

An Overview of the Linear Regression

Applied Machine Learning for Educational Data Science

true

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Contents

Model Description	1
Model Estimation	2
Matrix Solution	11
lm() function	16
Building a Prediction Model for Readability Scores	18
Initial Data Preparation	18
Train/Test Split	19
Model Fitting without Cross-validation	20
Model Fitting with 10-fold Cross-validation	24
Model Fitting Using the <code>caret</code> package	25
Using the Prediction Model for a New Text	27
Feature Redundancy, Multicollinearity, and Variable Selection	52

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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 ($X_1, X_2, X_3, \dots, X_p$) 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:

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

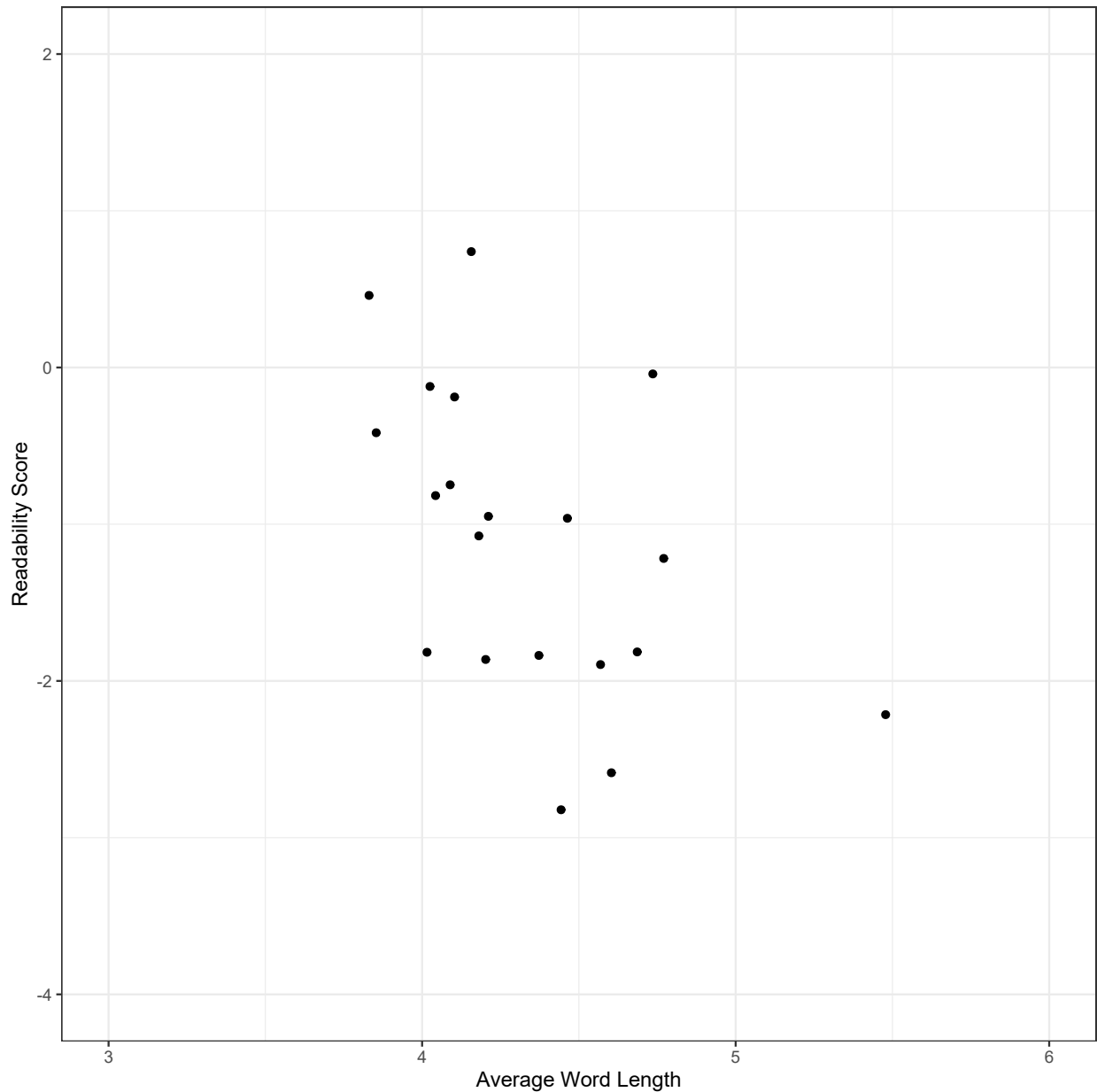
A model with both interaction terms and polynomial terms up to the 3rd degree added:

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

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
```

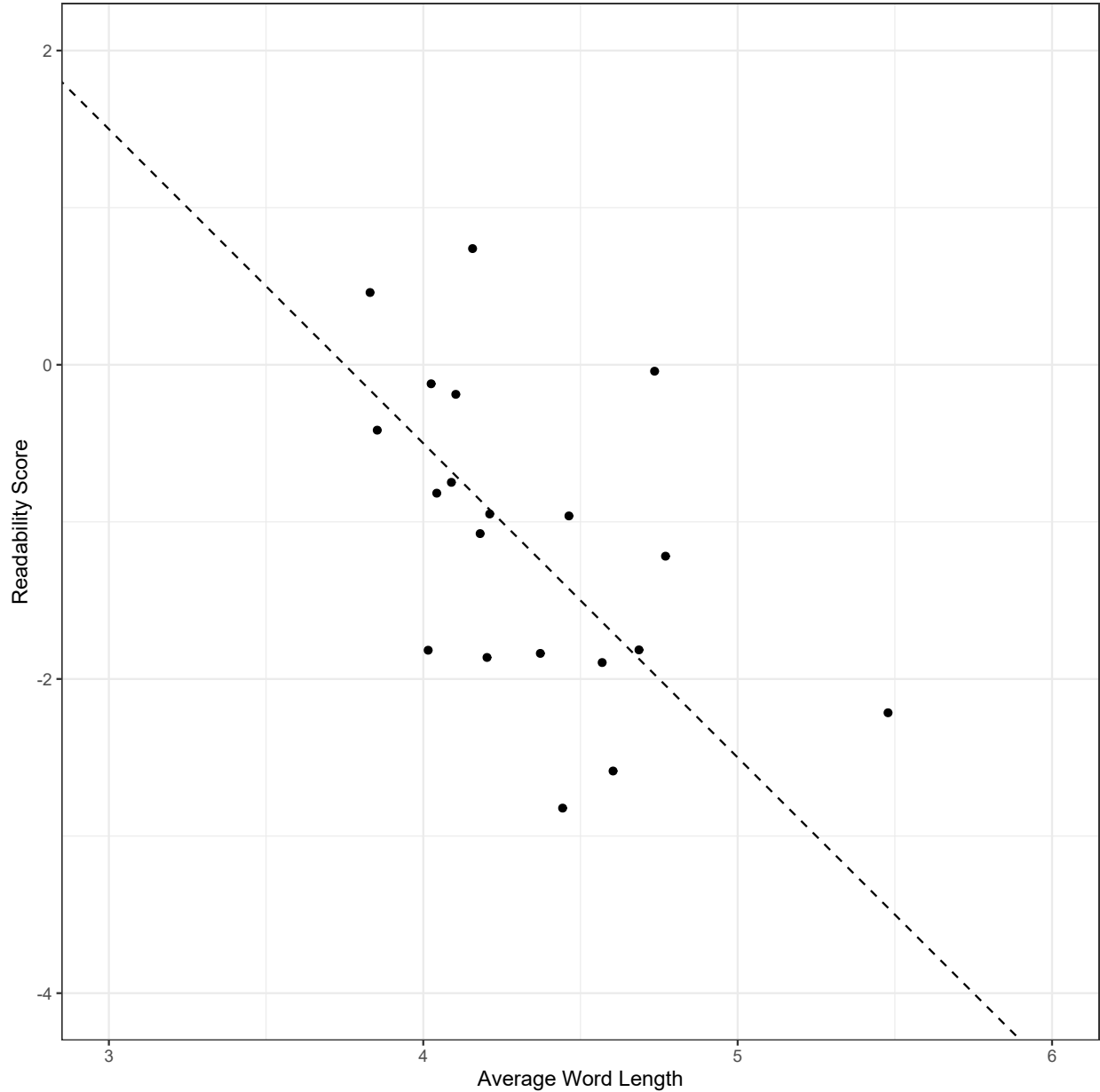


Let's consider a simple linear regression model such that the readability score is the outcome (Y) and average word length is the predictor(X). Our regression model would be

$$Y = \beta_0 + \beta_1 X + \epsilon.$$

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 be

$$Y = 7.5 - 2X + \epsilon.$$



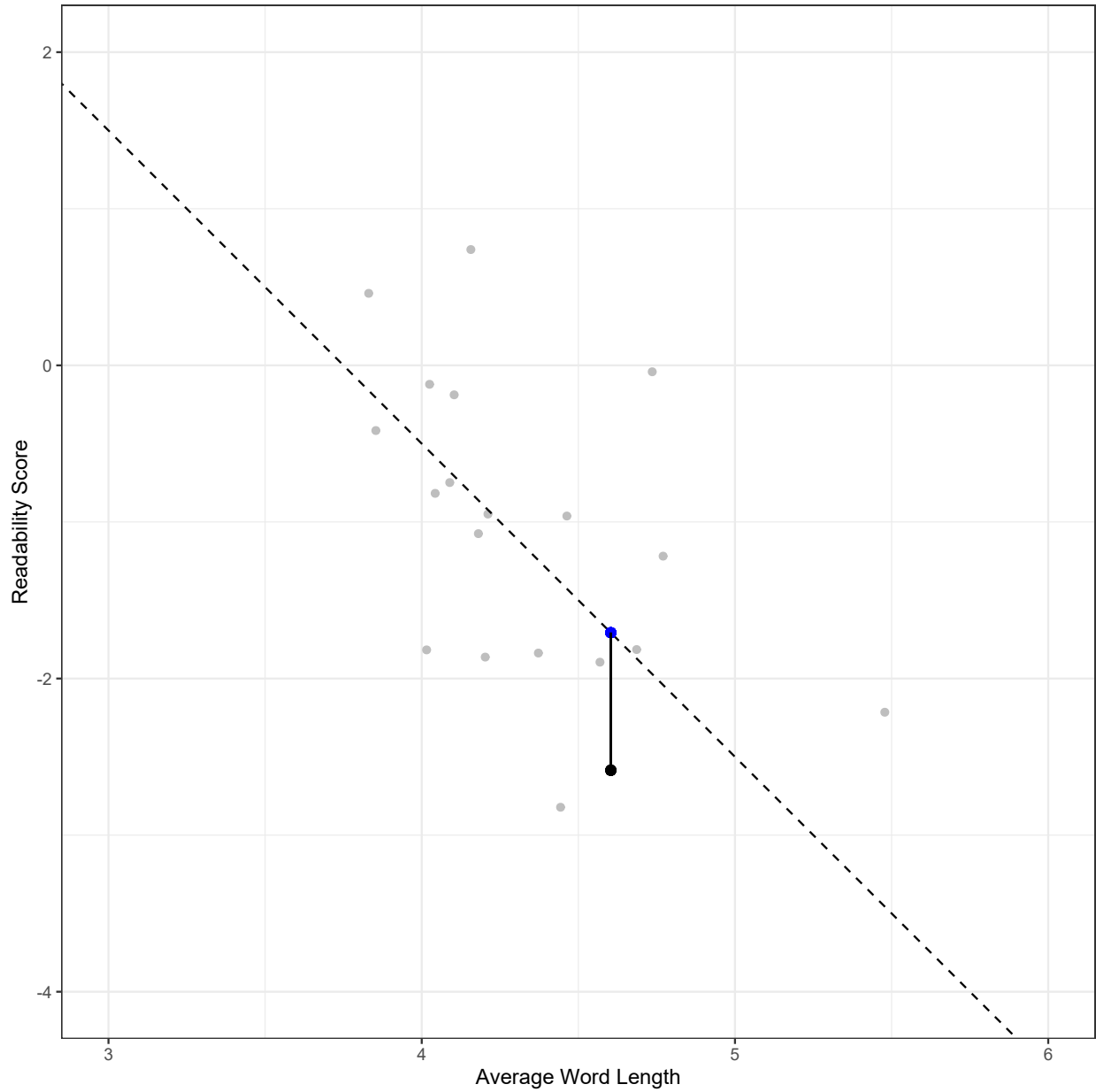
Using this model, I can predict the target readability score for any observation in my dataset. For instance, the average word length is 4.604 for the first reading passage. Then, my prediction of readability score based on this model would be -1.708. On the other side, the observed value of the readability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

$$Y_{(1)} = 7.5 - 2X_{(1)} + \epsilon_{(1)}.$$

$$\hat{Y}_{(1)} = 7.5 - 2 * 4.604 = -1.708$$

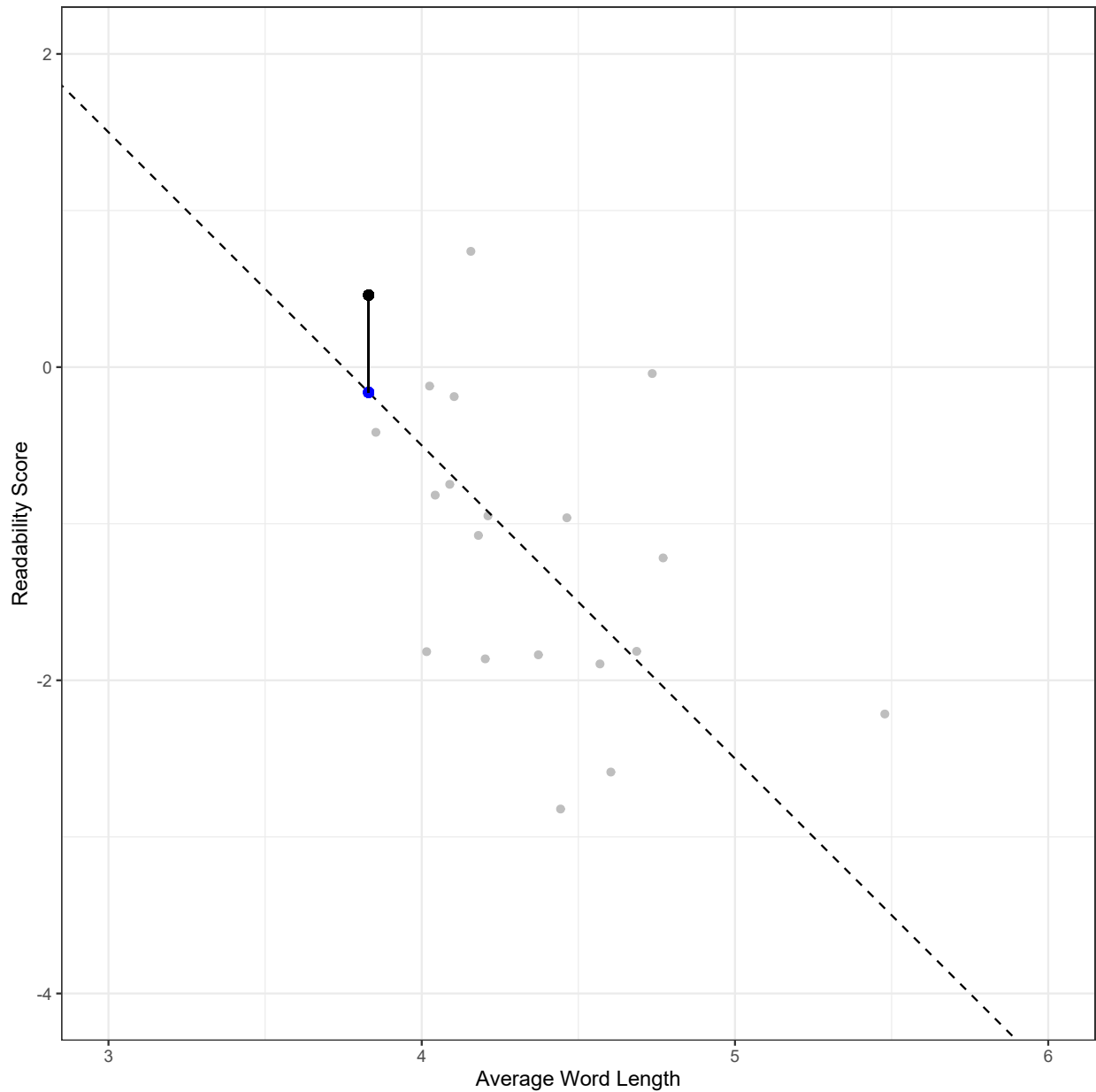
$$\hat{\epsilon}_{(1)} = -2.586 - (-1.708) = -0.878$$

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 thing 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 readability score for this observation is 0.459. Therefore the model error for the second observation would be 0.62.

$$\begin{aligned}
 Y_{(2)} &= 7.5 - 2X_{(2)} + \epsilon_{(2)}. \\
 \hat{Y}_{(2)} &= 7.5 - 2 * 3.830 = -0.161 \\
 \hat{\epsilon}_{(2)} &= 0.459 - (-0.161) = 0.62
 \end{aligned}$$



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

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

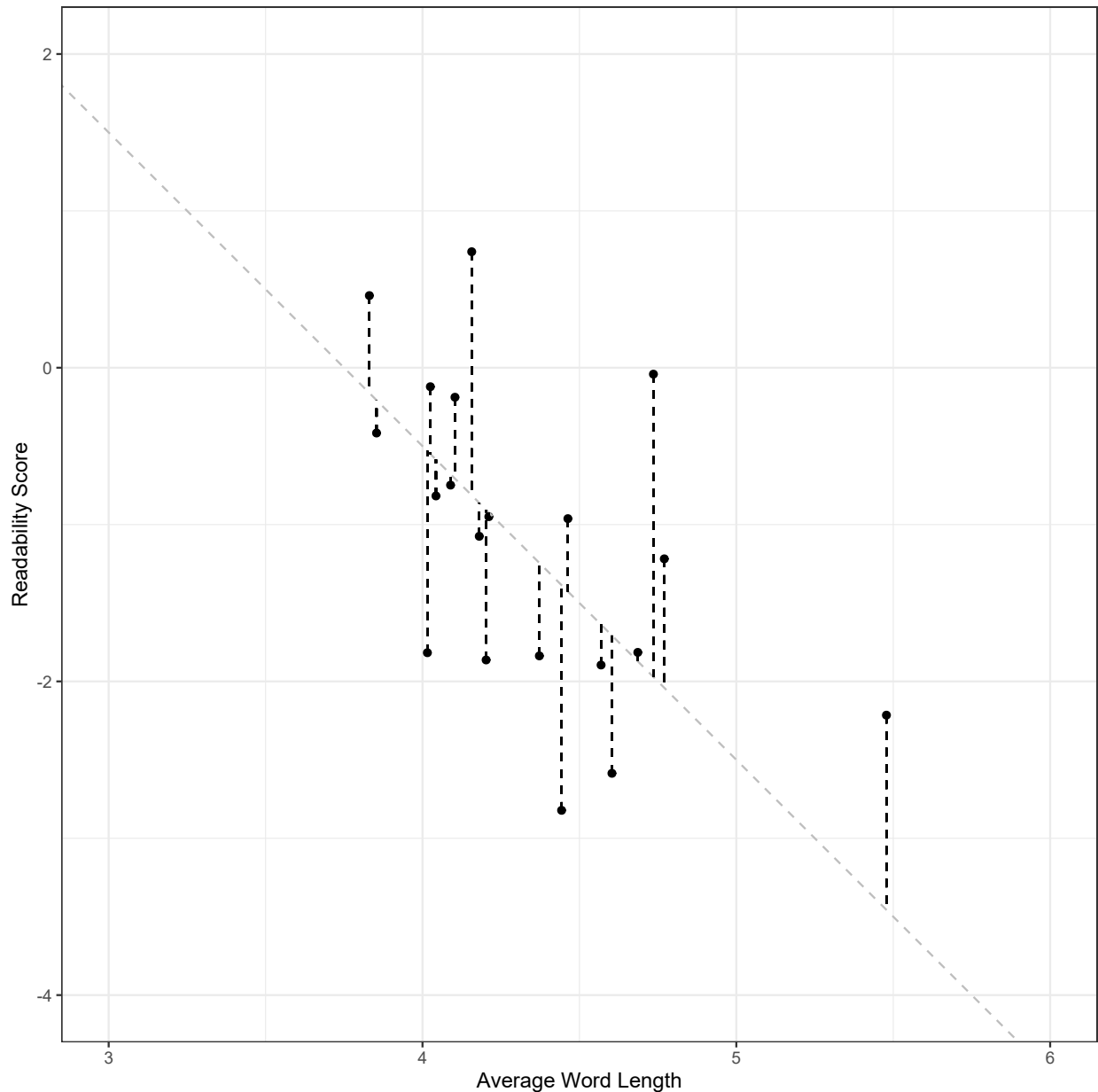
```
d$predicted <- d$mean.wl*-2 + 7.5
```

```
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, and it is mathematically easier 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 to 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.

WebGL is not supported by
your browser - visit
<https://get.webgl.org> for
more info

Finding the best set of $\{\beta_0, \beta_1\}$ coefficients that minimizes the sum of squared residuals is 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 operation. 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.

$$Y_{(1)} = \beta_0 + \beta_1 X_{(1)} + \epsilon_{(1)}.$$

$$Y_{(2)} = \beta_0 + \beta_1 X_{(2)} + \epsilon_{(2)}.$$

$$Y_{(3)} = \beta_0 + \beta_1 X_{(3)} + \epsilon_{(3)}.$$

...

...

...

$$Y_{(20)} = \beta_0 + \beta_1 X_{(20)} + \epsilon_{(20)}.$$

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* for the set of predictor variables including an intercept term, 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.

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

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.

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

$$\hat{\epsilon} = Y - \hat{Y}$$

$$RSS = \hat{\epsilon}^T \hat{\epsilon}$$

```
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
```

```
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
```

```
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 (β) 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

$$Y_{(i)} = \beta_0 + \beta_1 X_{1(i)} + \beta_2 X_{2(i)} + \epsilon_{(i)}.$$

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:

```
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
```

```
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 relevant 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/main/readability.csv')
```

This dataset has 2834 rows and 1072 columns. Each row represents a reading passage. The last column is the readability score, the outcome variable to predict (**target**), and the first 1071 columns are 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 print
```

```
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 recipe

- assigns the last column (**target**) as outcome and everything else as predictors,
- 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 datasets. 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

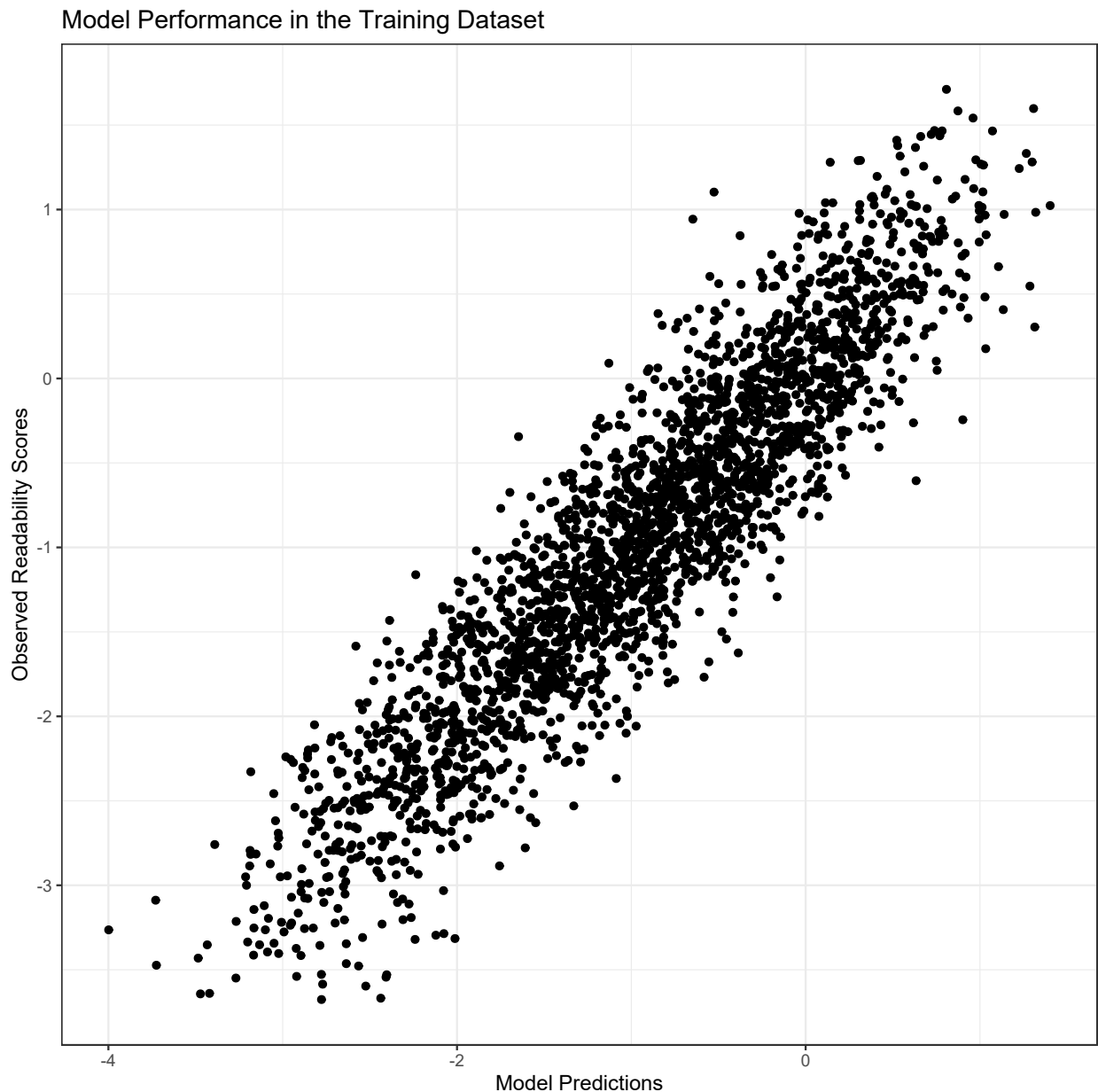
First, I will fit the model to the training dataset using all predictors in the dataset without any cross validation. Note that we will very likely overfit with more than 800 predictors and relatively small sample size.

```
mod <- lm(formula(baked_tr[,c(888,1:887)]), data=baked_tr)
summary(mod)$r.squared
```

```
[1] 0.8403438
```

```
predicted_tr <- predict(mod)

ggplot()+
  geom_point(aes(y=baked_tr$target,x=predicted_tr))+
  xlab('Model Predictions')+
  ylab('Observed Readability Scores')+
  theme_bw()+
  ggtitle('Model Performance in the Training Dataset')
```



In the training dataset, the model explains about 84% of the total variance in the outcome variable (WOW!). We can also calculate the MAE, MSE, and RMSE for the model predictions in the training dataset.

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

```
[1] 0.8403438
```

```
mae_tr <- mean(abs(baked_tr$target - predicted_tr))
mae_tr
```

```
[1] 0.3275843
```

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

```
[1] 0.1708515
```

```
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.

```
# first obtain the predictions according to the model for the observations
# in the test dataset
```

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

```
# Calculate the outcome metrics
```

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

```
[1] 0.6445438
```

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

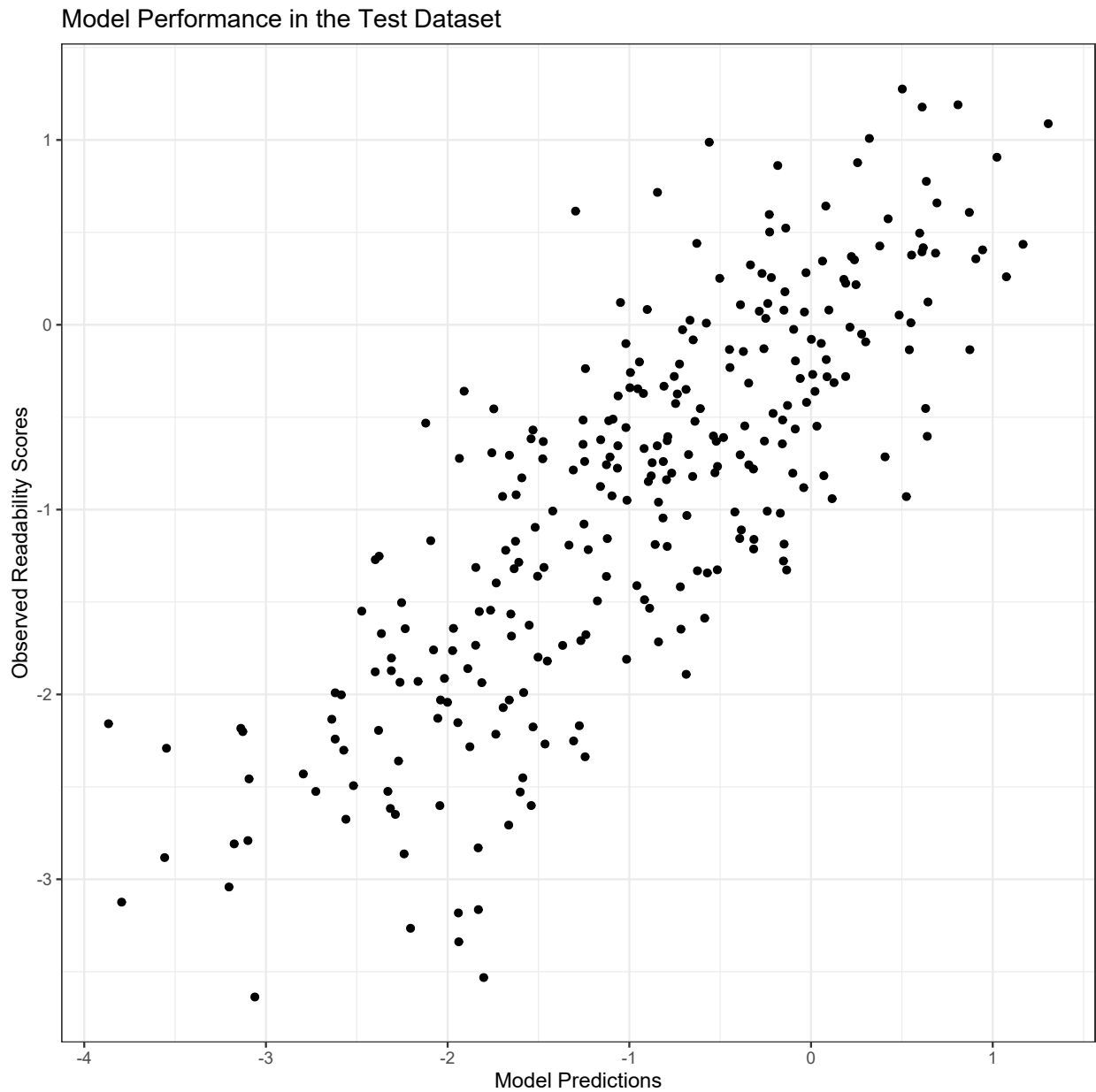
```
[1] 0.5217534
```

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

```
[1] 0.4152313
```

```
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 a classic 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 model for any future prediction, it is much better to consider the performance on the test data as it will be a more realistic picture of model performance.

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.

```
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()
mae <- c()
mse <- 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$target,pred)^2
  mse[i] <- mean(abs(data_te$target - pred))
  mse[i] <- mean((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
```

```
mean(rsq)
```

```
[1] 0.6233839
```



```
rmse
```

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

```
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 write your own code to conduct a 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, ]

# 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())
```

```

# ?getModelInfo()$lm

# 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: 2296, 2297, 2295, 2296, 2295, 2296, ...
Resampling results:

RMSE	Rsquared	MAE
0.6634752	0.6210505	0.5276424

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 can predict the outcome for the observations in the test dataset using
# the model

```

```

predicted_te <- predict(caret_mod, read_te)

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

```

```
[1] 0.6445438
```

```

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

```

```
[1] 0.5217534
```

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

```
[1] 0.4152313
```

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

```
[1] 0.6443844
```

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
```

```
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(feafreq(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

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	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
 PROPON 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
1	0.05771509	0.08124785	0.0312119	-0.01189761	0.005442077	0.02118172
	Dim292					
	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
1	-0.008202043	0.1182082	-0.504334	0.5523129	0.07487423	0.1484527
	Dim335					
	Dim336	Dim337	Dim338	Dim339	Dim340	Dim341
1	0.07115493	0.05266665	0.03712041	0.1231284	0.1140854	-0.09936048
	Dim342					
	Dim343	Dim344	Dim345	Dim346	Dim347	Dim348
1	0.01078093					
	Dim349					
1	-0.1328449	0.04264652	0.0278524	0.08925101	-0.01208034	-0.01879104
	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
1	Dim362					
	Dim363	Dim364	Dim365	Dim366	Dim367	Dim368
1	0.01463395	0.06802522	0.0190933	-0.02336735	-0.1009301	0.1280767
	Dim369	Dim370	Dim371	Dim372	Dim373	Dim374
1	0.07359837	-0.02260096	-0.008612545	-0.09422011	-0.02818615	0.0786788
	Dim375	Dim376	Dim377	Dim378	Dim379	Dim380
1	0.02272207	0.1002589	0.09570162	-0.04916206	0.004951689	0.005069547
	Dim381	Dim382	Dim383	Dim384	Dim385	Dim386
1	-0.01894144	-0.01217675	0.1045737	0.02512248	0.07700328	0.05863359
	Dim387	Dim388	Dim389	Dim390	Dim391	Dim392
1	-0.03486566	0.03618479	-0.03967949	0.03187413	0.1228099	0.004328088
	Dim393	Dim394	Dim395	Dim396	Dim397	Dim398
1	-0.05571836	-0.01382447	0.1014563	0.005540595	-0.002099469	0.04699913
	Dim399	Dim400	Dim401	Dim402	Dim403	Dim404
1	-0.02092642	-0.03988863	0.00658244	0.02015599	-0.01267892	-0.04250392
	Dim405	Dim406	Dim407	Dim408	Dim409	Dim410
1	0.03640548	-0.05950782	0.01229393	0.03474214	-0.003756263	0.07556196
	Dim411					
	Dim412	Dim413	Dim414	Dim415	Dim416	Dim417
1	-0.01581631	0.08982348	-0.119573	-0.01489228	0.0321744	0.01545453
	Dim418	Dim419	Dim420	Dim421	Dim422	Dim423
1	0.07060594	0.05067884	0.02162697	-0.007810039	-0.02777156	0.03783101
	Dim424	Dim425	Dim426	Dim427	Dim428	Dim429
1	-0.02935591	-0.008409697	-0.05037494	-0.08629285	0.04084516	-0.01418345
	Dim430					
	Dim431	Dim432	Dim433	Dim434	Dim435	Dim436
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
1	0.1278216	-0.0297847	0.01828551	0.01670286	0.03277786	0.09394352
	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
1	0.01635127	-0.05516074	0.07026093	0.01981271	0.1932934	0.06916854
	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
1	-0.0404612	-0.01502825	0.1068065	0.0599024	-0.0431066	0.03054362
	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
1	-0.09070309	0.08426145	0.01746497	0.0143929	0.1264933	0.05054398
	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
1	0.01929063	0.05036947	0.08373432	0.03119808	-0.02472931	10.40989
	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 938 variables. On the other hand, the original data we 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 happened 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 when we create features from 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 doesn't have a defined role in the recipe.

Try the following code and it should give an error message

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

So, we have to do a little bit of work to make sure the new dataset have all the features the model expects.

```

# feature names from the model

my_feats <- caret_mod$recipe$var_info$variable

# 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"	"lgVO"	"lgeVO"
[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"	"FORECAST"	"FORECAST.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"
[172]	"Dim2"	"Dim3"	"Dim4"
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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"	"VEN"	"WDT"
[13]	"WRB"	"acl.relcl"	"advcl"
[16]	"aux.pass"	"compound"	"mark"
[19]	"nsubj.pass"	"nummod"	"obl.npmmod"
[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)

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	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
1	0.01958121	0.03001023	-0.05471453	0.116444	0.03110751	0.008461111
	Dim18	Dim19	Dim20	Dim21	Dim22	Dim23
1	-0.00477997	-0.02568062	-0.07733209	0.03547738	-0.04466225	-0.02642173
	Dim24	Dim25	Dim26	Dim27	Dim28	Dim29
1	-0.01528819	0.01880905	-0.004117077	0.05099677	0.03213615	-0.03850309
	Dim30	Dim31	Dim32	Dim33	Dim34	Dim35
1	-0.01875267	-0.07710975	0.03183111	-0.03924842	-0.004964702	0.03409737
	Dim36	Dim37	Dim38	Dim39	Dim40	Dim41
1	0.04975318	0.01937219	0.0306441	0.03343704	-0.1781216	-0.1211262
	Dim42	Dim43	Dim44	Dim45	Dim46	Dim47
1	-0.03983452	0.04327423	0.004913424	-0.06031298	-0.02003438	0.02600088
	Dim48	Dim49	Dim50	Dim51	Dim52	Dim53
1	-0.03458053	0.04176696	0.06956099	0.02811206	0.01539411	-0.0369029
	Dim54	Dim55	Dim56	Dim57	Dim58	Dim59
1	0.01336424	0.1464066	0.04301799	0.01624574	-0.03928176	0.1635819
	Dim60	Dim61	Dim62	Dim63	Dim64	Dim65
1	-0.020654	0.01870028	-0.04506872	0.03214189	0.03903029	0.02988067
	Dim66	Dim67	Dim68	Dim69	Dim70	Dim71
1	0.05666397	-0.09702756	0.04471388	-0.01197373	0.01947797	0.01181384
	Dim72	Dim73	Dim74	Dim75	Dim76	Dim77
1	0.04100754	-3.755487	-0.04728175	0.06669956	0.06208374	-0.08338602
	Dim78	Dim79	Dim80	Dim81	Dim82	Dim83
1	0.03297196	-0.02081768	-0.1150639	0.02672025	0.00498704	-0.004569397
	Dim84	Dim85	Dim86	Dim87	Dim88	Dim89
1	0.03231616	0.01925556	-0.001559907	-0.0210035	0.1013899	0.02498922
	Dim90	Dim91	Dim92	Dim93	Dim94	Dim95
1	-0.01513632	0.4909967	-0.0013363	-0.04504698	0.01951685	-0.01925687
	Dim96	Dim97	Dim98	Dim99	Dim100	Dim101
1	0.08075197	-0.07083284	0.07294671	0.01257747	-0.04483311	0.05056348
	Dim102	Dim103	Dim104	Dim105	Dim106	Dim107
1	-0.008657346	-0.02187181	-0.0347401	0.06893411	-0.02378071	-0.01619653
	Dim108	Dim109	Dim110	Dim111	Dim112	Dim113
1	0.017487	-0.01827984	0.03730945	0.04513853	0.1384863	-0.03498841
	Dim114	Dim115	Dim116	Dim117	Dim118	Dim119
1	0.02513112	0.01840405	-0.0540553	0.02714446	-0.005429095	-0.04092931
	Dim120	Dim121	Dim122	Dim123	Dim124	Dim125
1	-0.02057803	0.01787887	-0.0277407	-0.3037597	0.01324851	0.02754409
	Dim126	Dim127	Dim128	Dim129	Dim130	Dim131
1	-0.02268834	0.05471192	0.0194234	0.001750701	-0.01453351	0.02751146
	Dim132	Dim133	Dim134	Dim135	Dim136	Dim137
1	0.06153563	-0.02328374	0.01968463	0.162699	0.07096836	-0.03563375
	Dim138	Dim139	Dim140	Dim141	Dim142	Dim143
1	0.03794007	0.06643526	0.06518798	-0.06979158	-0.01212464	0.00008351834
	Dim144	Dim145	Dim146	Dim147	Dim148	Dim149
	Dim150	Dim151	Dim152	Dim153	Dim154	

	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	NUM	PART	SCONJ	X.
1	0.03987939	-0.03054548	0.02145188	0	0	0	0
	CD	HYPH	MD	TO	VB	VBD	VCN
1	0	0	0	0	0	0	0
	WDT	WRB	acl	relcl	advcl	aux	pass
1	0	0	0	0	0	0	0
	compound	mark	nsubj	pass	nummod	obl	npmod
1	0	0	0	0	0	0	0
	xcomp	morph_case_Acc	morph_gender_Neut	morph_numtype_Card	morph_prontype_Rel		
1	0	0	0	0	0	0	0
	morph_tense_Past	morph_verbform_Ger	morph_verbform_Inf	morph_voice_Pass	X..		
1	0	0	0	0	0	0	0
	X...1	PRP.	RP	VBP	acl	ccomp	compound.prt
1	0	0	0	0	0	0	0
	flat	nmod	poss	parataxis			
1	0	0	0	0	0	0	0
	morph_gender_Fem	morph_person_1	morph_person_2	morph_reflex_Yes	PDT		
1	0	0	0	0	0	0	0
	det	predet	morph_mood_Imp	obl	tmod	EX	expl
1	0	0	0	0	0	0	0
	POS	fixed	RBR	morph_degree_Cmp	JJS		
1	0	0	0	0	0	0	0
	morph_degree_Sup	JJR	target				
1	0	0	0				

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  
  
  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(feafreq(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

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(feats_vec)),
               as.data.frame(embds$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)

predict(caret_mod, my.inputs2$input)

[1] -0.1224886
```

Feature Redundancy, Multicollinearity, and Variable Selection

There are a number of things to consider when we wit a standard multiple regression mode with many predictors. In our example above, we have a model with 887 predictors. The large number of predictors unnecessarily increases the complexity of model, and potentially increase model variance. So, it is a typical case of overfitting. This reduces the usefulness of the model as it is less likely for the model to provide good predictions for another dataset. When there are so many predictors in the regression model, it is important to check whether or not there are redundant features and quantify the degree of redundancy. Too many redundant features may also create computational issues due to singular or near-singular design matrix. In this section, we will first try to understand what feature redundancy is, then we will try to quantify it. At the end, we will present some potential solutions and remedial strategies to deal with highly complex models with so many predictors.

First, let's do a small example. Suppose we have a model with four predictors to predict the readability score. Our predictors are **number of sentences** (sents, X1), **average word length** (mean_wl, X2), **number of finite verbs** (morph_verbform_Fin, X3), and **78th dimension of word embeddings** (Dim78). First, let's do a quick check on the correlation matrix of these four predictors.

```
cor(readability[,c('sents', 'mean.wl', 'morph_verbform_Fin', 'Dim78')])
```

	sents	mean.wl	morph_verbform_Fin	Dim78
sents	1.0000000	-0.2304859	0.6559804	0.8248184
mean.wl	-0.2304859	1.0000000	-0.5387486	-0.3425791
morph_verbform_Fin	0.6559804	-0.5387486	1.0000000	0.5610935
Dim78	0.8248184	-0.3425791	0.5610935	1.0000000

You should notice there is relatively higher correlations among three predictors: number of sentences, number of finite verbs, and Dim78. It is possible that some of the information in any one of these variables is redundant because the same amount of information also exist in other two variables. In order to measure this, we will define a term called **tolerance**.

Tolerance: the amount of variance that is unique to a the predictor that can not be explained by the rest of the predictors.

In other words, if we fit a model such that the **number of sentences** is the outcome and other three variables are predictors and find the value of R^2 , and then substract the R^2 from 1, that would give us a measure of unique variance in the **number of sentences** that couldn't be explained by other three predictors. Let's find the tolerance value for the **number of sentences**.

```
tol_sents <- lm(sents ~ 1 + mean.wl + morph_verbform_Fin + Dim78,
               data=readability)

summary(tol_sents)
```

Call:

```
lm(formula = sents ~ 1 + mean.wl + morph_verbform_Fin + Dim78,
    data = readability)
```

Residuals:

Min	1Q	Median	3Q	Max
-12.8402	-1.3640	-0.0144	1.3324	18.4418

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	33.872841	0.922890	36.70	<0.0000000000000002 ***
mean.wl	2.176754	0.111025	19.61	<0.0000000000000002 ***
morph_verbform_Fin	0.306746	0.009665	31.74	<0.0000000000000002 ***
Dim78	6.428289	0.104052	61.78	<0.0000000000000002 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.204 on 2830 degrees of freedom

Multiple R-squared: 0.7665, Adjusted R-squared: 0.7663

F-statistic: 3097 on 3 and 2830 DF, p-value: < 0.00000000000000022

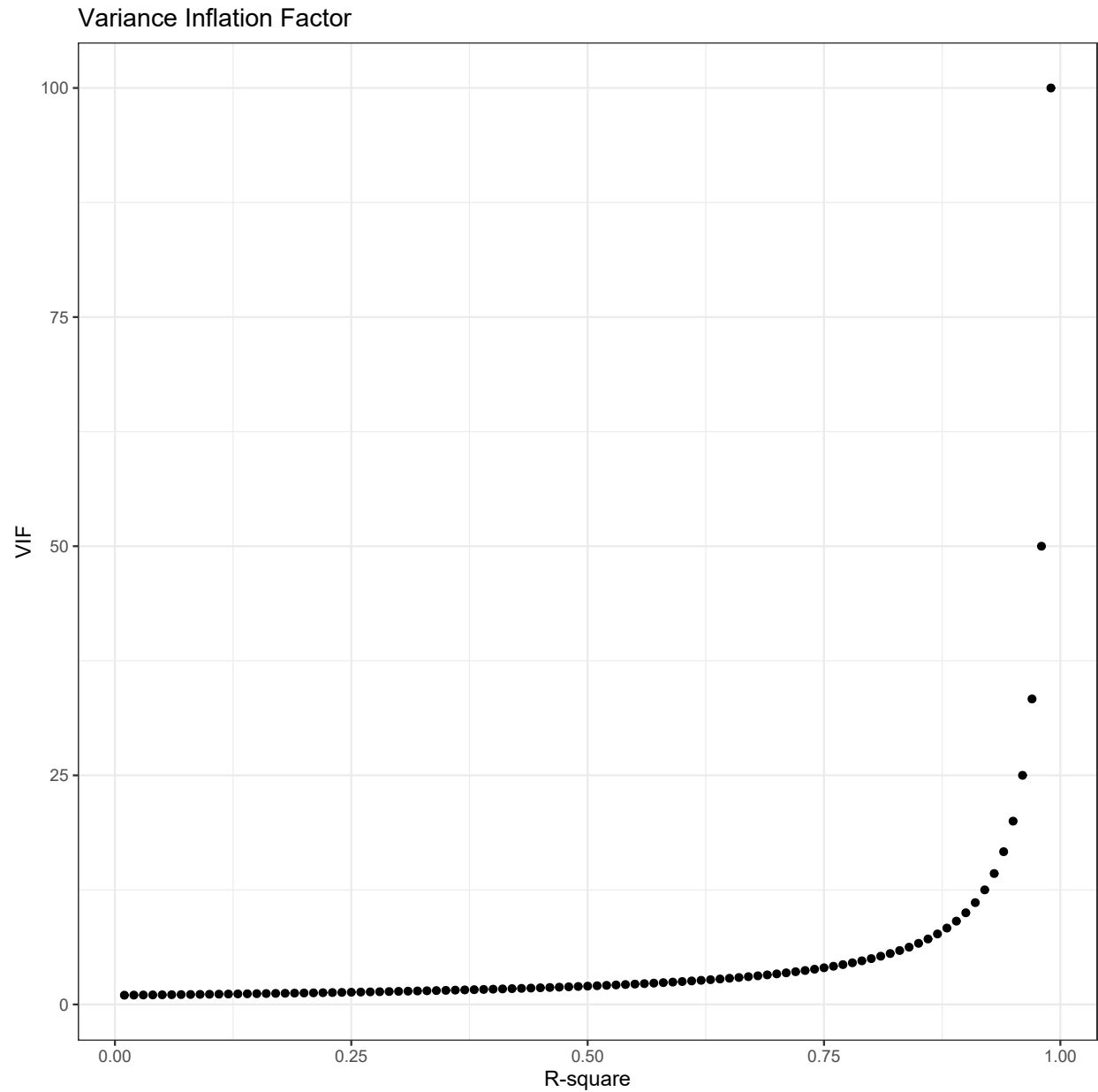
```
summary(tol_sents)$r.squared
```

```
[1] 0.7665061
```

This indicates that about 76.65% of the variance in the **number of sentences** can be explained by the other three predictors. Therefore, only 23.35% of the variance in the **number of sentences** is unique. In other words, whatever the information is stored in the **number of sentences**, 76.65% of that information is also shared by other three predictors, or redundant. So, the tolerance value for the **number of sentences** is 0.2335 (1-0.7665).

When tolerance is 0 or close to zero (when almost all of the variance in one predictor can be explained by other predictors), this is also known as **singularity**. In those situations, the least square solution is not unique, and most software will give you some sort of an error message about that.

The inverse of tolerance is known as something called **Variance Inflation Factor (VIF)**. For instance, VIF for the **number of sentences** would be 4.283 (1/0.2335). VIF can be considered as a measure of redundancy for a predictor in a model. Below is a plot showing VIF for a predictor as a function of variance in the predictor explained by remaining predictors in the model.



If we go back to our example, suppose we have a model with four predictors as mentioned before. The `vif()` function from the `car` package provides a simple and quick way of calculating VIF values for all the predictors in the model.

```
mod_ex <- lm(target ~ 1 + sentis + mean.wl + morph_verbform_Fin + Dim78,
             data=readability)

require(car)

vif(mod_ex)
```

sents	mean.wl	morph_verbform_Fin	Dim78
4.282767	1.605680	2.469260	3.439327

A VIF value indicates the degree of instability (sampling variance) for any regression coefficient. For instance, a VIF value of 4.283 for variable **sents** indicates that the standard error of the regression coefficient associated by this variable is 2.07 ($\sqrt{4.283}$) times larger than what it would be if this variable were uncorrelated with other three predictors in the model. This is important as the larger sampling variance for regression coefficients yield larger sampling variance of model predicted values. So, we don't like including variables with large VIF values in our models as they contribute to the model variance. There are arbitrary cut-off values for VIF depending on what textbook you read ($VIF < 4$ or $VIF < 10$).

Let's see the range of VIF values in our model with 887 predictors.

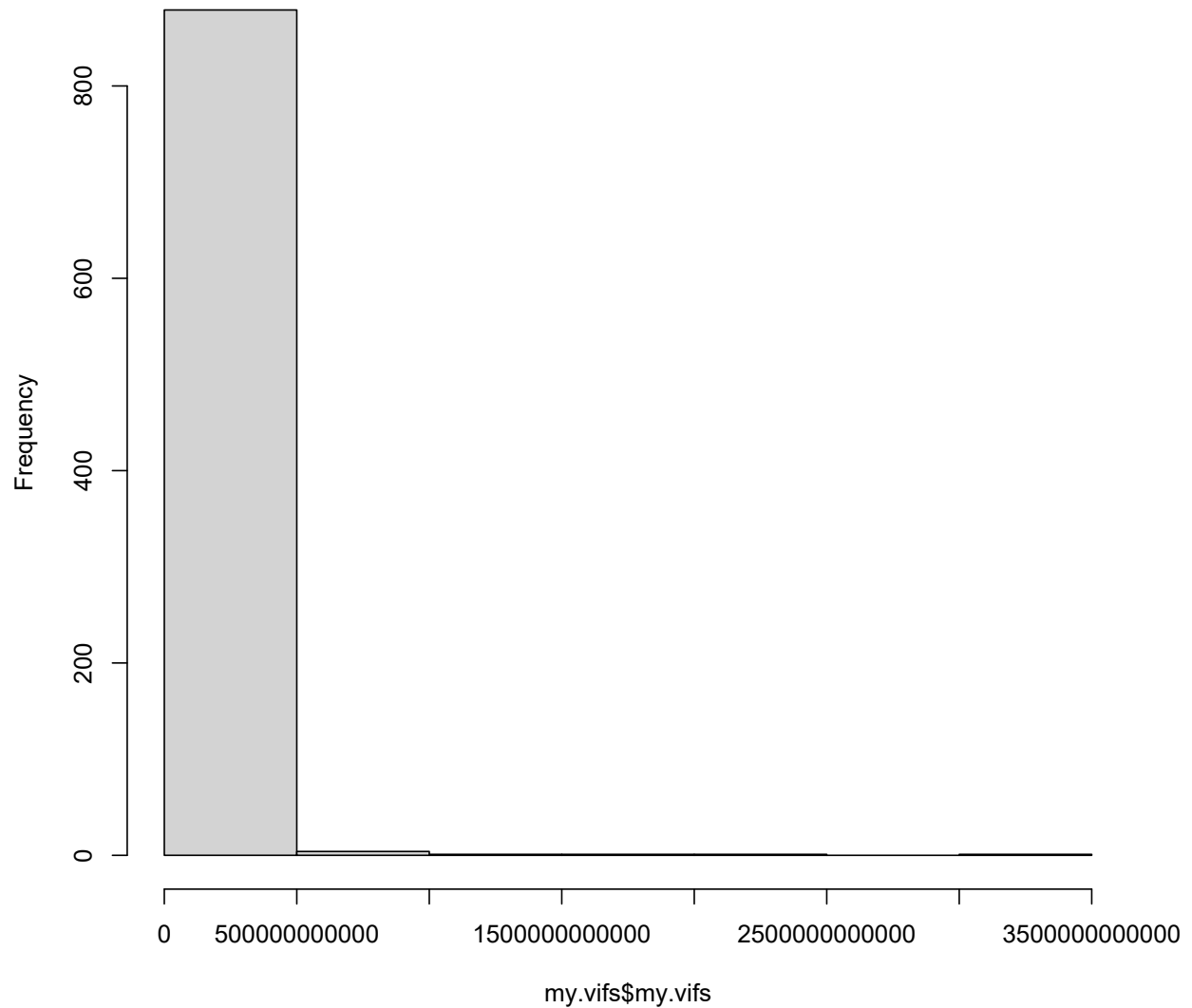
```
my.vifs <- read.csv('https://raw.githubusercontent.com/uo-datasci-specialization/c4-ml-fall-2021/main/d
require(psych)

describe(my.vifs$my.vifs)
```

	vars	n	mean	sd	median	trimmed	mad	min
X1	1	887	44372035413	159833144573	24738324617	26982945999	13415325381	1.63
			max	range	skew	kurtosis		se
X1	3342188962798	3342188962797	14.89	260.73	5366671766			

```
hist(my.vifs$my.vifs)
```

Histogram of my.vifs\$my.vifs



The variables with the 10 smallest variables

```
head(my.vifs[order(my.vifs$my.vifs),],10)
```

	X	my.vifs
867	parataxis	1.632100
882	POS	1.665525
877	morph_mood_Imp	1.725523
878	obl.tmod	1.805388
871	morph_reflex_Yes	1.894897
68	obl.npmod	1.965650
886	JJS	1.970530
880	WP	1.983349


```
884          RBR 2.010719
883      fixed 2.037255
```

```
# The variables with the 10 highest variables
```

```
head(my.vifs[order(my.vifs$my.vifs,decreasing=TRUE),],10)
```

```
      X      my.vifs
419 Dim331 3342188962798
166 Dim78 2297168899449
542 Dim454 1609578137016
186 Dim98 1206914009747
583 Dim495 886448110889
306 Dim218 599361142849
838 Dim750 564573101087
640 Dim552 556343375833
677 Dim589 458731818423
820 Dim732 412682088094
```

We clearly have problems in our model. It seems that there are so many redundant variables in our model that doesn't bring unique information when other variables are accounted in the model. That's also the main reason why our model didn't perform in the test dataset as well as it performed in the training dataset. All these redundant variables in the model contributed to the model variance.

There are a few approached to address this issue:

- **Data reduction:** Data reduction techniques such as Principal Component Analysis (PCA) is an approach to find highly correlated variables and combine the information in these variables in new composite variables. For instance, in its most naive form, suppose Variable 1, Variable 2, Variable 3, and Variable 4 are highly correlated. We can create a new composite variable by taking the sum or mean of these four variables, and use the new composite variable in our model as predictor instead of using all four variables. PCA is a little more detailed version of this process where we first estimate a weight for each variable, and create a weighted sum of these variables as a composite variable. We can decide the number of composites needed to represent the information in all variables, and reduce the number of variables in the model by finding clusters of highly correlated variables and creating a single composite variable for them. Since PCA is a technique on its own and probably requires a few lectures, we will not get into the details of that.
- **Variable selection:** Variable selection algorithms such as forward selection, backward elimination, or stepwise regression, or best subset are well known and taught in traditional statistics courses. These algorithms use certain model fit criteria (e.g., Mallows' C_p statistic, AIC, BIC) to eliminate variables with the least information and come up with a simpler model. With very large number of variables, these algorithms can be computationally exhaustive and an efficient search for the best simplest model with adequate predictive power may not even be possible. In other words, there is no guarantee for an optimal solution with these approached when you have hundreds of potential predictors in the model.
- **Regularization:** Regularization is adding penalty terms to avoid large coefficients and a trick to trade bias with variance when fitting a model. Some specific types of regularization (e.g., lasso) may indeed behave like a natural feature selection algorithm. They may produce simpler and more interpretable model.

In the following lecture, we will talk about different types of regularizations to apply while fitting a regression model and we will try to improve the performance of our unnecessarily complex linear regression model discussed above.