Studying the Impact of Job Descriptions on Data Science Salaries

Team Humilty

CHLOE NEO TZE CHING ENG JING KEAT GOH WEI LUN GLENN
KANEKO YOSHIKI TAN WEI KEONG

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Abstract

In this project, we aim to uncover key insights in data science salaries by comparing models that effectively associate keywords in job descriptions to high paying data science roles. The data is cleaned by preparing job description text for analysis, and filtering the keywords in job descriptions with a minimum occurrence of 40. Least Absolute Shrinkage and Selection Operator (LASSO) is then applied to select the most important variables to be used in three of the models. The models used are Multiple Linear Regression (MLR), Random Forest, XGBoost, Multivariate Adaptive Regression Splines (MARS), and Partial Least Squares (PLS), where their performances will be assessed in relation to one another. Across all models, MLR has the lowest Root Mean Square Error (RMSE) of 16.2. In other words, MLR is the best model that accurately predicts salary, and we identified keywords used in this model.

Contents

1 Introduction to the problem

1.1 Literature review

A rapid shift towards digitalisation of businesses has radically changed the employment landscape in Singapore, which means Singaporeans need to keep up with the changes if they wish to stay competitive at work (My Skills Future, 2021). Employers in Singapore are starting to place an emphasis on skills rather than education (Tan, 2021). New hires today are assessed not just by their qualifications and work history, but also by their soft skills as there are a variety of soft skills in demand (The Straits Times, 2021).

According to a new report by Instant Offices, 73% of Singaporean workers are dissatisfied with their jobs (Arora, 2022). When asked if they planned to change jobs over the following six months, 31% of respondents responded "yes" (Chong, 2022). Millions of workers worldwide are no longer willing to return home with just a fair paycheck. They prefer to know how well they are progressing towards a meaningful career, which is a wellness, freedom, security, and experience at work, so as to achieve job satisfaction. As a result, job seekers should take all these factors into consideration when applying for a job.

These factors can be further broken down into keywords in job descriptions. Keywords are crucial to job adverts because they allow job seekers to narrow their search related to a role, skill, or industry for suitable employment (Alexander, 2019). Suitable individuals are more likely to find the job post when hirers and recruiters add key terms and phrases that are relevant to a particular role. This increases the percentage of successfully matching job seekers with their ideal jobs.

1.2 Objective

As most employers will be impressed when they notice that the resume is customised, highlighting relevant skills and using certain keywords suited to that particular company or position, job seekers can use these findings to narrow down their job search based on their own preferences such as salary range or skills set. As such, this project aims to predict data science salary based on the keywords in job descriptions.

2 Dataset

Dataset: https://www.kaggle.com/datasets/nikhilbhathi/data-scientist-salary-us-glassdoor

2.1 Description of dataset

Import relevant libraries:

Below is a sample of our dataset:

Table 1: A sample of our dataset.

Avg.Salary.K.	company_txt	Job.Location	Age	Python	spark
72.0	Tecolote Research	NM	48	1	0
87.5	University of Maryland Medical System	MD	37	1	0
85.0	KnowBe4	FL	11	1	1
76.5	PNNL	WA	56	1	0
114.5	Affinity Solutions	NY	23	1	0
95.0	CyrusOne	TX	21	1	0

This dataset has 41 variables, consisting of numerical, categorical, and text. Some variables are derivations from others, and as such we will not be using all 41 variables.

2.2 Exploratory data analysis

2.2.1 Data cleaning

Note: the dataset downloaded has already been cleaned by the owner, but we will do some additional cleaning and data preparation so that it is suited for our needs.

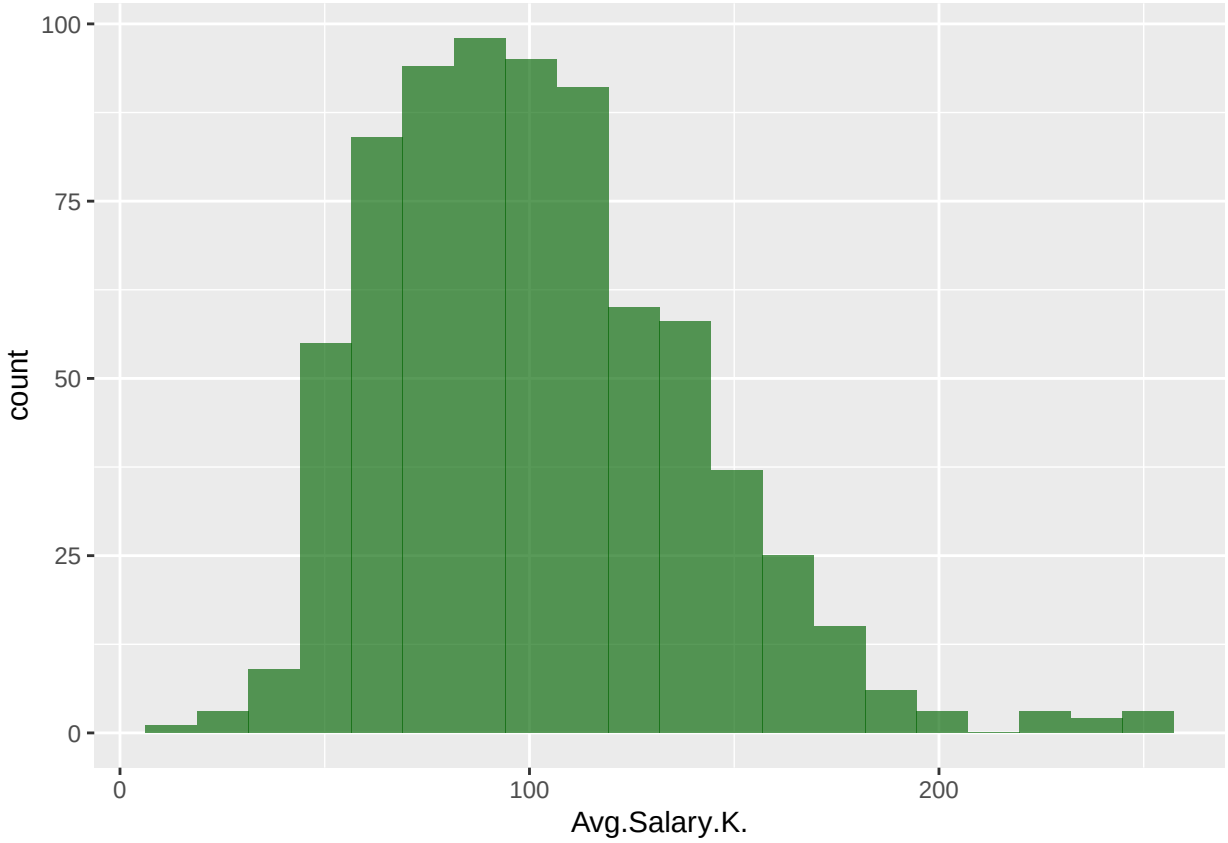
- Removing "\n" from job descriptions, cleaning job descriptions text, and creating a new variable to store lengths of job description texts:

2.2.2 Feature selection

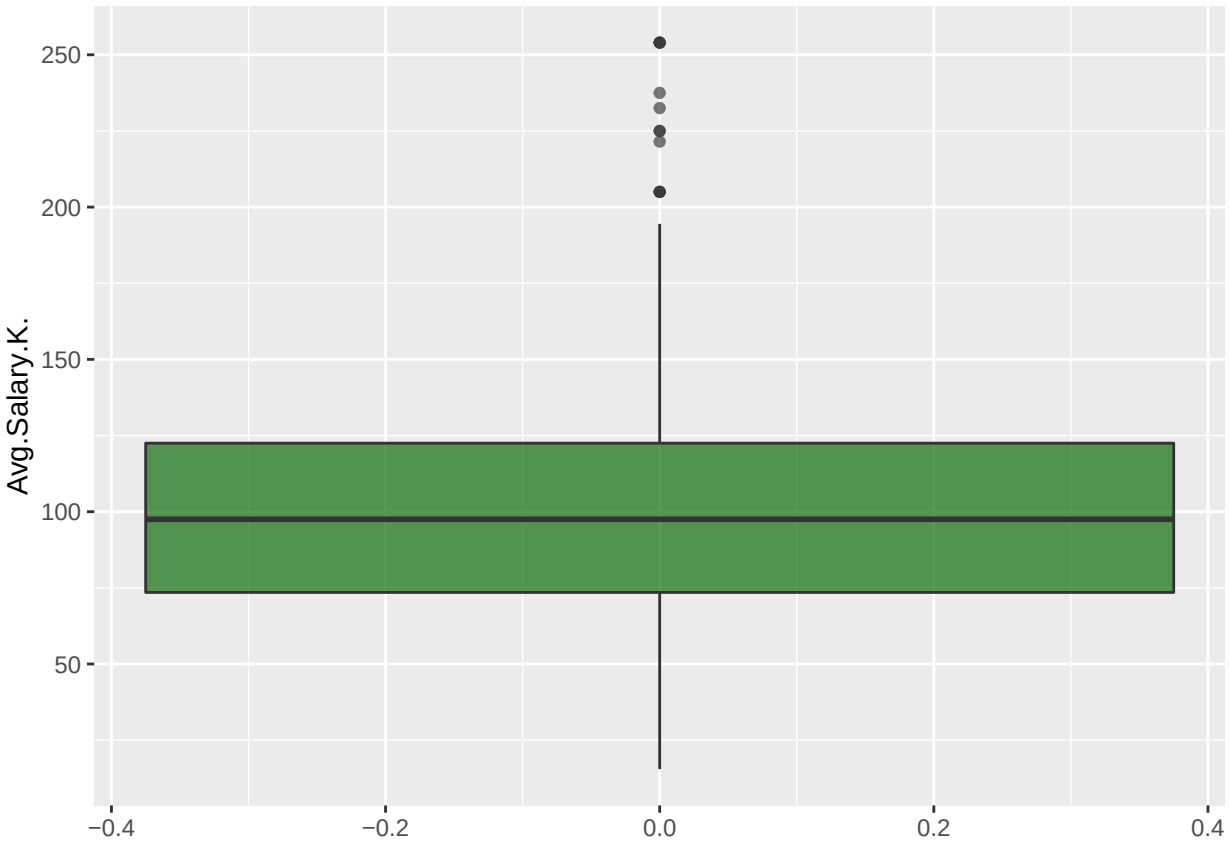
Our project's focus is on job descriptions and their relationship with data science salaries. As such, we will only keep these two variables

2.2.3 Data visualizations

1. Histograms of average salaries in thousands:



2. Boxplots of average salaries:



3. Word cloud for job descriptions:

We visualise the job descriptions with a word cloud after removal of words whose total frequency is below 40, and stopwords such as “the”, “he” etc. as these are common words that do not store any informational value in our analysis.

We set the minimum occurrence of words to 40, and show the 100 most common words above.

2.2.4 Feature engineering

Next we create a document-term matrix for our job descriptions, setting minimum word frequency to 40.

```
Setting minimum word frequency to 40, we retain 1306 words out of the original 10314 words.
Our document-term matrix consists of 742 job descriptions against 1238 words present in our vocab after
```

Next, we create a new dataframe for our DTM.

Table 2: A sample of our DTM.

Y_salary	000	100	2020	401
72.0	0	1	0	0
87.5	0	0	0	0
85.0	0	0	0	0
76.5	0	0	2	0
114.5	0	0	0	0
95.0	0	0	0	0

3 Modelling

3.1 Feature selection using LASSO

We will use LASSO regularization to select features to prepare our data for three of our models: Multiple LInear Regression, Random Forest, and XGBoost. The last two models use their own methods of feature selection, so we will not use features selected by LASSO for those two models, but the entire dataset instead.

The LASSO procedure is as follows:

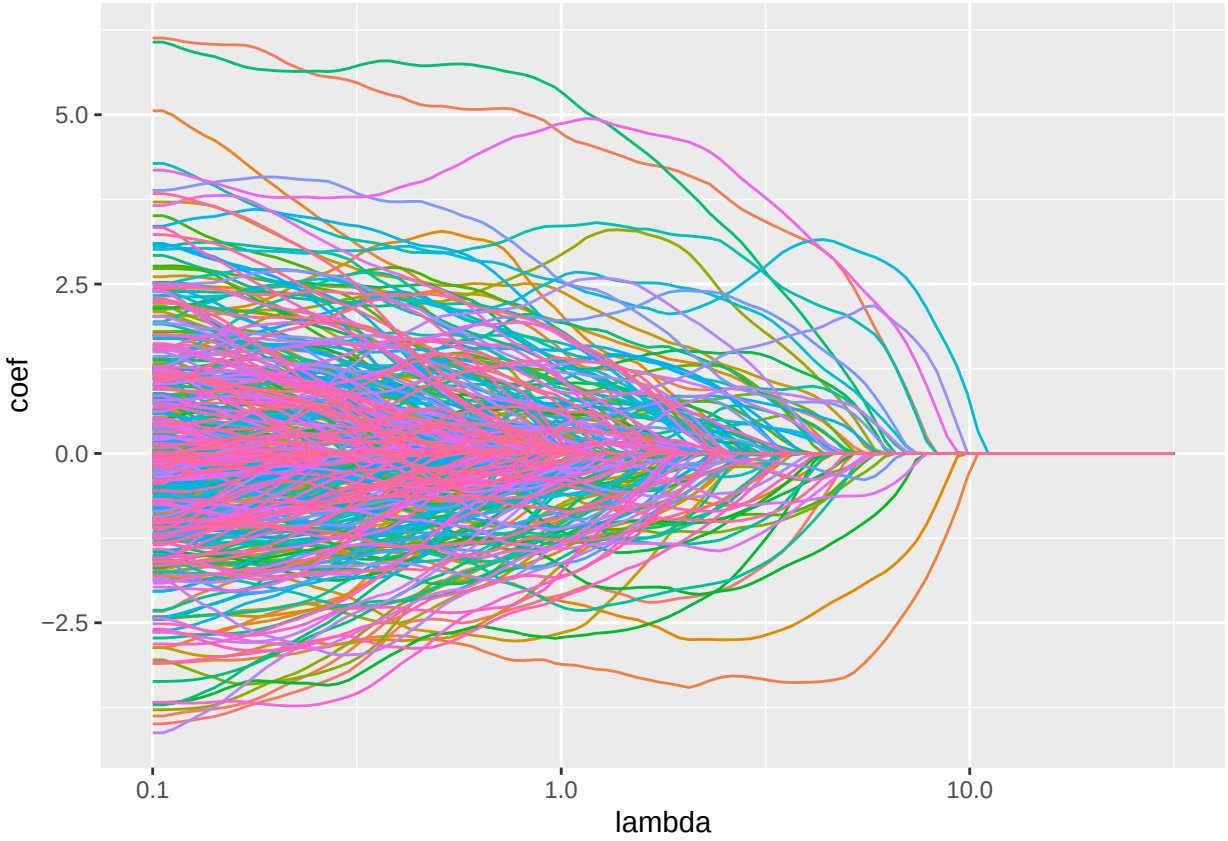
- We will try the following values of lambda for our LASSO regularization:

x
0.1000000
0.1291550
0.1668101
0.2154435
0.2782559
0.3593814
0.4641589
0.5994843
0.7742637
1.0000000

- Below we train our LASSO:

```
glmnet

 742 samples
1238 predictors

Pre-processing: centered (1238), scaled (1238)
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 668, 668, 666, 668, 669, 668, ...
Resampling results across tuning parameters:

  lambda     RMSE      Rsquared   MAE
  0.1000000  24.66909  0.6063107  13.82706
  0.1291550  24.53151  0.6058293  14.03125
  0.1668101  24.14206  0.6087953  14.26960
  0.2154435  23.72767  0.6121538  14.48610
  0.2782559  23.45697  0.6115914  14.90976
  0.3593814  23.43562  0.6065680  15.45128
  0.4641589  23.45016  0.6017484  16.05547
  0.5994843  23.82772  0.5869512  16.88018
  0.7742637  24.42560  0.5667097  17.74360
  1.0000000  24.97889  0.5501730  18.56066

Tuning parameter 'alpha' was held constant at a value of 1
RMSE was used to select the optimal model using the smallest value.
The final values used for the model were alpha = 1 and lambda = 0.3593814.
```

- Let us plot coefficients of LASSO.



- Now we store our variables selected by LASSO.
- Finally we prepare our final dataset to be used for our models.

Table 4: A sample of our final dataset.

Y_salary	2020	401k	academic	accordance	accountable
72.0	0	0	0	0	0
87.5	0	0	0	0	0
85.0	0	0	0	0	0
76.5	2	0	0	0	0
114.5	0	0	0	0	0
95.0	0	0	0	1	0

- Now we can prepare our training and test data for MLR, Random Forest, and XGBoost:

```
Dimensions of the training set are 585 355
Dimensions of the test set are 157 355
```

3.2 Models

3.2.1 Multiple Linear Regression

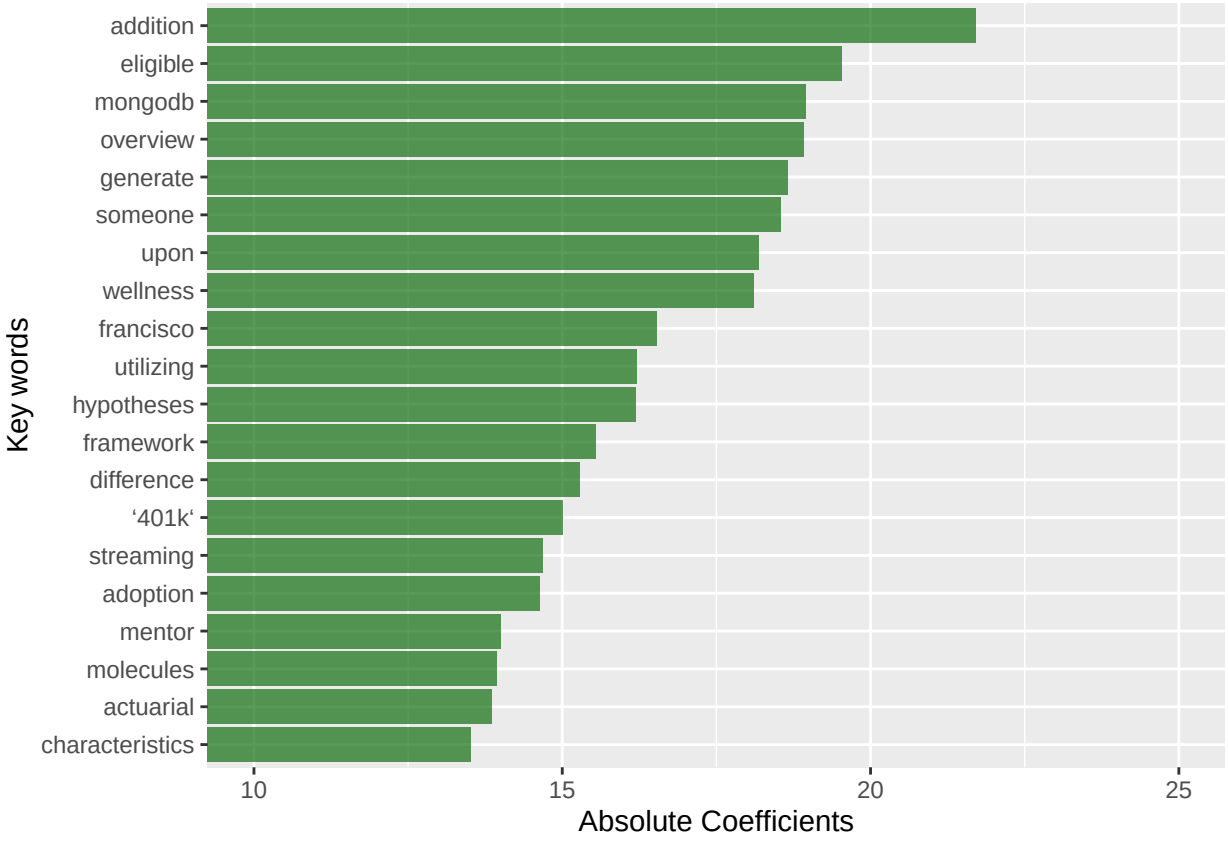
The first model we use is Multiple Linear Regression, using the 354 features selected by LASSO.

```
[1] 16.20561
```

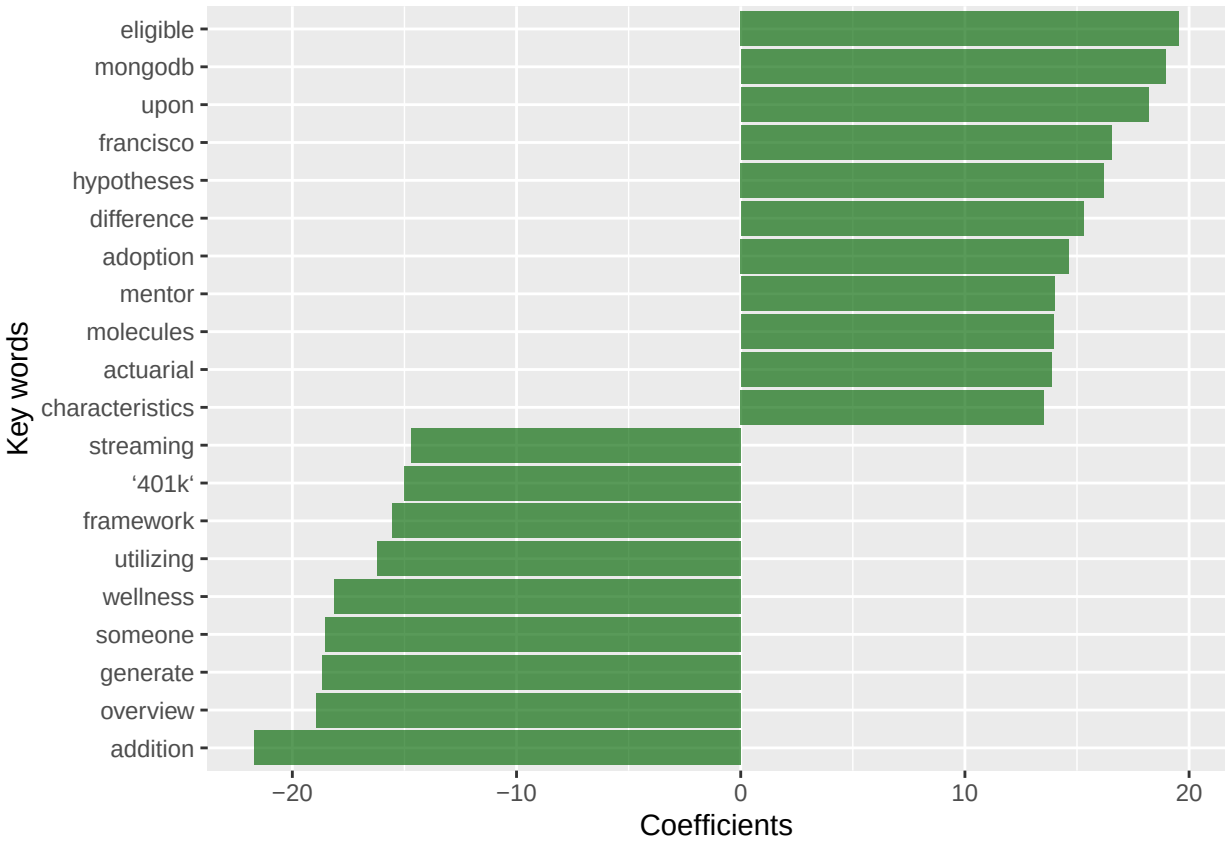
```
[1] 9.322398
```

Our MLR model's RMSE value is 16.20561, the lowest we will achieve in this project.

Below is a bar plot of the top 20 variables with the highest absolute coefficients.



Below is a bar plot of the top 20 variables with the highest absolute coefficients, but this time we reflect their relationship with salary as well.


eligible
mongodb
upon
francisco
hypotheses
difference
adoption
mentor
molecules
actuarial
characteristics
streaming
‘401k‘
framework
utilizing
wellness
someone
generate
overview
addition
Key words
−20
−10
0
10
20
Coefficients

3.2.2 Random Forest

The next step is to visualize our data using decision trees. Nevertheless, decision trees alone have a significant variance, which can make the trees trained on various datasets appear quite distinct from one another. Random forest was chosen over a bagged ensemble as there may be one or more really powerful predictors in our dataset, preventing other predictors from having a chance to be included. As a result, the predictions made by the trees will be strongly correlated and increasing the number of trees will not make the variance smaller Therefore, in order to lower the variance, we shall propose an ensemble technique.

We performed grid search with oob (out-of-bag error) while tuning the random forest to select the optimal values of the hyper-parameters try (number of variables) and min.node.size (minimal node size):

```
Random Forest

742 samples
354 predictors

No pre-processing
Resampling results across tuning parameters:

  mtry  splitrule   RMSE      Rsquared   MAE
    2   variance    24.92236  0.6605524  19.00513
    2   extratrees  25.83328  0.6527147  19.55866
  178   variance    19.34587  0.7448974  12.79872
  178   extratrees  19.05394  0.7682580  12.74025
  354   variance    19.84433  0.7306848  12.93958
  354   extratrees  19.35498  0.7467929  12.54374

Tuning parameter 'min.node.size' was held constant at a value of 5
RMSE was used to select the optimal model using the smallest value.
The final values used for the model were mtry = 178, splitrule = extratrees
 and min.node.size = 5.
```

The optimal values of the hyper-parameters are:

	mtry	splitrule	min.node.size
5	178	extratrees	5

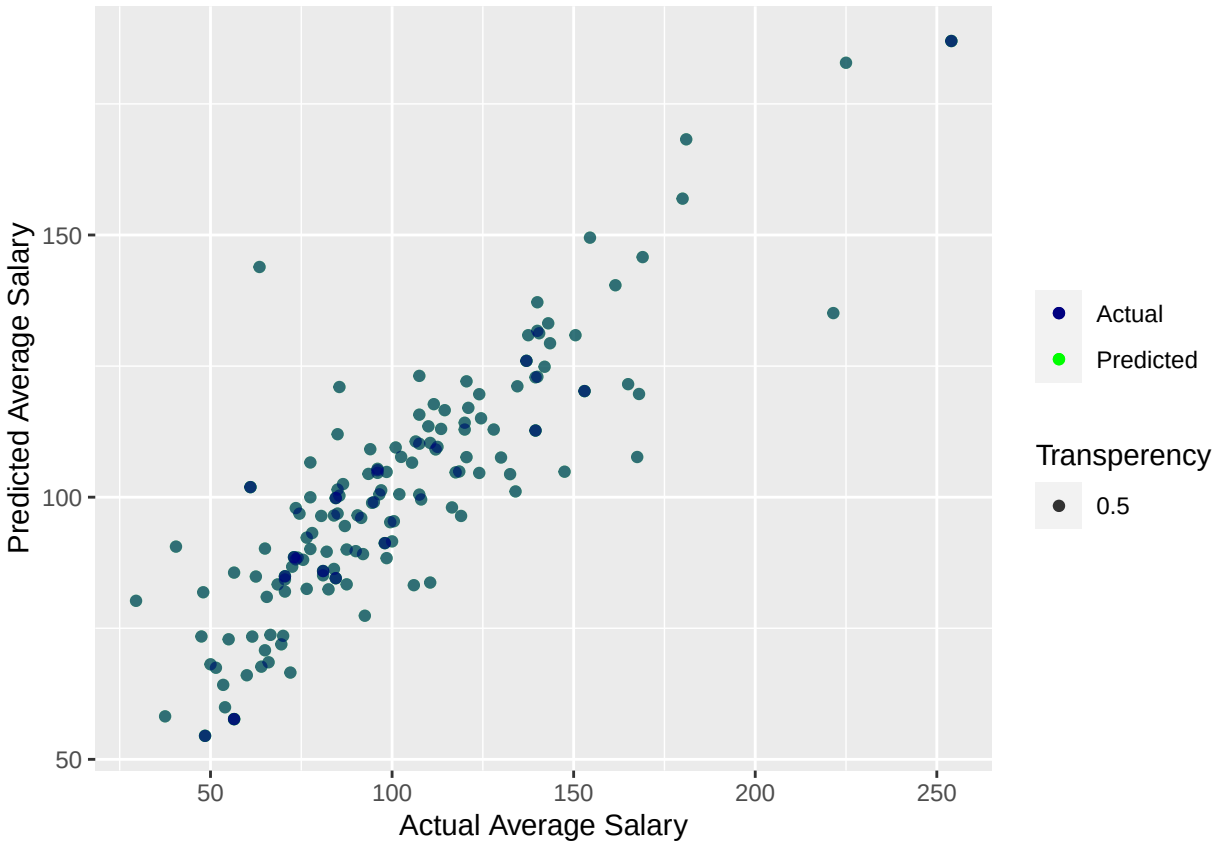
Now, we retrain the model with the selected hyperparameters.

Next, we perform random forest on the train data set

Table 6: A sample of our prediction results.

Y_salary	2020	401k	academic	accordance	accountable
73.5	0	0	0	0	0
85.0	0	0	0	0	0
47.5	1	0	0	0	0
96.0	0	0	0	0	0
121.0	0	0	0	0	0
106.0	0	0	0	0	0

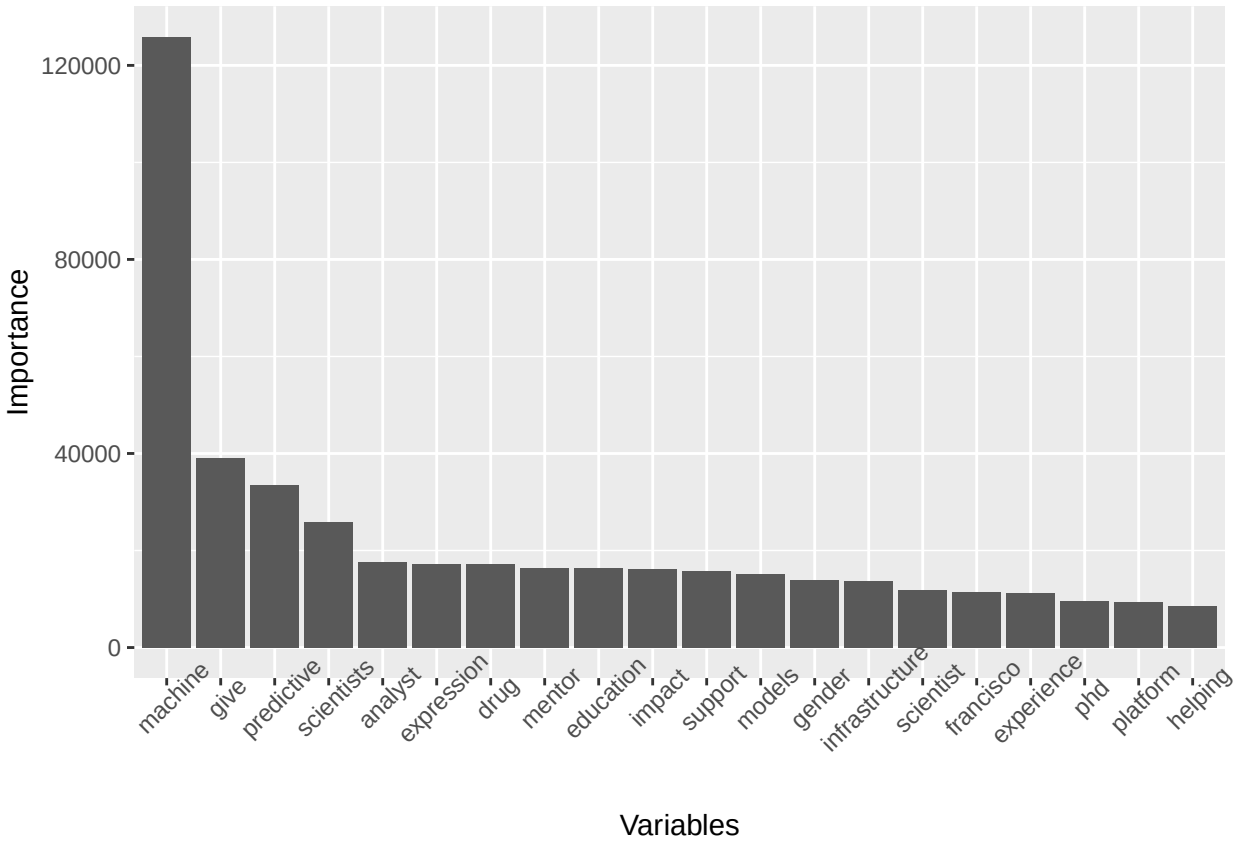
The graph below shows the data between Actual Average Salary vs. Predicted Average Salary




```
[1] "MAE: 15.391010829841"
```

```
[1] "RMSE: 21.5882240809054"
```

The bar graph below shows the top 20 most important variables in this prediction. Based on the bar graph, the top 5 most important variables are “machine”, “give”, “expression”, “predictive”, and “groups”.


Importance
120000
80000
40000
0
machine
give
predictive
scientists
analyst
expression
drug
mentor
education
impact
support
models
gender
infrastructure
scientist
francisco
experience
phd
platform
helping
Variables

3.2.3 XGBoost

Like random forests, gradient boosting machines does classification based on decision trees. However, while random forest builds an ensemble of deep (i.e complex) trees that are independent of one another, gradient boosting machines build shallow trees sequentially, where each tree learns and improves from the previous tree. This means that one would start with a weak model and sequentially boost its performance by allowing each new tree to focus on training data where the previous tree had the largest errors in prediction (or residuals). This is done by fitting each tree in the sequence according to the residuals of the previous tree.

Moreover, it computes the second-order gradients, i.e. second partial derivatives of the loss function, which provides more information about the direction of gradients and how to get to the minimum of our loss function while gradient boost uses the loss function of simple decision tree model as a proxy to minimize the error of the overall model. In addition, it uses advanced regularization (L1 and L2), which improves model generalization.

Each weight in all the trees would be multiplied by the learning rate in an XGBoost model, such that

$$w_j = \text{Learning Rate} \times \frac{\sum_{i \in I_j} \frac{\partial Loss}{\partial(\hat{y}=0)}}{\sum_{i \in I_j} \frac{\partial^2 Loss}{\partial(\hat{y}=0)^2} + \lambda}$$

where I_j is a set containing all the instances ((x, y) data points) at a leaf, and wj is the weight at leaf j with regularization from the λ constant.

We create our XGBoost model from the caret library, using hyperparameters as shown below:

```
+ Fold1: nrounds=650, eta=0.21, max_depth=3, gamma=0.04, colsample_bytree=1, min_child_weight=1, subsamp
- Fold1: nrounds=650, eta=0.21, max_depth=3, gamma=0.04, colsample_bytree=1, min_child_weight=1, subsamp
+ Fold2: nrounds=650, eta=0.21, max_depth=3, gamma=0.04, colsample_bytree=1, min_child_weight=1, subsamp
- Fold2: nrounds=650, eta=0.21, max_depth=3, gamma=0.04, colsample_bytree=1, min_child_weight=1, subsamp
+ Fold3: nrounds=650, eta=0.21, max_depth=3, gamma=0.04, colsample_bytree=1, min_child_weight=1, subsamp
- Fold3: nrounds=650, eta=0.21, max_depth=3, gamma=0.04, colsample_bytree=1, min_child_weight=1, subsamp
+ Fold4: nrounds=650, eta=0.21, max_depth=3, gamma=0.04, colsample_bytree=1, min_child_weight=1, subsamp
- Fold4: nrounds=650, eta=0.21, max_depth=3, gamma=0.04, colsample_bytree=1, min_child_weight=1, subsamp
+ Fold5: nrounds=650, eta=0.21, max_depth=3, gamma=0.04, colsample_bytree=1, min_child_weight=1, subsamp
- Fold5: nrounds=650, eta=0.21, max_depth=3, gamma=0.04, colsample_bytree=1, min_child_weight=1, subsamp
Aggregating results
Fitting final model on full training set
```

```
eXtreme Gradient Boosting

585 samples
354 predictors

No pre-processing
Resampling: Cross-Validated (5 fold)
Summary of sample sizes: 467, 469, 469, 468, 467
Resampling results:

  RMSE      Rsquared  MAE
  20.88346  0.678471  11.60141

Tuning parameter 'nrounds' was held constant at a value of 650
Tuning
 held constant at a value of 1
Tuning parameter 'subsample' was held
 constant at a value of 1
```

As shown above, we have used these hyperparameters:

1. *gamma*: Pseudo-regularisation hyperparameter that controls the complexity of each tree.
2. *nrounds*: Number of decision trees in the final model
3. *eta*: Learning rate; determines the contribution of each tree on the final outcome and also how quickly the algorithm goes down the gradient descent.
4. *max_depth*: Depth of each tree
5. *min_child_weight*: Minimum number of observations in terminal nodes; controls complexity of the trees
6. *colsample_bytree*: subsample of columns used for each tree (repeated for every tree)
7. *subsample*: subsampling ratio of training data for growing trees to prevent over-fitting

The hyperparameters were tuned using 5-fold cross validation and grid search to find the best model, and we arrived at the optimal values for the hyperparameters.

```
[1] 8.035509
```

```
[1] 16.5914
```

Overall, XGBoost gave an RMSE value of 16.5914.

Below we extracted the 20 most important features (words) from the XGBoost model.

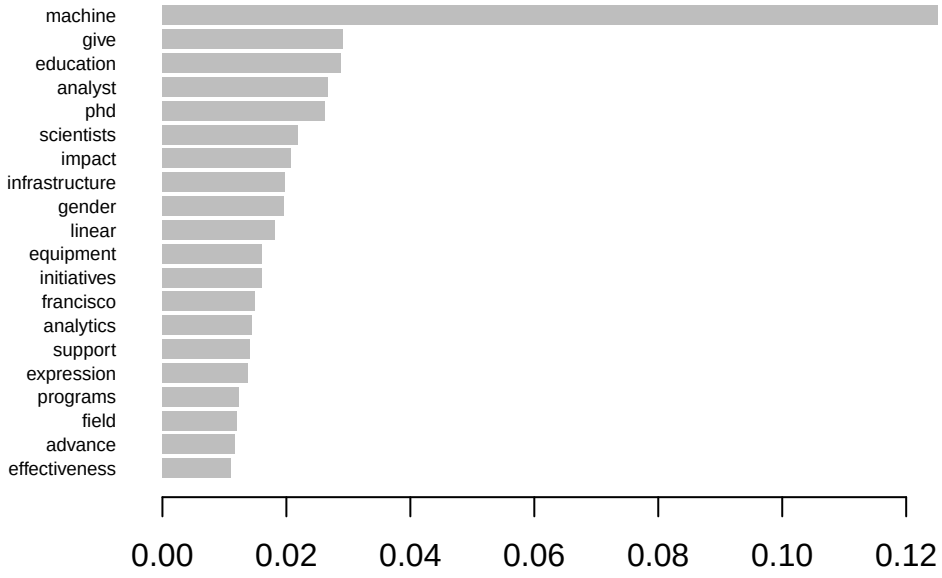
```
Attaching package: 'xgboost'
```

```
The following object is masked from 'package:dplyr':

    slice
```

Table 7: Some of our 20 most important features.

Feature	Gain	Cover	Frequency
machine	0.1251407	0.0105748	0.0093227
give	0.0291924	0.0036677	0.0021936
education	0.0287696	0.0024835	0.0024678
analyst	0.0266963	0.0013853	0.0019194
phd	0.0261783	0.0075795	0.0054840
scientists	0.0218101	0.0076164	0.0049356

Plotting our top 20 most important variables:


machine
give
education
analyst
phd
scientists
impact
infrastructure
gender
linear
equipment
initiatives
francisco
analytics
support
expression
programs
field
advance
effectiveness
0.00
0.02
0.04
0.06
0.08
0.10
0.12

3.2.4 Multivariate Adaptive Regression Splines (MARS)

We used multivariate adaptive regression splines (MARS) (Friedman 1991) model here, it is an approach that automatically generates a piecewise linear model that serves as an understandable stepping stone into non-linearity after learning the notion of multiple linear regression.

By evaluating cutpoints (knots) similar to step functions, MARS offers a practical method to capture the nonlinear relationships in the data. This method evaluates every data point for every predictor as a knot and builds a linear regression model using the candidate feature(s).

Consider non-linear, non-monotonic data where $Y = f(X)$. The MARS method will initially search for a single point within a range of X values where two distinct linear relationships between Y and X provide the lowest loss. The outcome is referred to as a hinge function $h(x - a)$, where a is the cutpoint value.

For example, if $a = 1$, our hinge function is $h(x - 1)$ such that the linear models for y are:

$$y = \begin{cases} \beta_0 + \beta_1(1 - x)\,, & x < 1 \\ \beta_0 + \beta_1(x - 1)\,, & x > 1 \end{cases}$$

After the first knot is identified, the search for a second one begins, and it is discovered at $x = 2$. Now the linear models for y are:

$$y = \begin{cases} \beta_0 + \beta_1(1 - x)\,, & x < 1 \\ \beta_0 + \beta_1(x - 1)\,, & 1 < x < 2 \\ \beta_0 + \beta_1(2 - x)\,, & x > 2 \end{cases}$$

This process is repeated until several knots are identified, leading to the creation of a highly non-linear prediction equation. Even if using a lot of knots could help us fit a particularly excellent relationship to our training data, it might not perform well to unseen data. Once all of the knots have been found, we may systematically eliminate knots that do not significantly improve predictive accuracy. This is pruning process, and we may use cross-validation to determine the optimal number of knots.

We will use the following packages. First of all, we divided the dataset into training dataset and test dataset:

```
Dimensions of the training dataset are 512 1239
```

```
Dimensions of the test dataset are 230 1239
```

MARS model have two hyperparameters: the maximum degree of interactions and the number of terms retained in the final model. To achieve the optimal combination of these tuning parameters, we must conduct a grid search that minimize the error of prediction.

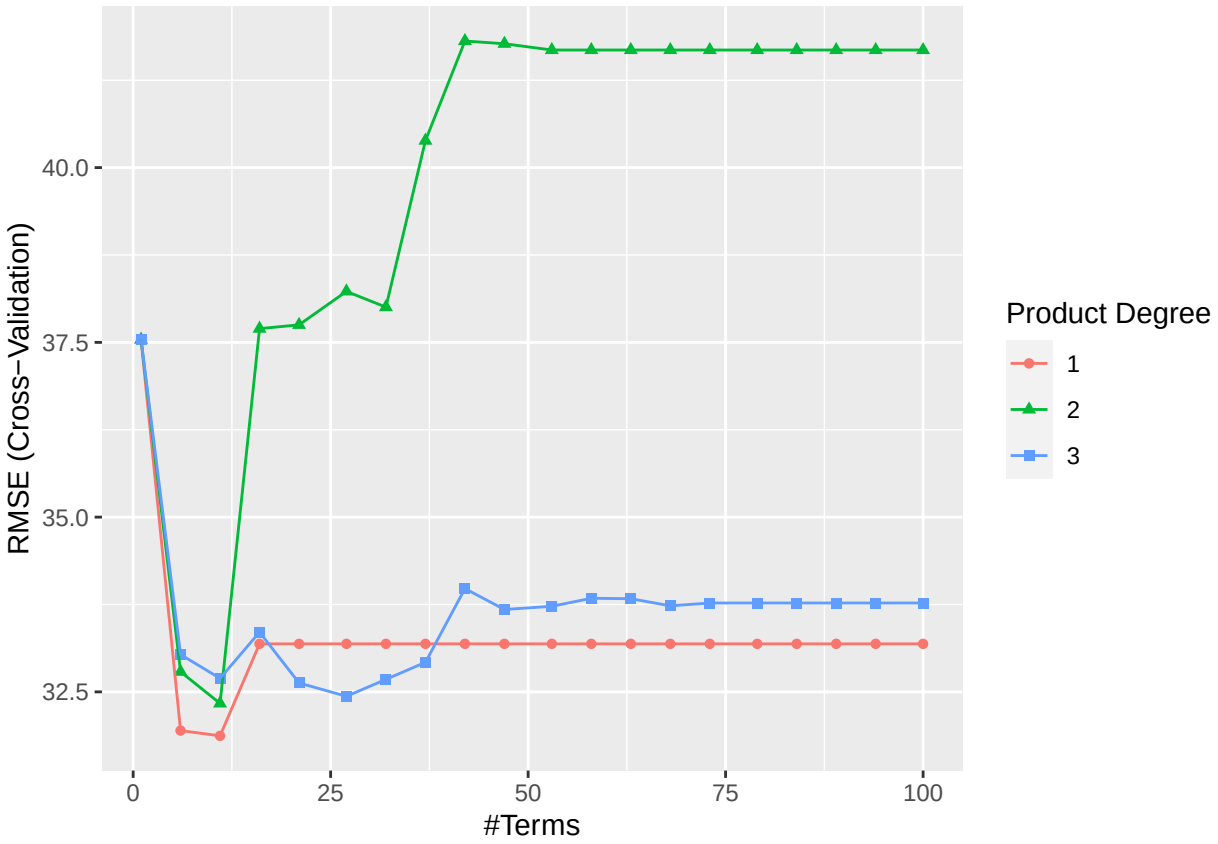
Here, we built up a grid with 30 different combinations of interaction complexity (degree) and the number of terms to include in the final model (nprune).

We performed required grid search by using 10-fold cross-validation:

- Our chosen parameters.

	nprune	degree
3	11	1

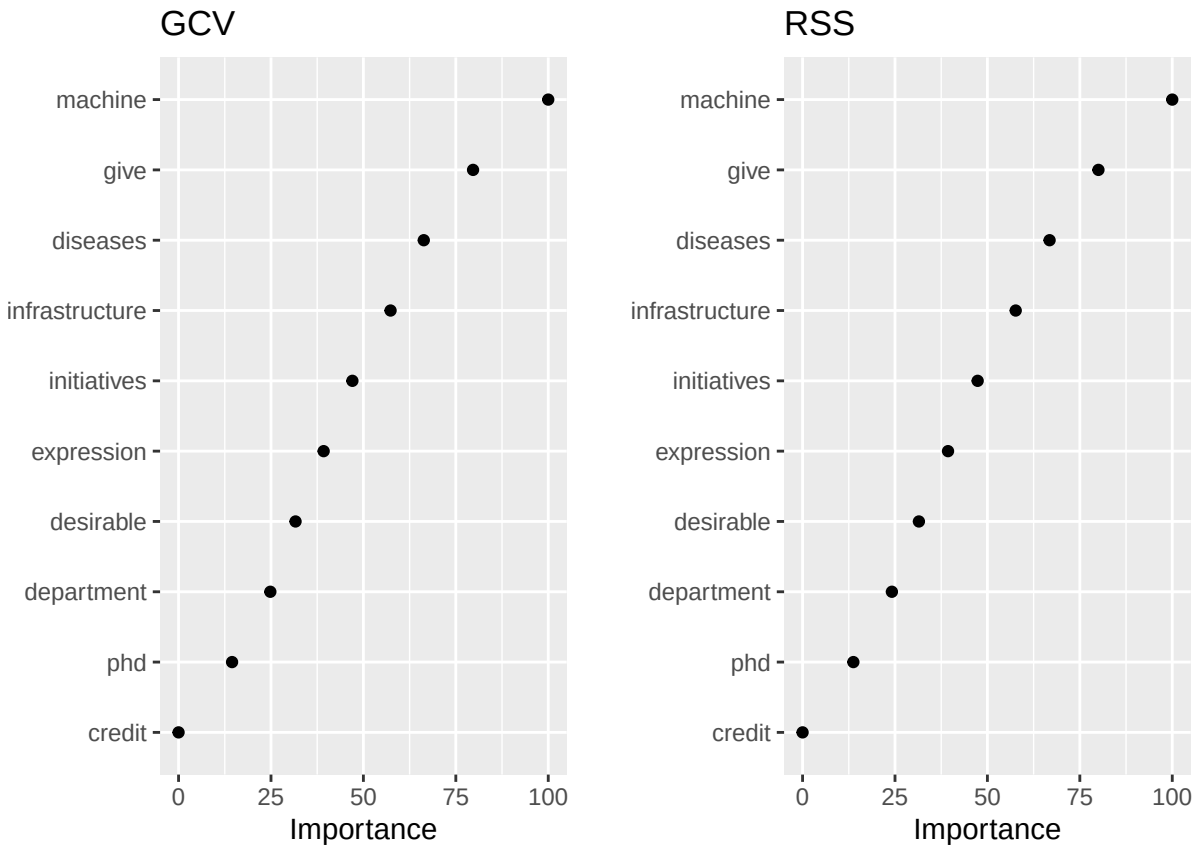
degree	nprune	RMSE	Rsquared	MAE	RMSESD	RsquaredSD	MAESD
1	11	31.87122	0.3140381	25.10864	2.810016	0.0945591	2.344299



The backwards elimination feature selection process used in MARS models seeks for reductions in the generalized cross-validation (GCV) estimate of error when each additional predictor is introduced to the model. The variable importance is based on this overall reduction. MARS effectively accomplishes automated feature selection since it will automatically include and remove variables throughout the pruning phase.

After pruning, a predictor's significance value is 0 if it was never used in any of the MARS basis functions in the final model. There are only 11 features have importance values greater than 0, whereas the other features all have importance values of zero since they were excluded from the final model.

We also kept track of how the residual sums of squares (RSS) change when terms are added. However, we noticed that there is no much difference between these two measures.



We used the optimal hyperparameters to train the model and then calculated the RMSE:

```
[1] 23.22016
```

```
[1] 30.0025
```

3.2.5 Partial Least Squares (PLS)

Partial Least Squares (PLS) is a common technique to analyse relative importance when the data includes more predictors than observations. It is an useful dimension reduction method which is similar with principal component analysis (PCA).

We do a regression against the response variable inside the narrower space created by mapping the predictor variables to a smaller set of variables. The response variable is not taken into account during the dimension reduction process in PCA. PLS, on the other hand, seeks to select newly mapped factors that best describe the response variable.

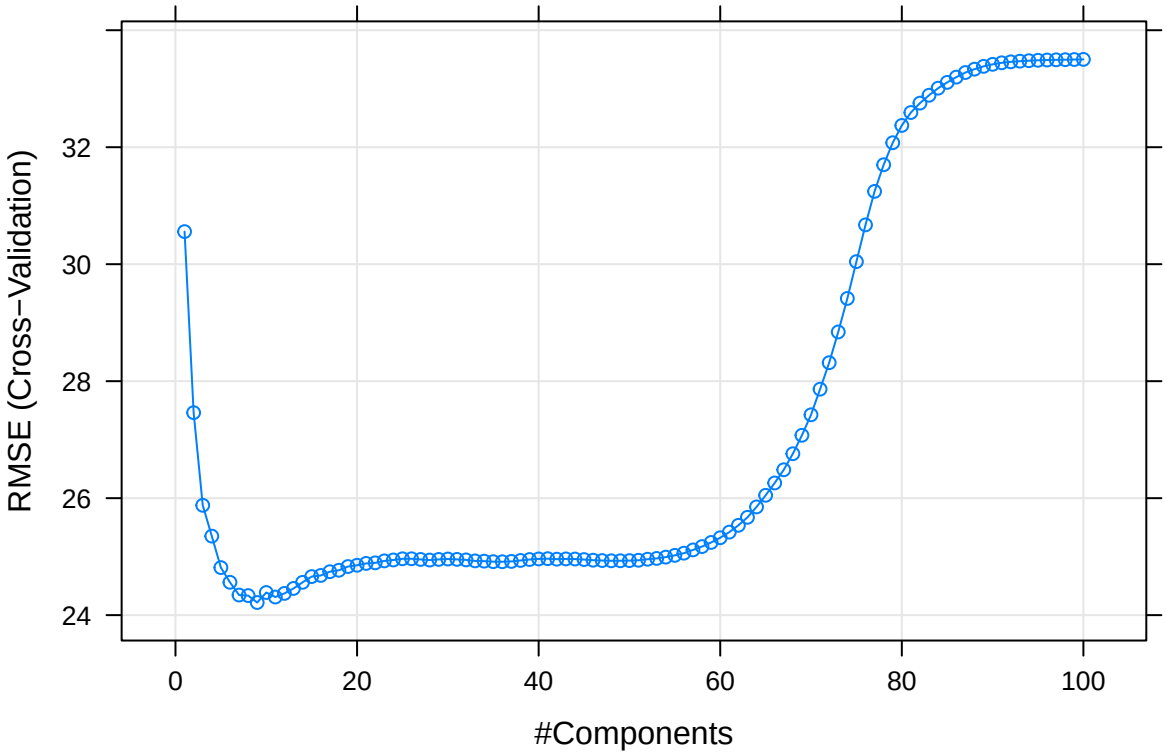
Below are the required packages. We divided the dataset into training dataset and test dataset first:

The hyperparameter for PLS model is the number of components used in the model (ncomp) .We conduct a grid search that minimize the prediction error to achieve the optimal hyperparameter. The grid search was conducted by 10-fold cross-validation:

```
Partial Least Squares

 522 samples
1238 predictors

Pre-processing: centered (1238), scaled (1238)
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 470, 470, 470, 470, 470, 470, ...
Resampling results across tuning parameters:

  ncomp  RMSE      Rsquared   MAE
    1    30.55685  0.3561268  23.85095
    2    27.46180  0.4790637  20.92784
    3    25.87809  0.5397913  18.80301
    4    25.35099  0.5627683  18.25695
    5    24.81328  0.5881916  17.57429
    6    24.56162  0.5937114  16.77198
    7    24.34335  0.6048332  16.25550
    8    24.33422  0.6083873  15.75751
    9    24.21590  0.6134054  15.33192
   10    24.38686  0.6123953  15.14165
   11    24.30930  0.6153090  14.84166
   12    24.37149  0.6153701  14.75219
   13    24.45631  0.6139073  14.63586
   14    24.56083  0.6128587  14.53326
   15    24.65877  0.6111942  14.46135
   16    24.67875  0.6119272  14.37184
   17    24.74250  0.6110657  14.32525
   18    24.76746  0.6107837  14.31129
   19    24.83094  0.6098625  14.28116
   20    24.85262  0.6102663  14.24766
   21    24.88418  0.6101602  14.22263
   22    24.89411  0.6104530  14.20213
   23    24.92743  0.6101396  14.18672
   24    24.94306  0.6101353  14.18171
   25    24.96360  0.6098228  14.16983
   26    24.96351  0.6098946  14.15406
   27    24.95206  0.6102344  14.13375
   28    24.94173  0.6105859  14.11613
```

29	24.95276	0.6103578	14.12949
30	24.95922	0.6104932	14.13336
31	24.95314	0.6108676	14.12952
32	24.94442	0.6111849	14.12934
33	24.92755	0.6116710	14.13662
34	24.92303	0.6119636	14.14047
35	24.91448	0.6122413	14.14332
36	24.91293	0.6123034	14.15126
37	24.91831	0.6124318	14.16217
38	24.93497	0.6120947	14.16408
39	24.95060	0.6118200	14.14368
40	24.96103	0.6116358	14.14237
41	24.96535	0.6115435	14.14120
42	24.95686	0.6117652	14.12223
43	24.96132	0.6116145	14.11387
44	24.95934	0.6116392	14.10458
45	24.95039	0.6117579	14.09207
46	24.93932	0.6119917	14.08525
47	24.93333	0.6120841	14.08155
48	24.92913	0.6121838	14.07734
49	24.92962	0.6121315	14.07476
50	24.93263	0.6120156	14.08027
51	24.93780	0.6119590	14.08329
52	24.95569	0.6115354	14.08895
53	24.96948	0.6113024	14.09910
54	24.99160	0.6107836	14.10741
55	25.02186	0.6102651	14.12571
56	25.05910	0.6096706	14.16597
57	25.11512	0.6086555	14.21128
58	25.17222	0.6076005	14.24717
59	25.24292	0.6063190	14.30495
60	25.32304	0.6049449	14.35376
61	25.41967	0.6031783	14.42555
62	25.53586	0.6011149	14.51264
63	25.67264	0.5989126	14.62360
64	25.85027	0.5958021	14.75393
65	26.04849	0.5924079	14.87680
66	26.25961	0.5891112	15.00149
67	26.48520	0.5854223	15.11939
68	26.75942	0.5810219	15.29575
69	27.07495	0.5757469	15.49269
70	27.42511	0.5699539	15.71880
71	27.86316	0.5626824	15.97971
72	28.31573	0.5555383	16.24821
73	28.84147	0.5471291	16.54778
74	29.41420	0.5379223	16.86831
75	30.04348	0.5279954	17.20660
76	30.67214	0.5183705	17.56716
77	31.24464	0.5097036	17.91835
78	31.69984	0.5031265	18.19972
79	32.07666	0.4978152	18.43163
80	32.37185	0.4936442	18.60105
81	32.59291	0.4906123	18.72859
82	32.75350	0.4886184	18.81300

```
  83    32.88793  0.4870460  18.88022
  84    33.00868  0.4855643  18.93815
  85    33.10833  0.4844639  18.99277
  86    33.19829  0.4833427  19.03446
  87    33.27666  0.4824162  19.07229
  88    33.33412  0.4817344  19.09775
  89    33.38200  0.4811172  19.11904
  90    33.41696  0.4806746  19.13089
  91    33.44293  0.4803971  19.13767
  92    33.45951  0.4802222  19.14236
  93    33.47079  0.4800991  19.14126
  94    33.47893  0.4799860  19.14255
  95    33.48559  0.4798903  19.14386
  96    33.49032  0.4798213  19.14601
  97    33.49402  0.4797704  19.14704
  98    33.49643  0.4797355  19.14803
  99    33.49889  0.4797001  19.14895
 100    33.50150  0.4796691  19.14942

RMSE was used to select the optimal model using the smallest value.
The final value used for the model was ncomp = 9.
```

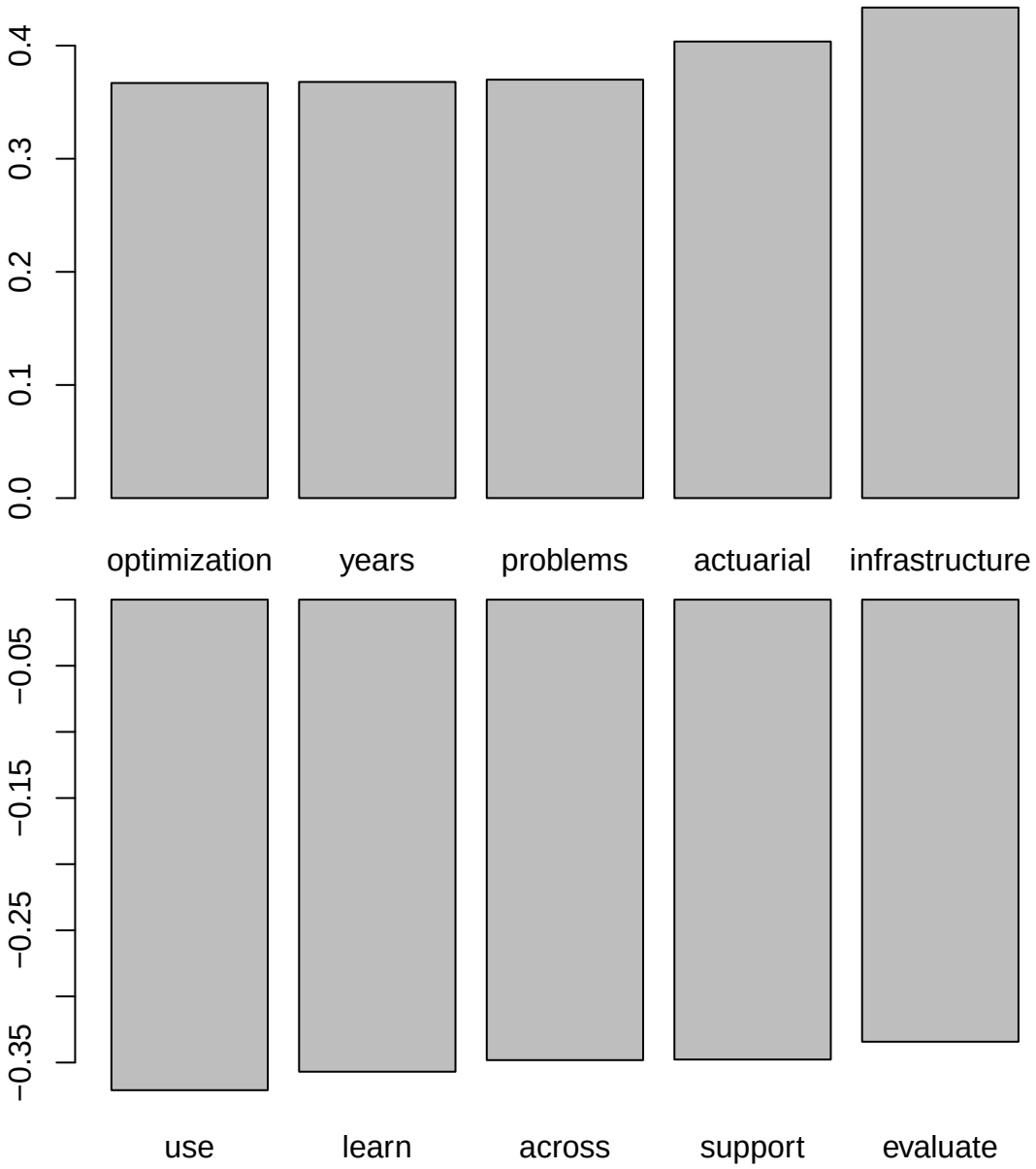


We used the optimal hyperparameter to train the model and calculated the RMSE as well:

```
[1] 16.63214
```

```
[1] 23.87552
```

The barplots below show that ‘credit’, ‘lead’, ‘mission’, ‘actuarial’ and ‘scientists’ are positive predictors, while ‘support’, ‘use’, ‘project’, ‘solutions’ and ‘food’ are negative predictors:


0.0
0.1
0.2
0.3
0.4
optimization
years
problems
actuarial
infrastructure
−0.35
−0.25
−0.15
−0.05
use
learn
across
support
evaluate

3.3 Summary of results

Table 10: Accuracy of models.

Model	RMSE
MLR	16.20561
Random Forest	21.62234
XGBoost	16.59140
MARS	30.00250
PLS	23.87552

4 Conclusion

Recommendation engines are a commonly found solution applied to job search portals, such as the Singapore government's national jobs portal, MyCareersFuture. However, more can be done to bridge the gap between job seekers and their desired careers. In this project, we have produced models that predict the expected average salary earned given a job description. Our best performing model, Multiple Linear Regression, can be used to help workers set expectations of salary based on keywords they value as important in search of a job. This will help job seekers focus on searching for their desired job role rather than focus on maximizing salary earned, which will hopefully increase job satisfaction. The model also identifies key terms such as "eligible", "mongodb", "upon", "francisco", and "hypotheses". Some of these keywords may not seem to make sense, and understanding the importance of these words is unclear. Some of these words, on the other hand, give insight into areas that job seekers can focus on, be it upskilling (for example, learning MongoDB), or narrowing their job search to sectors such as actuarial science or molecular chemistry in order to maximize their potential salary.

Based on RMSE, our best model uses Multiple Linear Regression, and it has identified key terms that have a significant impact on data science salary. However, Multiple Linear Regression does not identify the same important features (words) as our other models. Further research is required to better understand the difference between models and why they identify vastly different features as important.

5 References

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