Applied Regression Analysis: Final Report

Due on May 9, 2017

with Joshua French, Ph.D.
MATH 4387.001

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INTRODUCTION

Why should someone be interested in this problem? ***(Why is it interesting to analyze this data set?)***

As students prepare for future semesters they typically want the most information they can get before choosing their courses. For some students having a good instructor is very important to them. Resources like *RateMyProfessors.com* offer students a way to "rate" their previous instructors, in order to provide useful information for future students looking to take a course with that teacher. While it could be argued that the opinions of these students are subjective, and that the website could be augmented by non-students (outside the population of interest), the success of *RateMyProfessors.com* would imply a certain validity in their model of perceived quality.

Background information people need to know to understand the problem and/or data set.

This data is collected by presumed students going to *RateMyProfessors.com* and rating a professor. We will be looking at a data set that consists of 366 observations of professor ratings on a single Midwestern college campus. While this sample is far too constrained to formulate conclusions about the entire population of students in the country, it will at least give us a better understanding of perceived quality on this campus and will provide conjecture material for a larger study.

This information was collected between the years of 1999 and 2009, and asks the student to provide observational data, such as gender, number of years teaching, perceived easiness, clarity, etc. Each instructor in this data set has received at least 10 student ratings.

Is there any prior research on your topic that might be helpful for the audience?

Student Consensus on RateMyProfessors.com by Bleske-Rechek, et al (2011)[1], used this data set for an in-depth analysis on a similar topic.

From where did the data come? Is this an experiment or observational study? Who collected the data? Why was the data collected? ***(if you werent the one doing the collecting)***

The original data is readily available and public at *RateMyProfessors.com*. This data is observational, as the input comes from online reviews collected on the website. It should be noted that the data set we'll be working with has further calculated variables (such as standard deviation) that are not normally available on the *RateMyProfessors.com* website - presumably calculated for the study mentioned above. The data was collected by Bleske-Rechek, et al to, "investigate reliability in student ratings by analyzing variance in the ratings of instructor quality and easiness."

What are the questions of interest that you hope to answer?

1. Are Helpfulness, Clarity, Easiness, and Rater interest all statistically significant in the model?
2. Does Gender have an effect on perception of Overall Quality, given the model of best fit?
3. Does the Chili Pepper have an effect on perception of Overall Quality, given the model of best fit?

1. DATA SUMMARY The raw project data includes the summaries of the ratings of 366 instructors at one large campus in the Midwest from Bleske-Rechek and Fritsch (2011). Each instructor included in the data had at least 10 ratings over a several year period. **Students provided ratings on 5 point scales**. The data file provides the averages ratings and additional characteristics of the instructors.

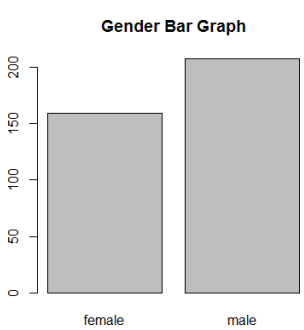
Field	Description (directly from `R`)
`gender`	Instructor gender, a factor with levels female male
`numYears`	A numeric vector, number of years in which this instructor had ratings between 1999 and 2009
`numRaters`	Number of ratings
`numCourses`	Number of different course titles included in the rating for this instructor
`pepper`	A factor with levels no and yes. In addition to rating for quality, instructors are rated as attractive or not. A value of yes means that the consensus is that the instructor is attractive
`discipline`	A factor with levels Hum for humanities, SocSci for social sciences, STEM for science, technology, engineering and mathematics and Pre-prof for professional training
`dept`	A qualitative variable with department names
`quality`	Average overall quality rating, between 1, worst, to 5, best (calculated)
`helpfulness`	Average helpfulness rating, between 1, worst, to 5, best (surveyed)
`clarity`	Average clarity rating, between 1, worst, to 5, best (surveyed)
`easiness`	Average easiness rating, between 1, worst, to 5, best (surveyed)
`raterInterest`	Average rater interest, between 1, lowest, to 5, highest (surveyed)
`sdQuality`	Standard Deviation of quality rating
`sdHelpfulness`	Standard Deviation of helpfulness rating
`sdClarity`	Standard Deviation of clarity rating
`sdEasiness`	Standard Deviation of easiness rating
`sdRaterInterest`	Standard Deviation of the Rater's interest

Next, we see numerical and graphical summaries of the project data set. The data values output in a preliminary summary were consistent with the data, i.e., the min, max, mean etc were within the bounds of the data with no obvious anomalies. There were no missing values or extreme data values we could detect.

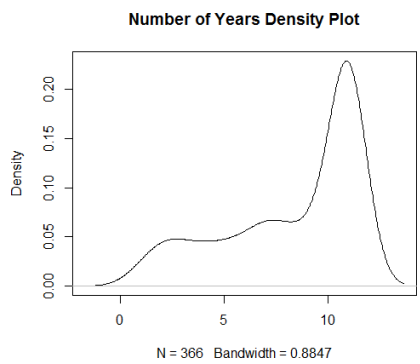
There is some natural skewness in some of the data - number of raters, years of experience etc, which is to be expected given the type of data collected.

Variable	Min	1st Q	Median	Mean	3rd Q	Max	[Other]	[Other]
`gender`							159 (female)	207 (male)
`numYears`	1.00	6.00	10.00	8.35	11.00	11.00		
`numRaters`	10.00	15.00	24.00	28.58	37.00	86.00		
`numCourses`	1.00	3.00	4.00	4.25	5.00	12.00		
`pepper`							46 (yes)	320 (no)
`quality`	1.41	2.936	3.61	3.58	4.25	4.98		
`helpfulness`	1.36	3.07	3.66	3.63	4.35	5.00		
`clarity`	1.33	2.87	3.60	3.53	4.21	5.00		
`easiness`	1.39	2.55	3.15	3.14	3.69	4.90		
`raterInterest`	1.10	2.93	3.31	3.31	3.69	4.91		

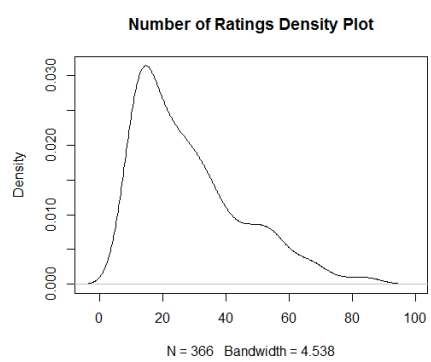
Next we'll inspect the graphical summaries:



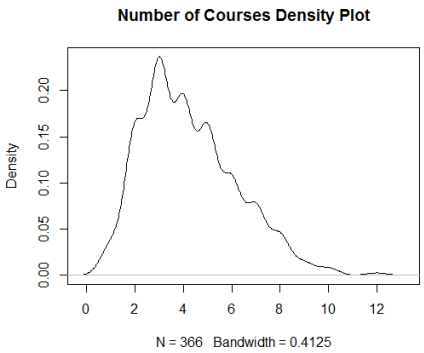
From the bar graph we learn that there are more male instructors than female in the data.



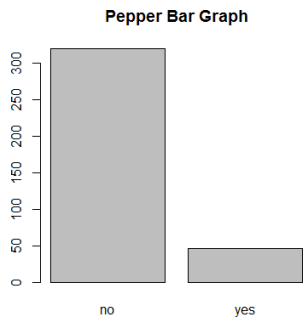
The number of years density plot is skewed left, so we can conclude that the majority of professors have been teaching for at least 8 years between 1999 and 2009. We can see that the most frequent number of years taught between 1999 and 2009 is 11 years.



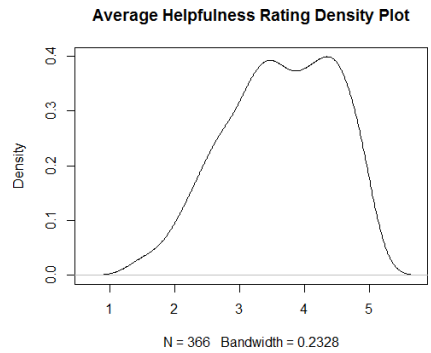
The number of ratings density plot is skewed right, so we can conclude that the majority of the professors have less than 40 total ratings, with the most frequent number of ratings falling between 10 and 20.



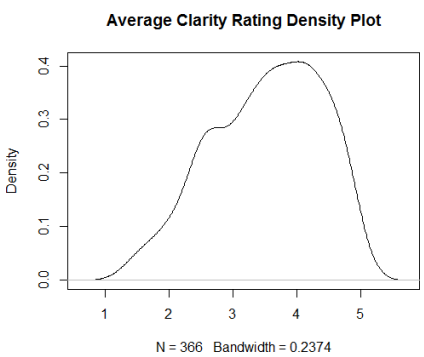
The number of courses density plot is skewed right, so we can conclude that the majority of professors have less than 6 courses that are rated. From the graph we can see the most frequent number of courses is 3. We can also see that there are a few unusually large values.



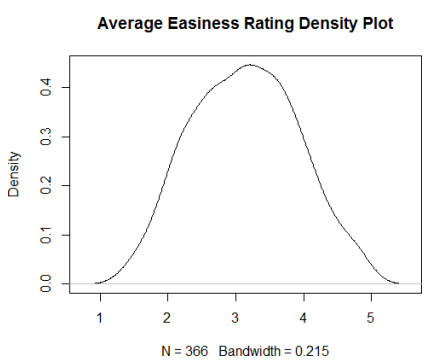
From the bar graph we learn that more instructors were rated as not attractive than those that were related as attractive.



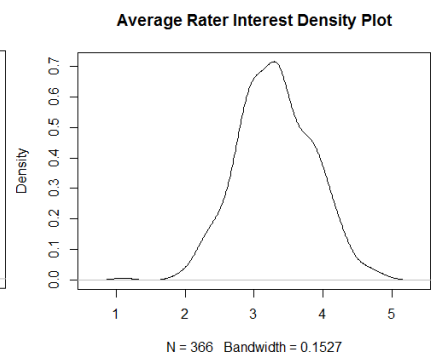
The average helpfulness rating density plot is bimodal, with the two most frequent average helpfulness ratings falling a little higher than 3, and at about 4.5.



The average clarity rating density plot is skewed left so we conclude the majority of instructors have high average clarity ratings, with the most frequent average rating falling around 4.



The average easiness rating density plot is normally distributed, and centered around an average rating of about 3.



Average rater interest appears to be normally distributed, with a few unusually low ratings.

Please note that we are immediately omitting all standard deviation calculations, as these were calculated specifically for use in the Bleske-Rechek et al. paper [1]. While these are used to produce reliable and interesting results in their research, it is beyond the scope of our paper and also not part of the original data set. We are also omitting departmental qualitative variables and the response, `quality`.

2. Collinearity Analysis

Model Summary ***Please note:*** *we analyze the summary for completeness' sake. It is not used as a primary decision tool in our analysis. Also,* `gender` *and* `pepper` *variables are omitted due to binary nature.* Little is gleaned from the summary in terms of correlation (Appendix, Figure 2.1). Of note are the p-values of `helpfulness` and `clarity`, which match precisely - this is improbable behavior. Furthermore, the only other regressor that maintains a strong p-value is `numRaters`.

Pairwise Correlation ***Please note:*** *we analyze the covariance matrix for completeness' sake. It is not used as a primary decision tool in our analysis. Also,* `gender` *and* `pepper` *variables are omitted due to binary nature.* This analysis (Appendix, Figure 2.2) offers a more telling story: `clarity` and `helpfulness` appear to maintain a strong correlation from both the plot and the pairwise correlation matrix (0.92), while moderate correlations appear to exist between `helpfulness` and `easiness`, and `clarity` and `easiness`.

Variance Inflation Factor (VIF) This analysis (Appendix, Figure 2.3) begins to clarify some of the issues in the original model: `helpfulness` and `clarity` appear to be correlated. It is likely that a recommendation to omit these two variables will be made.

Furthermore, it was discovered that `helpfulness` and `clarity` are not only correlated, but that they directly produce `quality` by means of a linear transformation (averaging). While this offers an explanation of collinearity, it also provides motive to omit both variables since leaving either one in would provide systemic issues in our analysis.

Condition Indices Our final collinearity analysis (Appendix, Figure 2.4) begins with the original model. Note that the binary, qualitative variables of `gender` and `pepper` have been omitted from this model; we wish to reserve them for later hypothesis testing.

We believe there is sufficient, systemic reason to omit both `helpfulness` and `clarity` immediately from the model. After removal, we note there still exists a relatively high condition number. Between `easiness` and `raterInterest`, the removal of `raterInterest` results in an acceptable condition number ($27.831 < 30$).

Model Statement Thus our current model, based solely off of correlation (and incidental systemic

removal) is:

$$\widehat{y}_{quality} = \beta_0 + \beta_1 x_{numYears} + \beta_2 x_{numRaters} + \beta_3 x_{numCourses} + \beta_4 x_{easiness} + \beta_5 x_{gender} + \beta_6 x_{pepper}.$$

3. Model Selection

Variable Selection allows us to find the "best" subset of predictors. We want the simplest model that adequately explains the data. Unnecessary regressors will add noise to all model estimates.

Taking our colinearity analysis into consideration, we are given the model of:

$$\widehat{y}_{quality} = \beta_0 + \beta_1 x_{numYears} + \beta_2 x_{numRaters} + \beta_3 x_{numCourses} + \beta_4 x_{easiness} + \beta_5 x_{gender} + \beta_6 x_{pepper}.$$

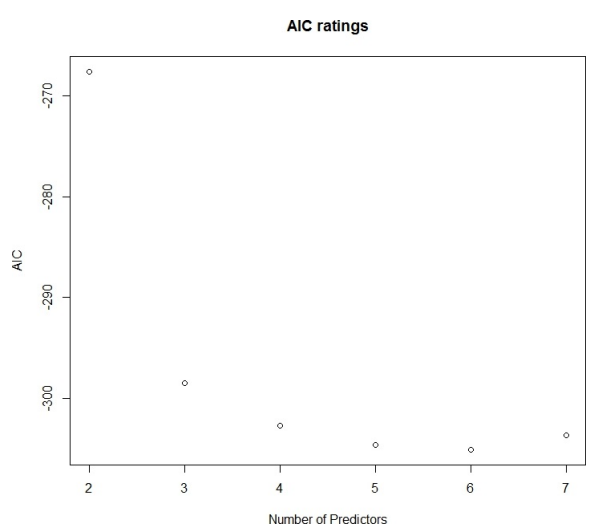
When performing Model Selection we need to fulfill two aspects 1. Search Strategy 2. Criterion for model comparisons.

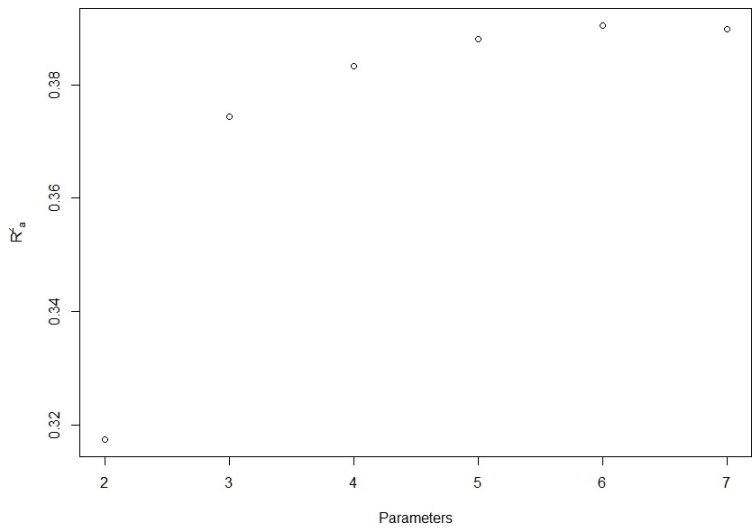
We choose to begin with an exhaustive search, which looks at all possible models using all available regressors, this is the best subset searching strategy due to having few variables.

	numYears	numRaters	numCourses	easiness	genderMale	pepperYes
1	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE
2	FALSE	FALSE	FALSE	TRUE	FALSE	TRUE
3	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE
4	TRUE	FALSE	FALSE	TRUE	TRUE	TRUE
5	TRUE	FALSE	TRUE	TRUE	TRUE	TRUE
6	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE

Next let's choose which model is best for us. We'll use Criterion such as AIC, Adjusted R^2, and Cp Statistics Our goal is to choose a model which minimizes AIC, the first term in the AIC is based on RSS which is made by improving the fit.

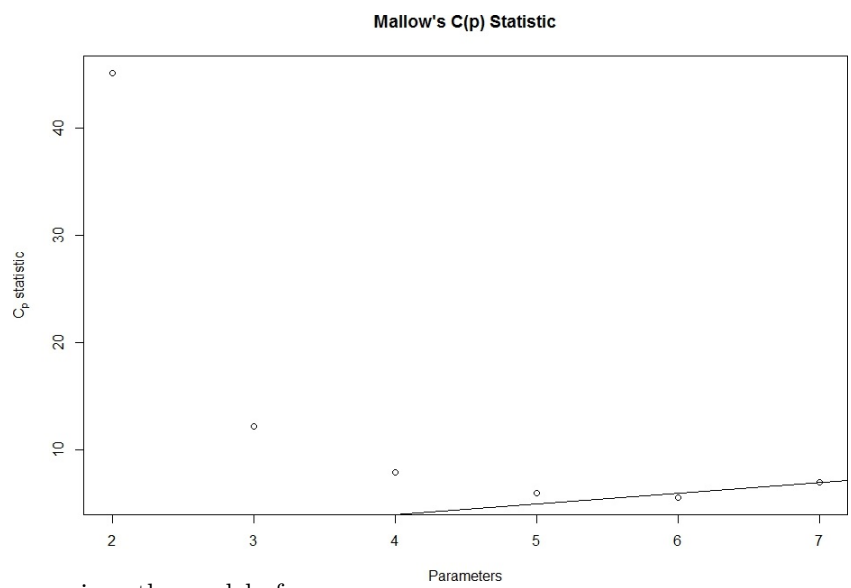
In plot to the right, we choose a number of predictors based on minimizing AIC. We observe that when P = 6 it suggests the five predictor model from above as being the best.





Next we compare the Adjusted R^2 to Parameters. We're looking for the largest Parameter value. We can see in the plot to the left that P=6 yet again is suggesting the same five predictor model as our AIC criteria.

Now we look at Mallows' Cp Statistic (right). For the Cp stat we want the smallest Cp value that is closest to the line x=y. Yet again we see it indicates 6 Parameters, meaning the five predictor model is ideal.



As a result of Model Selection, we are given the model of:

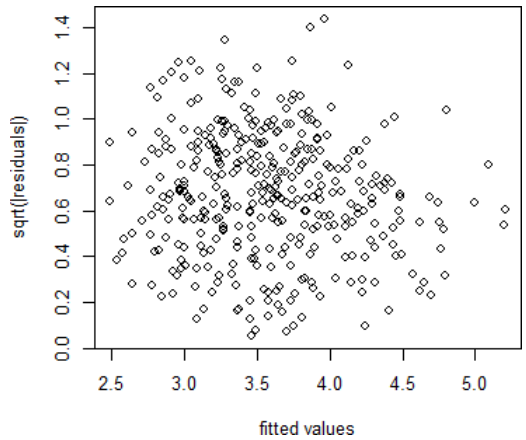
$$\widehat{y}_{quality} = \beta_0 + \beta_1 x_{numYears} + \beta_2 x_{numCourses} + \beta_3 x_{easiness} + \beta_4 x_{gender} + \beta_5 x_{pepper}.$$

Since variable selection can be affected by both Outliers/Influential observations, as well as the transformation of variables, we will next iterate over our model by performing diagnostics.

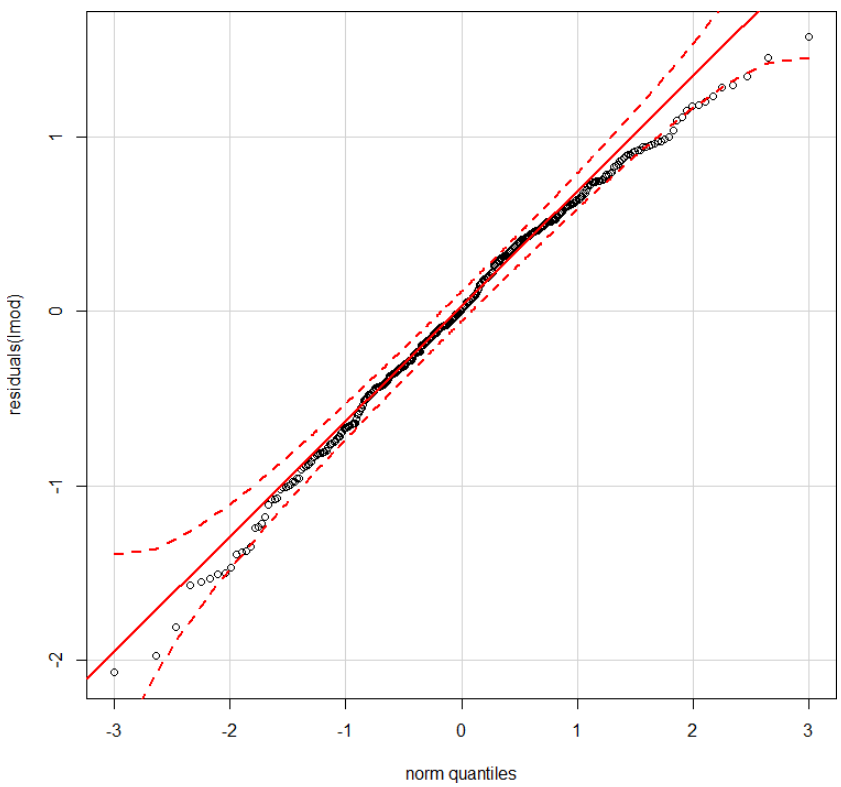
4. Diagnostics

Preliminary Analysis While not used formally in this analysis (due to lack of explanation), an examination of `R`'s `gvlma()` function (Appendix, Figure 4.1) reveals that the assumptions of kurtosis and heteroscedasticity are satisfied. However, the remaining assumptions are not met. We will attempt to explain the these results in the following section.

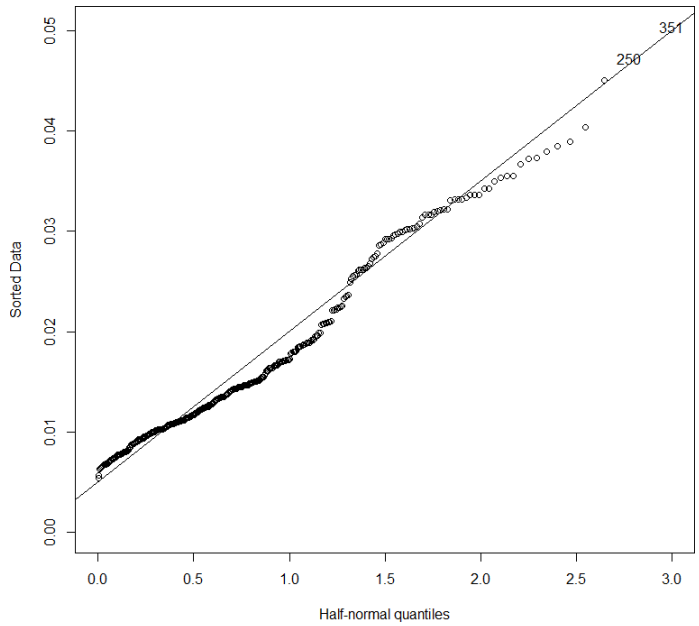
Constant Variance We note there is an apparent bound of residuals as the fitted values increase, possibly the result of a structural problem which we will address later in this section. While square-rooting the residuals does appear to diminish this effect, it does not eliminate it (`R` code in Appendix, Figure 4.2; relevant plot to the right).



Normality Observe the Q-Q plot with confidence bands to the right (`R` code in Appendix, Figure 4.3; plot left). Note that the normality assumption is indeed slightly breached, both left and right. However, the majority of the breach occurs to the right, indicating right-skew.

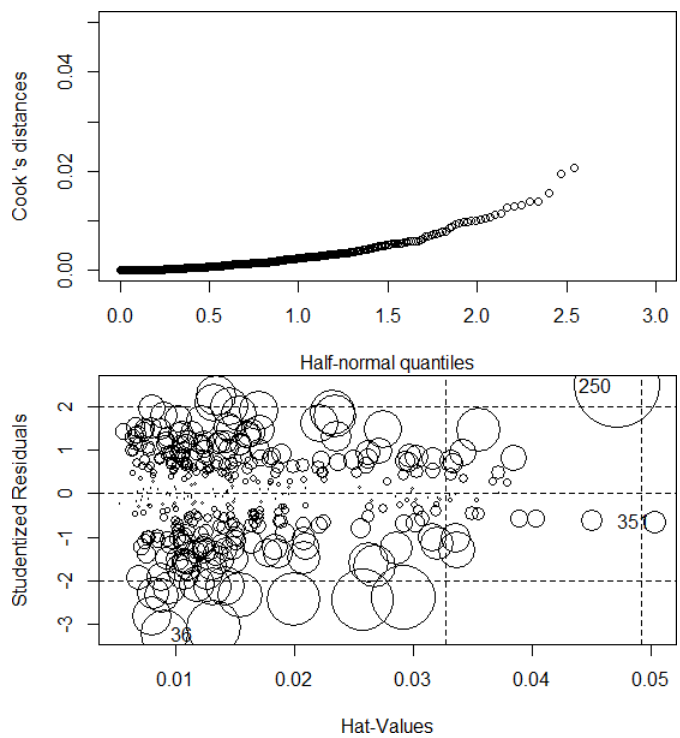


LEVERAGE POINTS Despite this model's breach of the normality assumption, there do not appear to be any leverage points that significantly affect the model. Observe the plot to the right (`R` code in Appendix, Figure 4.4): there appears to be a (roughly) linear relation between the sorted data and the half-normal quantiles. The lack of a significant off-shooting data point indicates a lack of leverage points.

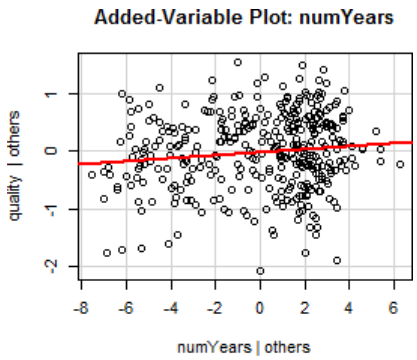


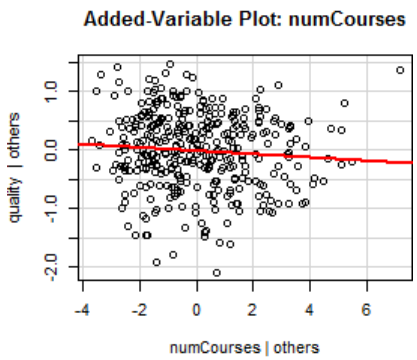
OUTLIERS By the Bonferonni p-value (`R` code in Appendix, Figure 4.5), we detect observation 36 as an outlier. In the next section we will examine the possibility for influential data.

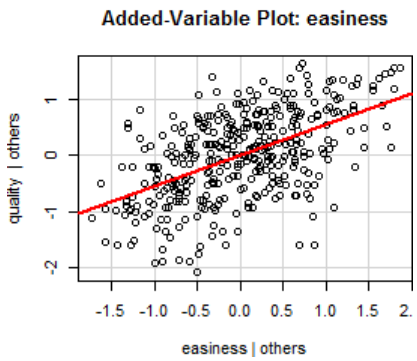
INFLUENTIAL POINTS Observe on the plots to the right (`R` code in Appendix, Figure 4.6) that there are two potential influence points indicated on the plot of studentized residuals versus hat-values (observations 250 and 351), and none indicated on the plot of Cook's distances. Since neither of these observations are indicated as outliers or leverage points, it is unlikely that they are candidates for removal. However, for completeness' sake we will consider their removal. In Appendix Figure 4.7, we observe the `summary()` of the original linear model, followed by a sequential removal of these two points (complete with abbreviated summaries). We note that there is no significant change between summaries, thus we are not inclined to remove any observation as an influential point.



STRUCTURE As noted at the beginning of this section, there appears to be a distinct structural problem that cannot be readily transformed. We will further this examination by considering the added-variable and component-plus-residual plots (below) of the quantitative data in our linear model.

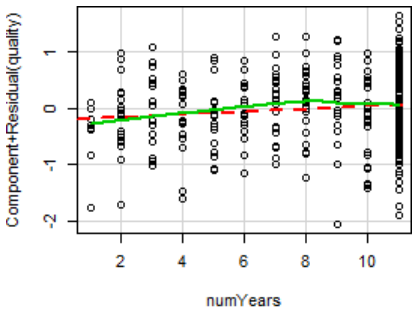


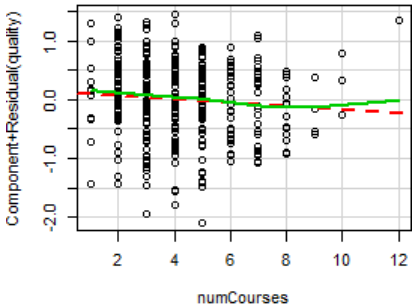


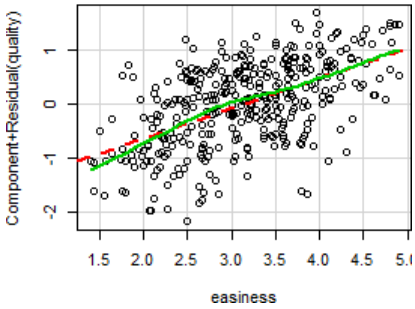


By the added-variable plots (left), the slope of the red lines somewhat indicate a linear relation between `quality` vs. `numYears`, and `quality` vs. `numCourses`. There appears to be a stronger linear relation between `quality` vs. `easiness`.

By the component-plus-residual plots (right), there is a slight indication that transformations may be called for on `numYears` and `numCourses`, however further investigation reveals that basic transformations do not improve our model significantly.







In Appendix Figure 4.8 (and the accompanying Appendix plot), we attempt four basic transformations: `numYears`^{2}, `numCourses`^{2}, `log(numYears)`, and `log(numCourses)`. While some of these transformations improve the linearity of the cpr plot (e.g. `numYears`^{2}, there were no significant changes in summary output). Furthermore, none of these models improved our `gvlma()` output. It was thus concluded to not transform any of the quantitative variables in this model.

5. HYPOTHESIS In this section we have identified three questions we wish to answer:

1. Are Helpfulness, Clarity, Easiness, and Rater interest all statistically significant in the model?
2. Does Gender have an effect on perception of Overall Quality, given the model of best fit?
3. Does the Chili Pepper have an effect on perception of Overall Quality, given the model of best fit?

To answer the first question, we must fit our model, regress on `quality`, and then observe the p-values.

EASINESS is statistically significant at the $\alpha = 0.001$ level, with a p-value of $< 2 \cdot 10^{-16}$. Hence there is very strong evidence `easiness` is useful in explaining the average `quality` rating, when `gender`, `pepper`, `numYears` and `numCourses` are already in the model.

GENDER is statistically significant at the $\alpha = 0.05$ level, with a p-value of 0.0208. Hence there is very strong evidence `gender` is useful in explaining the average `quality` rating, when `easiness`, `pepper`, `numYears` and `numCourses` are already in the model.

PEPPER is statistically significant at the $\alpha = 0.001$ level, with a p-value of $8.11 \cdot 10^{-11}$. Hence there is very strong evidence `pepper` is useful in explaining the average `quality` rating, when `gender`, `easiness`, `numYears` and `numCourses` are already in the model.

NUMYEARS is statistically significant at the $\alpha = 0.05$ level, with a p-value of 0.0225. Hence there is moderate evidence `numYears` is useful in explaining the average `quality` rating, when `gender`, `pepper`, `easiness` and `numCourses` are already in the model.

NUMCOURSES is not statistically significant with a p-value of 0.1200. Hence there is no evidence `numCourses` is useful in explaining the average `quality` rating, when `gender`, `pepper`, `numYears` and `easiness` are already in the model.

MODEL AND INTERPRETATION

Here we show our model with the appropriate β values input.

$$E(quality|numYears, numCourses, easiness, genderMale, pepperYes)$$
$$= 1.56261 + 0.02622(numYears) - 0.02829(numCourses) + 0.55364(easiness) + 0.16240(genderMale)$$
$$+ 0.68553(pepperYes)$$

INTERPRETATION (`numYears`)

If two professors are identical to one another except that one professor has been teaching one more year than the other, then we predict the average quality rating for the professor with an extra year of teaching will be

0.02622 points higher than the other.

INTERPRETATION (`numCourses`)

If two professors are identical to one another except that one professor has one more course title included in their ratings, then we predict the average quality rating for the professor with more course titles will be 0.028929 less than the other professor.

INTERPRETATION (`easiness`)

If two professors are identical to one another except that one professor has an average easiness score that is one point higher than the other, then we predict the average quality rating will be about 0.55364 points higher than the other professor.

INTERPRETATION (`genderMale`)

If two professors are identical to one another except that one is male and the other is female, then we predict the average quality rating will be 0.16240 points higher for the female than the male.

INTERPRETATION (`pepperYes`)

If two professors are identical to one another except that one is rated as attractive and the other is not, then we predict the average quality rating for the attractive professor will be 0.68553 points higher than the other professor.

HYPOTHESIS TESTING We wanted to test whether the `gender` and `pepper` regressor variables should be simultaneously dropped from the model that already includes `easiness`, `numYears`, and `numCourses`.

$$H_0 : \beta_{gender} = 0 \text{ and } \beta_{pepper} = 0 \Big| \beta_{easiness} \neq 0, \beta_{numYears} \neq 0, \beta_{numCourses} \neq 0$$

$$H_\alpha : \beta_{Gender} \neq 0 \text{ or } \beta_{Pepper} \neq 0 \Big| \beta_{easiness} \neq 0, \beta_{numYears} \neq 0, \beta_{numCourses} \neq 0$$

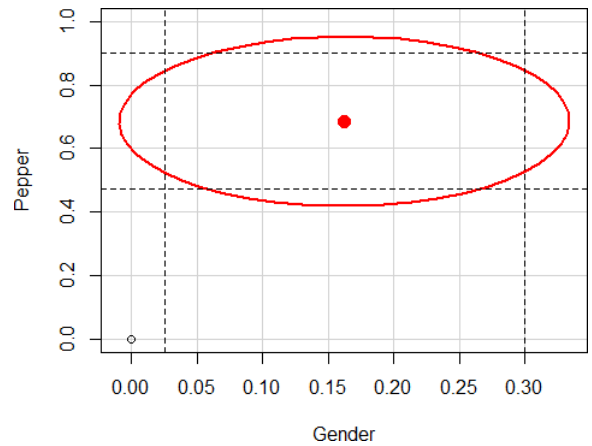
F-STATISTIC:

$$\begin{aligned} F &= [(RSS_\omega - RSS_\Omega)/(df_\omega - df_\Omega)]/(RSS_\Omega/df_\Omega) \\ &= [(173.16 - 153.91)/(362 - 360)]/(153.91/360) = 9.625/0.427527 \\ &= 22.5 \end{aligned}$$

P-VALUE: $6.075 \cdot 10^{-10}$

CONCLUSION IN CONTEXT There is very strong evidence that `gender` or `pepper` should be included in the model given that `easiness`, `numYears`, and `numCourses` are already in the model.

We can also see from the Ellipse Confidence Interval Graph Plot Below between `gender` and `pepper` that $\beta_{gender} = \beta_{pepper} = 0$ is not plausible because $(0, 0)$ falls into the rejection region.



We do not believe prediction is appropriate for this model. Not only are our assumptions violated (see conclusion below), but there are systemic issues with predicting students' perception: this data set is based on a single school. We would need a much larger, randomized pool of students to formulate useful predictions on the entire student population.

6. Conclusion

Summarizing From our data exploration and analysis, we learned that the best linear model for our data set when regressing on Quality is the model that includes Gender, Pepper, Easiness, Number of Years, and Number of Courses. After running diagnostics on our data we found that our normality assumption failed (indicated by skewness). In addition, our linear model assumptions failed the global stat, and link function tests. We also found when testing our structure that there appears to be clear structure in the residuals versus fitted values plot, on the back end of the data, coming to a point. However, at this time we are unequipped to make adjustments to the data in order to correct this issue. Due to these issues it is important we note that our conclusions are unreliable. We are providing the tests and the interpretations to supply evidence of our ability to perform and interpret such tests, if our structure and normality assumptions were held. Finally, we must also note that these observations are based on students' *perceptions* of instructor quality, adding another layer of unreliability.

By finding appropriate test statistics and p-values associated with the variables in our model we are able to answer our questions of interest. The first question we asked was, "Does Gender have an effect on perception of Overall Quality given the model of best fit?" When comparing our full model of best fit which included `easiness`, `gender`, `pepper`, `numYears`, and `numCourses`, to the model with just `easiness`, `Pepper`, `numYears`, and `numCourses`; we found moderate evidence that `gender` was useful in explaining overall quality perception. The second question we looked into being, "Does the Chili Pepper have an effect on perception

of overall `quality` given the model of best fit?" We found when comparing our full model of best fit, which included `easiness`, `gender`, `pepper`, `numYears`, and `numCourses`, to the model with just `easiness`, `gender`, `numYears`, and `numCourses`, there was very strong evidence that the Chili Pepper was useful in explaining overall `quality` perception. The third question we proposed was"Are Helpfulness, Clarity, Easiness, and Rater Interest all statistically significant in the model of best fit?" As we researched more about how the data was collected from the paper "Student Consensus on *RateMyProfessors.com*" we learned that `helpfulness` and `clarity` are directly used to calculate `quality` perception [1]. Due to this we removed `helpfulness` and `clarity` from the model from the beginning. When we did diagnostics and checked for collinearity we found that `raterInterest` should be removed from the model. After both diagnostics and model selection we did test if `easiness` was statistically significant and found that it was significant with a p-value of less than $2 \cdot 10^{-16}$. So we can conclude that there is very strong evidence `easiness` is useful in explaining `quality` perception when `gender`, `pepper`, `numYears`, and `numCourses` are already in the model.

LEARNING As a team we learned a lot about model selection and diagnostics. The model selection and diagnostics sections were more difficult for us as we found a clear structure in our residuals versus fitted values that we did not know how to correct for. It was also difficult dealing with diagnostics as we learned our normality assumptions failed and therefore made our interpretations and hypotheses unreliable.

IMPROVING The major change we would make to improve the design of our study would be to find a way to transform the data that would fit our normality assumptions and a way to adjust for the evident structural issues. Due to the fact that these lead our conclusions to be unreliable this would be the most important improvement we could make so that conclusions could be drawn. To do this it may include using more of the variables from the original study of the data like the standard deviations of the rating variables.

FUTURE WORK To extend the research we would expand the data collection beyond just the large single campus in the Midwest. Due to the data being only from one specific campus, all of the interpretations and conclusions would be held within that campus and cannot be extended beyond that campus. By adding other campuses we could extend interpretations to other campuses. However, not only should we extend the sample size and parameters (more schools), but we would also recommend randomly selecting professors across those campuses to extend our interpretations to all the professors within the population.

Appendix

FIGURE 1.1

```
> summary(Rateprof)
Output:
gender       numYears        numRaters       numCourses     pepper   discipline
female:159   Min.   : 1.000   Min.   :10.00   Min.   : 1.000   no :320   Hum      :134
male  :207   1st Qu.: 6.000   1st Qu.:15.00   1st Qu.: 3.000   yes: 46   SocSci   : 66
             Median :10.000   Median :24.00   Median : 4.000             STEM     :103
             Mean   : 8.347   Mean   :28.58   Mean   : 4.251             Pre-prof: 63
             3rd Qu.:11.000   3rd Qu.:37.00   3rd Qu.: 5.000
             Max.   :11.000   Max.   :86.00   Max.   :12.000

         dept        quality       helpfulness       clarity         easiness
 English    : 49   Min.   :1.409   Min.   :1.364   Min.   :1.333   Min.   :1.391
 Math       : 34   1st Qu.:2.936   1st Qu.:3.069   1st Qu.:2.871   1st Qu.:2.548
 Biology    : 20   Median :3.612   Median :3.662   Median :3.600   Median :3.148
 Chemistry  : 20   Mean   :3.575   Mean   :3.631   Mean   :3.525   Mean   :3.135
 Psychology: 20   3rd Qu.:4.250   3rd Qu.:4.351   3rd Qu.:4.214   3rd Qu.:3.692
 Spanish    : 20   Max.   :4.981   Max.   :5.000   Max.   :5.000   Max.   :4.900
 (Other)    :203
 raterInterest     sdQuality       sdHelpfulness      sdClarity        sdEasiness
 Min.   :1.098   Min.   :0.09623   Min.   :0.0000   Min.   :0.0000   Min.   :0.3162
 1st Qu.:2.934   1st Qu.:0.87508   1st Qu.:0.9902   1st Qu.:0.9085   1st Qu.:0.9045
 Median :3.305   Median :1.15037   Median :1.2860   Median :1.1712   Median :1.0247
 Mean   :3.310   Mean   :1.05610   Mean   :1.1719   Mean   :1.0970   Mean   :1.0196
 3rd Qu.:3.692   3rd Qu.:1.28730   3rd Qu.:1.4365   3rd Qu.:1.3328   3rd Qu.:1.1485
 Max.   :4.909   Max.   :1.67739   Max.   :1.8091   Max.   :1.8091   Max.   :1.6293

 sdRaterInterest
 Min.   :0.3015
 1st Qu.:1.0848
 Median :1.2167
 Mean   :1.1965
 3rd Qu.:1.3326
 Max.   :1.7246
```

FIGURE 1.2

```
> plot(density(Rateprof$numYears, na.rm = TRUE), main = "Number of Years Density Plot")
> plot(density(Rateprof$numCourses, na.rm = TRUE), main = "Number of Courses Density Plot")
> plot(density(Rateprof$numRaters, na.rm = TRUE), main = "Number of Ratings Density Plot")
> plot(density(Rateprof$easiness, na.rm = TRUE), main = "Average Easiness Rating Density Plot")
> plot(density(Rateprof$helpfulness, na.rm = TRUE), main = "Average Helpfulness Rating Density Plot")
> plot(density(Rateprof$clarity, na.rm = TRUE), main = "Average Clarity Rating Density Plot")
```

```
> plot(density(Rateprof$raterInterest, na.rm = TRUE), main = "Average Rater
    Interest Density Plot")
```

FIGURE 1.3

```
> gender1 <- Rateprof$gender
> gender.freq = table(gender1)
> barplot(gender.freq, main = "Gender Bar Graph")

> peppery <- Rateprof$pepper
> pepper.freq = table(peppery)
> barplot(pepper.freq, main = "Pepper Bar Graph")
```

FIGURE 2.1

```
> summary(lmod)

Call:
lm(formula = quality ~ gender + numYears + numRaters + numCourses +
    pepper + helpfulness + clarity + easiness + raterInterest,
    data = Rateprof)

Residuals:
     Min       1Q   Median       3Q      Max
-0.74521 -0.00749  0.00243  0.01238  0.16384

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)   -0.0143292  0.0183639  -0.780   0.4357
gendermale     0.0026288  0.0048498   0.542   0.5881
numYears       0.0009020  0.0008273   1.090   0.2763
numRaters     -0.0003962  0.0001526  -2.597   0.0098 **
numCourses    -0.0013853  0.0012826  -1.080   0.2808
pepperyes      0.0013419  0.0078707   0.170   0.8647
helpfulness    0.5360712  0.0074231  72.216   <2e-16 ***
clarity        0.4637251  0.0071509  64.849   <2e-16 ***
easiness       0.0063883  0.0037449   1.706   0.0889 .
raterInterest -0.0010421  0.0049108  -0.212   0.8321
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.04493 on 356 degrees of freedom
Multiple R-squared:  0.9972,  Adjusted R-squared:  0.9971
F-statistic: 1.405e+04 on 9 and 356 DF,  p-value: < 2.2e-16
```

FIGURE 2.2

```
> round(cor(Rateprof[,c ("numYears", "numRaters", "numCourses", "helpfulness", "
    clarity", "easiness", "raterInterest")]),4)
               numYears numRaters numCourses helpfulness clarity easiness raterI...
numYears         1.0000    0.3420     0.2570     -0.0429 -0.0245  -0.1405   -0.0126
numRaters        0.3420    1.0000     0.2599     -0.0770 -0.0753  -0.1065   -0.1363
numCourses       0.2570    0.2599     1.0000     -0.0673 -0.0948  -0.0901    0.0233
helpfulness     -0.0429   -0.0770    -0.0673      1.0000  0.9208   0.5635    0.4630
clarity         -0.0245   -0.0753    -0.0948      0.9208  1.0000   0.5359    0.4611
easiness        -0.1405   -0.1065    -0.0901      0.5635  0.5359   1.0000    0.2052
raterInterest   -0.0126   -0.1363     0.0233      0.4630  0.4611   0.2052    1.0000
> plot ( Rateprof[,c ("numYears", "numRaters", "numCourses", "helpfulness", "
    clarity", "easiness", "raterInterest") ])
```

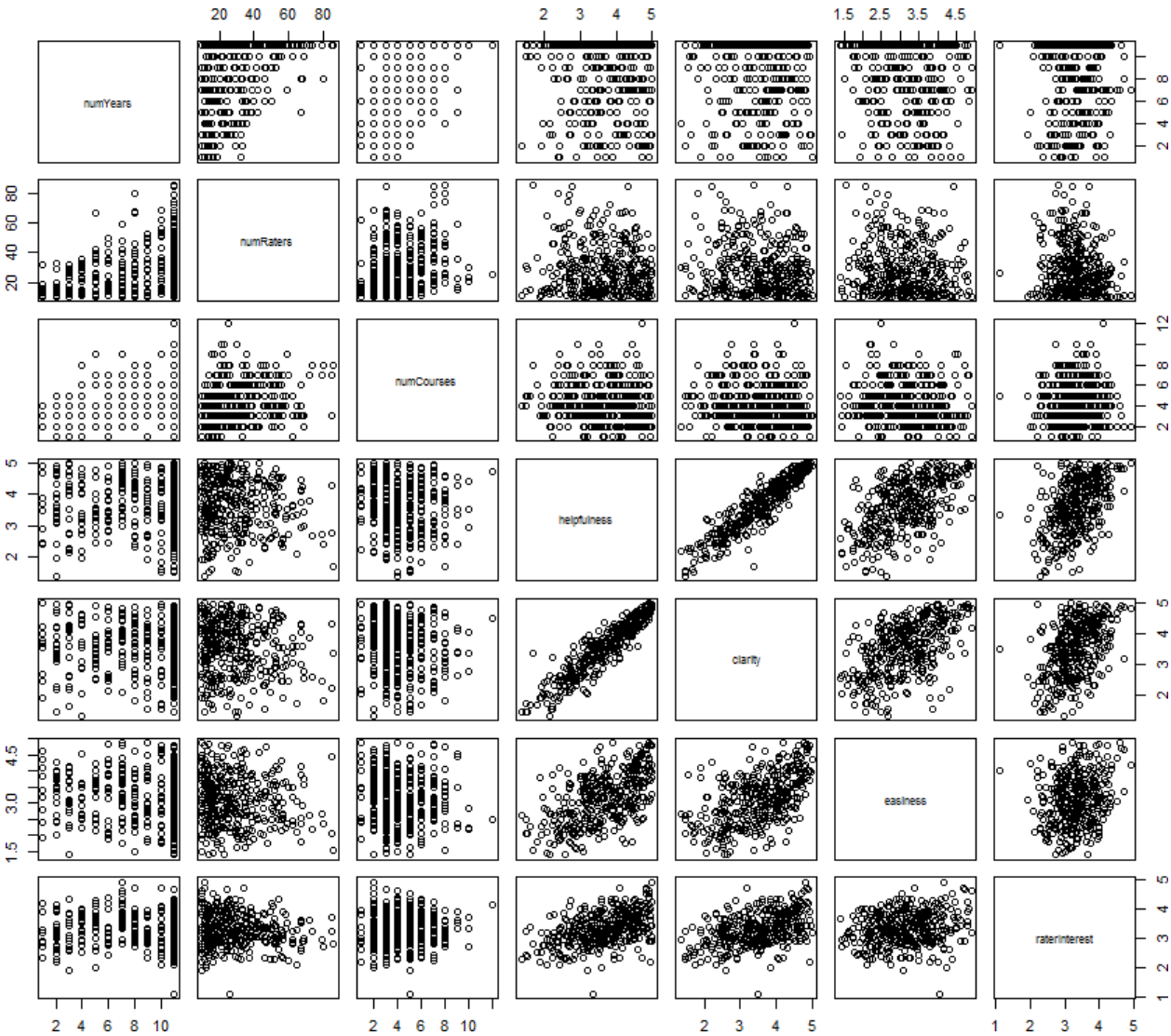


FIGURE 2.3

```
> round(vif(lmod),4)
gender numYears numRaters numCourses pepper helpfulness clarity easiness raterI...
1.0478   1.2678     1.203     1.1417 1.2342      7.0681  6.8206   1.5337    1.3312
```

FIGURE 2.4

```
> lmod <- lm(quality ~ numYears + numRaters + numCourses + helpfulness + clarity +
    easiness + raterInterest, Rateprof)
> X <- model.matrix(lmod)[,-1]
> sqrt(eigen(crossprod(X,X))$val[1]/eigen(crossprod(X,X))$val)
[1]   1.000000   6.419884  15.145677  19.321868  57.575535  63.491312 146.986953
> colldiag(lmod, scale=FALSE, add.intercept=FALSE)
Condition
Index Variance Decomposition Proportions
           numYears numRaters numCourses helpfulness clarity easiness raterInt...
1    1.000 0.000    0.184     0.000      0.000       0.000   0.000    0.000
2    6.420 0.153    0.789     0.011      0.000       0.000   0.001    0.001
3   15.146 0.783    0.002     0.039      0.003       0.003   0.010    0.005
4   19.322 0.022    0.023     0.880      0.002       0.002   0.005    0.001
5   57.576 0.013    0.001     0.000      0.016       0.026   0.961    0.089
6   63.491 0.026    0.001     0.061      0.037       0.051   0.009    0.901
7  146.987 0.002    0.000     0.008      0.943       0.918   0.014    0.002
> lmod <- lm(quality ~ numYears + numRaters + numCourses + easiness +
    raterInterest, Rateprof)
> X <- model.matrix(lmod)[,-1]
> sqrt(eigen(crossprod(X,X))$val[1]/eigen(crossprod(X,X))$val)
[1]  1.000000  6.972014 17.109728 23.419540 59.091063
> colldiag(lmod, scale=FALSE, add.intercept=FALSE)
Condition
Index Variance Decomposition Proportions
          numYears numRaters numCourses easiness raterInterest
1   1.000 0.000    0.191     0.000      0.000    0.000
2   6.972 0.247    0.792     0.017      0.002    0.002
3  17.110 0.603    0.014     0.503      0.014    0.009
4  23.420 0.110    0.002     0.455      0.139    0.065
5  59.091 0.040    0.002     0.025      0.845    0.924
> lmod_0 <- lm(quality ~ numYears + numRaters + numCourses + raterInterest,
    Rateprof)
> X <- model.matrix(lmod_0)[,-1]
> sqrt(eigen(crossprod(X,X))$val[1]/eigen(crossprod(X,X))$val)
[1]  1.000000  7.181937 17.535442 31.334791
> colldiag(lmod_0, scale=FALSE, add.intercept=FALSE)
Condition
Index Variance Decomposition Proportions
          numYears numRaters numCourses raterInterest
1   1.000 0.000    0.194     0.000      0.000
2   7.182 0.290    0.785     0.019      0.005
3  17.535 0.467    0.021     0.694      0.015
4  31.335 0.242    0.000     0.286      0.980
> lmod_1 <- lm(quality ~ numYears + numRaters + numCourses + easiness, Rateprof)
> X <- model.matrix(lmod_1)[,-1]
> sqrt(eigen(crossprod(X,X))$val[1]/eigen(crossprod(X,X))$val)
[1]  1.00000  7.22862 17.52871 27.38139
> colldiag(lmod_1, scale=FALSE, add.intercept=FALSE)
Condition
Index Variance Decomposition Proportions
          numYears numRaters numCourses easiness
1   1.000 0.000    0.193     0.000      0.000
2   7.229 0.336    0.783     0.021      0.005
3  17.529 0.517    0.022     0.735      0.024
4  27.381 0.147    0.001     0.243      0.971
```

FIGURE 3.1

```
> b <- regsubsets(quality ~ gender + pepper + easiness + numYears + numRaters +
    numCourses,data = Rateprof)
> rs <- summary(b) #summarize model that minimizes RSS for each p
> rs$which
  (Intercept) gendermale pepperyes easiness numYears numRaters numCourses
1        TRUE      FALSE     FALSE     TRUE    FALSE     FALSE      FALSE
2        TRUE      FALSE      TRUE     TRUE    FALSE     FALSE      FALSE
3        TRUE       TRUE      TRUE     TRUE    FALSE     FALSE      FALSE
4        TRUE       TRUE      TRUE     TRUE     TRUE     FALSE      FALSE
5        TRUE       TRUE      TRUE     TRUE     TRUE     FALSE       TRUE
6        TRUE       TRUE      TRUE     TRUE     TRUE      TRUE       TRUE
```

FIGURE 3.2

```
> AIC <- 366*log(rs$rss/366) + (2:7)*2
> plot(AIC ~ I(2:7), ylab="AIC", xlab="Number of Predictors", main = "AIC ratings
    ")
```

FIGURE 3.3

```
> adjr = rs$adjr
> plot(adjr ~ p, xlab= "Parameters", ylab = expression({R^2}[a]), main= "Adjusted
    R Squared Ratings")
```

FIGURE 3.4

```
> cp = rs$cp
> plot(cp ~ p,xlab = "Parameters" ,ylab = expression(paste(C[p], " statistic")),
    main = "Mallow's C(p) Statistic")
```

FIGURE 4.1

```
> library(gvlma)
> lmod <- lm(quality ~ numYears + numCourses + easiness + gender + pepper,
    Rateprof)
> gvlma(lmod)

Call:
lm(formula = quality ~ numYears + numCourses + easiness + gender +
    pepper, data = Rateprof)

Coefficients:
(Intercept)     numYears   numCourses     easiness   gendermale    pepperyes
    1.56261      0.02622     -0.02829      0.55364      0.16240      0.68553


ASSESSMENT OF THE LINEAR MODEL ASSUMPTIONS
USING THE GLOBAL TEST ON 4 DEGREES-OF-FREEDOM:
Level of Significance =  0.05

Call:
 gvlma(x = lmod)

                      Value  p-value                   Decision
Global Stat        13.18612 0.010401 Assumptions NOT satisfied!
Skewness            7.40233 0.006514 Assumptions NOT satisfied!
Kurtosis            0.09833 0.753837    Assumptions acceptable.
Link Function       5.36589 0.020534 Assumptions NOT satisfied!
Heteroscedasticity  0.31957 0.571869    Assumptions acceptable.
```

FIGURE 4.2

```
> plot(fitted(lmod), residuals(lmod), xlab = "fitted values", ylab = "residuals")
> plot(fitted(lmod), sqrt(abs(residuals(lmod))), xlab = "fitted values", ylab = "
    sqrt(|residuals|)")
```

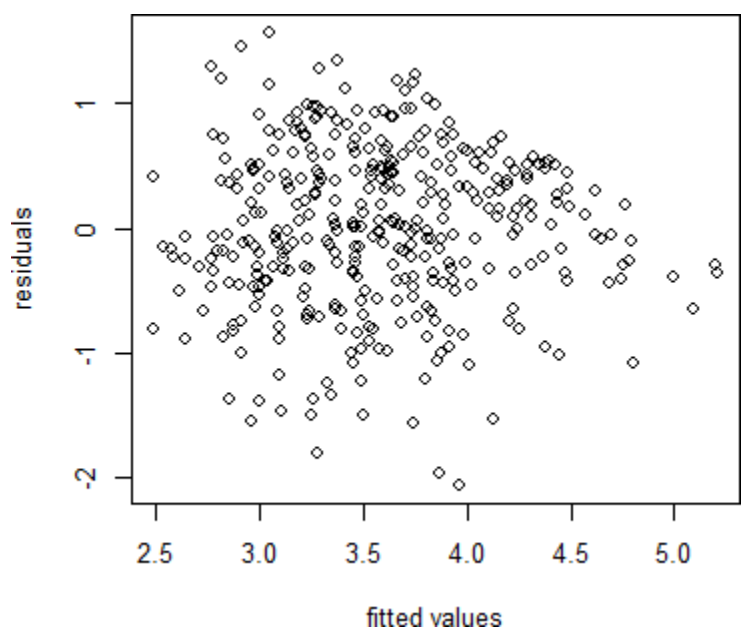


FIGURE 4.3

```
> library(car)
> qqPlot(residuals(lmod))
```

FIGURE 4.4

```
> halfnorm (hatvalues(lmod), nlab = 2)
```

FIGURE 4.5

```
> outlierTest(lmod)

No Studentized residuals with Bonferonni p < 0.05
Largest |rstudent|:
    rstudent unadjusted p-value Bonferonni p
36 -3.222465          0.0013872      0.50772
```

FIGURE 4.6

```
> influencePlot(lmod)
       StudRes         Hat       CookD
36  -3.2224651 0.009108198 0.015504419
250  2.4822783 0.047188045 0.050140857
351 -0.6386189 0.050363798 0.003610842
> halfnorm (cooks.distance(lmod), n=3, labs=row.names(teengamb), ylab = "Cook 's
    distances")
```

FIGURE 4.7 *(Truncated output)*

```
> lmod2 <- lm(quality ~ numYears + numCourses + easiness + gender + pepper,
    Rateprof, subset=(sdQuality != 0.72571800))
> lmod3 <- lm(quality ~ numYears + numCourses + easiness + gender + pepper,
    Rateprof, subset=(sdQuality != 0.80750000))
> summary(lmod)
# ...
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.56261    0.19289   8.101 8.55e-15 ***
numYears     0.02622    0.01144   2.291   0.0225 *
numCourses  -0.02829    0.01815  -1.559   0.1200
easiness     0.55364    0.04580  12.088  < 2e-16 ***
gendermale   0.16240    0.06994   2.322   0.0208 *
pepperyes    0.68553    0.10861   6.312 8.11e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6538 on 360 degrees of freedom
Multiple R-squared:  0.3988,  Adjusted R-squared:  0.3905
F-statistic: 47.77 on 5 and 360 DF,  p-value: < 2.2e-16

> summary(lmod2)
# ...
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.58675    0.19177   8.274 2.56e-15 ***
numYears     0.02673    0.01136   2.352   0.0192 *
numCourses  -0.03742    0.01839  -2.034   0.0427 *
easiness     0.55623    0.04549  12.228  < 2e-16 ***
gendermale   0.15785    0.06947   2.272   0.0237 *
pepperyes    0.68822    0.10784   6.382 5.41e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6492 on 359 degrees of freedom
Multiple R-squared:  0.4064,  Adjusted R-squared:  0.3982
F-statistic: 49.16 on 5 and 359 DF,  p-value: < 2.2e-16

> summary(lmod3)
# ...
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.54834    0.19434   7.967 2.17e-14 ***
numYears     0.02663    0.01147   2.322   0.0208 *
numCourses  -0.02682    0.01831  -1.464   0.1440
easiness     0.55565    0.04595  12.093  < 2e-16 ***
gendermale   0.15934    0.07016   2.271   0.0237 *
pepperyes    0.69462    0.10963   6.336 7.06e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6544 on 359 degrees of freedom
Multiple R-squared:  0.3981,  Adjusted R-squared:  0.3897
F-statistic: 47.49 on 5 and 359 DF,  p-value: < 2.2e-16
```

FIGURE 4.8 *(Truncated output)*

```
> lmod1 <- lm(quality ~ numYears + I(numYears^2) + numCourses + easiness + gender
    + pepper, Rateprof)
> lmod2 <- lm(quality ~ numYears + numCourses + I(numCourses^2) + easiness +
    gender + pepper, Rateprof)
> lmod3 <- lm(quality ~ numYears + I(log(numYears)) + numCourses + easiness +
    gender + pepper, Rateprof)
> lmod4 <- lm(quality ~ numYears + numCourses + I(log(numCourses)) + easiness +
    gender + pepper, Rateprof)
> gvlma(lmod1)

Call:
lm(formula = quality ~ numYears + I(numYears^2) + numCourses +
    easiness + gender + pepper, data = Rateprof)

Coefficients:
(Intercept) numYears I(numYears^2) numCourses easiness gendermale pepperyes
   1.321938 0.127810     -0.007281  -0.030381 0.547801   0.161652  0.700914


ASSESSMENT OF THE LINEAR MODEL ASSUMPTIONS
USING THE GLOBAL TEST ON 4 DEGREES-OF-FREEDOM:
Level of Significance =  0.05

Call:
 gvlma(x = lmod1)

                      Value  p-value                   Decision
Global Stat        13.99849 0.007300 Assumptions NOT satisfied!
Skewness            7.13596 0.007555 Assumptions NOT satisfied!
Kurtosis            0.05934 0.807536    Assumptions acceptable.
Link Function       6.52272 0.010651 Assumptions NOT satisfied!
Heteroscedasticity  0.28047 0.596391    Assumptions acceptable.
> gvlma(lmod2)

Call:
lm(formula = quality ~ numYears + numCourses + I(numCourses^2) +
    easiness + gender + pepper, data = Rateprof)

Coefficients:
(Intercept) numYears numCourses I(numCourses^2) easiness gendermale pepperyes
    1.80680  0.02714   -0.14026         0.01127  0.54730    0.15627   0.69139


ASSESSMENT OF THE LINEAR MODEL ASSUMPTIONS
USING THE GLOBAL TEST ON 4 DEGREES-OF-FREEDOM:
Level of Significance =  0.05

Call:
 gvlma(x = lmod2)

                      Value  p-value                   Decision
Global Stat        15.9397 0.003101 Assumptions NOT satisfied!
Skewness            7.9075 0.004923 Assumptions NOT satisfied!
Kurtosis            0.4124 0.520744    Assumptions acceptable.
Link Function       7.1894 0.007334 Assumptions NOT satisfied!
Heteroscedasticity  0.4303 0.511819    Assumptions acceptable.
> gvlma(lmod3)
```

```

Call:
lm(formula = quality ~ numYears + I(log(numYears)) + numCourses +
    easiness + gender + pepper, data = Rateprof)

Coefficients:
(Intercept) numYears I(log(numYears)) numCourses easiness gendermale pepperyes
    1.38695 -0.03620          0.35732   -0.03004  0.54990    0.16348   0.70120


ASSESSMENT OF THE LINEAR MODEL ASSUMPTIONS
USING THE GLOBAL TEST ON 4 DEGREES-OF-FREEDOM:
Level of Significance =  0.05

Call:
 gvlma(x = lmod3)

                     Value  p-value                   Decision
Global Stat        13.7759 0.008046 Assumptions NOT satisfied!
Skewness            7.2223 0.007200 Assumptions NOT satisfied!
Kurtosis            0.1099 0.740234    Assumptions acceptable.
Link Function       6.1064 0.013469 Assumptions NOT satisfied!
Heteroscedasticity  0.3372 0.561429    Assumptions acceptable.
> gvlma(lmod4)

Call:
lm(formula = quality ~ numYears + numCourses + I(log(numCourses)) +
    easiness + gender + pepper, data = Rateprof)

Coefficients:
(Intercept) numYears numCourses I(log(numCourses)) easiness gendermale pepperyes
1.63770      0.02668    0.02053           -0.20416  0.54937    0.16054   0.68901


ASSESSMENT OF THE LINEAR MODEL ASSUMPTIONS
USING THE GLOBAL TEST ON 4 DEGREES-OF-FREEDOM:
Level of Significance =  0.05

Call:
 gvlma(x = lmod4)

                     Value  p-value                   Decision
Global Stat        14.6813 0.005410 Assumptions NOT satisfied!
Skewness            7.5824 0.005894 Assumptions NOT satisfied!
Kurtosis            0.2389 0.624975    Assumptions acceptable.
Link Function       6.4615 0.011024 Assumptions NOT satisfied!
Heteroscedasticity  0.3986 0.527831    Assumptions acceptable.
> summary(lmod1)

Call:
lm(formula = quality ~ numYears + I(numYears^2) + numCourses +
    easiness + gender + pepper, data = Rateprof)

Residuals:
     Min       1Q   Median       3Q      Max
-2.12070 -0.40753  0.02513  0.46038  1.61747

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
```

```
(Intercept)    1.321938   0.238681   5.539 5.91e-08 ***
numYears       0.127810   0.060717   2.105   0.0360 *
I(numYears^2) -0.007281   0.004274  -1.704   0.0893 .
numCourses    -0.030381   0.018145  -1.674   0.0949 .
easiness       0.547801   0.045810  11.958  < 2e-16 ***
gendermale     0.161652   0.069757   2.317   0.0210 *
pepperyes      0.700914   0.108699   6.448 3.66e-10 ***
---
Signif. codes:  0    ***    0.001    **    0.01    *    0.05    .    0.1         1

Residual standard error: 0.6521 on 359 degrees of freedom
Multiple R-squared:  0.4036,  Adjusted R-squared:  0.3937
F-statistic:  40.5 on 6 and 359 DF,  p-value: < 2.2e-16

> summary(lmod2)

Call:
lm(formula = quality ~ numYears + numCourses + I(numCourses^2) +
    easiness + gender + pepper, data = Rateprof)

Residuals:
     Min       1Q   Median       3Q      Max
-2.01419 -0.42344  0.00212  0.47517  1.48825

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)      1.806796   0.241812   7.472 6.08e-13 ***
numYears         0.027144   0.011429   2.375   0.0181 *
numCourses      -0.140265   0.069559  -2.016   0.0445 *
I(numCourses^2)  0.011266   0.006757   1.667   0.0963 .
easiness         0.547296   0.045847  11.937  < 2e-16 ***
gendermale       0.156271   0.069864   2.237   0.0259 *
pepperyes        0.691394   0.108398   6.378 5.52e-10 ***
---
Signif. codes:  0    ***    0.001    **    0.01    *    0.05    .    0.1         1

Residual standard error: 0.6522 on 359 degrees of freedom
Multiple R-squared:  0.4034,  Adjusted R-squared:  0.3935
F-statistic: 40.46 on 6 and 359 DF,  p-value: < 2.2e-16

> summary(lmod3)

Call:
lm(formula = quality ~ numYears + I(log(numYears)) + numCourses +
    easiness + gender + pepper, data = Rateprof)

Residuals:
     Min       1Q   Median       3Q      Max
-2.09605 -0.40564  0.05068  0.46388  1.60778

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)       1.38695    0.21914   6.329 7.36e-10 ***
numYears         -0.03620    0.03898  -0.929   0.3537
I(log(numYears))  0.35732    0.21337   1.675   0.0949 .
numCourses       -0.03004    0.01814  -1.657   0.0985 .
easiness          0.54990    0.04574  12.022  < 2e-16 ***
gendermale        0.16348    0.06977   2.343   0.0197 *
pepperyes         0.70120    0.10874   6.448 3.65e-10 ***
```

```
---
Signif. codes:  0    ***    0.001    **    0.01    *    0.05    .    0.1         1

Residual standard error: 0.6522 on 359 degrees of freedom
Multiple R-squared:  0.4035,  Adjusted R-squared:  0.3935
F-statistic: 40.47 on 6 and 359 DF,  p-value: < 2.2e-16

> summary(lmod4)

Call:
lm(formula = quality ~ numYears + numCourses + I(log(numCourses)) +
    easiness + gender + pepper, data = Rateprof)

Residuals:
     Min       1Q   Median       3Q      Max
-2.04694 -0.42327 -0.00303  0.47966  1.47451

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)          1.63770    0.21140   7.747 9.74e-14 ***
numYears             0.02668    0.01146   2.328   0.0205 *
numCourses           0.02053    0.05900   0.348   0.7281
I(log(numCourses)) -0.20416    0.23480  -0.869   0.3852
easiness             0.54937    0.04608  11.922  < 2e-16 ***
gendermale           0.16054    0.07000   2.294   0.0224 *
pepperyes            0.68901    0.10872   6.338 7.00e-10 ***
---
Signif. codes:  0    ***    0.001    **    0.01    *    0.05    .    0.1         1

Residual standard error: 0.6541 on 359 degrees of freedom
Multiple R-squared:  0.4001,  Adjusted R-squared:  0.3901
F-statistic:  39.9 on 6 and 359 DF,  p-value: < 2.2e-16

> crPlot(lmod1, variable = "numYears")
> crPlot(lmod1, variable = "I(numYears^2)")
> crPlot(lmod1, variable = "numCourses")
> crPlot(lmod1, variable = "easiness")
> crPlot( lmod2, variable = "numYears")
> crPlot( lmod2, variable = "numCourses")
> crPlot( lmod2, variable = "I(numCourses^2)")
> crPlot( lmod2, variable = "easiness")
> crPlot(lmod3, variable = "numYears")
> crPlot(lmod3, variable = "I(log(numYears))")
> crPlot(lmod3, variable = "numCourses")
> crPlot(lmod3, variable = "easiness")
> crPlot( lmod4, variable = "numYears")
> crPlot( lmod4, variable = "numCourses")
> crPlot( lmod4, variable = "I(log(numCourses))")
> crPlot( lmod4, variable = "easiness")
```

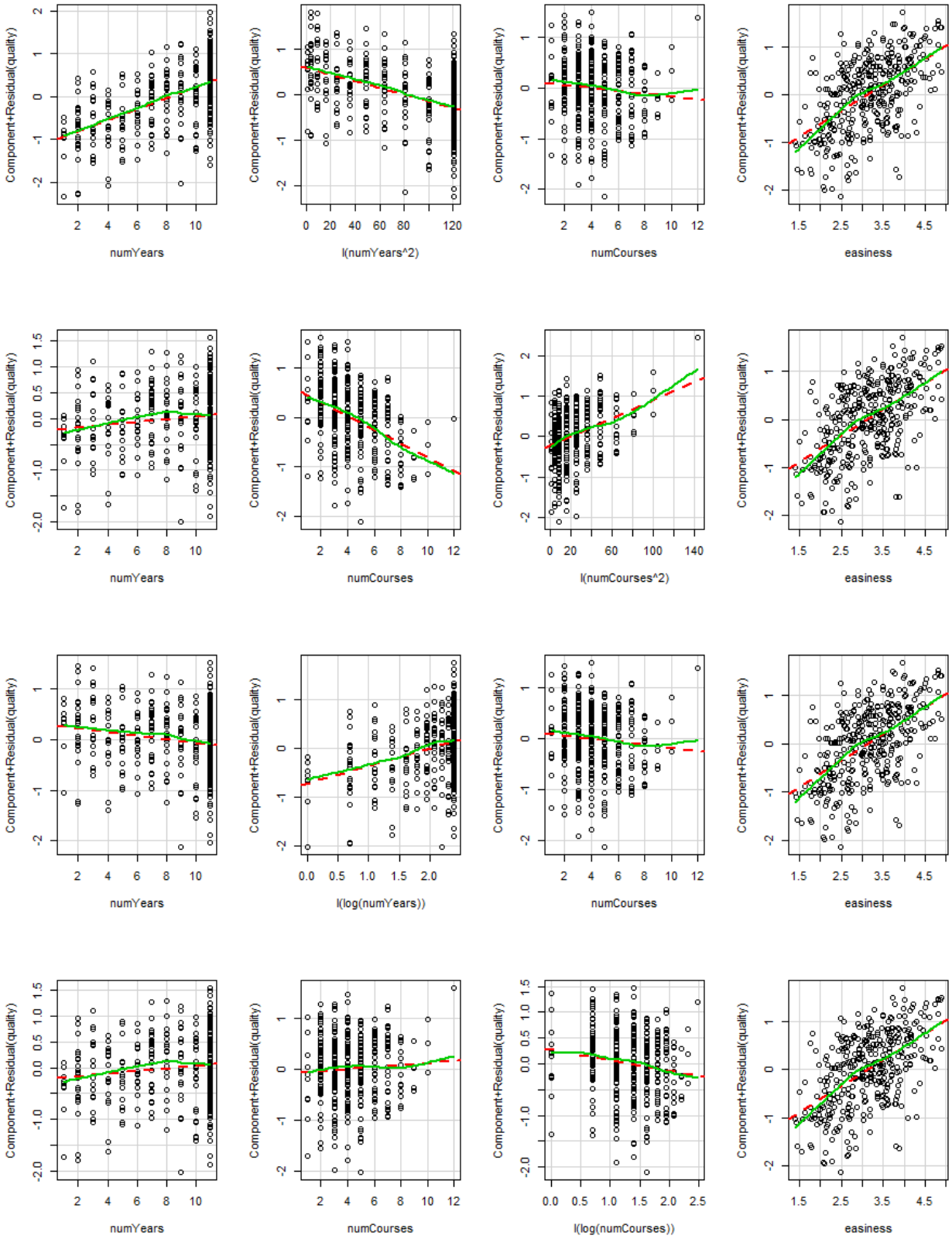

Component+Residual(quality)
numYears
I(numYears^2)
numCourses
easiness
I(numCourses^2)
I(log(numYears))
I(log(numCourses))

FIGURE 5.1

```
> data(Rateprof, package = "alr4")
> lmod <- lm(quality ~ easiness + gender + pepper + numYears + numCourses, data =
    Rateprof)
> summary(lmod)

Output:
Call:
lm(formula = quality ~ easiness + gender + pepper + numYears +
    numCourses, data = Rateprof)

Residuals:
     Min       1Q   Median       3Q      Max
-2.07057 -0.41488  0.01105  0.47686  1.57304

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.56261    0.19289   8.101 8.55e-15 ***
easiness     0.55364    0.04580  12.088  < 2e-16 ***
gendermale   0.16240    0.06994   2.322   0.0208 *
pepperyes    0.68553    0.10861   6.312 8.11e-10 ***
numYears     0.02622    0.01144   2.291   0.0225 *
numCourses  -0.02829    0.01815  -1.559   0.1200
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6538 on 360 degrees of freedom
Multiple R-squared:  0.3988,  Adjusted R-squared:  0.3905
F-statistic: 47.77 on 5 and 360 DF,  p-value: < 2.2e-16
```

FIGURE 5.2

```
lmod2 <- lm(quality ~ easiness + numYears + numCourses, data = Rateprof)
anova(lmod2, lmod)

#95% CI Ellipse
library(car)
confidenceEllipse(lmod, which.coef = c(3, 4), levels = 0.95, ylim = c(0,1), ylab =
    "Pepper", xlab = "Gender")
# add origin to plot
points(0, 0)
abline(v = confint(lmod)[3,], lty = 2)
abline(h = confint(lmod)[4,], lty = 2)
```

Works Cited

[1] Bleske-Rechek, A. and Fritsch, A. (2011). Student Consensus on RateMyProfessors.com. Practical Assessment, Research & Evaluation, 16(18), http://pareonline.net/getvn.asp?v=16&n=18

Work Breakdown

Faith Blair Graphical summaries and interpretations; hypothesis testing; model interpretations; introduction; conclusion.

Larry Breeden Graphical and numerical summaries.

Luke Mattingly Model selection; preliminary diagnostic analysis; introduction; document editing and LaTeX content injection.

Wyatt Miller Collinearity analysis; final diagnostic analysis; introduction; document formatting, layout, content injection, and LaTeX encoding.