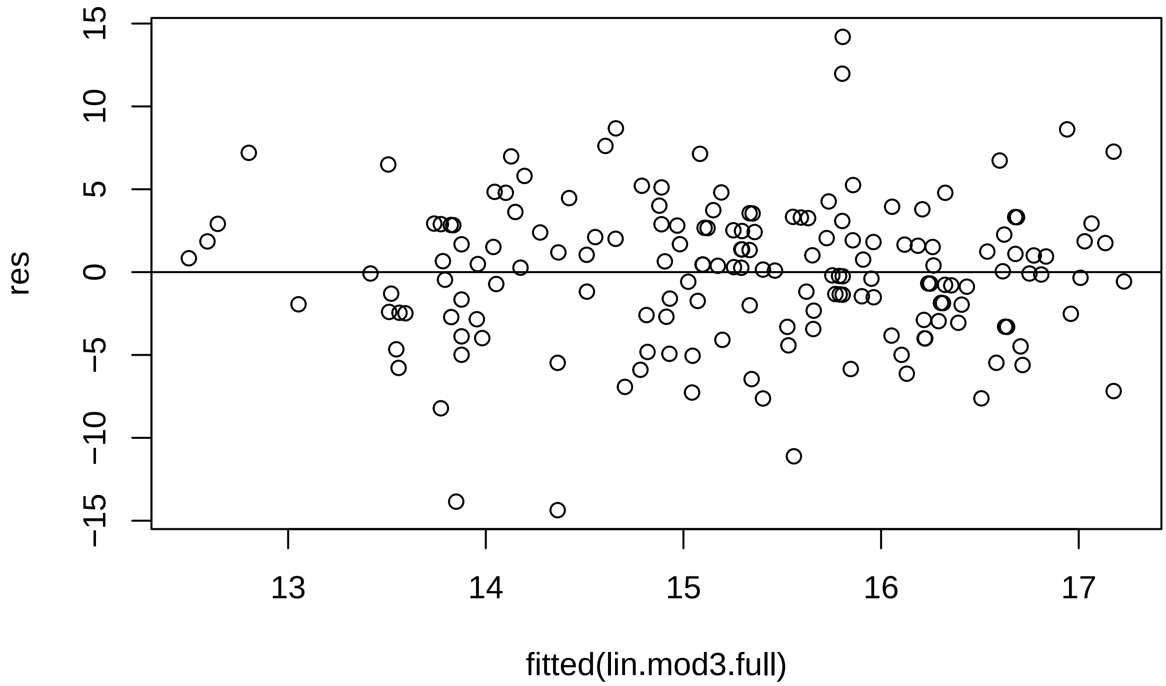
```
## -16.2823  -2.9776  -0.3663   2.9275  11.1426
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 10.52353    3.32595   3.164  0.00187 **
## site2        3.08586    1.08270   2.850  0.00496 **
## site3       -2.85941    1.05103  -2.721  0.00726 **
## site4       -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
```

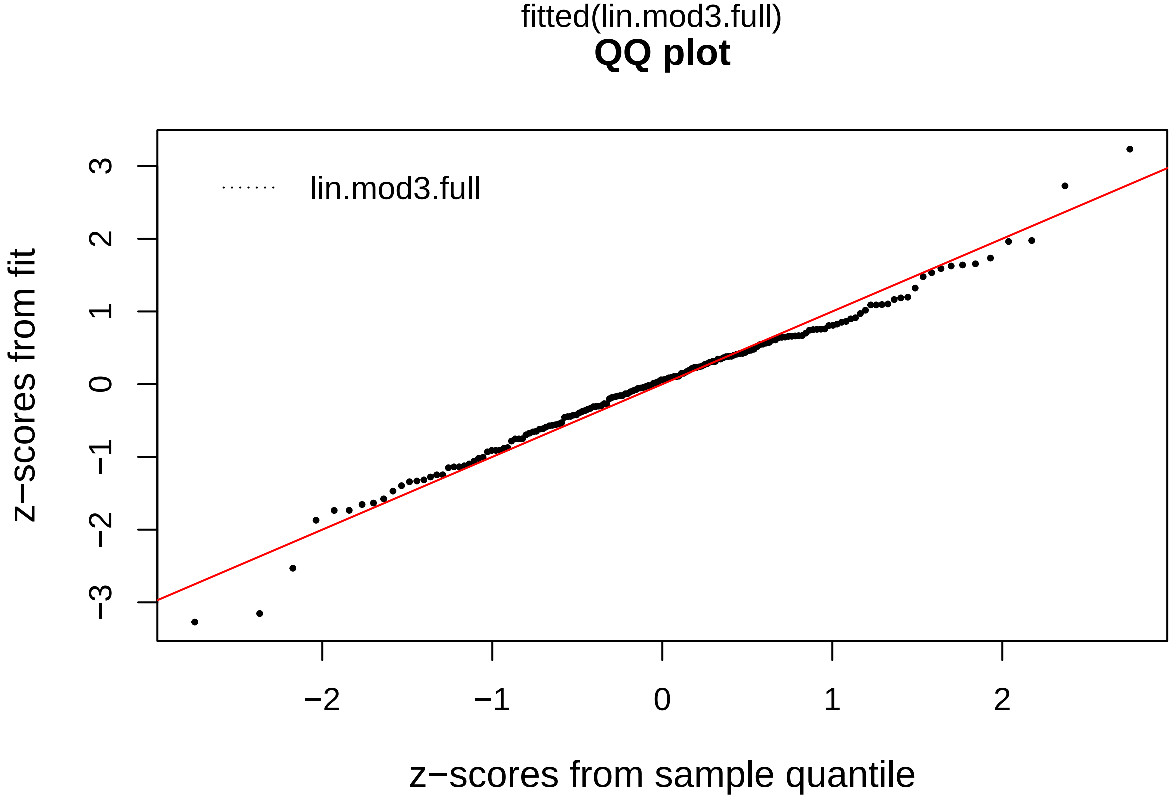





```
## [1] 14.19572

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



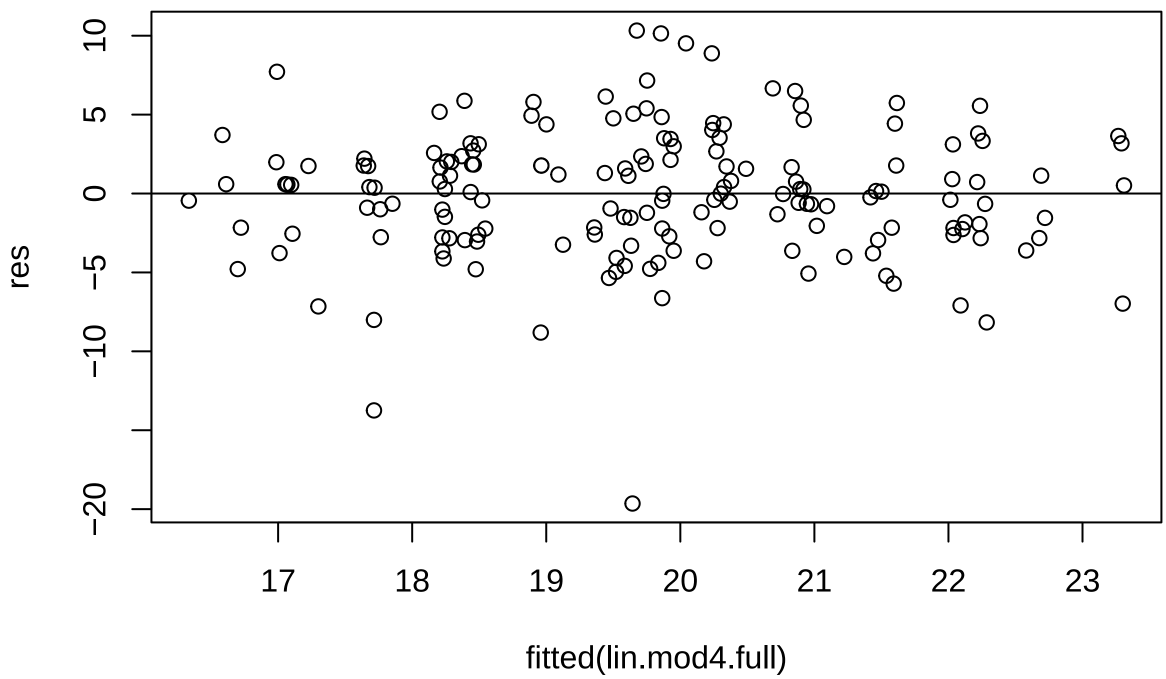


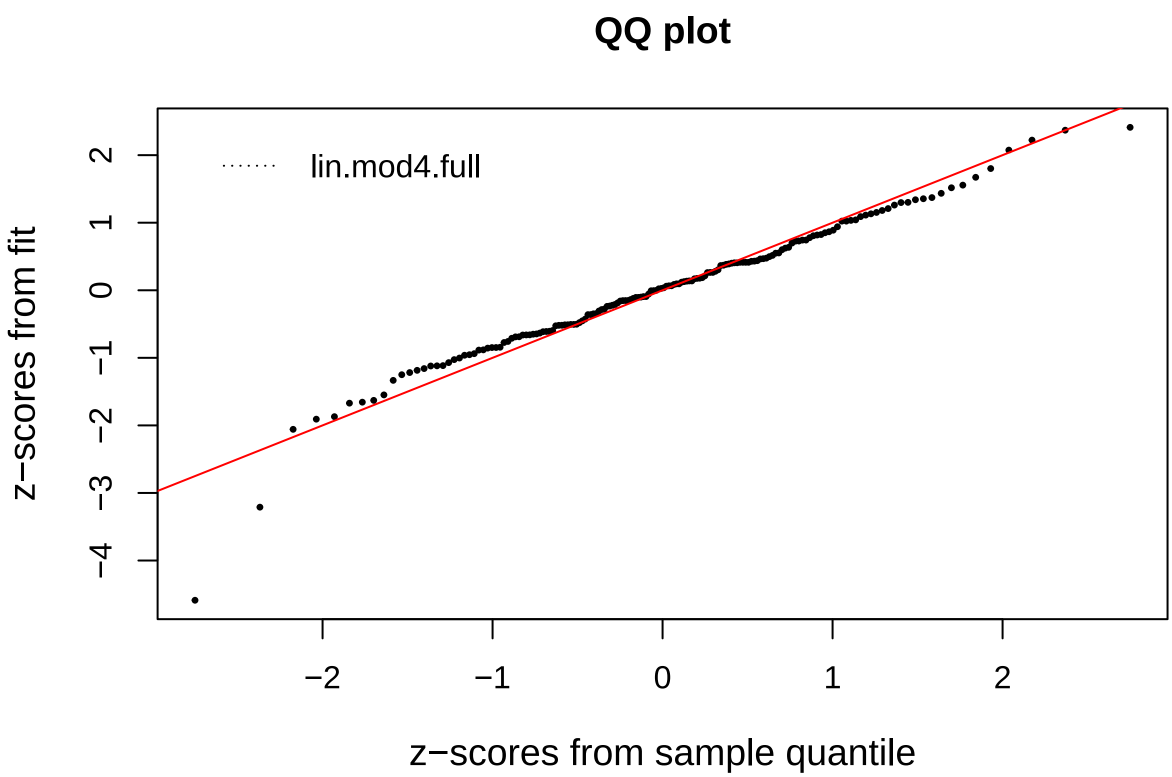

```
## [1] 12.82502
##
## Call:
```

```
## lm(formula = numbDiff ~ (site + sex + age + viewcat + setting +
##     viewenc), data = training, y = TRUE)
##
## 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
```

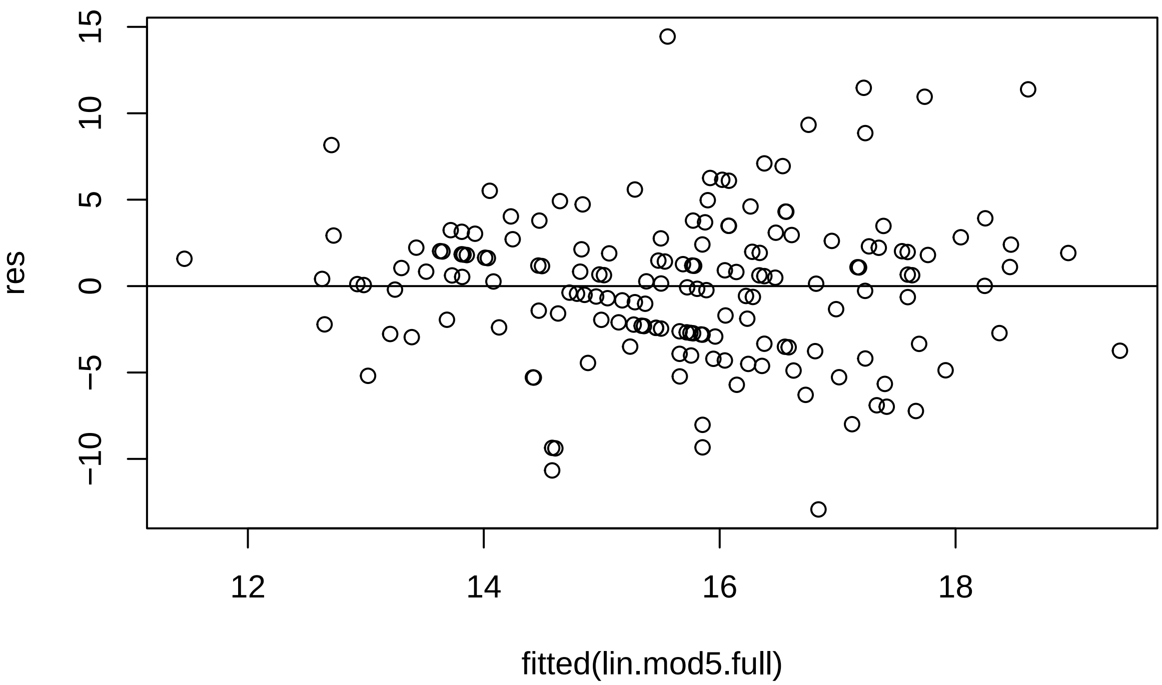
```
## [1] 15.5095
```

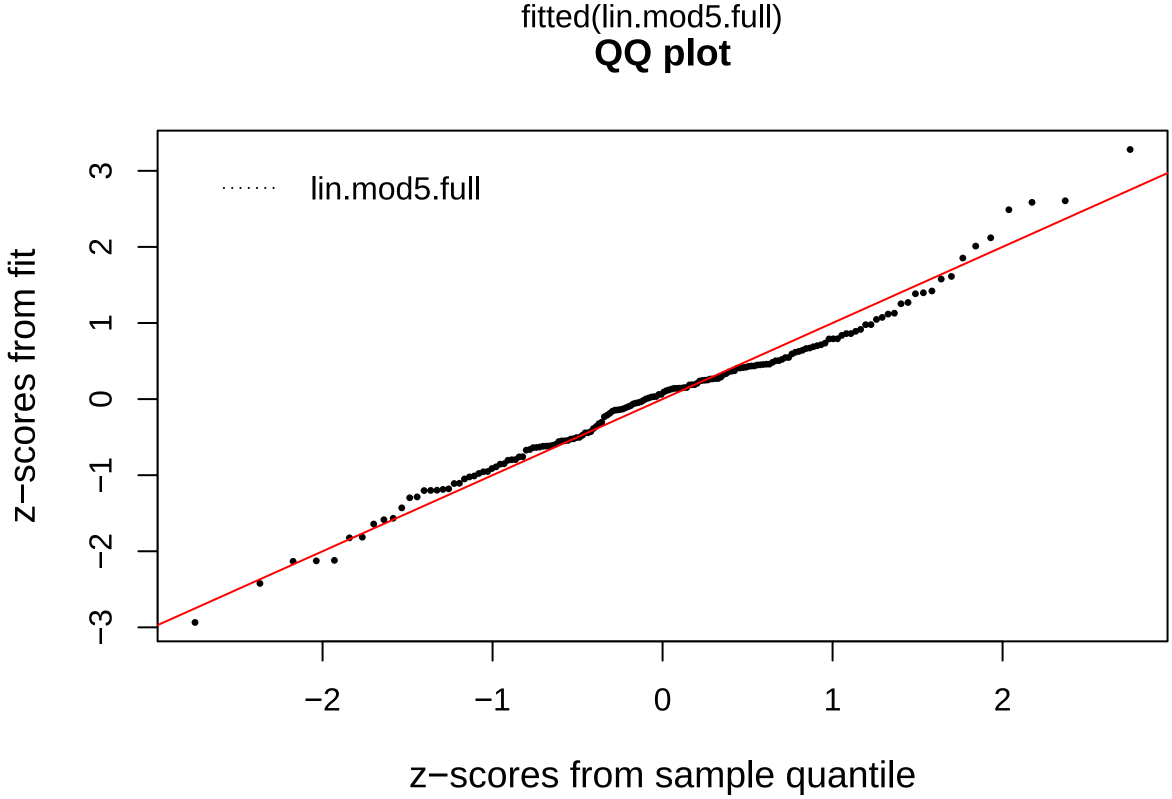





```
## [1] 14.62731
##
## Call:
## lm(formula = relatDiff ~ (site + sex + age + viewcat + setting +
##     viewenc), data = training, y = TRUE)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12.9246  -2.7114   0.3439   2.2185  14.4415
##
## Coefficients:
##             Estimate 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
```



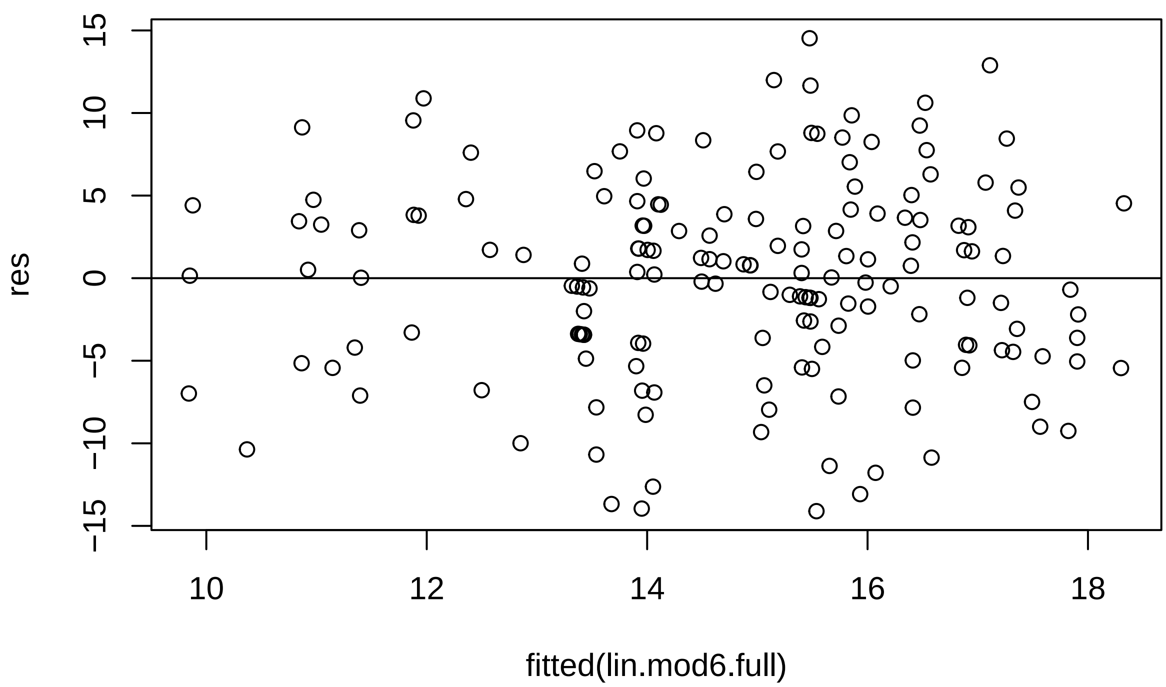


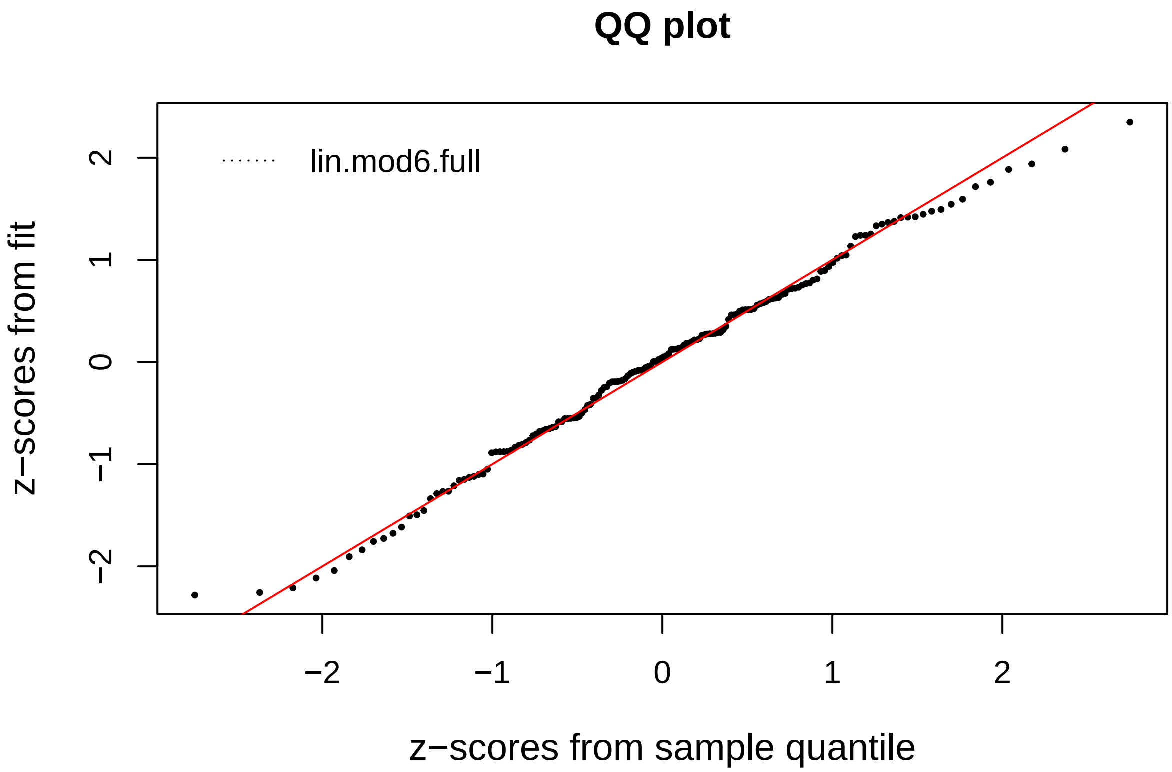

```
## [1] 19.86283

##
## Call:
```

```
## lm(formula = clasfDiff ~ (site + sex + age + viewcat + setting +
##     viewenc), data = training, y = TRUE)
##
## 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
```



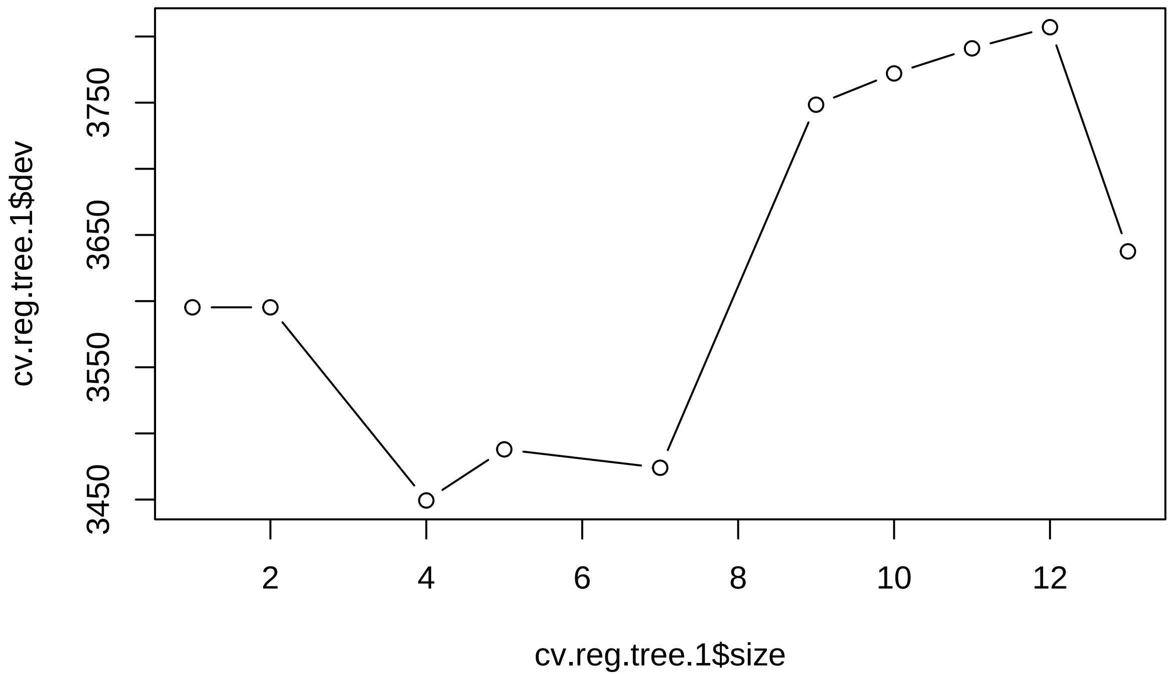


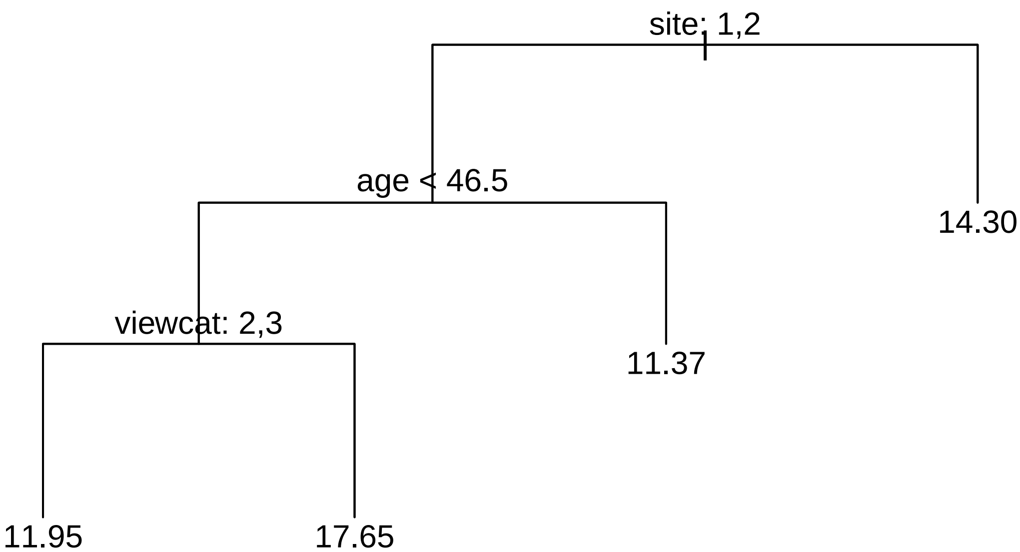

```
## [1] 44.26185
```

Research Question 1: 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
```

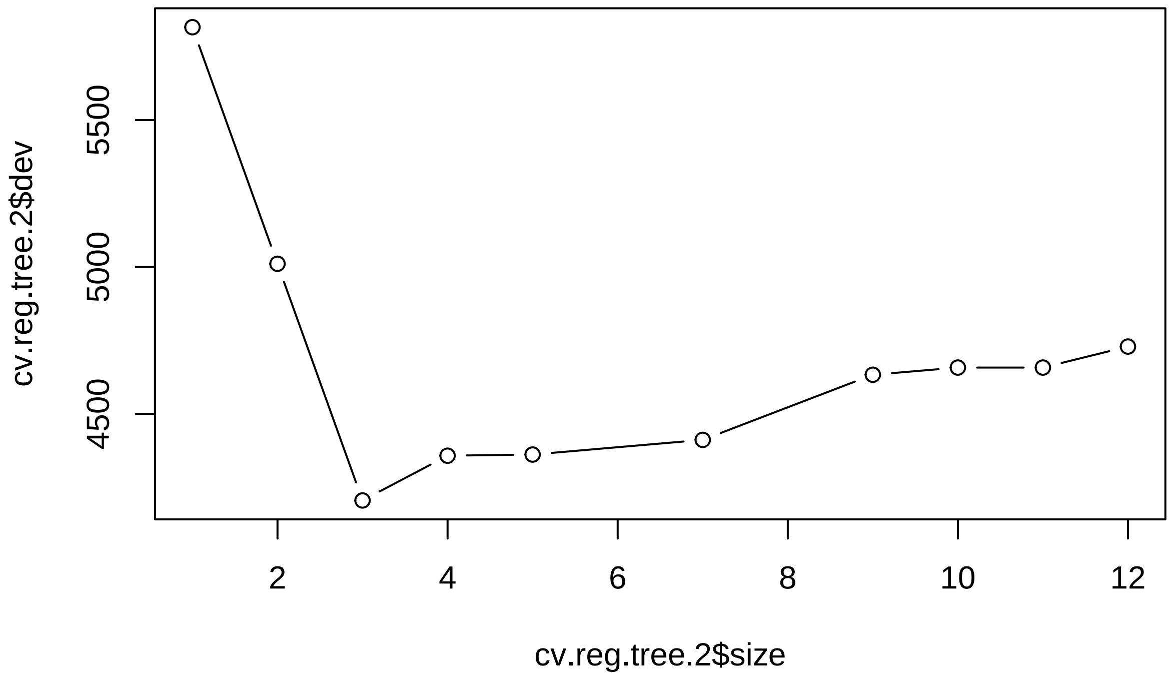


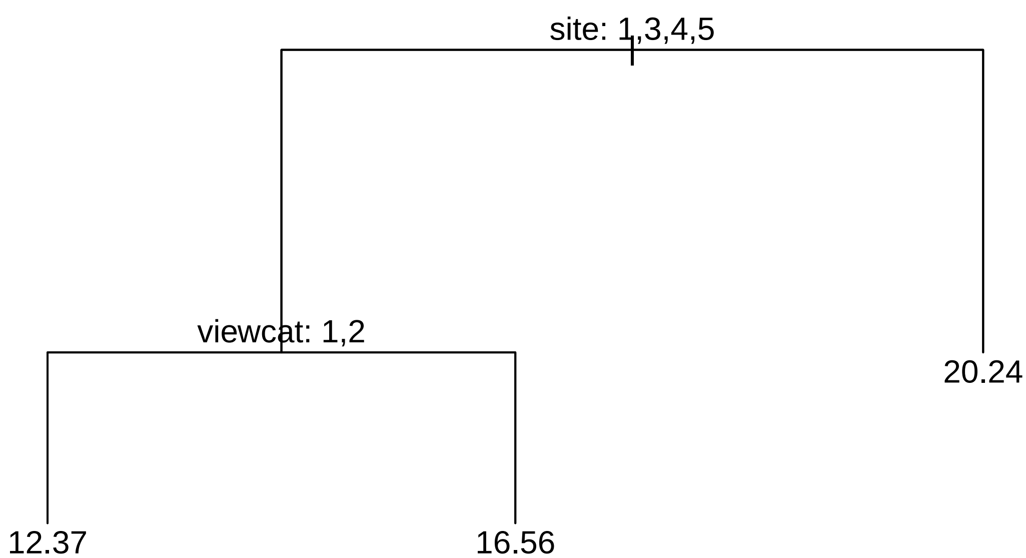



```
## [1] 20.60159
```

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
```

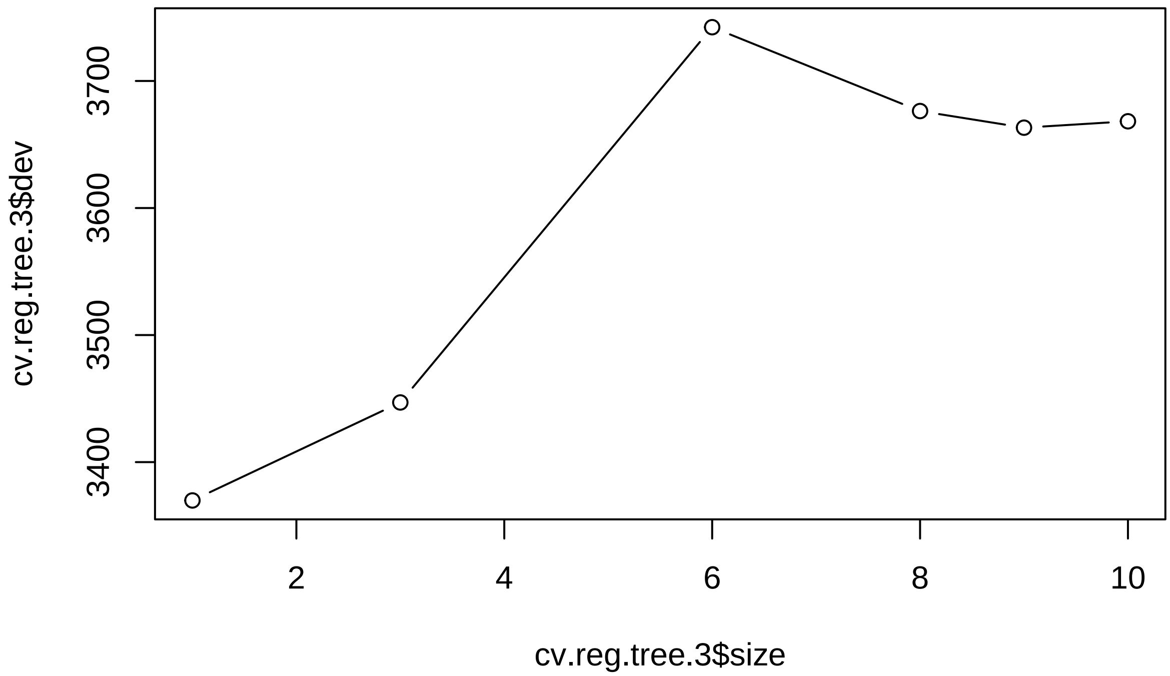


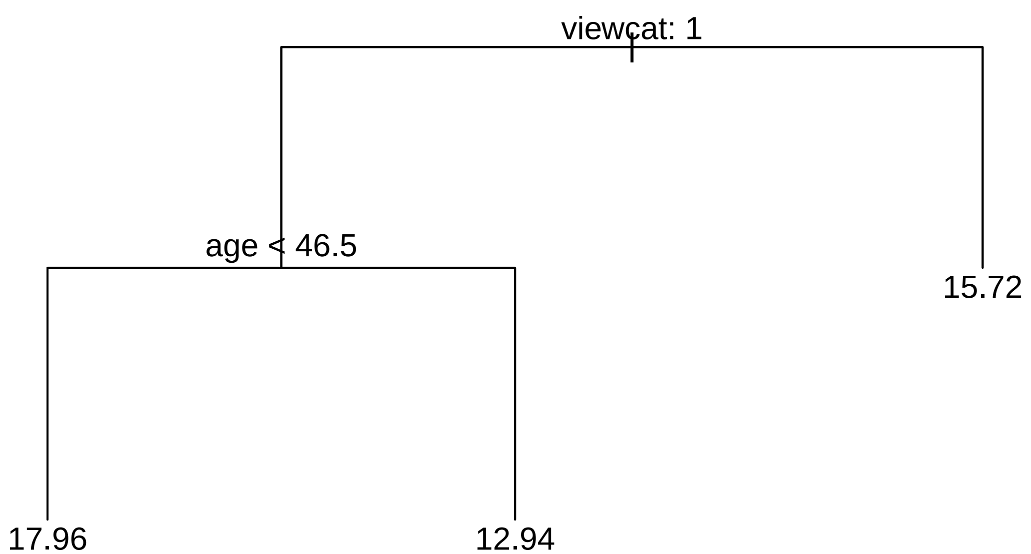



```
## [1] 15.4124
```

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
```

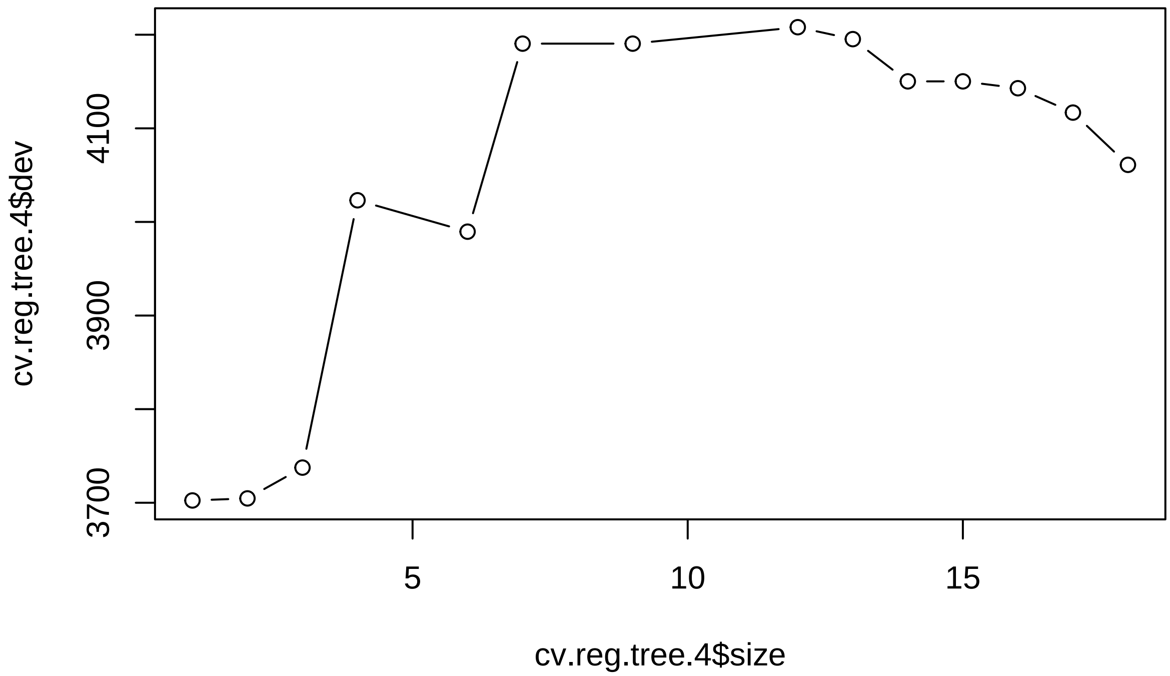


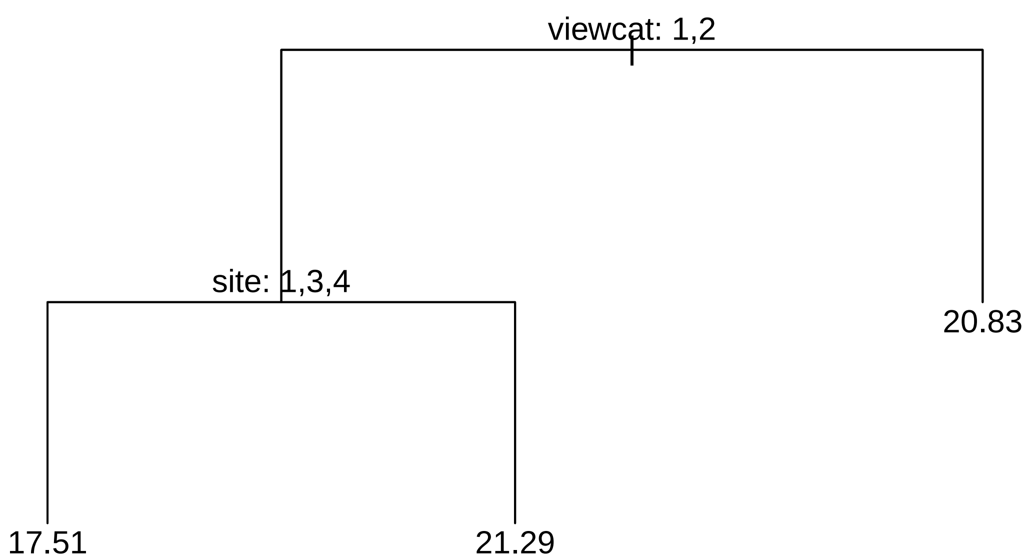



```
## [1] 14.92273
```

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
```

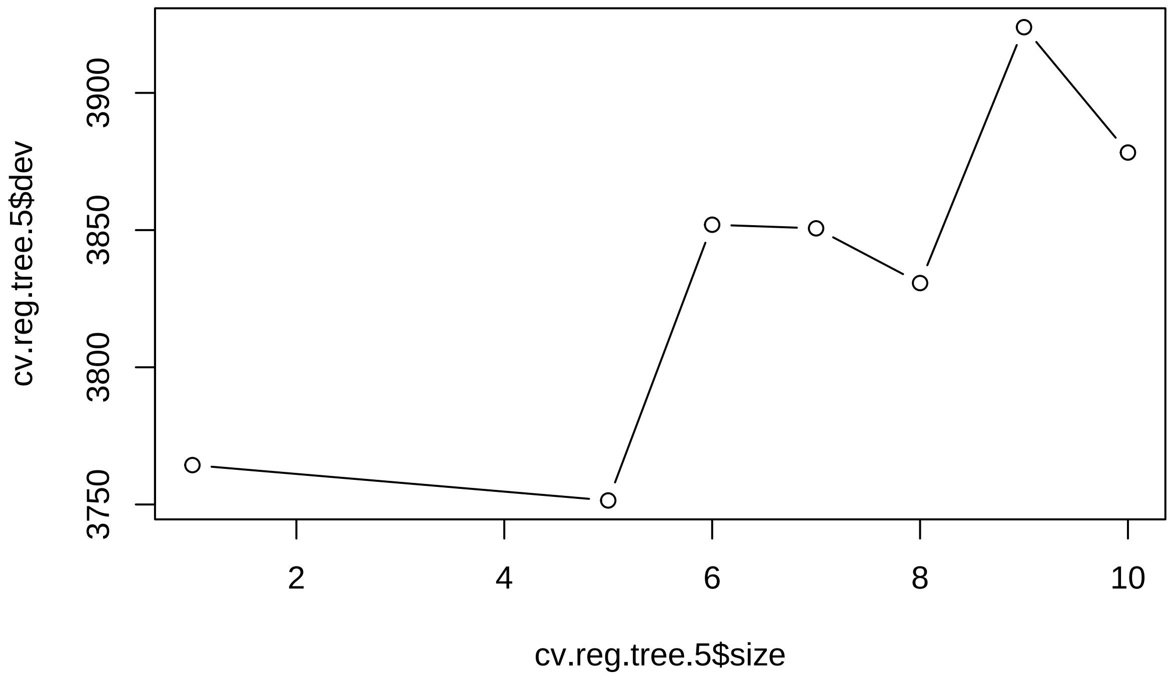


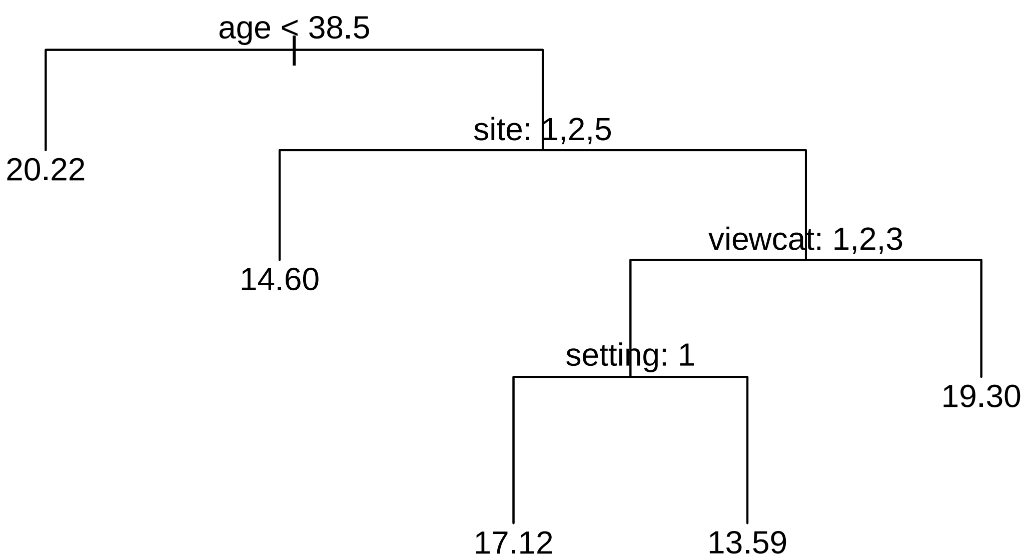



```
## [1] 15.90771
```

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
```

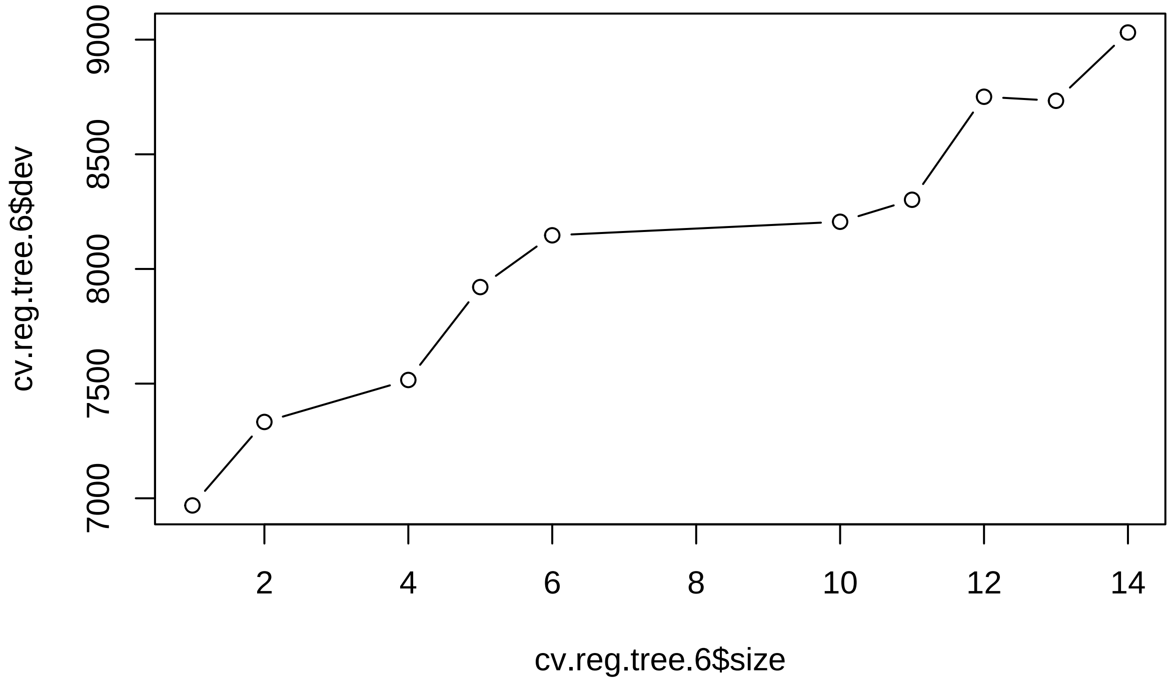


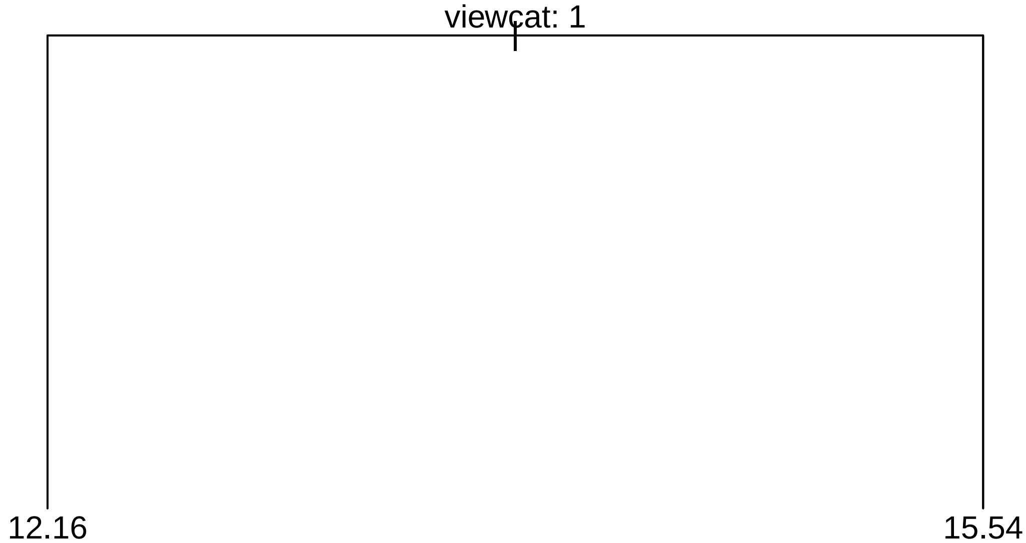



```
## [1] 19.88506
```

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
```






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

Research Question 2: Extra SVM models