An Overview of the Linear Regression

Applied Machine Learning for Educational Data Science

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Contents

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In the machine learning literature, the prediction algorithms are classified into two main categories: *supervised* and *unsupervised*. Supervised algorithms are being used when the dataset has an actual outcome of interest to predict (labels), and the goal is to build the "best" model predicting the outcome of interest that exists in the data. On the other side, unsupervised algorithms are being used when the dataset doesn't have an outcome of interest, and the goal is typically to identify similar groups of observations (rows of data) or similar groups of variables (columns of data) in data. In this course, we plan to cover a number of *supervised* algorithms. Linear regression is one of the simplest approach among supervised algorithms, and also one of the easiest to interpret.

Model Description

In most general terms, the linear regression model with P predictors (X_1,X_2,X_3,...,X_p) to predict an outcome (Y) can be written as the following:

$$Y = \beta_0 + \sum_{p=1}^{P} \beta_p X_p + \epsilon.$$

In this model, Y represents the observed value for the outcome for an observation, X_p represents the observed value of the p^{th} variable for the same observation, and β_p is the associated model parameter for the p^{th} variable. ϵ is the model error (residual) for the observation.

This model includes only the main effects of each predictor and can be easily extended by including a quadratic or higher-order polynomial terms for all (or a specific subset of) predictors. For instance, the model below includes all first-order, second-order, and third-order polynomial terms for all predictors.

$$Y = \beta_0 + \sum_{p=1}^{P} \beta_p X_p + \sum_{k=1}^{P} \beta_{k+P} X_k^2 + \sum_{m=1}^{P} \beta_{m+2P} X_m^3 + \epsilon.$$

The simple first-order, second-order, and third-order polynomial terms can also be replaced by corresponding terms obtained from B-splines or natural splines.

Sometimes, the effect of predictor variables on the outcome variable are not additive, and the effect of one predictor on the response variable can depend on the levels of another predictor. These non-additive effects are also called interaction effects. The interaction effects can also be a first-order interaction (interaction between two variables, e.g., $X_1 * X_2$), second-order interaction ($X_1 * X_2 * X_3$), or higher orders. It is also possible to add the interaction effects to the model. For instance, the model below also adds the first-order interactions.

$$Y = \beta_0 + \sum_{p=1}^{P} \beta_p X_p + \sum_{k=1}^{P} \beta_{k+P} X_k^2 + \sum_{m=1}^{P} \beta_{m+2P} X_m^3 + \sum_{i=1}^{P} \sum_{j=i+1}^{P} \beta_{i,j} X_i X_j + \epsilon.$$

If you are not comfortable or confused with notational representation, below is an example for different models you can write with 5 predictors (X_1, X_2, X_3).

A model with only main-effects:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon.$$

A model with polynomial terms up to the 3rd degree added:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_1^2 + \beta_5 X_2^2 + \beta_6 X_3^2 + \beta_7 X_1^3 + \beta_8 X_2^3 + \beta_9 X_3^3$$

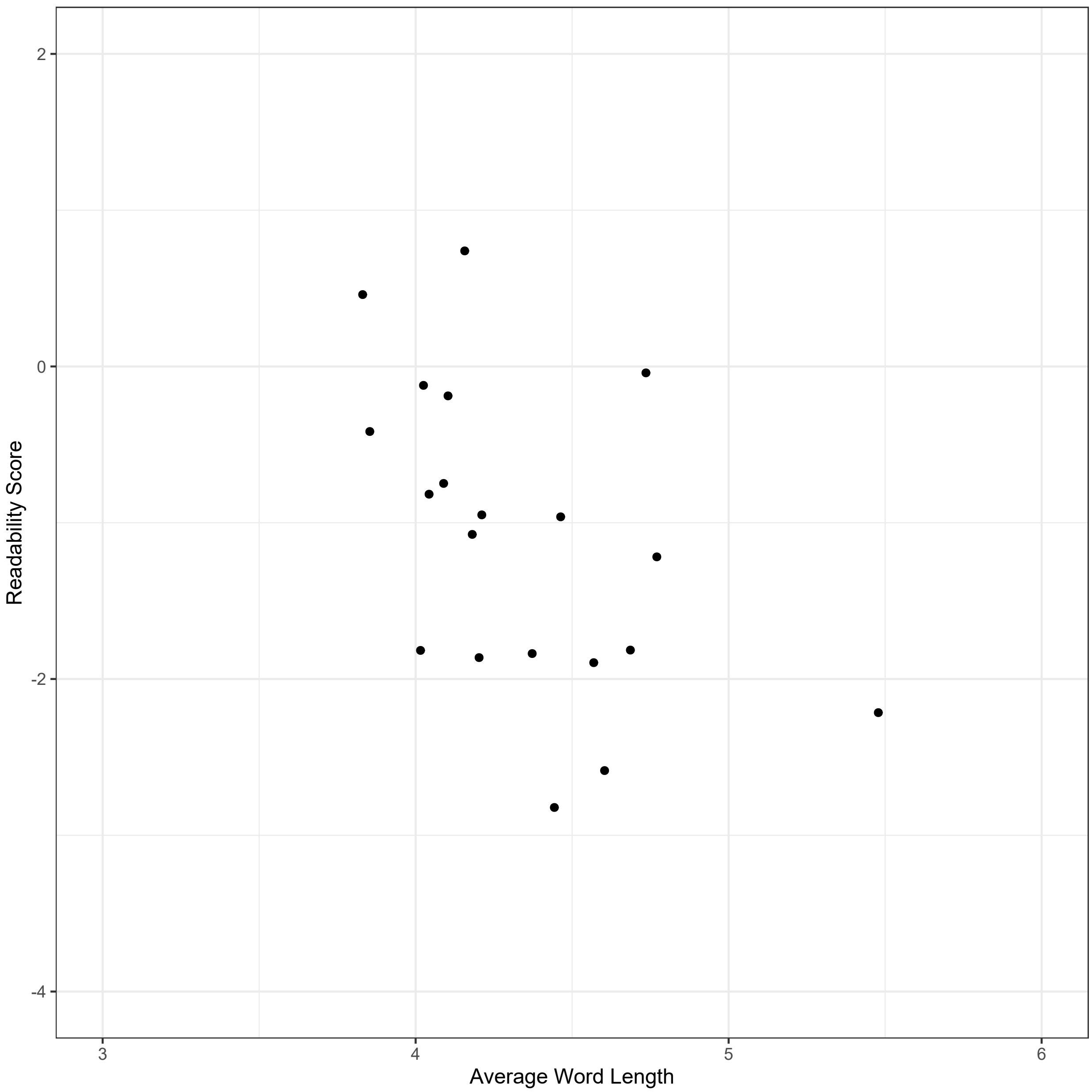
A model with both interaction terms and polynomial terms up to the 3rd degree added:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_1^2 + \beta_5 X_2^2 + \beta_6 X_3^2 + \beta_7 X_1^3 + \beta_8 X_2^3 + \beta_9 X_3^3 + \beta_{1,2} X_1 X_2 + \beta_{1,3} X_1 X_3 + \beta_{2,3} X_2 X_3 + \epsilon$$

Model Estimation

Suppose that we would like to predict the target readability score for a given text from average word length in the text. Below is a scatterplot to show the relationship between these two variables for a random sample of 20 observations. There seems to be a moderate negative correlation. So, we can tell that the higher the average word length is in a given text, the lower the readability score (more difficult to read).

```
readability_sub <- read.csv('https://raw.githubusercontent.com/uo-datasci-specialization/c4-ml-fall-202
```

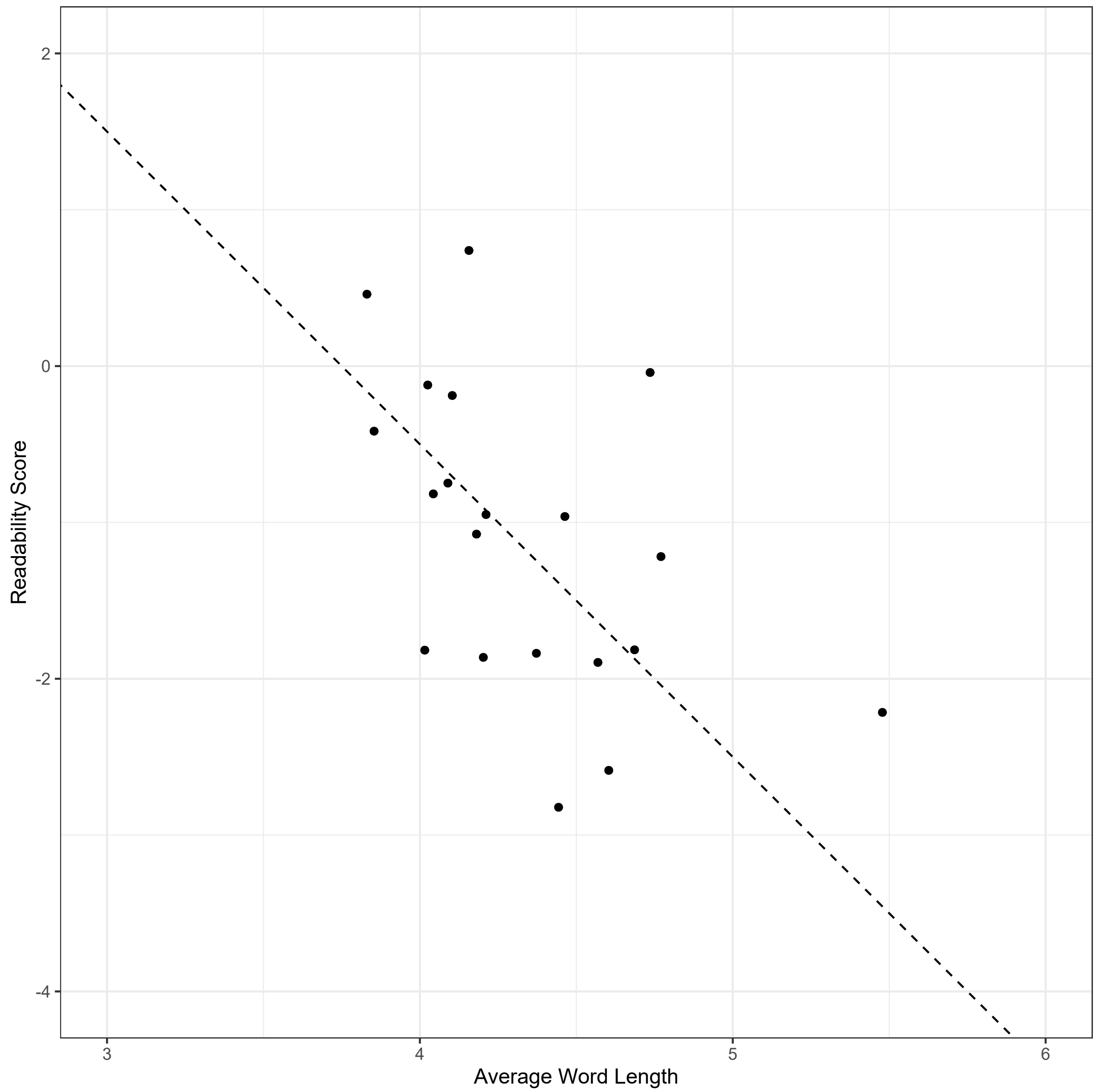


Let's consider a simple linear regression model such that the readability score is the outcome (Y) and average word length is the predictor($X1$). Our regression model would be

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i.$$

In this case, the set of coefficients, $\{\beta_0, \beta_1\}$, represents a linear line. We can come up with any set of $\{\beta_0, \beta_1\}$ coefficients and use it as our model. For instance, suppose I guesstimate that these coefficients are $\{\beta_0, \beta_1\}$ = {7.5,-2}. Then, my model would look like the following.

$$Y_i = 7.5 - 2X_i + \epsilon_i.$$



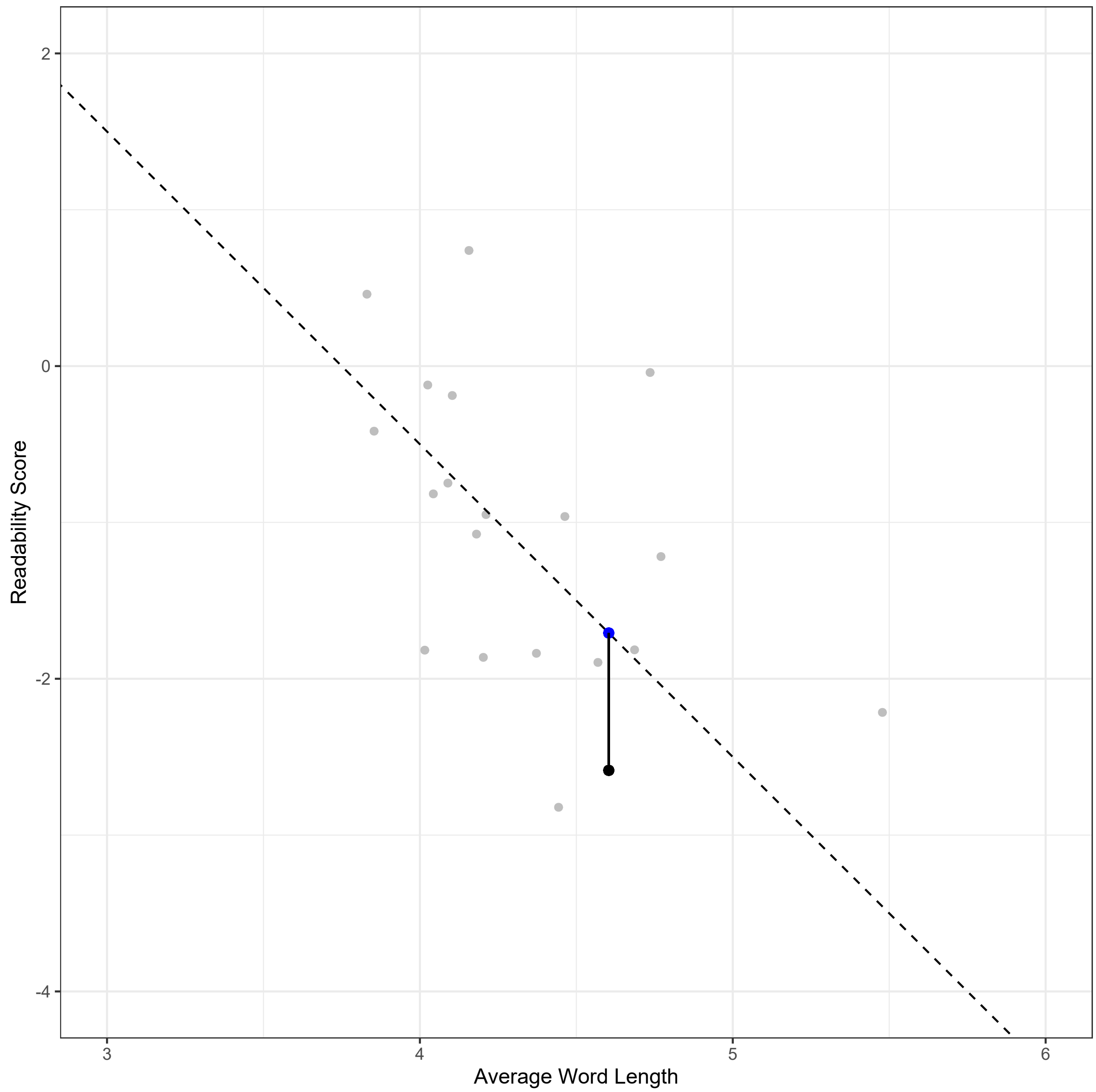
Using this model, I can predict the target readability score for all the observation in my dataset. For instance, the average word length is 4.604 for the first reading passage. Then, my prediction of readability score based on this model would be -1.708. On the other side, the observed value of the target score for this observation is -2.586. This discrepancy between the observed value and my model predicts is the model error (residual) for the first observation and captured in the ϵ term in the model.

$$Y_1 = 7.5 - 2X_1 + \epsilon_1.$$

$$\hat{Y_1} = 7.5 - 2 * 4.604 = -1.708$$

$$\hat{\epsilon_1} = -2.586 - (-1.708) = -0.878$$

We can visualize this in the plot. The black dot represents the observed data point, and the blue dot on the line represents the model prediction for a given X value. The vertical distance between these two data points is the model error for this particular observation.

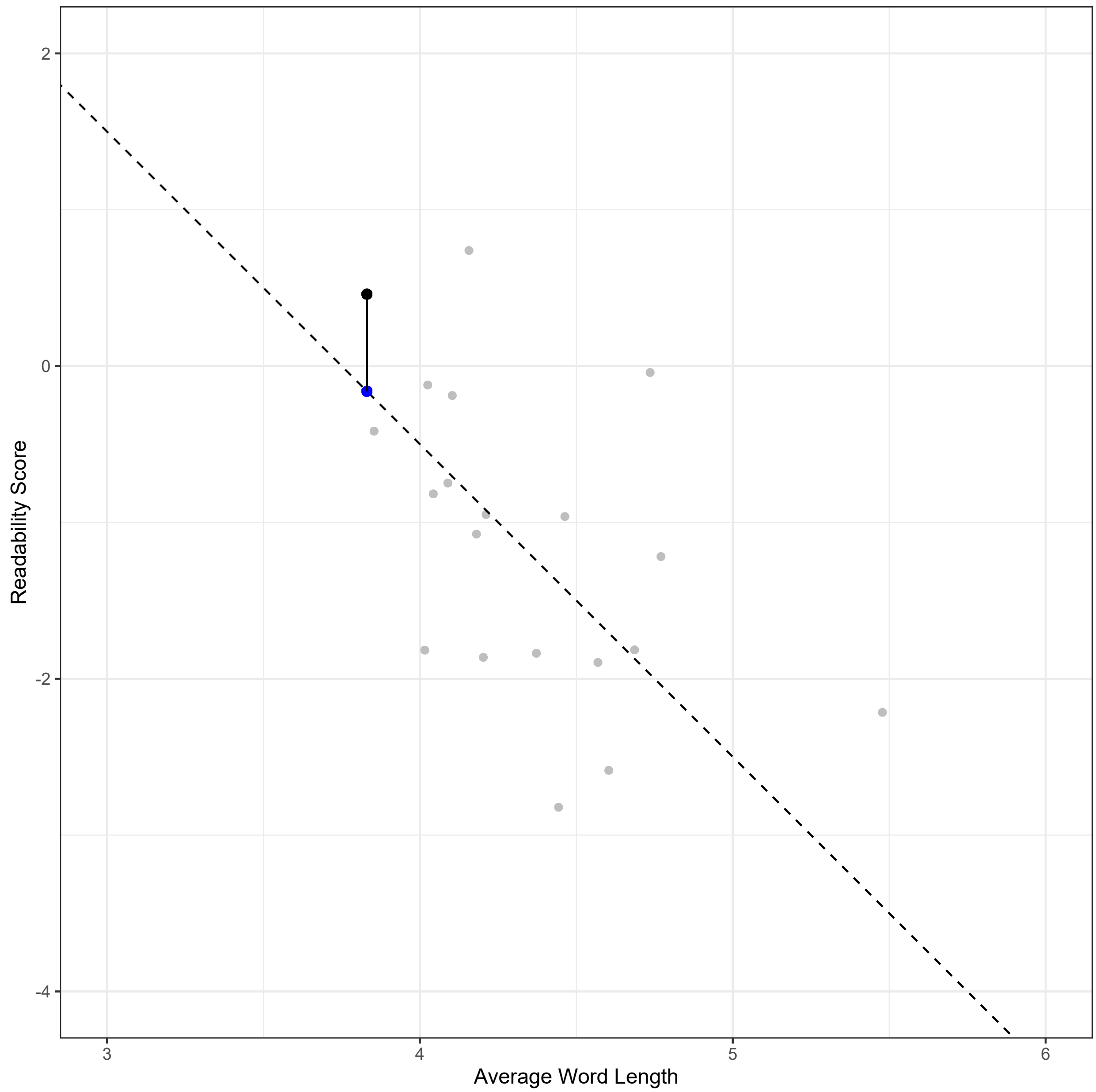


We can do the same experiment for the second observation. The average word length is 3.830 for the second reading passage. The model predicts a readability score of be -0.161. Observed value of the target score for this observation is 0.459. Therefore the model error for the second observation would be 0.62.

$$Y_2 = 7.5 - 2X_2 + \epsilon_2.$$

$$\hat{Y_2} = 7.5 - 2 * 3.830 = -0.161$$

$$\hat{\epsilon_2} = 0.459 - (-0.161) = 0.62$$



Using a similar approach, we can calculate the model error for every single observation.

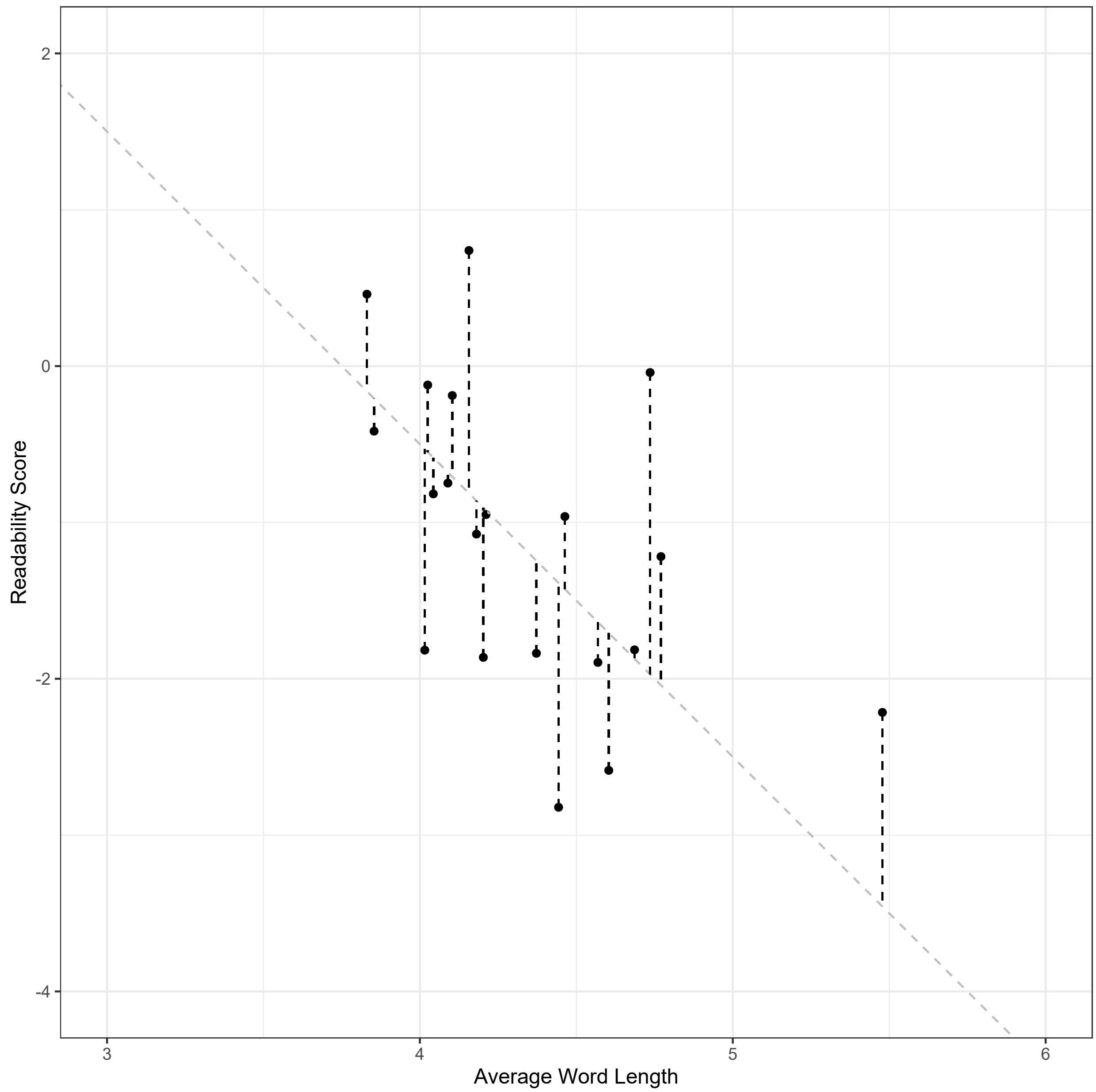
```
d <-  readability_sub[,c('mean.wl','target')]

d$predicted <- d$mean.wl*-2 + 7.5
d$error     <- d$target - d$predicted

d
```

```
    mean.wl      target  predicted       error
1  4.603659 -2.58590836 -1.7073171 -0.87859129
2  3.830688  0.45993224 -0.1613757  0.62130790
3  4.180851 -1.07470758 -0.8617021 -0.21300545
```

4	4.015544	-1.81700402	-0.5310881	-1.28591594
5	4.686047	-1.81491744	-1.8720930	0.05717559
6	4.211340	-0.94968236	-0.9226804	-0.02700194
7	4.025000	-0.12103065	-0.5500000	0.42896935
8	4.443182	-2.82200582	-1.3863636	-1.43564218
9	4.089385	-0.74845172	-0.6787709	-0.06968077
10	4.156757	0.73948755	-0.8135135	1.55300107
11	4.463277	-0.96218937	-1.4265537	0.46436430
12	5.478261	-2.21514888	-3.4565217	1.24137286
13	4.770492	-1.21845136	-2.0409836	0.82253224
14	4.568966	-1.89544351	-1.6379310	-0.25751247
15	4.735751	-0.04101056	-1.9715026	1.93049203
16	4.372340	-1.83716516	-1.2446809	-0.59248431
17	4.103448	-0.18818586	-0.7068966	0.51871069
18	4.042857	-0.81739314	-0.5857143	-0.23167886
19	4.202703	-1.86307557	-0.9054054	-0.95767016
20	3.853535	-0.41630158	-0.2070707	-0.20923088



While it is helpful to see the model error for every single observation, we will need to aggregate them in some way to form an overall measure of the total amount of error for this model. Some alternatives for aggregating these individual errors could be using

a. the sum of the residuals (SR),
b. the sum of absolute value of residuals (SAR), or
c. the sum of squared residuals (SSR)

Among these alternatives, (a) is not a useful aggregation as the positive residuals and negative residuals will cancel each other and (a) may misrepresent the total amount of error for all observations. Both (b) and (c) are plausible alternatives and can be used. On the other hand, (b) is less desirable because the absolute values are mathematically more difficult to deal with (ask a calculus professor!). So, (c) seems to be a good way of aggregating the total amount of error, it is mathematically easy to work with. We can show (c) in a mathematical notation as the following.

$$SSR = \sum_{i=1}^{N}(Y_i - (\beta_0 + \beta_1 X_i))^2$$

$$SSR = \sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2$$

$$SSR = \sum_{i=1}^{N}\epsilon_i^2$$

For our model, the sum of squared residuals would be 15.384.

```
sum(d$error^2)
```

```
[1] 15.38364
```

Now, how do we know that the set of coefficients we guesstimate ,$\{\beta_0, \beta_1\}$ = {7.5,-2}, is a good model? Is there any other set of coefficients that would provide less error than this model? The only way of knowing this is to try a bunch of different models and see if we can find a better one that gives us better predictions (smaller residuals). But, there is literally infinite pairs of $\{\beta_0, \beta_1\}$ coefficients, so which ones we should try?

Below, I will do a quick exploration. For instance, suppose the potential range for my intercept (β_0) is from -10 to 10 and I will consider every single possible value from -10 t 10 with increments of .1. Also, suppose the potential range for my slope (β_1) is from -2 to 2 and I will consider every single possible value from -2 to 2 with increments of .01. Given that every single combination of β_0 and β_1 indicates a different model, these settings suggest a total of 80,601 models to explore. If you are crazy enough, you can try every single model and compute the SSR. Then, we can plot them in a 3D by putting β_0 on the X-axis, β_1 on the Y-axis, and SSR on the Z-axis. Check the plot below and tell me if you can explore and find the minimum of this surface.

The finding the best set of $\{\beta_0, \beta_1\}$ coefficients that minimizes the sum of squared residuals is indeed an optimization problem. For any optimization problem, there is a **loss function** we either try to minimize or maximize. In this case, our loss function is the sum of squared residuals.

$$Loss = \sum_{i=1}^{N} (Y_i - (\beta_0 + \beta_1 X_i))^2$$

In this loss function, X and Y values are observed data, and $\{\beta_0, \beta_1\}$ are unknown parameters. The goal of optimization is to find the set $\{\beta_0, \beta_1\}$ coefficients that provides the minimum value of this function. Once this minima of this function is found, we can argue that the corresponding coefficients are our best solution for the regression model.

In this case, this is a good-looking surface with a single global minima, and it is not difficult to find the minimum of this loss function. We also have an analytical solution to find its minima because of its simplicity. Most of the time, the optimization problems are more difficult, and we solve them using numerical techniques such as steepest ascent (or descent), newton-raphson, quasi-newton, genetic algorithm and many more.

Matrix Solution

For most regression problems, we can find the best set of coefficients with a simple matrix operations. Let's first see how we can represent the regression problem in matrix form. Suppose that I wrote the regression model presented in the earlier section for every single observation in a dataset with a sample size of N.

$$Y_1 = \beta_0 + \beta_1 X_1 + \epsilon_1.$$

$$Y_2 = \beta_0 + \beta_1 X_2 + \epsilon_2.$$
$$Y_3 = \beta_0 + \beta_1 X_3 + \epsilon_3.$$
$$...$$
$$...$$
$$...$$
$$Y_{20} = \beta_0 + \beta_1 X_{20} + \epsilon_2 0.$$

We can write all of these equations in a much simpler format as

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon},$$

such that $\mathbf{Y}$ is an N x 1 column vector of observed values for the outcome variable, $\mathbf{X}$ is an N x (P+1) design matrix of observed values for predictor variables, and $\boldsymbol{\beta}$ is an (P+1) x 1 column vector of regression coefficients, and $\boldsymbol{\epsilon}$ is an N x 1 column vector of residuals. For the problem above with our small dataset, these matrix elements would look like the following.

$$\begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \\ Y_4 \\ Y_5 \\ Y_6 \\ Y_7 \\ Y_8 \\ Y_9 \\ Y_{10} \\ Y_{11} \\ Y_{12} \\ Y_{13} \\ Y_{14} \\ Y_{15} \\ Y_{16} \\ Y_{17} \\ Y_{18} \\ Y_{19} \\ Y_{20} \end{bmatrix} = \begin{bmatrix} 1 & X_1 \\ 1 & X_2 \\ 1 & X_3 \\ 1 & X_4 \\ 1 & X_5 \\ 1 & X_6 \\ 1 & X_7 \\ 1 & X_8 \\ 1 & X_9 \\ 1 & X_{10} \\ 1 & X_{11} \\ 1 & X_{12} \\ 1 & X_{13} \\ 1 & X_{14} \\ 1 & X_{15} \\ 1 & X_{16} \\ 1 & X_{17} \\ 1 & X_{18} \\ 1 & X_{19} \\ 1 & X_{20} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \\ \epsilon_5 \\ \epsilon_6 \\ \epsilon_7 \\ \epsilon_8 \\ \epsilon_9 \\ \epsilon_{10} \\ \epsilon_{11} \\ \epsilon_{12} \\ \epsilon_{13} \\ \epsilon_{14} \\ \epsilon_{15} \\ \epsilon_{16} \\ \epsilon_{17} \\ \epsilon_{18} \\ \epsilon_{19} \\ \epsilon_{20} \end{bmatrix}$$

Or, more specifically, we can replace the observed values of $\mathbf{X}$ and $\mathbf{Y}$ with the corresponding elements.

$$
\begin{bmatrix} -2.59 \\ 0.46 \\ -1.07 \\ -1.82 \\ -1.81 \\ -0.95 \\ -0.12 \\ -2.82 \\ -0.75 \\ 0.74 \\ -0.96 \\ -2.22 \\ -1.22 \\ -1.90 \\ -0.04 \\ -1.84 \\ -0.19 \\ -0.82 \\ -1.86 \\ -0.42 \end{bmatrix} = \begin{bmatrix} 1 & 4.60 \\ 1 & 3.83 \\ 1 & 4.18 \\ 1 & 4.02 \\ 1 & 4.69 \\ 1 & 4.21 \\ 1 & 4.03 \\ 1 & 4.44 \\ 1 & 4.09 \\ 1 & 4.16 \\ 1 & 4.46 \\ 1 & 5.48 \\ 1 & 4.77 \\ 1 & 4.57 \\ 1 & 4.74 \\ 1 & 4.37 \\ 1 & 4.10 \\ 1 & 4.04 \\ 1 & 4.20 \\ 1 & 3.85 \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \\ \epsilon_5 \\ \epsilon_6 \\ \epsilon_7 \\ \epsilon_8 \\ \epsilon_9 \\ \epsilon_{10} \\ \epsilon_{11} \\ \epsilon_{12} \\ \epsilon_{13} \\ \epsilon_{14} \\ \epsilon_{15} \\ \epsilon_{16} \\ \epsilon_{17} \\ \epsilon_{18} \\ \epsilon_{19} \\ \epsilon_{20} \end{bmatrix}
$$

It can be shown that the set of $\{\beta_0, \beta_1\}$ coefficients that yields the minimum sum of squared residuals for this model can be analytically found using the following matrix operation.

$$\hat{\boldsymbol{\beta}} = (\mathbf{X^T X})^{-1} \mathbf{X^T Y}$$

If we apply this matrix operation to our small datasets, we will find that the best set of $\{\beta_0, \beta_1\}$ coefficients to predict the readability score with the least amount of error using the average word length as a predictor is $\{\beta_0, \beta_1\}$ = {4.494,-1.290}. These estimates are also known as the **least square estimates**, and the best linear unbiased estimators (BLUE) for the given regression model.

```
Y <-  as.matrix(readability_sub$target)
X <-  as.matrix(cbind(1,readability_sub$mean.wl))

Y
```

```
             [,1]
 [1,] -2.58590836
 [2,]  0.45993224
 [3,] -1.07470758
 [4,] -1.81700402
 [5,] -1.81491744
 [6,] -0.94968236
 [7,] -0.12103065
 [8,] -2.82200582
```

```
 [9,] -0.74845172
[10,]  0.73948755
[11,] -0.96218937
[12,] -2.21514888
[13,] -1.21845136
[14,] -1.89544351
[15,] -0.04101056
[16,] -1.83716516
[17,] -0.18818586
[18,] -0.81739314
[19,] -1.86307557
[20,] -0.41630158
```

```
X
```

```
      [,1]     [,2]
 [1,]    1 4.603659
 [2,]    1 3.830688
 [3,]    1 4.180851
 [4,]    1 4.015544
 [5,]    1 4.686047
 [6,]    1 4.211340
 [7,]    1 4.025000
 [8,]    1 4.443182
 [9,]    1 4.089385
[10,]    1 4.156757
[11,]    1 4.463277
[12,]    1 5.478261
[13,]    1 4.770492
[14,]    1 4.568966
[15,]    1 4.735751
[16,]    1 4.372340
[17,]    1 4.103448
[18,]    1 4.042857
[19,]    1 4.202703
[20,]    1 3.853535
```

```
beta <- solve(t(X)%*%X)%*%t(X)%*%Y

beta
```

```
          [,1]
[1,]  4.493847
[2,] -1.290571
```

Once we find the best estimates for the model coefficients, we can also calculate the model predicted values and residual sum of squares for the given model and dataset.

$$\hat{\boldsymbol{Y}} = \mathbf{X}\hat{\boldsymbol{\beta}}$$

$$\hat{\boldsymbol{\epsilon}} = \boldsymbol{Y} - \hat{\boldsymbol{Y}}$$
$$RSS = \hat{\boldsymbol{\epsilon}}^{\boldsymbol{T}}\hat{\boldsymbol{\epsilon}}$$

```r
Y_hat <-  X%*%beta

Y_hat
```

```
            [,1]
 [1,] -1.4475035
 [2,] -0.4499296
 [3,] -0.9018403
 [4,] -0.6884998
 [5,] -1.5538311
 [6,] -0.9411887
 [7,] -0.7007034
 [8,] -1.2403969
 [9,] -0.7837974
[10,] -0.8707449
[11,] -1.2663309
[12,] -2.5762403
[13,] -1.6628138
[14,] -1.4027297
[15,] -1.6179787
[16,] -1.1489710
[17,] -0.8019465
[18,] -0.7237493
[19,] -0.9300414
[20,] -0.4794160
```

```r
E <- Y - Y_hat
E
```

```
              [,1]
 [1,] -1.138404820
 [2,]  0.909861867
 [3,] -0.172867283
 [4,] -1.128504242
 [5,] -0.261086332
 [6,] -0.008493645
 [7,]  0.579672713
 [8,] -1.581608945
 [9,]  0.035345700
[10,]  1.610232426
[11,]  0.304141555
[12,]  0.361091438
[13,]  0.444362421
[14,] -0.492713788
[15,]  1.576968115
[16,] -0.688194163
[17,]  0.613760605
[18,] -0.093643860
[19,] -0.933034170
[20,]  0.063114409
```

```r
RSS <- t(E)%*%E

RSS
```

```
         [,1]
[1,] 13.81062
```

Note that the matrix formulation is generalized to a regression model for more than one predictor. When there are more predictors in the model, the dimensions of the design matrix ($\mathbf{X}$) and regression coefficient matrix ($\boldsymbol{\beta}$) will be different, but the matrix calculations will be identical. It is difficult to visualize the surface we are trying to minimize beyond two coefficients, but we know that the matrix solution will always provide us the set of coefficients that yields the least amount of error in our predictions.

Let's assume that we would like to expand our model by adding the number of sentences as the second predictor. Our new model will be

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \epsilon_i.$$

Note that I added a subscript for X to differentiate different predictors. Let's say X_1 represents the mean word length and X_2 represents the total number of sentence length. Now, we are looking for the best set of three coefficients, $\{\beta_0, \beta_1, \beta_2\}$ that would yield the least amount of error in predicting the readability. Now, our matrix elements will look like the following:

```r
Y <-  as.matrix(readability_sub$target)
X <-  as.matrix(cbind(1,readability_sub[,c('mean.wl','sents')]))

Y
```

```
             [,1]
 [1,] -2.58590836
 [2,]  0.45993224
 [3,] -1.07470758
 [4,] -1.81700402
 [5,] -1.81491744
 [6,] -0.94968236
 [7,] -0.12103065
 [8,] -2.82200582
 [9,] -0.74845172
[10,]  0.73948755
[11,] -0.96218937
[12,] -2.21514888
[13,] -1.21845136
[14,] -1.89544351
[15,] -0.04101056
[16,] -1.83716516
[17,] -0.18818586
[18,] -0.81739314
[19,] -1.86307557
[20,] -0.41630158
```

```r
X
```

```
      1  mean.wl sents
 [1,] 1 4.603659     7
 [2,] 1 3.830688    23
 [3,] 1 4.180851    17
 [4,] 1 4.015544     7
 [5,] 1 4.686047     6
 [6,] 1 4.211340    18
 [7,] 1 4.025000    10
 [8,] 1 4.443182     4
 [9,] 1 4.089385     9
[10,] 1 4.156757    28
[11,] 1 4.463277    15
[12,] 1 5.478261    10
[13,] 1 4.770492    10
[14,] 1 4.568966     8
[15,] 1 4.735751    19
[16,] 1 4.372340    15
[17,] 1 4.103448     6
[18,] 1 4.042857     6
[19,] 1 4.202703     7
[20,] 1 3.853535    19
```

We will get the following estimates for $\{\beta_0, \beta_1, \beta_2\}$ = {1.821, -.929, .090} yielding a value of 7.365 for the residual sum of squares.

```
beta <- solve(t(X)%*%X)%*%t(X)%*%Y

beta
```

```
               [,1]
1        1.82055156
mean.wl -0.92858249
sents    0.09029887
```

```
Y_hat <-  X%*%beta

E <- Y - Y_hat

RSS <- t(E)%*%E

RSS
```

```
         [,1]
[1,] 7.365244
```

`lm()` function

While it is always exciting to learn the inner mechanics of how numbers work behind the scene, it is handy to use already existing packages and tools to do all these computations. A simple go-to function for fitting linear regression to predict a continuous outcome is the `lm()` function.

Let's fit the models we talked about in earlier section using the `lm()` function and see if we get the same regression coefficients.

Model 1: Predicting readability scores from average word length

```
mod <- lm(target ~ 1 + mean.wl,data=readability_sub)

summary(mod)
```

```

Call:
lm(formula = target ~ 1 + mean.wl, data = readability_sub)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.58161 -0.54158  0.01343  0.47819  1.61023 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)  
(Intercept)   4.4938     2.2387   2.007   0.0600 .
mean.wl      -1.2906     0.5137  -2.513   0.0217 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.8759 on 18 degrees of freedom
Multiple R-squared:  0.2596,	Adjusted R-squared:  0.2185 
F-statistic: 6.313 on 1 and 18 DF,  p-value: 0.02173
```

In the **Coefficients** table, the numbers under the **Estimate** column are the estimated regression coefficients, and they are identical to the numbers we obtained before using matrix calculations. We ignore the other numbers in this table since our focus in this class is not significance testing. Another number in this table is **Residual Standard Error (RSE)**, and this number is directly related to the Residual Sum of Squares (RSS) for this model. Note that we obtained a value of 13.811 for RSS when we fitted the model. The relationship between RSS and RSE is

$$RSE = \sqrt{\frac{RSS}{df_{regression}}} = \sqrt{\frac{RSS}{N-k}},$$

where the degrees of freedom for the regression model in this case is equal to the difference between the number of observations (N) and the number of coefficients in the model (k).

$$RSE = \sqrt{\frac{13.811}{20-2}} = 0.8759$$

RSE is a measure that summarizes the amount of uncertainty for individual predictions. Another relavant number reported is the R-squared (0.2596) which is simply the square of the correlation between predicted values observed values.

Model 2: Predicting readability scores from average word length and number of sentences

```
mod <- lm(target ~ 1 + mean.wl + sents,data=readability_sub)

summary(mod)
```

```

Call:
lm(formula = target ~ 1 + mean.wl + sents, data = readability_sub)
```

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.95212 -0.49900  0.06346  0.43368  1.25986

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.82055    1.81947   1.001  0.33105
mean.wl     -0.92858    0.39723  -2.338  0.03189 *
sents        0.09030    0.02341   3.857  0.00126 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6582 on 17 degrees of freedom
Multiple R-squared:  0.6052,    Adjusted R-squared:  0.5587
F-statistic: 13.03 on 2 and 17 DF,  p-value: 0.0003711
```

Building a Prediction Model for Readability Scores

In earlier weeks, we discussed how to process text data and constructed more than 1000 features for a given text. All these features were numeric features. These features are saved as a separate dataset, and can be downloaded from the website.

```
readability <- read.csv('https://raw.githubusercontent.com/uo-datasci-specialization/c4-ml-fall-2021/mai
                        header=TRUE)
```

This dataset has 2834 rows and 1072 columns. Each row represents a reading passage. The last column is the outcome variable to predict (`target`), and the first 1071 columns are unprocessed numerical features we can potentially use as predictors.

Initial Data Preparation

We will first do some initial exploration of the variables. First, we will look at the percentage of missing values. Particularly, I will look for any feature with more than 80% of values are missing. Then, I will remove those features from the data.

```
require(finalfit)

missing_ <- ff_glimpse(readability)$Continuous

head(missing_)
```

```
          label var_type    n missing_n missing_percent  mean    sd   min
chars     chars    <int> 2834         0             0.0 972.6 117.4 669.0
sents     sents    <int> 2834         0             0.0   9.5   4.6   2.0
tokens   tokens    <int> 2834         0             0.0 172.8  17.1 113.0
types     types    <int> 2834         0             0.0 104.8  13.1  37.0
puncts   puncts    <int> 2834         0             0.0   0.0   0.0   0.0
numbers numbers    <int> 2834         0             0.0   0.0   0.0   0.0
        quartile_25 median quartile_75    max
chars         886.0  972.0      1059.0 1343.0
```

```
sents           7.0    8.0         11.0   41.0
tokens        159.0  174.0        187.0  208.0
types          96.0  105.0        114.0  143.0
puncts          0.0    0.0          0.0    0.0
numbers         0.0    0.0          0.0    0.0
```

```
# Because there is more than 1000 variables, it is not practical to print them all
# I filter the ones with missing data, and then pring

flag_na <- which(as.numeric(missing_$missing_percent) > 80)
flag_na
```

```
 [1]  155  178  959  964  970  972  984  993  994  995  998  999 1001 1003 1004
[16] 1005 1006 1007 1008 1009 1010 1011 1012 1013 1014 1015 1016 1017 1018 1019
[31] 1020 1021 1022 1023 1024 1025 1026 1027 1028 1029 1030 1031 1032 1033 1034
[46] 1035 1036 1037 1038 1039 1040 1041 1042 1044 1045 1046 1047 1048 1049 1050
[61] 1051 1052 1053 1054 1055 1056 1057 1058 1059 1060 1061 1062 1063 1064 1065
[76] 1066 1067 1068 1069 1070 1071
```

```
# Remove the flagged variables with high missing data percentages

readability <- readability[,-flag_na]
```

Then, I will use the `recipes` package to create a recipe for this dataset. Note that all my features are numeric, and the last column is outcome variable while every other column is a predictor variable. This receipe

- assigns the last column (`target`) as outcome and everythin else as predictor,
- removes any variable with zero variance or near-zero variance,
- impute the missing values using the mean,
- standardize all variables,
- and removes variables highly correlated with one another (>.9).

```
require(recipes)

blueprint <- recipe(x     = readability,
                    vars  = colnames(readability),
                    roles = c(rep('predictor',990),'outcome')) %>%
  step_zv(all_numeric()) %>%
  step_nzv(all_numeric()) %>%
  step_impute_mean(all_numeric()) %>%
  step_normalize(all_numeric_predictors()) %>%
  step_corr(all_numeric(),threshold=0.9)
```

Train/Test Split

In order to obtain a realistic measure of model performance, we will split the data into two subsamples: training and test. Due to the relatively small sample size, I will use a 90-10 split (typically a 80-20 or 70-30 split is used).

```
set.seed(10152021)  # for reproducibility

loc      <- sample(1:nrow(readability), round(nrow(readability) * 0.9))
read_tr  <- readability[loc, ]
read_te  <- readability[-loc, ]
```

We will first train the blueprint using the training dataset, and then bake it for both training and test datasets.

```
prepare <- prep(blueprint,
                training = read_tr)
prepare
```

```
Recipe

Inputs:

      role #variables
   outcome          1
 predictor        990

Training data contained 2551 data points and 2551 incomplete rows.

Operations:

Zero variance filter removed puncts, numbers, symbols, urls, tags, e... [trained]
Sparse, unbalanced variable filter removed wl.16, wl.17, wl.18, wl.19, wl.20, wl.2... [trained]
Mean Imputation for chars, sents, tokens, types, wl.1, wl.2, wl.3, ... [trained]
Centering and scaling for chars, sents, tokens, types, wl.1, wl.2, wl.3, ... [trained]
Correlation filter removed TTR, C, R, CTTR, U, S, Vm, Maas, lgV0, lg... [trained]
```

```
baked_tr <- bake(prepare, new_data = read_tr)

baked_te <- bake(prepare, new_data = read_te)
```

The smaller test dataset will be used as a final hold-out set, and training dataset will be used to build the model.

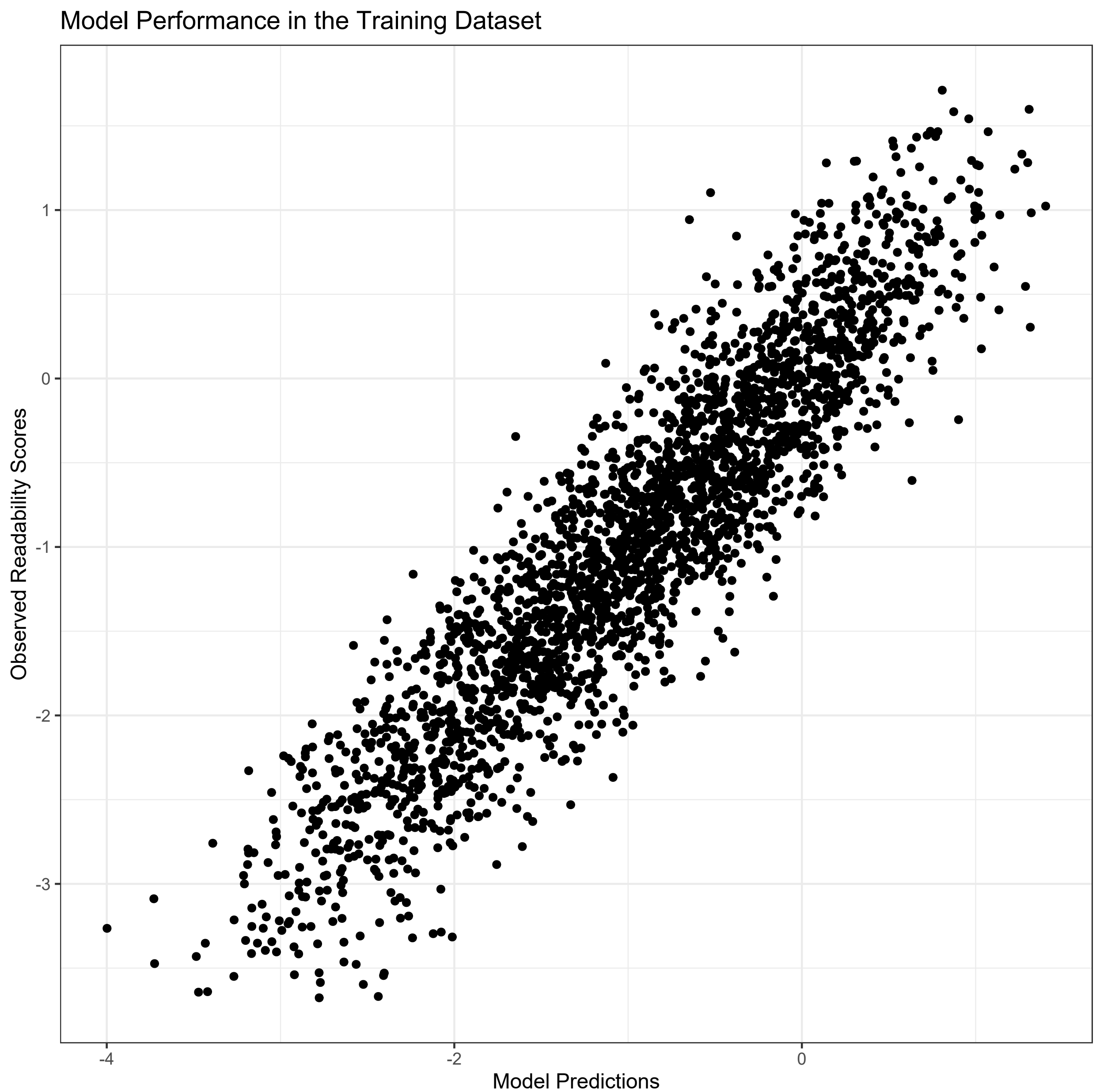
Model Fitting without Cross-validation

First, I will fit the model to the training dataset using all predictors in the dataset without any cross validation. Note that we will very likely overfit with more than 900 predictors and relatively small sample size.

```
mod <- lm(formula(baked_tr[,c(888,1:887)]),data=baked_tr)

summary(mod)$r.squared
```

```
[1] 0.8403438
```



In the training dataset, the model explains about `paste0(round(summary(mod)$r.squared*100,2),'%')` of the total variance in the outcome variable (WOW!). We can also calculate the RMSE or MSE for the model predictions in the training dataset.

```
predicted_tr <- predict(mod)

rsq_tr <- cor(baked_tr$target,predicted_tr)^2
rsq_tr
```

```
[1] 0.8403438
```

```
rmse_tr <- sqrt(mean((baked_tr$target - predicted_tr)^2))
rmse_tr
```

```
[1] 0.4133418
```

Something is too good to be true! As we suspected, the model predictions are unusually good in the training data because we are fitting a super complex model, and we are overfitting. This is why you should never judge how well a model is by looking at the performance of the model on the dataset it is trained. Let's check how well this model does on the test data which we didn't use in the estimation.

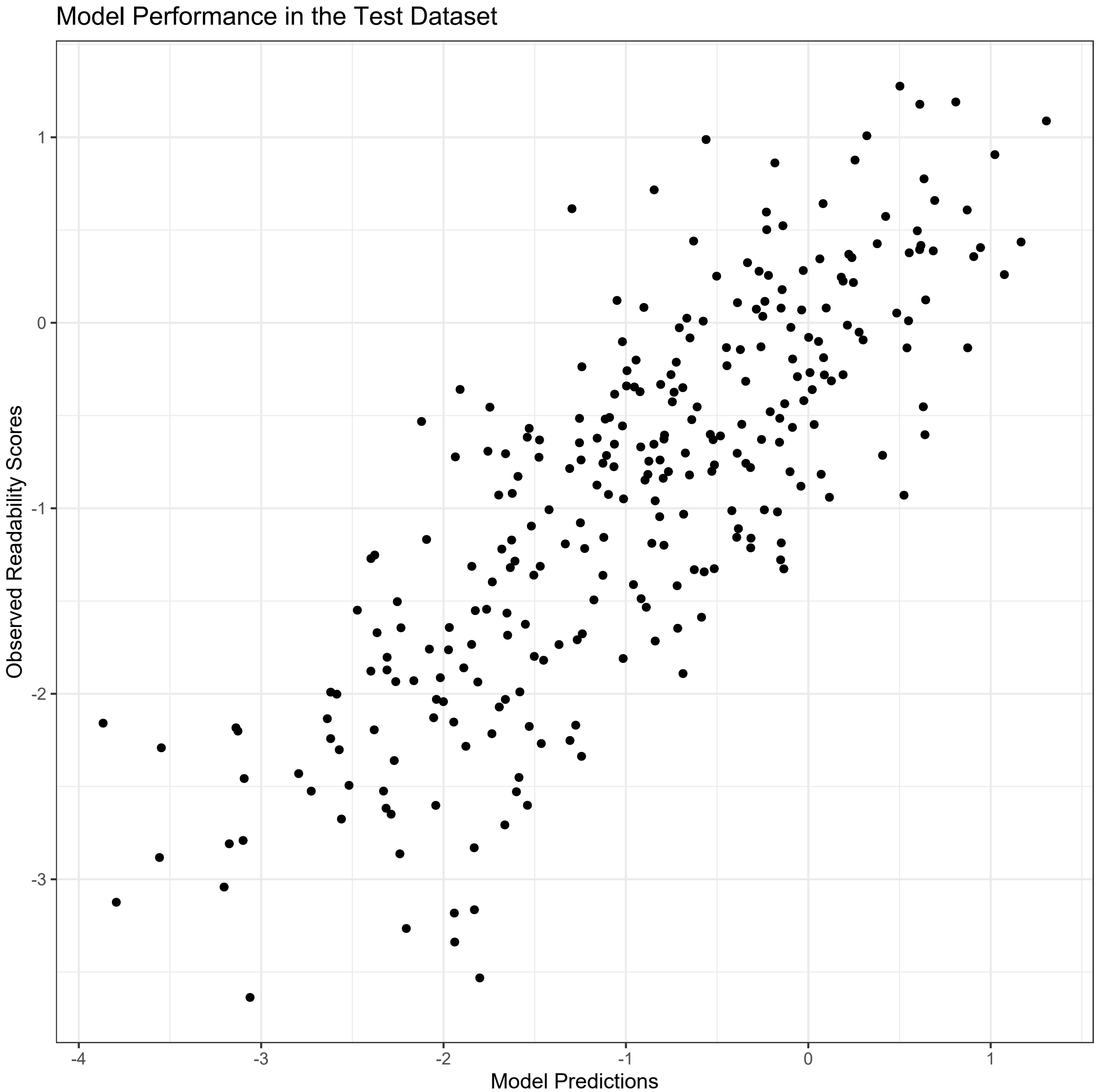
```
predicted_te <- predict(mod,newdata=baked_te)

rsq_te <- cor(baked_te$target,predicted_te)^2
rsq_te
```

```
[1] 0.6445438
```

```
rmse_te <- sqrt(mean((baked_te$target - predicted_te)^2))
rmse_te
```

```
[1] 0.6443844
```



The model performance significantly dropped in the testing dataset. This is just another example of model variance (overfitting). We have a very complex model that does a great job in the training dataset but does not perform at the same level in a different dataset. If we are planning to use this dataset for any future task, it is much better to consider the performance on the test data as it will be a more realistic expectation.

Model Fitting with 10-fold Cross-validation

One way of obtaining realistic performance values while we train the dataset is to use k-fold cross validation. The code below first creates 10 folds for the training dataset. Then, it fits the model using the nine folds while it evaluates the performance on the tenth fold.

```r
set.seed(10152021)  # for reproducibility

# Randomly shuffle the data

baked_tr = baked_tr[sample(nrow(baked_tr)),]

# Create 10 folds with equal size

folds = cut(seq(1,nrow(baked_tr)),breaks=10,labels=FALSE)

# Create empty vectors for performance measures

rsq <- c()
rmse <- c()

# Fit the model by excluding one of the folds, and then evaluate the performance
# on the excluded fold

for(i in 1:10){

  data_tr <- baked_tr[which(folds!=i),] # observation for the 9 folds
  data_te <- baked_tr[which(folds==i),] # observation for the 10th fold

  mod  <- lm(formula(data_tr[,c(888,1:887)]),data=data_tr)

  pred <- predict(mod,newdata=data_te)

  rsq[i]  <- cor(data_te$target,pred)^2
  rmse[i] <-  sqrt(mean((data_te$target - pred)^2))

  #cat(paste0('Fold ',i,' is completed.'),'\n')
}

rsq
```

```
 [1] 0.6127930 0.6391534 0.5992858 0.6413778 0.6558642 0.6545124 0.6889783
 [8] 0.5365948 0.5753779 0.6299013
```

```r
mean(rsq)
```

```
[1] 0.6233839
```

```r
rmse
```

```
 [1] 0.6609228 0.6510225 0.6470804 0.6304163 0.6762909 0.6617385 0.6165307
 [8] 0.6930926 0.6900921 0.6552426
```

```r
mean(rmse)
```

```
[1] 0.6582429
```

The performance evaluations we obtain from k-fold cross validation is more similar to the one we get from the test data, so they provide a more realistic picture of model performance. We will frequently use k-fold cross-validation for tuning the hyperparameters for several models in later classes.

Model Fitting Using the `caret` package

It is not always the most pleasant experience to writing your own code to conduct k-fold cross validation. Packages like `caret` provides built-in functions for conducting cross-validation and also brings a number of user-friendly experiences in modeling. `caret` provides a standardized user experience for fitting a lot of different models beyond linear regression. So, one doesn't have to learn the nuances of all different types of functions to fit different types of models. Packages like `caret` provides a more consistent workflow while working with different types of models. On the other hand, this also brings less flexibility. During this class, I will try to demonstrate both how to work with direct functions and how to work with `caret` for fitting different types of models.

Below is how one could implement the whole process using the `caret` package.

```
require(caret)
require(recipes)

set.seed(10152021)  # for reproducibility

# Train/Test Split

loc      <- sample(1:nrow(readability), round(nrow(readability) * 0.9))
read_tr  <- readability[loc, ]
read_te  <- readability[-loc, ]
set.seed(10152021)  # for reproducibility

# Blueprint

blueprint <- recipe(x     = readability,
                    vars  = colnames(readability),
                    roles = c(rep('predictor',990),'outcome')) %>%
  step_zv(all_numeric()) %>%
  step_nzv(all_numeric()) %>%
  step_impute_mean(all_numeric()) %>%
  step_normalize(all_numeric_predictors()) %>%
  step_corr(all_numeric(),threshold=0.9)

# For available methods in the train function

names(getModelInfo())
```

```
  [1] "ada"                   "AdaBag"                "AdaBoost.M1"
  [4] "adaboost"              "amdai"                 "ANFIS"
  [7] "avNNet"                "awnb"                  "awtan"
 [10] "bag"                   "bagEarth"              "bagEarthGCV"
 [13] "bagFDA"                "bagFDAGCV"             "bam"
 [16] "bartMachine"           "bayesglm"              "binda"
 [19] "blackboost"            "blasso"                "blassoAveraged"
 [22] "bridge"                "brnn"                  "BstLm"
 [25] "bstSm"                 "bstTree"               "C5.0"
 [28] "C5.0Cost"              "C5.0Rules"             "C5.0Tree"
 [31] "cforest"               "chaid"                 "CSimca"
 [34] "ctree"                 "ctree2"                "cubist"
 [37] "dda"                   "deepboost"             "DENFIS"
 [40] "dnn"                   "dwdLinear"             "dwdPoly"
```

```
 [43] "dwdRadial"           "earth"               "elm"
 [46] "enet"                "evtree"              "extraTrees"
 [49] "fda"                 "FH.GBML"             "FIR.DM"
 [52] "foba"                "FRBCS.CHI"           "FRBCS.W"
 [55] "FS.HGD"              "gam"                 "gamboost"
 [58] "gamLoess"            "gamSpline"           "gaussprLinear"
 [61] "gaussprPoly"         "gaussprRadial"       "gbm_h2o"
 [64] "gbm"                 "gcvEarth"            "GFS.FR.MOGUL"
 [67] "GFS.LT.RS"           "GFS.THRIFT"          "glm.nb"
 [70] "glm"                 "glmboost"            "glmnet_h2o"
 [73] "glmnet"              "glmStepAIC"          "gpls"
 [76] "hda"                 "hdda"                "hdrda"
 [79] "HYFIS"               "icr"                 "J48"
 [82] "JRip"                "kernelpls"           "kknn"
 [85] "knn"                 "krlsPoly"            "krlsRadial"
 [88] "lars"                "lars2"               "lasso"
 [91] "lda"                 "lda2"                "leapBackward"
 [94] "leapForward"         "leapSeq"             "Linda"
 [97] "lm"                  "lmStepAIC"           "LMT"
[100] "loclda"              "logicBag"            "LogitBoost"
[103] "logreg"              "lssvmLinear"         "lssvmPoly"
[106] "lssvmRadial"         "lvq"                 "M5"
[109] "M5Rules"             "manb"                "mda"
[112] "Mlda"                "mlp"                 "mlpKerasDecay"
[115] "mlpKerasDecayCost"   "mlpKerasDropout"     "mlpKerasDropoutCost"
[118] "mlpML"               "mlpSGD"              "mlpWeightDecay"
[121] "mlpWeightDecayML"    "monmlp"              "msaenet"
[124] "multinom"            "mxnet"               "mxnetAdam"
[127] "naive_bayes"         "nb"                  "nbDiscrete"
[130] "nbSearch"            "neuralnet"           "nnet"
[133] "nnls"                "nodeHarvest"         "null"
[136] "OneR"                "ordinalNet"          "ordinalRF"
[139] "ORFlog"              "ORFpls"              "ORFridge"
[142] "ORFsvm"              "ownn"                "pam"
[145] "parRF"               "PART"                "partDSA"
[148] "pcaNNet"             "pcr"                 "pda"
[151] "pda2"                "penalized"           "PenalizedLDA"
[154] "plr"                 "pls"                 "plsRglm"
[157] "polr"                "ppr"                 "PRIM"
[160] "protoclass"          "qda"                 "QdaCov"
[163] "qrf"                 "qrnn"                "randomGLM"
[166] "ranger"              "rbf"                 "rbfDDA"
[169] "Rborist"             "rda"                 "regLogistic"
[172] "relaxo"              "rf"                  "rFerns"
[175] "RFlda"               "rfRules"             "ridge"
[178] "rlda"                "rlm"                 "rmda"
[181] "rocc"                "rotationForest"      "rotationForestCp"
[184] "rpart"               "rpart1SE"            "rpart2"
[187] "rpartCost"           "rpartScore"          "rqlasso"
[190] "rqnc"                "RRF"                 "RRFglobal"
[193] "rrlda"               "RSimca"              "rvmLinear"
[196] "rvmPoly"             "rvmRadial"           "SBC"
[199] "sda"                 "sdwd"                "simpls"
[202] "SLAVE"               "slda"                "smda"
```

```
[205] "snn"                 "sparseLDA"           "spikeslab"
[208] "spls"                "stepLDA"             "stepQDA"
[211] "superpc"             "svmBoundrangeString" "svmExpoString"
[214] "svmLinear"           "svmLinear2"          "svmLinear3"
[217] "svmLinearWeights"    "svmLinearWeights2"   "svmPoly"
[220] "svmRadial"           "svmRadialCost"       "svmRadialSigma"
[223] "svmRadialWeights"    "svmSpectrumString"   "tan"
[226] "tanSearch"           "treebag"             "vbmpRadial"
[229] "vglmAdjCat"          "vglmContRatio"       "vglmCumulative"
[232] "widekernelpls"       "WM"                  "wsrf"
[235] "xgbDART"             "xgbLinear"           "xgbTree"
[238] "xyf"
```

```
getModelInfo()$lm
```

```
$label
[1] "Linear Regression"

$library
NULL

$loop
NULL

$type
[1] "Regression"

$parameters
  parameter   class     label
1 intercept logical intercept

$grid
function(x, y, len = NULL, search = "grid")
                    data.frame(intercept = TRUE)

$fit
function(x, y, wts, param, lev, last, classProbs, ...) {
                    dat <- if(is.data.frame(x)) x else as.data.frame(x, stringsAsFactors = TRUE)
                    dat$.outcome <- y
                    if(!is.null(wts))
                    {
                      if (param$intercept)
                        out <- lm(.outcome ~ ., data = dat, weights = wts, ...)
                      else
                        out <- lm(.outcome ~ 0 + ., data = dat, weights = wts, ...)
                    } else
                    {
                      if (param$intercept)
                        out <- lm(.outcome ~ ., data = dat, ...)
                      else
                        out <- lm(.outcome ~ 0 + ., data = dat, ...)
                    }
                    out
                  }
```

```
$predict
function(modelFit, newdata, submodels = NULL) {
                    if(!is.data.frame(newdata)) newdata <- as.data.frame(newdata, stringsAsFactors = TRU
                    predict(modelFit, newdata)
                  }

$prob
NULL

$predictors
function(x, ...) predictors(x$terms)

$tags
[1] "Linear Regression"    "Accepts Case Weights"

$varImp
function(object, ...) {
                    values <- summary(object)$coef
                    varImps <-  abs(values[ !grepl( rownames(values), pattern = 'Intercept' ),
                                            grep("value$", colnames(values)), drop = FALSE])
                    out <- data.frame(varImps)
                    colnames(out) <- "Overall"
                    if(!is.null(names(varImps))) rownames(out) <- names(varImps)
                    out
                  }

$sort
function(x) x
```

```r
# Cross validation settings

cv <- trainControl(method = "cv",
                   p      = 10)

# Train the model

  # note that I provide the blueprint and original unprocessed training dataset
  # as input

caret_mod <- caret::train(blueprint,
                          data      = read_tr,
                          method    = "lm",
                          trControl = cv)

caret_mod
```

```
Linear Regression

2551 samples
 990 predictor

Recipe steps: zv, nzv, impute_mean, normalize, corr
Resampling: Cross-Validated (10 fold)
```

```
Summary of sample sizes: 2297, 2296, 2295, 2295, 2296, 2296, ...
Resampling results:

  RMSE       Rsquared  MAE
  0.6512673  0.630639  0.5173725

Tuning parameter 'intercept' was held constant at a value of TRUE
```

```
# Once you train the model, then you apply the same blueprint to the test dataset,
# and then predict the values using the model

predicted_te <- predict(caret_mod, read_te)

rsq_te <- cor(read_te$target,predicted_te)^2
rsq_te
```

```
[1] 0.6445438
```

```
rmse_te <- sqrt(mean((read_te$target - predicted_te)^2))
rmse_te
```

```
[1] 0.6443844
```

```
mae_te <- mean(abs(read_te$target - predicted_te))
mae_te
```

```
[1] 0.5217534
```

Using the Prediction Model for a New Text

We now have a model to predict the readability scores using 887 features. We also have a rough idea how well it works. It is not a great model (wouldn't win any prize in the Kaggle competition), but good enough to satisfy your advisor or boss. Now, how do we use this model to predict a readability score for a new text.

Suppose, I have the following passage:

> Mittens sits in the grass. He is all alone. He is looking for some fun. Mittens hits his old ball. Smack! He smells a worm. Sniff! Mittens flips his tail back and forth, back and forth. Then he hears, Scratch! Scratch! What's that, Mittens? What's scratching behind the fence? Mittens runs to the fence. He scratches in the dirt. Scratch! Scratch! Ruff! Ruff! What's that, Mittens? What's barking behind the fence? Mittens meows by the fence. Meow! Meow!

What would be the predicted readability score for this reading passage?

Moving forward, all you need is the R object (`caret_mod`) you created to save all the information from the fitted model using the `caret::train()` function.

First, let's do a cleanup. I will remove everything but the model object from my environment.

```
# This is pretty old school, but works!

rm(list= ls()[!(ls() %in% c('caret_mod'))])
```

Now, we have to remember how we processed the text data and constructed all the features before for the data we used to build the model. We should apply the exact same procedure to a new text and generate the same features for the new text.

```
################################################################################

  require(quanteda)
  require(quanteda.textstats)
  require(udpipe)
  require(reticulate)
  require(text)

  ud_eng <- udpipe_load_model(here('english-ewt-ud-2.5-191206.udpipe'))

  reticulate::import('torch')
```

```
Module(torch)
```

```
  reticulate::import('numpy')
```

```
Module(numpy)
```

```
  reticulate::import('transformers')
```

```
Module(transformers)
```

```
  reticulate::import('nltk')
```

```
Module(nltk)
```

```
  reticulate::import('tokenizers')
```

```
Module(tokenizers)
```

```
################################################################################

new.text <- "Mittens sits in the grass. He is all alone. He is looking for some fun. Mittens hits his o


    # Tokenization and document-feature matrix

      tokenized <- tokens(new.text,
                          remove_punct = TRUE,
                          remove_numbers = TRUE,
                          remove_symbols = TRUE,
                          remove_separators = TRUE)

      dm <- dfm(tokenized)

    # basic text stats
```

```r
  text_sm <- textstat_summary(dm)
  text_sm$sents <- nsentence(new.text)
  text_sm$chars <- nchar(new.text)

    # text_sm[2:length(text_sm)]

# Word-length features

  wl <- nchar(tokenized[[1]])

  wl.tab <- table(wl)

  wl.features <- data.frame(matrix(0,nrow=1,nco=30))
  colnames(wl.features) <- paste0('wl.',1:30)

  ind <- colnames(wl.features)%in%paste0('wl.',names(wl.tab))

  wl.features[,ind] <- wl.tab

  wl.features$mean.wl  <-   mean(wl)
  wl.features$sd.wl    <-   sd(wl)
  wl.features$min.wl   <-   min(wl)
  wl.features$max.wl   <-   max(wl)

  # wl.features

# Text entropy/Max entropy ratio

  t.ent <- textstat_entropy(dm)
  n     <-  sum(featfreq(dm))
  p     <- rep(1/n,n)
  m.ent <- -sum(p*log(p,base=2))

  ent <- t.ent$entropy/m.ent

  # ent

# Lexical diversity

  text_lexdiv <- textstat_lexdiv(tokenized,
                              remove_numbers = TRUE,
                              remove_punct   = TRUE,
                              remove_symbols = TRUE,
                              measure        = 'all')

  # text_lexdiv[,2:ncol(text_lexdiv)]

# Measures of readability

  text_readability <- textstat_readability(new.text,measure='all')

# POS tag frequency
```

```r
  annotated <- udpipe_annotate(ud_eng, x = new.text)
  annotated <- as.data.frame(annotated)
  annotated <- cbind_morphological(annotated)

  pos_tags <- c(table(annotated$upos),table(annotated$xpos))

# Syntactic relations

  dep_rel <- table(annotated$dep_rel)

# morphological features

  feat_names <- c('morph_abbr','morph_animacy','morph_aspect','morph_case',
                  'morph_clusivity','morph_definite','morph_degree',
                  'morph_evident','morph_foreign','morph_gender','morph_mood',
                  'morph_nounclass','morph_number','morph_numtype',
                  'morph_person','morph_polarity','morph_polite','morph_poss',
                  'morph_prontype','morph_reflex','morph_tense','morph_typo',
                  'morph_verbform','morph_voice')

  feat_vec <- c()

  for(j in 1:length(feat_names)){

    if(feat_names[j]%in%colnames(annotated)){
      morph_tmp   <- table(annotated[,feat_names[j]])
      names_tmp   <- paste0(feat_names[j],'_',names(morph_tmp))
      morph_tmp   <- as.vector(morph_tmp)
      names(morph_tmp) <- names_tmp
      feat_vec  <- c(feat_vec,morph_tmp)
    }
  }

# Sentence Embeddings

  embeds <- textEmbed(x     = new.text,
                      model = 'roberta-base',
                      layers = 12,
                      context_aggregation_layers = 'concatenate')


# combine them all into one vector and store in the list object

  input <- cbind(text_sm[2:length(text_sm)],
                         wl.features,
                         as.data.frame(ent),
                         text_lexdiv[,2:ncol(text_lexdiv)],
                         text_readability[,2:ncol(text_readability)],
                         t(as.data.frame(pos_tags)),
                         t(as.data.frame(c(dep_rel))),
                         t(as.data.frame(feat_vec)),
                         as.data.frame(embeds$x)
                         )
```

```
input
```

```
  chars sents tokens types puncts numbers symbols urls tags emojis wl.1 wl.2
1   454    23     78    44      0       0       0    0    0      0    1   11
  wl.3 wl.4 wl.5 wl.6 wl.7 wl.8 wl.9 wl.10 wl.11 wl.12 wl.13 wl.14 wl.15 wl.16
1   14   17   13    7   13    0    1     1     0     0     0     0     0     0
  wl.17 wl.18 wl.19 wl.20 wl.21 wl.22 wl.23 wl.24 wl.25 wl.26 wl.27 wl.28 wl.29
1     0     0     0     0     0     0     0     0     0     0     0     0     0
  wl.30  mean.wl    sd.wl min.wl max.wl      ent       TTR         C        R
1     0 4.487179 1.863829      1     10 0.814852 0.5641026 0.8685891 4.982019
      CTTR       U         S        K        I          D        Vm      Maas
1 3.522819 14.3983 0.7790676 371.4661 10.63736 0.02464202 0.1200806 0.2635387
      MATTR     MSTTR     lgV0    lgeV0      ARI ARI.simple   ARI.NRI
1 0.5641026 0.5641026 3.316535 7.636603 1.400268   43.77592 0.8795987
  Bormuth.MC Bormuth.GP  Coleman Coleman.C2 Coleman.Liau.ECP Coleman.Liau.grade
1 -0.2080375  -469366.8 64.08846   97.89615         77.39033           1.858691
  Coleman.Liau.short Dale.Chall Dale.Chall.old Dale.Chall.PSK Danielson.Bryan
1            1.85641   58.00615      0.7755164       3.913553        4.400226
  Danielson.Bryan.2 Dickes.Steiwer      DRP       ELF Farr.Jenkins.Paterson
1          84.24513      -162.5317 120.8037 0.6956522             -33.68817
   Flesch Flesch.PSK Flesch.Kincaid      FOG   FOG.PSK    FOG.NRI  FORCAST
1 101.439   3.544277    -0.04687848 1.356522 0.9124766 -0.1773913 8.076923
  FORCAST.RGL    Fucks Linsear.Write      LIW       nWS    nWS.2      nWS.3
1    7.314615 15.21739             0 22.62207 0.7510004 1.663981 -0.4683565
       nWS.4       RIX Scrabble   SMOG   SMOG.C SMOG.simple SMOG.de   Spache
1 -0.7922696 0.6521739 1.809249 3.1291 5.112437           3      -2 3.171912
  Spache.old   Strain Traenkle.Bailer Traenkle.Bailer.2 Wheeler.Smith
1   3.522302 1.226087       -188.3027         -222.1848      6.956522
  meanSentenceLength meanWordSyllables ADJ ADP ADV AUX CCONJ DET INTJ NOUN PRON
1           3.391304          1.205128   4   7   6   6     2   8    2   12   13
  PROPN PUNCT VERB ,  . CC DT IN JJ NN NNP NNPS NNS PRP PRP$ RB UH VBG VBZ WP
1    12    27   10 4 23  2 10  7  4 11  10    2   1   5    2  6  2   3  13  4
  advmod amod appos aux case cc conj cop det nmod nmod:poss nsubj obj obl punct
1      4    2     1   3    7  2    4   3   8    1         2    13   3   6    27
  root morph_case_Nom morph_definite_Def morph_definite_Ind morph_degree_Pos
1   23              5                  6                  1                4
  morph_gender_Masc morph_mood_Ind morph_number_Plur morph_number_Sing
1                 7             13                 3                43
  morph_person_3 morph_poss_Yes morph_prontype_Art morph_prontype_Dem
1             20              2                  7                  3
  morph_prontype_Int morph_prontype_Prs morph_tense_Pres morph_verbform_Fin
1                  4                  7               16                 13
  morph_verbform_Part        Dim1       Dim2      Dim3         Dim4      Dim5
1                   3 -0.02706356 0.07567356 0.0537662 -0.007016965 0.2224346
        Dim6        Dim7      Dim8       Dim9       Dim10       Dim11
1 0.04939023 -0.02959983 0.0514404 0.06070077 -0.05404988 -0.09747072
       Dim12      Dim13       Dim14    Dim15      Dim16       Dim17       Dim18
1 0.01958121 0.03001023 -0.05471453 0.116444 0.03110751 0.008461111 -0.03273323
        Dim19       Dim20       Dim21      Dim22       Dim23       Dim24
1 -0.00477997 -0.02568062 -0.07733209 0.03547738 -0.04466225 -0.02642173
        Dim25      Dim26        Dim27      Dim28      Dim29       Dim30
1 -0.01528819 0.01880905 -0.004117077 0.05099677 0.03213615 -0.03850309
        Dim31       Dim32      Dim33       Dim34        Dim35      Dim36
```

```
1 -0.01875267 -0.07710975 0.03183111 -0.03924842 -0.004964702 0.03409737
       Dim37      Dim38     Dim39      Dim40      Dim41      Dim42       Dim43
1 0.04975318 0.01937219 0.0306441 0.03343704 -0.1781216 -0.1211262 -0.06195378
        Dim44      Dim45       Dim46       Dim47       Dim48      Dim49
1 -0.03983452 0.04327423 0.004913424 -0.06031298 -0.02003438 0.02600088
        Dim50      Dim51      Dim52      Dim53      Dim54      Dim55      Dim56
1 -0.03458053 0.04176696 0.06956099 0.02811206 0.01539411 -0.0369029 0.03900474
       Dim57     Dim58      Dim59      Dim60       Dim61     Dim62       Dim63
1 0.01336424 0.1464066 0.04301799 0.01624574 -0.03928176 0.1635819 -0.07011154
      Dim64      Dim65       Dim66      Dim67      Dim68      Dim69       Dim70
1 -0.020654 0.01870028 -0.04506872 0.03214189 0.03903029 0.02988067 0.007619148
       Dim71       Dim72      Dim73       Dim74      Dim75      Dim76
1 0.05666397 -0.09702756 0.04471388 -0.01197373 0.01947797 0.01181384
       Dim77     Dim78       Dim79      Dim80      Dim81       Dim82     Dim83
1 0.04100754 -3.755487 -0.04728175 0.06669956 0.06208374 -0.08338602 0.7477216
       Dim84       Dim85      Dim86      Dim87      Dim88        Dim89
1 0.03297196 -0.02081768 -0.1150639 0.02672025 0.00498704 -0.004569397
       Dim90      Dim91        Dim92      Dim93     Dim94      Dim95      Dim96
1 0.03231616 0.01925556 -0.001559907 -0.0210035 0.1013899 0.02498922 0.01998869
        Dim97     Dim98      Dim99      Dim100     Dim101      Dim102    Dim103
1 -0.01513632 0.4909967 -0.0013363 -0.04504698 0.01951685 -0.01925687 0.0945139
      Dim104      Dim105     Dim106     Dim107      Dim108     Dim109
1 0.08075197 -0.07083284 0.07294671 0.01257747 -0.04483311 0.05056348
        Dim110      Dim111     Dim112     Dim113      Dim114      Dim115
1 -0.008657346 -0.02187181 -0.0347401 0.06893411 -0.02378071 -0.01619653
    Dim116      Dim117     Dim118     Dim119    Dim120      Dim121     Dim122
1 0.017487 -0.01827984 0.03730945 0.04513853 0.1384863 -0.03498841 0.05956505
      Dim123     Dim124     Dim125     Dim126       Dim127      Dim128
1 0.02513112 0.01840405 -0.0540553 0.02714446 -0.005429095 -0.04092931
       Dim129     Dim130     Dim131     Dim132     Dim133     Dim134     Dim135
1 -0.02057803 0.01787887 -0.0277407 -0.3037597 0.01324851 0.02754409 0.04661173
       Dim136     Dim137    Dim138      Dim139      Dim140     Dim141
1 -0.02268834 0.05471192 0.0194234 0.001750701 -0.01453351 0.02751146
      Dim142      Dim143     Dim144   Dim145     Dim146      Dim147      Dim148
1 0.06153563 -0.02328374 0.01968463 0.162699 0.07096836 -0.03563375 -0.03947923
      Dim149     Dim150     Dim151      Dim152      Dim153        Dim154
1 0.03794007 0.06643526 0.06518798 -0.06979158 -0.01212464 0.00008351834
      Dim155    Dim156     Dim157    Dim158      Dim159    Dim160    Dim161
1 0.09422596 0.1242531 0.01644855 0.1783978 -0.02061414 0.1537144 0.1332055
       Dim162      Dim163      Dim164      Dim165     Dim166     Dim167
1 -0.01335572 0.005136131 -0.03188151 -0.02107196 0.02390574 0.01111268
       Dim168       Dim169      Dim170     Dim171   Dim172       Dim173
1 0.005455089 -0.001085651 -0.05858055 -0.0309496 0.064103 -0.007506766
      Dim174      Dim175      Dim176      Dim177      Dim178      Dim179
1 0.01675711 -0.01900868 -0.02708992 0.007471044 -0.01638369 0.003488106
      Dim180     Dim181     Dim182      Dim183      Dim184     Dim185
1 0.01583095 0.02703102 0.01505022 -0.05409031 -0.06259391 0.02703082
      Dim186     Dim187     Dim188     Dim189    Dim190     Dim191       Dim192
1 0.06376115 0.04706535 -0.0533913 0.03212536 0.1225724 0.09776939 0.006072238
      Dim193     Dim194     Dim195    Dim196      Dim197      Dim198    Dim199
1 0.04005886 0.03815003 0.03690949 0.1071005 -0.03470944 -0.02419928 0.0993732
      Dim200     Dim201     Dim202     Dim203      Dim204      Dim205
1 -0.0349644 0.03788871 -0.0896448 0.09789985 -0.01650451 0.008594197
      Dim206       Dim207     Dim208      Dim209      Dim210      Dim211
```

```
1 0.03339729 -0.001833718 0.03931317 -0.02594167 -0.05752807 -0.06062524
     Dim212     Dim213    Dim214     Dim215     Dim216     Dim217
1 0.09902632 -0.01489959 0.1059247 0.08952547 -0.03465532 -0.02865703
     Dim218     Dim219    Dim220     Dim221     Dim222     Dim223     Dim224
1 -0.4604221 0.03485171 0.0448519 0.04513314 -0.01278944 0.03543267 0.06323306
      Dim225    Dim226     Dim227     Dim228     Dim229     Dim230
1 0.003524951 0.0430416 0.08765961 -0.01575762 0.004051357 0.00966449
      Dim231     Dim232     Dim233     Dim234     Dim235     Dim236
1 -0.01163762 -0.02366546 0.009014995 -0.06540983 0.05872543 -0.1206237
      Dim237      Dim238      Dim239     Dim240     Dim241    Dim242
1 -0.03210227 -0.001160354 -0.003590591 0.01495555 -0.1546848 0.1052845
    Dim243     Dim244     Dim245     Dim246      Dim247    Dim248     Dim249
1 0.0657018 0.05770402 0.06140059 -0.07159876 -0.009812683 0.1166845 0.05277905
     Dim250     Dim251     Dim252        Dim253       Dim254     Dim255
1 0.01015359 0.01368594 -0.06787519 -0.0005879147 0.0008820305 0.05449436
      Dim256     Dim257     Dim258     Dim259     Dim260      Dim261
1 -0.06892669 -0.1041239 0.02042176 -0.06112328 -0.0495022 0.007336825
      Dim262     Dim263      Dim264     Dim265     Dim266     Dim267
1 -0.08096835 0.05881691 -0.07769445 -0.0469258 0.03575953 0.03662355
     Dim268      Dim269      Dim270     Dim271      Dim272     Dim273
1 0.07139029 -0.002513315 -0.05604061 0.01551373 -0.002937071 0.03161258
     Dim274     Dim275     Dim276      Dim277     Dim278      Dim279
1 0.07215895 0.00929201 0.02886985 -0.006060768 0.03395056 0.001992457
      Dim280     Dim281      Dim282      Dim283      Dim284      Dim285
1 -0.02386326 0.06078118 -0.02561207 -0.02657414 0.009780701 -0.04107339
     Dim286     Dim287    Dim288      Dim289      Dim290     Dim291     Dim292
1 0.05771509 0.08124785 0.0312119 -0.01189761 0.005442077 0.02118172 0.06831161
      Dim293      Dim294      Dim295     Dim296    Dim297      Dim298
1 0.005624752 -0.01724207 -0.05921534 -0.0163984 0.1066697 -0.01965118
     Dim299     Dim300    Dim301      Dim302      Dim303      Dim304
1 0.04835701 0.01711501 0.1276233 -0.01874138 -0.02966389 0.007723091
       Dim305      Dim306     Dim307      Dim308      Dim309    Dim310
1 -0.008173925 -0.01010179 0.09693575 -0.01644602 -0.03305898 0.0924959
       Dim311      Dim312      Dim313    Dim314     Dim315      Dim316
1 -0.005221166 -0.07871117 -0.02659134 0.1126804 0.02638598 -0.01897332
     Dim317     Dim318     Dim319     Dim320      Dim321      Dim322
1 0.07200745 0.01983377 0.07517022 0.03761548 -0.01294152 -0.06255002
     Dim323     Dim324     Dim325      Dim326     Dim327      Dim328
1 0.08980877 0.02221829 0.01777704 -0.01418209 -0.1208573 -0.001556365
       Dim329    Dim330    Dim331    Dim332     Dim333    Dim334     Dim335
1 -0.008202043 0.1182082 -0.504334 0.5523129 0.07487423 0.1484527 0.07207321
     Dim336     Dim337     Dim338    Dim339    Dim340      Dim341     Dim342
1 0.07115493 0.05266665 0.03712041 0.1231284 0.1140854 -0.09936048 0.01078093
     Dim343     Dim344    Dim345     Dim346      Dim347      Dim348    Dim349
1 -0.1328449 0.04264652 0.0278524 0.08925101 -0.01208034 -0.01879104 0.1194623
       Dim350     Dim351      Dim352     Dim353      Dim354      Dim355
1 -0.007769841 0.01397669 -0.02011757 0.03728889 0.008268313 -0.02807958
     Dim356     Dim357    Dim358      Dim359     Dim360    Dim361   Dim362
1 0.01463395 0.06802522 0.0190933 -0.02336735 -0.1009301 0.1280767 0.194199
     Dim363      Dim364       Dim365      Dim366      Dim367    Dim368
1 0.07359837 -0.02260096 -0.008612545 -0.09422011 -0.02818615 0.0786788
     Dim369    Dim370     Dim371      Dim372      Dim373      Dim374
1 0.02272207 0.1002589 0.09570162 -0.04916206 0.004951689 0.005069547
      Dim375      Dim376    Dim377     Dim378     Dim379     Dim380
```

```
1 -0.01894144 -0.01217675 0.1045737 0.02512248 0.07700328 0.05863359
       Dim381     Dim382      Dim383     Dim384    Dim385      Dim386
1 -0.03486566 0.03618479 -0.03967949 0.03187413 0.1228099 0.004328088
       Dim387      Dim388    Dim389      Dim390       Dim391     Dim392
1 -0.05571836 -0.01382447 0.1014563 0.005540595 -0.002099469 0.04699913
       Dim393      Dim394     Dim395     Dim396      Dim397      Dim398
1 -0.02092642 -0.03988863 0.00658244 0.02015599 -0.01267892 -0.04250392
      Dim399      Dim400     Dim401     Dim402       Dim403     Dim404
1 0.03640548 -0.05950782 0.01229393 0.03474214 -0.003756263 0.07556196
       Dim405     Dim406    Dim407      Dim408    Dim409     Dim410      Dim411
1 -0.01581631 0.08982348 -0.119573 -0.01489228 0.0321744 0.01545453 -0.01062769
      Dim412     Dim413     Dim414       Dim415      Dim416     Dim417
1 0.07060594 0.05067884 0.02162697 -0.007810039 -0.02777156 0.03783101
       Dim418       Dim419      Dim420      Dim421     Dim422      Dim423
1 -0.02935591 -0.008409697 -0.05037494 -0.08629285 0.04084516 -0.01418345
       Dim424     Dim425     Dim426    Dim427      Dim428     Dim429
1 -0.06365343 0.09158956 0.01061955 0.1100217 0.005894495 0.02905461
       Dim430      Dim431     Dim432     Dim433      Dim434     Dim435
1 -0.05902156 -0.03096861 0.03136865 -0.1127055 0.003991385 0.01402383
        Dim436     Dim437     Dim438      Dim439     Dim440     Dim441
1 -0.002818544 0.03812404 0.01630672 -0.01887866 0.02094255 0.03740776
       Dim442     Dim443     Dim444      Dim445      Dim446      Dim447
1 -0.02140117 0.04006733 0.03938072 -0.02091419 0.002862708 -0.04301161
      Dim448      Dim449      Dim450      Dim451     Dim452     Dim453
1 0.06656485 0.002899278 -0.07097059 0.006268004 0.07627844 -0.1656777
     Dim454     Dim455      Dim456     Dim457      Dim458      Dim459
1 -1.303071 0.03292015 0.001216001 0.01929163 0.006321201 -0.06444547
      Dim460     Dim461      Dim462     Dim463      Dim464     Dim465
1 0.03222056 0.03787213 -0.04272534 0.01621736 -0.03500902 0.05988663
       Dim466      Dim467     Dim468      Dim469     Dim470     Dim471
1 -0.05526236 -0.02389414 0.01373466 -0.08350613 0.04199342 0.04698859
       Dim472      Dim473     Dim474      Dim475      Dim476     Dim477
1 0.001606023 -0.05817793 -0.1181426 -0.01995927 -0.03852597 0.09707201
     Dim478     Dim479     Dim480     Dim481     Dim482     Dim483    Dim484
1 0.1278216 -0.0297847 0.01828551 0.01670286 0.03277786 0.09394352 0.0245835
       Dim485      Dim486       Dim487     Dim488    Dim489      Dim490
1 -0.06042151 -0.06419709 -0.001968642 0.03546384 0.1266303 -0.03766909
      Dim491      Dim492     Dim493     Dim494    Dim495     Dim496     Dim497
1 0.01635127 -0.05516074 0.07026093 0.01981271 0.1932934 0.06916854 -0.2436134
      Dim498    Dim499      Dim500       Dim501      Dim502      Dim503
1 0.01315579 0.1548217 -0.05302637 -0.005513271 -0.01395114 -0.01270218
      Dim504     Dim505    Dim506      Dim507      Dim508      Dim509
1 0.07853533 0.01600896 0.1132618 -0.02287428 -0.04421847 -0.01170723
      Dim510      Dim511    Dim512    Dim513     Dim514     Dim515      Dim516
1 -0.0404612 -0.01502825 0.1068065 0.0599024 -0.0431066 0.03054362 -0.01285851
      Dim517      Dim518      Dim519     Dim520     Dim521     Dim522
1 -0.0191697 -0.03153732 0.004567779 0.07818143 -0.0116552 0.04245283
       Dim523      Dim524      Dim525        Dim526     Dim527     Dim528
1 -0.04132793 -0.02695129 -0.03815959 -0.0002546331 0.05014114 0.05791585
      Dim529      Dim530      Dim531     Dim532     Dim533        Dim534
1 0.07237219 -0.03172074 -0.03670841 -0.1283303 0.09187798 0.00001823028
      Dim535     Dim536     Dim537     Dim538      Dim539       Dim540
1 0.01670865 0.03138058 0.05869025 0.02617778 -0.04369681 0.0009510192
       Dim541     Dim542     Dim543    Dim544    Dim545     Dim546     Dim547
```

```
1 -0.09070309 0.08426145 0.01746497 0.0143929 0.1264933 0.05054398 0.04296028
       Dim548      Dim549      Dim550     Dim551     Dim552     Dim553
1 -0.04752717 -0.01427257 0.002091692 0.01990349 -0.3774972 0.01090082
      Dim554     Dim555      Dim556     Dim557     Dim558      Dim559
1 0.04931559 0.01802916 -0.01944041 0.08597497 0.01587856 -0.05492282
       Dim560      Dim561     Dim562     Dim563     Dim564       Dim565
1 -0.07542327 0.006113836 0.02933785 0.01319544 0.01346067 -0.003360703
      Dim566    Dim567     Dim568       Dim569     Dim570     Dim571
1 0.01182955 0.0711575 0.01069196 -0.004726301 0.08904852 -0.1245938
       Dim572      Dim573     Dim574      Dim575     Dim576     Dim577
1 -0.02400672 -0.08335184 0.03032804 -0.06834591 0.03303309 0.08116671
      Dim578      Dim579    Dim580      Dim581       Dim582     Dim583
1 0.08852118 -0.04060681 0.1080719 -0.02857596 -0.002249636 0.07120091
      Dim584     Dim585     Dim586     Dim587      Dim588   Dim589      Dim590
1 0.01929063 0.05036947 0.08373432 0.03119808 -0.02472931 10.40989 -0.03335479
         Dim591    Dim592     Dim593     Dim594     Dim595      Dim596
1 0.00001590491 0.1020112 0.02520605 0.01922344 0.03705714 -0.03027939
      Dim597     Dim598      Dim599     Dim600      Dim601      Dim602
1 0.02878415 0.04377271 -0.02517537 0.06638837 -0.03684153 -0.07039945
      Dim603      Dim604     Dim605      Dim606    Dim607     Dim608     Dim609
1 0.02370637 -0.02010491 -0.1700441 -0.04967063 0.1437444 0.03364382 0.02854263
      Dim610      Dim611    Dim612       Dim613     Dim614     Dim615
1 0.07468463 -0.01405938 0.3746885 -0.003721654 0.05870501 0.08688462
      Dim616      Dim617      Dim618     Dim619     Dim620     Dim621
1 0.09220773 -0.02893779 -0.02598942 0.01744768 0.07500677 0.02593593
      Dim622     Dim623     Dim624     Dim625     Dim626    Dim627     Dim628
1 -0.0115939 0.07953761 0.05151355 -0.0124666 0.07785031 0.0837042 0.07169254
      Dim629     Dim630     Dim631     Dim632       Dim633    Dim634
1 0.01535143 0.03094547 0.02479821 0.00341702 -0.006340763 0.0334576
       Dim635     Dim636    Dim637     Dim638     Dim639       Dim640
1 0.005409091 0.07502079 0.0159725 0.02834773 0.03345724 -0.002944542
      Dim641     Dim642     Dim643      Dim644       Dim645      Dim646
1 0.05821856 0.06789106 -0.0207611 0.007156217 -0.009964033 -0.02734437
      Dim647      Dim648     Dim649     Dim650      Dim651   Dim652  Dim653
1 0.02922359 -0.03934267 0.04159756 0.05500067 -0.02733942 0.146259 0.01465
     Dim654     Dim655     Dim656     Dim657     Dim658       Dim659
1 0.0749637 0.01639464 0.07828537 0.03919239 0.02469708 -0.008865423
       Dim660      Dim661      Dim662     Dim663      Dim664      Dim665
1 -0.02033695 -0.04864632 0.002052276 0.08007035 -0.07448118 -0.08672906
       Dim666     Dim667     Dim668    Dim669    Dim670     Dim671     Dim672
1 -0.04434929 -0.0139097 -0.0387153 0.1097544 0.0047587 0.01440835 0.05295185
      Dim673     Dim674    Dim675    Dim676       Dim677       Dim678
1 0.05340496 0.05685382 0.1365726 0.0125056 0.0004585826 -0.007205268
      Dim679     Dim680     Dim681      Dim682     Dim683      Dim684
1 0.02306118 0.08900418 0.03653014 -0.02864028 0.07297028 -0.02717314
       Dim685      Dim686    Dim687      Dim688      Dim689     Dim690
1 -0.05350105 -0.09152712 0.1127953 0.003779681 -0.07994445 0.09819646
        Dim691     Dim692     Dim693       Dim694      Dim695      Dim696
1 -0.009219781 0.02686084 0.03176724 -0.004313332 -0.05570009 -0.04668238
      Dim697      Dim698     Dim699      Dim700     Dim701      Dim702
1 0.03821168 -0.01559122 0.00415158 0.002860376 -0.0194193 -0.02450354
      Dim703       Dim704     Dim705     Dim706     Dim707     Dim708
1 0.04198655 -0.007422571 0.04795915 0.04825007 0.01933656 0.06055188
       Dim709     Dim710      Dim711      Dim712     Dim713      Dim714
```

```
1 -0.07695175 0.05314383 -0.05001539 -0.01423458 0.01145514 0.007925465
       Dim715     Dim716      Dim717     Dim718     Dim719     Dim720    Dim721
1 -0.00940827 0.04849743 -0.01017194 0.02336836 0.01915652 0.07499151 0.2166015
       Dim722     Dim723      Dim724       Dim725   Dim726      Dim727
1 -0.03781433 0.02676561 -0.03970993 -0.002401707 0.109841 0.001826969
       Dim728      Dim729      Dim730        Dim731     Dim732     Dim733
1 0.005976692 -0.01576971 0.005927811 -0.0003839743 -0.2864483 0.07543286
       Dim734     Dim735      Dim736     Dim737    Dim738     Dim739
1 -0.03299744 0.06050834 -0.08300675 0.06494612 0.0186879 0.09525949
       Dim740      Dim741      Dim742       Dim743     Dim744     Dim745
1 -0.02274143 -0.04441616 -0.06460027 0.0005368666 0.01415091 0.01319657
      Dim746     Dim747      Dim748      Dim749     Dim750    Dim751     Dim752
1 0.07915809 0.02910089 -0.01064941 -0.01160094 -0.4062178 0.1150987 0.07628248
      Dim753      Dim754       Dim755     Dim756     Dim757       Dim758
1 0.09187859 0.008078155 -0.005122755 0.02323424 0.06230292 -0.002234648
       Dim759     Dim760      Dim761      Dim762     Dim763    Dim764    Dim765
1 -0.01456664 0.03246233 -0.09130879 -0.06135602 0.02928847 0.0785887 0.1399621
      Dim766      Dim767     Dim768
1 0.03987939 -0.03054548 0.02145188
```

Here, we have a small issue to deal with. Our new input vector has `ncol(input` variables. On the other hand, our original data being used to develop the model had 991 variables. We can access to this information using the model object.

```
caret_mod$recipe$var_info
```

```
# A tibble: 991 x 4
   variable type    role      source
   <chr>    <chr>   <chr>     <chr>
 1 chars    numeric predictor original
 2 sents    numeric predictor original
 3 tokens   numeric predictor original
 4 types    numeric predictor original
 5 puncts   numeric predictor original
 6 numbers  numeric predictor original
 7 symbols  numeric predictor original
 8 urls     numeric predictor original
 9 tags     numeric predictor original
10 emojis   numeric predictor original
# ... with 981 more rows
```

This happended because some of the features don't exist for our new text. They exist but the value for these features are zero, and they just don't appear in the new text. So, we have to append these missing features to the new text, and make their values to zero. Without these features, the model will look for them to apply the formula and return an error message when it can't find any information about these features in the new dataset. In addition, there were some extra features in the new text that doesn't exist in our model. However, we don't have to worry about them because our recipe is going to ignore any extra column in the new dataset that is not defined a role in the recipe.

```
# feature names from the model

  my_feats <- caret_mod$recipe$var_info$variable
```

```r
# column names from the new text

  colnames(input)
```

```
  [1] "chars"                  "sents"                "tokens"
  [4] "types"                  "puncts"               "numbers"
  [7] "symbols"                "urls"                 "tags"
 [10] "emojis"                 "wl.1"                 "wl.2"
 [13] "wl.3"                   "wl.4"                 "wl.5"
 [16] "wl.6"                   "wl.7"                 "wl.8"
 [19] "wl.9"                   "wl.10"                "wl.11"
 [22] "wl.12"                  "wl.13"                "wl.14"
 [25] "wl.15"                  "wl.16"                "wl.17"
 [28] "wl.18"                  "wl.19"                "wl.20"
 [31] "wl.21"                  "wl.22"                "wl.23"
 [34] "wl.24"                  "wl.25"                "wl.26"
 [37] "wl.27"                  "wl.28"                "wl.29"
 [40] "wl.30"                  "mean.wl"              "sd.wl"
 [43] "min.wl"                 "max.wl"               "ent"
 [46] "TTR"                    "C"                    "R"
 [49] "CTTR"                   "U"                    "S"
 [52] "K"                      "I"                    "D"
 [55] "Vm"                     "Maas"                 "MATTR"
 [58] "MSTTR"                  "lgV0"                 "lgeV0"
 [61] "ARI"                    "ARI.simple"           "ARI.NRI"
 [64] "Bormuth.MC"             "Bormuth.GP"           "Coleman"
 [67] "Coleman.C2"             "Coleman.Liau.ECP"     "Coleman.Liau.grade"
 [70] "Coleman.Liau.short"     "Dale.Chall"           "Dale.Chall.old"
 [73] "Dale.Chall.PSK"         "Danielson.Bryan"      "Danielson.Bryan.2"
 [76] "Dickes.Steiwer"         "DRP"                  "ELF"
 [79] "Farr.Jenkins.Paterson" "Flesch"                "Flesch.PSK"
 [82] "Flesch.Kincaid"         "FOG"                  "FOG.PSK"
 [85] "FOG.NRI"                "FORCAST"              "FORCAST.RGL"
 [88] "Fucks"                  "Linsear.Write"        "LIW"
 [91] "nWS"                    "nWS.2"                "nWS.3"
 [94] "nWS.4"                  "RIX"                  "Scrabble"
 [97] "SMOG"                   "SMOG.C"               "SMOG.simple"
[100] "SMOG.de"                "Spache"               "Spache.old"
[103] "Strain"                 "Traenkle.Bailer"      "Traenkle.Bailer.2"
[106] "Wheeler.Smith"          "meanSentenceLength"   "meanWordSyllables"
[109] "ADJ"                    "ADP"                  "ADV"
[112] "AUX"                    "CCONJ"                "DET"
[115] "INTJ"                   "NOUN"                 "PRON"
[118] "PROPN"                  "PUNCT"                "VERB"
[121] ","                      "."                    "CC"
[124] "DT"                     "IN"                   "JJ"
[127] "NN"                     "NNP"                  "NNPS"
[130] "NNS"                    "PRP"                  "PRP$"
[133] "RB"                     "UH"                   "VBG"
[136] "VBZ"                    "WP"                   "advmod"
[139] "amod"                   "appos"                "aux"
[142] "case"                   "cc"                   "conj"
[145] "cop"                    "det"                  "nmod"
```

```
[148] "nmod:poss"            "nsubj"                "obj"
[151] "obl"                  "punct"                "root"
[154] "morph_case_Nom"       "morph_definite_Def"   "morph_definite_Ind"
[157] "morph_degree_Pos"     "morph_gender_Masc"    "morph_mood_Ind"
[160] "morph_number_Plur"    "morph_number_Sing"    "morph_person_3"
[163] "morph_poss_Yes"       "morph_prontype_Art"   "morph_prontype_Dem"
[166] "morph_prontype_Int"   "morph_prontype_Prs"   "morph_tense_Pres"
[169] "morph_verbform_Fin"   "morph_verbform_Part"  "Dim1"
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[937] "Dim767"                    "Dim768"
```

```
# Find the features missing from the new text

  missing_feats <- ! my_feats %in% colnames(input)

  my_feats[missing_feats]
```

```
 [1] "NUM"                 "PART"                "SCONJ"
 [4] "X."                  "CD"                  "HYPH"
 [7] "MD"                  "TO"                  "VB"
[10] "VBD"                 "VBN"                 "WDT"
[13] "WRB"                 "acl.relcl"           "advcl"
[16] "aux.pass"            "compound"            "mark"
[19] "nsubj.pass"          "nummod"              "obl.npmod"
[22] "xcomp"               "morph_case_Acc"      "morph_gender_Neut"
[25] "morph_numtype_Card" "morph_prontype_Rel" "morph_tense_Past"
[28] "morph_verbform_Ger" "morph_verbform_Inf" "morph_voice_Pass"
[31] "X.."                 "X...1"               "PRP."
[34] "RP"                  "VBP"                 "acl"
[37] "ccomp"               "compound.prt"        "flat"
[40] "nmod.poss"           "parataxis"           "morph_gender_Fem"
[43] "morph_person_1"      "morph_person_2"      "morph_reflex_Yes"
[46] "PDT"                 "det.predet"          "morph_mood_Imp"
[49] "obl.tmod"            "EX"                  "expl"
[52] "POS"                 "fixed"               "RBR"
[55] "morph_degree_Cmp"    "JJS"                 "morph_degree_Sup"
[58] "JJR"                 "target"
```

```
# Add the missing features (with assigned values of zeros)

  temp           <- data.frame(matrix(0,1,sum(missing_feats)))
  colnames(temp) <- my_feats[missing_feats]

  input <- cbind(input,temp)
```

Now, we are ready to apply our model to the new input data and predict the readability score.

```
  predict(caret_mod, input)
```

```
[1] 0.2738756
```

In order to make things a little easier, I will compile the code we are using to generate input features as a function. This function will require two inputs, a model object and a new text. The function will then return a a matrix of input features.

```
generate_feats <- function(my.model,new.text){

    # Tokenization and document-feature matrix

      tokenized <- tokens(new.text,
                          remove_punct = TRUE,
                          remove_numbers = TRUE,
                          remove_symbols = TRUE,
                          remove_separators = TRUE)

      dm <- dfm(tokenized)

    # basic text stats
```

```r
  text_sm <- textstat_summary(dm)
  text_sm$sents <- nsentence(new.text)
  text_sm$chars <- nchar(new.text)

# Word-length features

  wl <- nchar(tokenized[[1]])

  wl.tab <- table(wl)

  wl.features <- data.frame(matrix(0,nrow=1,nco=30))
  colnames(wl.features) <- paste0('wl.',1:30)

  ind <- colnames(wl.features)%in%paste0('wl.',names(wl.tab))

  wl.features[,ind] <- wl.tab

  wl.features$mean.wl  <-   mean(wl)
  wl.features$sd.wl    <-   sd(wl)
  wl.features$min.wl   <-   min(wl)
  wl.features$max.wl   <-   max(wl)

# Text entropy/Max entropy ratio

  t.ent <- textstat_entropy(dm)
  n     <-  sum(featfreq(dm))
  p     <- rep(1/n,n)
  m.ent <- -sum(p*log(p,base=2))

  ent <- t.ent$entropy/m.ent

# Lexical diversity

  text_lexdiv <- textstat_lexdiv(tokenized,
                                remove_numbers = TRUE,
                                remove_punct   = TRUE,
                                remove_symbols = TRUE,
                                measure        = 'all')

# Measures of readability

  text_readability <- textstat_readability(new.text,measure='all')

# POS tag frequency

  annotated <- udpipe_annotate(ud_eng, x = new.text)
  annotated <- as.data.frame(annotated)
  annotated <- cbind_morphological(annotated)

  pos_tags <- c(table(annotated$upos),table(annotated$xpos))

# Syntactic relations
```

```r
  dep_rel <- table(annotated$dep_rel)

# morphological features

  feat_names <- c('morph_abbr','morph_animacy','morph_aspect','morph_case',
                  'morph_clusivity','morph_definite','morph_degree',
                  'morph_evident','morph_foreign','morph_gender','morph_mood',
                  'morph_nounclass','morph_number','morph_numtype',
                  'morph_person','morph_polarity','morph_polite','morph_poss',
                  'morph_prontype','morph_reflex','morph_tense','morph_typo',
                  'morph_verbform','morph_voice')

  feat_vec <- c()

  for(j in 1:length(feat_names)){

    if(feat_names[j]%in%colnames(annotated)){
      morph_tmp   <- table(annotated[,feat_names[j]])
      names_tmp   <- paste0(feat_names[j],'_',names(morph_tmp))
      morph_tmp   <- as.vector(morph_tmp)
      names(morph_tmp) <- names_tmp
      feat_vec  <- c(feat_vec,morph_tmp)
    }
  }

# Sentence Embeddings

  embeds <- textEmbed(x     = new.text,
                      model = 'roberta-base',
                      layers = 12,
                      context_aggregation_layers = 'concatenate')


# combine them all into one vector and store in the list object

  input <- cbind(text_sm[2:length(text_sm)],
                           wl.features,
                           as.data.frame(ent),
                           text_lexdiv[,2:ncol(text_lexdiv)],
                           text_readability[,2:ncol(text_readability)],
                           t(as.data.frame(pos_tags)),
                           t(as.data.frame(c(dep_rel))),
                           t(as.data.frame(feat_vec)),
                           as.data.frame(embeds$x)
                           )

# feature names from the model

  my_feats <- my.model$recipe$var_info$variable

# Find the features missing from the new text

  missing_feats <- ! my_feats %in% colnames(input)
```

```
    # Add the missing features (with assigned values of zeros)

      temp           <- data.frame(matrix(0,1,sum(missing_feats)))
      colnames(temp) <- my_feats[missing_feats]

      input <- cbind(input,temp)

      return(list(input=input))
}
```

Now, we can get the features for any text using this function and then predict the scores, all in a few lines of code.

```
# For the next few lines of codes to work, you will need the following
# in your R environment
  # 1. R Libraries (quanteda, quanteda.text, text, udpipe, reticulate)
  # 2. Supplemental Python libraries (torch, tokenizers, nltk, transformers,numpy)
  # 3. Model object (caret_mod)
  # 4. A function to generate the features in the model (generate_feats)


# Sample text 1

my.text1   <- 'Sora has a new kite. The kite is red. It is a good kite to fly. '

my.inputs1 <- generate_feats(my.model = caret_mod,
                             new.text = my.text1)

predict(caret_mod, my.inputs1$input)
```

```
[1] 0.7821635
```

```
# Sample text 2

my.text2  <- 'Saguaros have roots underground that grow outward rather than downward.'

my.inputs2 <- generate_feats(my.model = caret_mod,
                             new.text = my.text2)

my.inputs2
```

```
$input
  chars sents tokens types puncts numbers symbols urls tags emojis wl.1 wl.2
1    71     1     10    10      0       0       0    0    0      0    0    0
  wl.3 wl.4 wl.5 wl.6 wl.7 wl.8 wl.9 wl.10 wl.11 wl.12 wl.13 wl.14 wl.15 wl.16
1    0    4    1    1    1    2    0     0     1     0     0     0     0     0
  wl.17 wl.18 wl.19 wl.20 wl.21 wl.22 wl.23 wl.24 wl.25 wl.26 wl.27 wl.28 wl.29
1     0     0     0     0     0     0     0     0     0     0     0     0     0
  wl.30 mean.wl    sd.wl min.wl max.wl ent TTR C        R     CTTR   U  S    K
1     0     6.1 2.378141      4     11   1   1 1 3.162278 2.236068 Inf NA 1000
  I D                Vm Maas MATTR MSTTR lgV0 lgeV0    ARI ARI.simple ARI.NRI
1 0 0 0.00000000372529    0     1     1  Inf   Inf 12.301       64.9    13.2
```

```
  Bormuth.MC Bormuth.GP Coleman Coleman.C2 Coleman.Liau.ECP Coleman.Liau.grade
1  -1.706639   12534201   26.05      34.85         21.73832           17.10756
  Coleman.Liau.short Dale.Chall Dale.Chall.old Dale.Chall.PSK Danielson.Bryan
1             17.108       28.6         8.8695         7.3282        7.601989
  Danielson.Bryan.2 Dickes.Steiwer      DRP ELF Farr.Jenkins.Paterson Flesch
1          61.99751      -385.1449 270.6639   5              -40.8675 52.865
  Flesch.PSK Flesch.Kincaid FOG  FOG.PSK FOG.NRI FORCAST FORCAST.RGL Fucks
1     6.3101           8.37  12 4.658636    -0.8    12.5       12.18    61
  Linsear.Write LIW   nWS nWS.2  nWS.3 nWS.4 RIX Scrabble     SMOG   SMOG.C
1             8  50 9.517 9.782 6.7166 6.451   4  1.57377 11.20814 10.93047
  SMOG.simple  SMOG.de Spache Spache.old Strain Traenkle.Bailer
1    10.74597 5.745967  6.789      7.409    5.1       -397.6158
  Traenkle.Bailer.2 Wheeler.Smith meanSentenceLength meanWordSyllables ADP ADV
1         -372.7133            50                 10               1.7   3   1
  NOUN PRON PUNCT VERB . IN NN NNS RB VBP WDT acl:relcl advmod case fixed nsubj
1    3    1     1    2 1  3  1   2  1   2   1         1      1    2     1     1
  obj obl punct root morph_mood_Ind morph_number_Plur morph_number_Sing
1   1   2     1    1              2                 2                 1
  morph_prontype_Rel morph_tense_Pres morph_verbform_Fin       Dim1      Dim2
1                  1                2                  2 0.05528715 0.1470418
        Dim3        Dim4      Dim5      Dim6        Dim7      Dim8      Dim9
1 0.06986057 -0.01858158 0.2191458 0.1045616 -0.05874057 0.1172505 0.1970386
       Dim10      Dim11      Dim12       Dim13      Dim14      Dim15     Dim16
1 -0.0617718 0.03862775 -0.3552499 0.007455591 -0.1699106 0.08311476 0.2537729
       Dim17      Dim18      Dim19       Dim20       Dim21       Dim22
1 0.06665616 0.02998496 0.01657086 -0.02418766 -0.04881609 -0.01067119
       Dim23       Dim24      Dim25        Dim26       Dim27     Dim28
1 -0.1230952 -0.03098966 -0.2478379 -0.002678271 -0.01709052 0.1102759
       Dim29     Dim30      Dim31      Dim32      Dim33     Dim34      Dim35
1 -0.0656739 0.1033969 0.02026837 -0.1096219 0.02588799 -0.020846 0.04588335
       Dim36      Dim37      Dim38     Dim39       Dim40      Dim41      Dim42
1 0.06190892 0.01031027 0.08172554 0.3027073 0.001283012 -0.2680633 -0.1498191
       Dim43      Dim44      Dim45      Dim46      Dim47      Dim48      Dim49
1 -0.0900186 0.04649156 0.04518933 0.01351951 0.04103527 0.06572589 0.07080774
      Dim50      Dim51      Dim52       Dim53      Dim54      Dim55       Dim56
1 0.1025247 0.01699213 0.02433206 -0.06309998 -0.1169119 -0.1871392 -0.01134908
       Dim57      Dim58      Dim59       Dim60       Dim61      Dim62
1 0.01037304 0.03377421 0.08285915 -0.08867099 -0.02970115 -0.0719273
        Dim63        Dim64      Dim65       Dim66     Dim67      Dim68
1 -0.05232855 -0.009636357 0.07179029 -0.01206168 0.1484595 -0.0845878
      Dim69     Dim70      Dim71      Dim72      Dim73       Dim74      Dim75
1 0.1356556 0.1029465 0.04038985 -0.0513265 0.02573596 -0.00698741 0.06792847
         Dim76       Dim77     Dim78     Dim79     Dim80     Dim81       Dim82
1 -0.005479446 -0.01978568 -5.370555 0.1401159 0.1019721 0.0913927 -0.03066399
      Dim83      Dim84      Dim85     Dim86      Dim87      Dim88        Dim89
1 0.5510804 -0.1815587 -0.0587592 -0.180113 0.03474354 0.03548509 -0.009899561
       Dim90      Dim91     Dim92      Dim93       Dim94     Dim95     Dim96
1 0.01067116 0.01703983 0.0266629 0.01754268 -0.09531183 0.1078587 0.2131933
        Dim97     Dim98       Dim99        Dim100    Dim101       Dim102
1 0.009398299 0.4264129 -0.08472901 -0.003606338 0.1530254 -0.002107865
     Dim103       Dim104      Dim105      Dim106     Dim107     Dim108
1 0.1201232 -0.006140986 -0.03439667 0.006513693 0.04547394 0.04183529
      Dim109      Dim110    Dim111     Dim112    Dim113     Dim114    Dim115
1 0.03740743 0.004189802 0.0492082 -0.1129486 0.1025133 0.03233098 0.1053422
```

```
     Dim116     Dim117    Dim118    Dim119     Dim120     Dim121    Dim122
1 -0.0702045 0.02900758 0.1060363 0.0413786 0.07771926 0.08738551 0.1813841
      Dim123     Dim124      Dim125     Dim126        Dim127      Dim128
1 0.06843294 0.03039432 -0.09473884 -0.1458843 -0.0007297364 -0.08370116
       Dim129     Dim130      Dim131     Dim132      Dim133    Dim134
1 -0.03839614 0.06006945 -0.07515578 0.05210375 -0.01041711 0.1834239
       Dim135      Dim136       Dim137     Dim138     Dim139     Dim140
1 0.003333554 0.006136341 -0.001956367 0.01787031 0.07150078 0.05734417
      Dim141    Dim142      Dim143       Dim144      Dim145     Dim146
1 0.02188161 0.0605893 -0.06045199 -0.005311981 -0.03435024 0.07505877
       Dim147    Dim148     Dim149      Dim150    Dim151      Dim152
1 -0.01654805 -0.135323 0.02441458 -0.01271025 0.0498052 0.007825251
       Dim153     Dim154      Dim155    Dim156    Dim157    Dim158     Dim159
1 -0.06476944 -0.0250025 -0.01638445 0.2412671 0.2238978 0.1662578 -0.0722558
       Dim160    Dim161     Dim162     Dim163      Dim164     Dim165     Dim166
1 0.009896833 0.1182216 0.08601105 0.04673061 0.003970463 -0.1021658 0.01716744
     Dim167      Dim168     Dim169      Dim170      Dim171     Dim172
1 0.1426557 -0.02780475 0.08421211 -0.06989152 -0.09814868 0.03905216
       Dim173     Dim174      Dim175      Dim176     Dim177      Dim178
1 -0.03236538 0.04442581 -0.06148162 -0.05428453 0.08169579 -0.09637594
      Dim179     Dim180      Dim181      Dim182      Dim183     Dim184
1 0.00706386 0.03826702 -0.03033785 -0.07258525 -0.09080315 0.02857036
       Dim185    Dim186      Dim187     Dim188      Dim189    Dim190     Dim191
1 -0.04270558 0.2278139 -0.01204044 0.03103844 -0.01319283 0.1144015 0.01565978
       Dim192     Dim193     Dim194      Dim195     Dim196     Dim197
1 -0.03039088 -0.0849579 0.06038656 -0.06622443 0.01412176 0.03763787
       Dim198       Dim199      Dim200      Dim201     Dim202     Dim203
1 -0.01925833 -0.006176034 -0.07129187 -0.05200815 0.04254975 0.07226231
      Dim204    Dim205     Dim206     Dim207     Dim208      Dim209     Dim210
1 -0.1350243 0.1120641 0.05964107 0.04718864 0.07583441 -0.01950815 -0.1678818
       Dim211       Dim212     Dim213    Dim214     Dim215     Dim216
1 -0.09196261 -0.009269821 -0.1132182 0.1372624 0.02390693 0.06419052
      Dim217    Dim218     Dim219     Dim220     Dim221    Dim222     Dim223
1 0.06936817 -0.753914 0.04104683 0.05656242 0.04296647 0.0249878 0.03032066
       Dim224    Dim225     Dim226      Dim227      Dim228   Dim229     Dim230
1 -0.09870362 0.1052297 0.04887008 0.007374333 -0.08783393 0.168577 0.06878476
      Dim231    Dim232     Dim233      Dim234      Dim235     Dim236     Dim237
1 0.02254646 0.1066861 0.09285481 -0.05063489 -0.08885245 0.06516313 0.05421298
      Dim238      Dim239     Dim240     Dim241     Dim242     Dim243    Dim244
1 0.04004948 -0.01794386 0.06345819 -0.5081334 0.05551376 0.01440259 0.1725836
      Dim245   Dim246      Dim247     Dim248    Dim249     Dim250      Dim251
1 0.07368217 0.102998 -0.03312773 -0.1461103 0.1158917 0.07936288 -0.03020152
       Dim252       Dim253       Dim254      Dim255      Dim256    Dim257
1 -0.06359584 -0.007420865 -0.003105763 -0.02933648 -0.09562055 -0.118291
      Dim258    Dim259   Dim260     Dim261     Dim262     Dim263     Dim264
1 0.06583817 0.1656352 0.324916 0.02451921 -0.1623721 0.07584237 -0.1139088
       Dim265      Dim266     Dim267     Dim268      Dim269     Dim270
1 -0.02080946 -0.01260102 0.02624531 0.05960417 -0.01247324 -0.0803403
      Dim271      Dim272      Dim273     Dim274    Dim275       Dim276
1 0.09526868 -0.01118323 -0.06333578 0.07129539 0.0326982 -0.006071104
       Dim277      Dim278      Dim279     Dim280     Dim281     Dim282
1 -0.06237698 -0.07956257 0.002517405 0.04901855 0.08042085 -0.1125483
      Dim283     Dim284        Dim285      Dim286     Dim287      Dim288
1 -0.1602062 0.01619933 -0.0005944736 -0.07665619 -0.2056468 -0.09835126
```

```
     Dim289     Dim290     Dim291      Dim292     Dim293       Dim294
1 -0.0193121 0.03904628 0.03055695 -0.02666575 -0.1196018 -0.004114747
      Dim295     Dim296     Dim297      Dim298     Dim299       Dim300
1 -0.01264288 0.04943202 0.04914877 -0.03012024 0.09696863 -0.003902916
    Dim301      Dim302     Dim303       Dim304     Dim305      Dim306
1 0.1374887 -0.06792628 -0.1031354 -0.005781878 0.02750041 -0.02444551
    Dim307       Dim308     Dim309     Dim310      Dim311     Dim312
1 0.1199436 -0.001519875 0.05088037 0.07980249 -0.05723593 -0.1442795
     Dim313    Dim314      Dim315      Dim316    Dim317      Dim318    Dim319
1 0.01102278 0.1478931 -0.06125982 -0.04699306 0.1403043 -0.09422657 0.0773035
      Dim320       Dim321      Dim322     Dim323     Dim324      Dim325
1 -0.04463473 -0.009524462 -0.02604978 0.08930463 0.04768093 -0.01309682
       Dim326    Dim327    Dim328      Dim329     Dim330    Dim331   Dim332
1 -0.009405635 -0.218014 0.2228607 -0.01773874 0.01811215 0.4096357 1.000012
    Dim333    Dim334     Dim335     Dim336      Dim337    Dim338    Dim339
1 0.1141741 0.3336742 0.06364824 0.05899757 -0.01538922 0.1056346 0.1602375
     Dim340      Dim341     Dim342     Dim343    Dim344      Dim345     Dim346
1 0.02972367 0.006893257 0.01800837 -0.1589596 0.1369679 0.001885477 0.08894256
      Dim347     Dim348    Dim349     Dim350      Dim351      Dim352
1 -0.03473411 0.00715857 0.1069481 0.07351498 -0.09334074 -0.03023842
      Dim353     Dim354     Dim355     Dim356      Dim357      Dim358
1 -0.08587234 0.03548157 0.01980248 0.07724328 -0.00794035 -0.06966759
      Dim359     Dim360    Dim361     Dim362     Dim363     Dim364    Dim365
1 -0.03674282 -0.1414044 0.1413571 0.04262654 0.04900469 0.05395078 -0.113146
     Dim366      Dim367     Dim368    Dim369     Dim370    Dim371      Dim372
1 0.02004359 -0.03161474 0.02954893 0.1181542 0.08670004 0.1292822 -0.06028303
     Dim373      Dim374     Dim375     Dim376    Dim377       Dim378    Dim379
1 0.01449715 -0.02104686 0.01776842 0.07524348 0.1749266 -0.006099543 0.1574728
     Dim380      Dim381      Dim382      Dim383      Dim384     Dim385
1 0.08560938 -0.04501753 -0.02250708 -0.05588667 -0.02819166 0.08241295
    Dim386        Dim387     Dim388      Dim389    Dim390      Dim391
1 0.1172941 -0.0006386536 -0.1034469 -0.03628385 0.1069113 -0.04320255
       Dim392      Dim393      Dim394     Dim395      Dim396     Dim397
1 -0.006774352 -0.07726677 -0.07341855 0.02039514 -0.04380173 0.06815659
    Dim398    Dim399      Dim400    Dim401      Dim402     Dim403    Dim404
1 -0.181229 0.1237796 -0.04760855 0.0383847 -0.04547143 0.06537882 0.1127001
    Dim405     Dim406      Dim407     Dim408    Dim409   Dim410     Dim411
1 0.0325666 -0.1053098 -0.03671732 0.02387121 0.1682441 0.140999 0.07858445
     Dim412    Dim413      Dim414     Dim415      Dim416      Dim417
1 -0.1368509 0.0236069 -0.08843862 0.09525738 -0.06321354 -0.06554395
     Dim418    Dim419      Dim420    Dim421     Dim422       Dim423
1 0.05671033 0.1395135 -0.03223676 -0.097188 -0.0131987 -0.002741856
      Dim424    Dim425     Dim426     Dim427     Dim428      Dim429
1 -0.03576544 0.1622343 0.01062272 0.06990091 0.05299715 -0.07870863
      Dim430      Dim431     Dim432     Dim433      Dim434     Dim435
1 -0.06935347 -0.07542775 0.02447789 0.01884264 -0.03664386 -0.0347052
      Dim436       Dim437      Dim438     Dim439    Dim440   Dim441     Dim442
1 -0.01606799 -0.006753043 -0.02909693 -0.1088497 -0.101024 0.163503 0.02108093
    Dim443    Dim444    Dim445      Dim446      Dim447       Dim448     Dim449
1 0.1120763 0.1338506 -0.100697 -0.01133472 -0.06754479 -0.005884321 0.06982728
      Dim450    Dim451     Dim452     Dim453     Dim454    Dim455     Dim456
1 -0.04103985 0.1205692 -0.0122188 -0.1067728 -0.2894375 0.1140478 0.08866693
      Dim457     Dim458     Dim459     Dim460    Dim461      Dim462
1 -0.04735582 -0.0239081 -0.1804139 0.07689639 0.1366579 -0.02460801
```

```
        Dim463      Dim464     Dim465      Dim466      Dim467     Dim468
1 -0.01592649 0.008486393 0.01131488 0.007040891 0.004922397 0.01861288
      Dim469      Dim470      Dim471     Dim472     Dim473     Dim474
1 0.04956753 -0.05540395 -0.06672812 0.02556119 0.06853761 -0.1436086
        Dim475      Dim476    Dim477     Dim478     Dim479     Dim480     Dim481
1 0.005096357 -0.01837247 0.1488071 0.08628092 -0.1058889 0.01713501 0.01324976
      Dim482     Dim483     Dim484      Dim485     Dim486      Dim487    Dim488
1 0.06826691 0.07606495 0.07010778 -0.04377156 -0.0616848 -0.03025019 0.1000552
      Dim489      Dim490     Dim491     Dim492     Dim493     Dim494    Dim495
1 0.07472002 -0.01959371 -0.1033791 0.08716304 0.05774419 0.04647094 0.1854566
      Dim496     Dim497      Dim498      Dim499     Dim500      Dim501
1 0.09233526 -0.4112881 -0.04775667 -0.05174592 0.03365434 -0.03774179
      Dim502     Dim503      Dim504     Dim505   Dim506    Dim507      Dim508
1 0.04127111 0.05770488 -0.02000027 0.02421681 0.150697 0.0413116 -0.05944095
      Dim509      Dim510      Dim511       Dim512     Dim513      Dim514
1 0.09310142 -0.07390439 -0.04057381 -0.008286882 0.04265339 -0.03755733
      Dim515      Dim516    Dim517      Dim518    Dim519    Dim520     Dim521
1 0.01605074 -0.05838799 0.0238131 -0.01755752 0.1477167 0.1832436 0.07730884
      Dim522       Dim523     Dim524      Dim525      Dim526     Dim527
1 0.07493916 -0.006833738 0.02746714 -0.04769004 -0.05481363 0.02235271
      Dim528     Dim529     Dim530      Dim531      Dim532    Dim533     Dim534
1 0.02504474 0.05937603 0.06195519 -0.02177023 -0.03576083 0.1869653 0.01856058
        Dim535     Dim536      Dim537    Dim538   Dim539     Dim540      Dim541
1 -0.09380048 0.06904146 -0.05793783 0.1436841 0.187244 0.07420418 -0.01865634
        Dim542      Dim543     Dim544     Dim545     Dim546    Dim547
1 -0.03247853 -0.07927277 0.01486553 0.07578162 0.06380614 0.1088267
         Dim548      Dim549     Dim550     Dim551       Dim552      Dim553
1 -0.006551243 -0.02163188 -0.1084187 0.06145734 0.0009005296 -0.03397786
      Dim554      Dim555      Dim556     Dim557     Dim558      Dim559
1 0.04093422 0.002709882 -0.02784154 0.00293496 0.02625804 -0.01308685
      Dim560     Dim561     Dim562      Dim563      Dim564     Dim565
1 -0.2256601 0.03225087 0.06700278 -0.02930937 -0.06373558 0.08390759
        Dim566     Dim567    Dim568    Dim569     Dim570      Dim571     Dim572
1 0.008100995 0.06185453 0.0264405 -0.019164 0.08495046 -0.09927193 0.03945214
      Dim573     Dim574     Dim575     Dim576    Dim577     Dim578     Dim579
1 0.02465301 -0.1189673 -0.2489261 0.00574941 0.1031828 0.03871722 -0.1042052
      Dim580     Dim581     Dim582    Dim583     Dim584     Dim585     Dim586
1 0.02165837 0.06399908 0.08534153 0.1108268 0.07131157 0.03486218 0.07075623
     Dim587      Dim588   Dim589      Dim590    Dim591    Dim592    Dim593
1 0.1446261 -0.05683227 9.886532 -0.02088336 0.0625632 0.0447973 0.1705246
      Dim594     Dim595      Dim596    Dim597     Dim598     Dim599     Dim600
1 0.06296498 0.05590236 0.009769287 0.1403786 -0.0176278 -0.1257751 0.05422907
        Dim601     Dim602     Dim603      Dim604     Dim605      Dim606
1 -0.03763636 -0.1165356 0.07703213 -0.05793516 -0.2358393 0.004466248
          Dim607      Dim608      Dim609     Dim610      Dim611    Dim612
1 -0.0004181797 -0.03786283 0.004993718 0.04179882 0.003848733 0.3534592
      Dim613    Dim614      Dim615      Dim616      Dim617     Dim618
1 0.09216478 0.1100405 0.006995993 -0.01531398 -0.07191593 0.02102609
        Dim619      Dim620    Dim621    Dim622      Dim623     Dim624     Dim625
1 -0.02058924 -0.05256345 0.0727169 0.0622322 -0.09026854 0.06906135 -0.2246087
     Dim626     Dim627    Dim628     Dim629      Dim630     Dim631     Dim632
1 0.1390391 0.08913307 0.1571774 0.04613747 -0.01770229 0.02869009 0.05951322
      Dim633       Dim634     Dim635     Dim636    Dim637     Dim638    Dim639
1 0.05598733 -0.002055514 0.08533524 0.06901469 0.0610513 0.04664684 0.1004793
```

```
       Dim640    Dim641     Dim642      Dim643      Dim644      Dim645
1 0.0191923 0.1456021 0.01039198 0.004232386 0.007571019 -0.05668546
       Dim646     Dim647     Dim648     Dim649    Dim650      Dim651    Dim652
1 -0.02240037 0.05837143 -0.1397329 -0.0420193 0.1297161 -0.01188557 0.1415349
       Dim653      Dim654      Dim655      Dim656      Dim657      Dim658
1 -0.02437607 -0.09443933 -0.01390689 -0.04294688 -0.02400241 -0.02039965
       Dim659    Dim660    Dim661     Dim662     Dim663     Dim664   Dim665
1 -0.03863604 0.0167268 -0.120606 -0.0460438 0.08944667 0.08828356 0.232326
      Dim666     Dim667      Dim668     Dim669     Dim670      Dim671    Dim672
1 0.05506571 -0.0666268 -0.01423872 0.06734122 0.07553644 -0.03645496 0.1447864
       Dim673     Dim674     Dim675     Dim676      Dim677      Dim678
1 -0.09283034 0.03176177 0.03684504 0.03549365 -0.04607771 -0.09805468
       Dim679    Dim680     Dim681       Dim682       Dim683       Dim684
1 -0.03624212 0.2519387 0.05752834 -0.003213047 0.0006513626 0.0006746107
     Dim685      Dim686     Dim687      Dim688     Dim689    Dim690     Dim691
1 0.1201407 -0.02414758 0.09703185 -0.02574956 -0.0972315 0.1385874 0.02874356
      Dim692     Dim693      Dim694      Dim695     Dim696      Dim697
1 0.08689204 0.02956045 -0.01039111 -0.04060345 -0.1196783 -0.00755839
       Dim698     Dim699     Dim700     Dim701     Dim702     Dim703
1 -0.03078387 0.02330763 -0.1753094 0.03879166 0.03964969 -0.0195798
       Dim704     Dim705     Dim706      Dim707    Dim708      Dim709
1 -0.06034459 0.02998138 0.04139998 -0.01626347 0.1125855 -0.07857001
      Dim710     Dim711     Dim712      Dim713     Dim714        Dim715
1 0.04018486 0.01019369 0.07974425 -0.03610035 0.07339616 -0.0009073861
       Dim716     Dim717     Dim718    Dim719    Dim720    Dim721     Dim722
1 -0.09846423 -0.0595244 0.04743357 0.0851715 0.1092154 0.4213681 -0.1100926
      Dim723       Dim724     Dim725     Dim726      Dim727    Dim728
1 0.05959106 -0.001658417 0.01335441 0.09698394 -0.03721931 0.1146252
      Dim729    Dim730     Dim731     Dim732    Dim733      Dim734      Dim735
1 0.07261933 -0.112156 0.02549234 0.01674436 0.1290601 -0.01019531 -0.05865718
     Dim736     Dim737      Dim738      Dim739     Dim740      Dim741
1 -0.165266 -0.1052265 -0.01251509 -0.09844494 0.01702193 -0.03409383
       Dim742      Dim743     Dim744    Dim745    Dim746     Dim747      Dim748
1 -0.02508877 -0.01925946 0.04337427 0.0205747 0.1562016 0.01503866 -0.08056241
       Dim749     Dim750   Dim751    Dim752      Dim753      Dim754     Dim755
1 -0.05841339 -0.7976129 0.126325 0.1753311 -0.08718352 -0.01675772 -0.1231623
      Dim756    Dim757      Dim758      Dim759     Dim760     Dim761
1 0.05919836 0.1185438 -0.04270717 -0.04834053 0.02558083 0.05244999
       Dim762    Dim763    Dim764    Dim765   Dim766     Dim767     Dim768 ADJ
1 -0.06120107 0.1219493 0.1062101 0.1047492 0.123484 0.03737937 0.02298719   0
  AUX CCONJ DET NUM PART PROPN SCONJ X. CC CD DT HYPH JJ MD NNP PRP TO VB VBD
1   0     0   0   0    0     0     0  0  0  0  0    0  0  0   0   0  0  0   0
  VBG VBN WRB acl.relcl advcl amod aux aux.pass cc compound conj cop det mark
1   0   0   0         0     0    0   0        0  0        0    0   0   0    0
  nmod nsubj.pass nummod obl.npmod xcomp morph_case_Acc morph_case_Nom
1    0          0      0         0     0              0              0
  morph_definite_Def morph_definite_Ind morph_degree_Pos morph_gender_Neut
1                  0                  0                0                 0
  morph_numtype_Card morph_person_3 morph_prontype_Art morph_prontype_Dem
1                  0              0                  0                  0
  morph_prontype_Int morph_prontype_Prs morph_tense_Past morph_verbform_Ger
1                  0                  0                0                  0
  morph_verbform_Inf morph_verbform_Part morph_voice_Pass X.. X...1 PRP. RP acl
1                  0                   0                0   0     0    0  0   0
```

```
  appos ccomp compound.prt flat nmod.poss parataxis morph_gender_Fem
1     0     0            0    0         0         0                0
  morph_person_1 morph_person_2 morph_poss_Yes morph_reflex_Yes PDT VBZ
1              0              0              0                0   0   0
  det.predet morph_gender_Masc morph_mood_Imp obl.tmod EX WP expl POS RBR
1          0                 0              0        0  0  0    0   0   0
  morph_degree_Cmp JJS morph_degree_Sup JJR target
1                0   0                0   0      0
```

```
predict(caret_mod, my.inputs2$input)
```

```
[1] -0.1224886
```

Feature Redundancy, Multicollinearity, and Variable Selection