Data Scientist Salary Prediction

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Data Scienctist Salary Prediction Overview

- I started my career path as a Data Scietist and working as this role can be intellectual challenging. I wonder whether a Data Scientist get paid well ? How much a Data Scientist salary ? What skills are needed to improve ? ... so It would be great to go through the data and answer my questions by myself. This is my motivation to start this project.

Modelling Process

- First, I use **Multiple Linear Regression** as a based line model for Regression problem.
  - First to improve this linear model for better prediction accuracy and model interpretability, I use the **best subset selection** method for selecting subsets of predictors. This method is known as among our various predictors, we believe just a subset of those be really related to the response (Salary).
  - Then use the **validation set approach** to test and select the best model for this data and run the multiple linear regression.
  - The result from Multiple Linear Regression with MSE is 995.8831. Then I consider the **heteroscedasticity** phenomenon from that result, that is the reason why I use the Lasso
- The **Lasso** : hope the coefficiet estimates can significantly reduce their variance for a more accurate prediction.
  - First, split the sample data into a training set and a test set in order to estimate the test error of the lasso.
  - Then perform **cross-validation** and compute the associated test error.
  - As expected, the lasso regression perform better than multiple linear regression compared MSE = 762.544 (mean square errors) in predicting the salary.
- **Random Forest**
  - Next consider even more general non-linear model tree-based.
  - The Random Forest model far outperformed the other approaches on the test and validation sets.

```
rm(list=ls())
library(ggplot2)
# Load data
data <- read.csv('E:/ThanhTam_DA/Project/Prediction/Data Scientist Salary/data_model_2.csv')
```

```r
# Tranform columns
names(data)[names(data) == 'avg.salary.k.'] <- 'salary'
data$type.of.ownership = factor(data$type.of.ownership)
data$sector = factor(data$sector)
data$job.location = factor(data$job.location)
data$job_title_sim = factor(data$job_title_sim)
data$seniority_by_title = factor(data$seniority_by_title)
data$degree = factor(data$degree)
```

```r
# Best variable selection
library(leaps)
```

```
## Warning: package 'leaps' was built under R version 4.1.3
```

```r
regfit.fwd = regsubsets(salary~., data, nvmax = 30, method = "forward")
fwd.summary = summary(regfit.fwd)
```

```r
fwd.summary$rsq
```

```
##  [1] 0.1419651 0.2574784 0.3487904 0.4135071 0.4305654 0.4439358 0.4598250
##  [8] 0.4889180 0.5152634 0.5264122 0.5386571 0.5475069 0.5546571 0.5596790
## [15] 0.5653519 0.5709860 0.5769100 0.5809774 0.5844411 0.5878818 0.5913969
## [22] 0.5946584 0.5979972 0.6008059 0.6046067 0.6071140 0.6095831 0.6116869
## [29] 0.6135834 0.6158089
```

- we see that the R2 statistic increases from 14 %, when only one variable is included in the model, to almost 62 %, when all variables are included. As expected, the R2 statistic increases monotonically as more variables are included.

```r
# Plot RSS, adjusted R squared, Cp and BIC for all of the models
par(mfrow = c(2,2))
plot(fwd.summary$rss, xlab = "Number of Variales", ylab = "RSS", type = "l")
plot(fwd.summary$adjr2, xlab = "Number of Variables", ylab = "Adjusted R sqd", type = "l")
# Identify the location of the maximum point of Adjusted R squared
which.max(fwd.summary$adjr2) # 30
```

```
## [1] 30
```

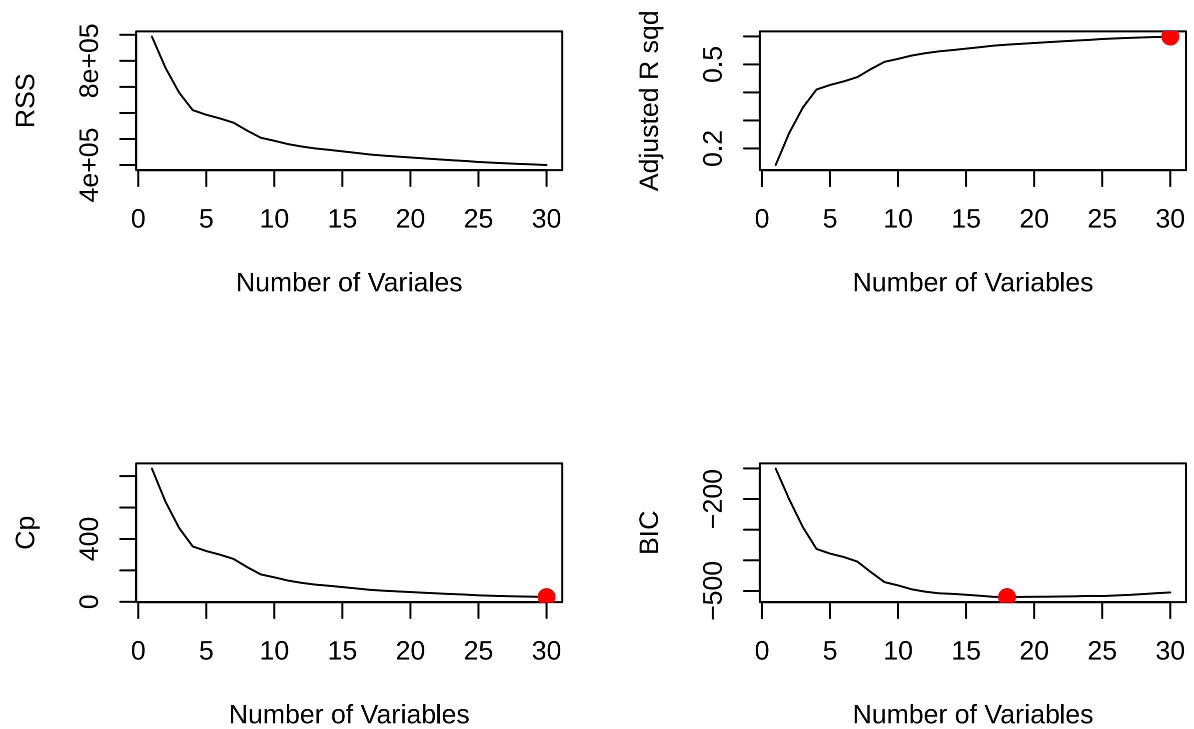
```r
# Plot a red dot to indicate the model with the largest adjusted R squared statistic
points(30, fwd.summary$adjr2[30], col = "red", cex = 2, pch = 20)

plot(fwd.summary$cp, xlab = "Number of Variables", ylab = "Cp", type = "l")
which.min(fwd.summary$cp) #30
```

```
## [1] 30
```

```r
points(30, fwd.summary$cp[30], col = "red", cex = 2, pch = 20)

plot(fwd.summary$bic, xlab = "Number of Variables", ylab = "BIC", type = "l")
which.min(fwd.summary$bic) # 18
```

```
## [1] 18
```

```
points(18, fwd.summary$bic[18],col = "red", cex = 2, pch = 20 )
```



- We see the best model with the highest Adjusted R squared and lowest Cp is 30-variable model.

```
# Check the coefficient estimates associated with the model
coef(regfit.fwd, 2)
```

```
##         (Intercept)      job_title_simDA seniority_by_titleSR
##            98.70957            -39.95864             27.88535
```

- For this data, the best one-variable model contains only **job__title__sim** for Data Analyst position, the best two-variable model additionally includes **seniority__by__title** with Senior level.
- However, to obtain the accuracy of that, we need to perform on the test set
- Next step I will use the the validation set approach to test and select the best model for this data and run the multiple linear regression

```
# write function for predict for regsubsets
predict.regsubsets=function(object,newdata,id,...){
  form=as.formula(object$call[[2]])
  mat=model.matrix(form,newdata)
```

```r
  coefi=coef(object,id=id)
  xvars=names(coefi)
  mat[,xvars]%*%coefi
}

set.seed(1)
train=sample(c(TRUE,FALSE), nrow(data), rep=TRUE)
test=(!train)

regfit.best=regsubsets(salary~., data=data[train,], nvmax=30, method = "forward")
```

```
## Warning in leaps.setup(x, y, wt = wt, nbest = nbest, nvmax = nvmax, force.in =
## force.in, : 3 linear dependencies found
```

```
## Reordering variables and trying again:
```

```r
test.mat=model.matrix(salary~., data=data[test,])
val.errors=rep(NA, 30)
for(i in 1:30){
  coefi=coef(regfit.best, id=i)
  pred=test.mat[,names(coefi)]%*%coefi
  val.errors[i]=mean((data$salary[test]-pred)^2)
}
which.min(val.errors) #29
```

```
## [1] 23
```

```r
val.errors # 995.8831
```

```
##  [1] 1353.443 1350.942 1310.342 1501.777 1399.094 1397.928 1384.211 1382.629
##  [9] 1390.316 1390.316 1390.381 1410.483 1411.305 1358.165 1193.508 1195.587
## [17] 1196.232 1195.864 1202.385 1181.803 1171.491 1159.845 1075.581 1084.768
## [25] 1084.304 1086.497 1090.953 1090.710 1083.671 1084.314
```

```r
# perform on the full data
regfit.best=regsubsets(salary~., data=data, nvmax=30,method="forward")
coef(regfit.best, 29) # select the best  29-variables model
```

```
##                (Intercept) type.of.ownershipNonprofit
##               150.17574160               -15.78661700
##                    sector4                    sector5
##               -35.49952098                11.76052117
##                    sector7                   sector13
##               -46.11832206                 8.61749668
##                   sector18                   sector19
##                17.72221970               -19.03778925
##                     hourly         employer.provided
##               -11.74302734                42.71252574
##              job.locationAZ            job.locationCA
##               -18.08492549                22.98298272
##              job.locationCT            job.locationFL
```

```
##              -23.57062976              -16.32591917
##            job.locationGA            job.locationNM
##              -28.87810490              -40.88225180
##            job.locationTN                       age
##              -18.96916595                0.06431561
##                    python                       sas
##                6.88794567                9.18734423
##                     keras                   pytorch
##               17.74438133               -8.38286690
##           job_title_simDA           job_title_simDE
##             -100.59759389              -67.23090906
##           job_title_simDS            job_title_simM
##              -60.25438536              -80.60934710
##          job_title_simMLE            job_title_simN
##              -47.52067898              -82.92112034
##      seniority_by_titleSR                  num_comp
##               25.92271992                1.39228862
```

```
# note we already perform the best subsets selection on the full data and select the best 29-variables 
###-___________\
#
```

- Our final best model after using validation set approach including 29 variables and the MSE is 995.8831

Consider the result from multiple linear regression

```
lm.fit=lm(salary~., data)
summary(lm.fit)
```

```
##
## Call:
## lm(formula = salary ~ ., data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -106.085  -13.048   -0.471   10.372  115.062
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 1.347e+02  2.664e+01   5.057 5.57e-07 ***
## rating                      8.327e-01  1.724e+00   0.483 0.629302
## type.of.ownershipHospital   -1.552e+01  1.661e+01  -0.934 0.350551
## type.of.ownershipNonprofit  -1.735e+01  1.468e+01  -1.182 0.237796
## type.of.ownershipOther      -6.771e+00  1.831e+01  -0.370 0.711682
## type.of.ownershipPrivate     2.316e+00  1.422e+01   0.163 0.870638
## type.of.ownershipPublic      4.701e+00  1.426e+01   0.330 0.741720
## type.of.ownershipSchool      1.004e+01  1.899e+01   0.529 0.597137
## type.of.ownershipSubsidiary  1.235e+01  1.499e+01   0.824 0.410300
## sector1                      2.625e+00  2.738e+01   0.096 0.923653
## sector2                      1.734e+01  1.414e+01   1.226 0.220635
## sector3                      9.779e+00  2.879e+01   0.340 0.734201
```

```
## sector4                          -2.964e+00  2.054e+01  -0.144 0.885295
## sector5                           1.320e+01  1.253e+01   1.053 0.292678
## sector6                           6.653e+00  1.298e+01   0.513 0.608309
## sector7                          -4.901e+01  1.895e+01  -2.587 0.009914 **
## sector8                           7.857e+00  1.775e+01   0.443 0.658264
## sector9                          -4.247e+00  1.536e+01  -0.277 0.782236
## sector10                          1.250e+01  1.344e+01   0.930 0.352551
## sector11                          9.559e+00  1.534e+01   0.623 0.533448
## sector12                          1.429e+01  1.345e+01   1.063 0.288345
## sector13                          1.475e+01  1.278e+01   1.155 0.248672
## sector14                          5.874e+00  1.283e+01   0.458 0.647187
## sector15                          2.504e+00  1.372e+01   0.182 0.855260
## sector16                          1.314e+01  1.630e+01   0.806 0.420459
## sector17                         -2.422e+01  2.011e+01  -1.204 0.228962
## sector18                          2.327e+01  1.737e+01   1.339 0.180952
## sector19                         -1.667e+01  1.946e+01  -0.857 0.391951
## sector20                         -1.275e+00  1.618e+01  -0.079 0.937184
## sector21                          1.451e+01  1.431e+01   1.014 0.311083
## sector22                         -2.630e+00  1.721e+01  -0.153 0.878565
## sector23                          2.636e+00  1.583e+01   0.166 0.867821
## sector24                         -3.825e+00  1.592e+01  -0.240 0.810247
## revenue                           4.221e-01  1.139e+00   0.370 0.711166
## hourly                           -1.045e+01  8.419e+00  -1.241 0.215147
## employer.provided                 4.435e+01  9.991e+00   4.439 1.06e-05 ***
## job.locationAZ                   -5.004e+00  1.288e+01  -0.388 0.697810
## job.locationCA                    3.950e+01  9.962e+00   3.965 8.16e-05 ***
## job.locationCO                    2.107e+01  1.262e+01   1.670 0.095499 .
## job.locationCT                   -4.921e+00  1.479e+01  -0.333 0.739506
## job.locationDC                    2.776e+01  1.246e+01   2.227 0.026285 *
## job.locationDE                    2.409e+01  1.674e+01   1.439 0.150519
## job.locationFL                   -1.440e+00  1.159e+01  -0.124 0.901209
## job.locationGA                   -6.148e+00  1.436e+01  -0.428 0.668811
## job.locationIA                    1.271e+01  1.502e+01   0.846 0.397678
## job.locationID                    1.521e+01  1.954e+01   0.779 0.436499
## job.locationIL                    2.094e+01  1.083e+01   1.934 0.053545 .
## job.locationIN                    5.489e-01  1.285e+01   0.043 0.965941
## job.locationKS                   -2.097e+01  1.932e+01  -1.086 0.278070
## job.locationKY                    4.508e+01  1.496e+01   3.013 0.002692 **
## job.locationLA                    3.280e+00  1.621e+01   0.202 0.839723
## job.locationMA                    2.005e+01  1.023e+01   1.960 0.050399 .
## job.locationMD                    1.892e+01  1.046e+01   1.809 0.070858 .
## job.locationMI                    1.367e+01  1.471e+01   0.930 0.352927
## job.locationMN                    2.882e+01  2.012e+01   1.432 0.152529
## job.locationMO                    2.348e+01  1.329e+01   1.767 0.077778 .
## job.locationNC                    1.681e+01  1.152e+01   1.460 0.144876
## job.locationNE                    1.162e+01  1.660e+01   0.700 0.484149
## job.locationNJ                    2.469e+01  1.152e+01   2.144 0.032445 *
## job.locationNM                   -2.497e+01  1.697e+01  -1.472 0.141533
## job.locationNY                    2.018e+01  1.026e+01   1.966 0.049715 *
## job.locationOH                    1.901e+01  1.190e+01   1.597 0.110770
## job.locationOR                    4.806e+00  1.617e+01   0.297 0.766437
## job.locationPA                    2.187e+01  1.099e+01   1.990 0.047019 *
## job.locationRI                    4.762e+01  2.726e+01   1.747 0.081142 .
## job.locationSC                   -2.902e+00  2.603e+01  -0.111 0.911259
```

```
## job.locationTN                 -6.470e+00  1.226e+01  -0.528 0.597996
## job.locationTX                  1.467e+01  1.107e+01   1.326 0.185272
## job.locationUT                  2.863e+01  1.454e+01   1.968 0.049462 *
## job.locationVA                  1.046e+01  1.018e+01   1.027 0.304837
## job.locationWA                  2.288e+01  1.257e+01   1.821 0.069070 .
## job.locationWI                  1.099e+01  1.287e+01   0.854 0.393240
## age                             5.544e-02  2.559e-02   2.167 0.030627 *
## python                          8.900e+00  2.462e+00   3.614 0.000325 ***
## spark                          -1.870e+00  3.223e+00  -0.580 0.562019
## aws                             1.504e+00  2.580e+00   0.583 0.560180
## excel                           6.642e-01  2.094e+00   0.317 0.751193
## sql                            -4.398e+00  2.634e+00  -1.670 0.095422 .
## sas                             1.018e+01  3.913e+00   2.602 0.009483 **
## keras                           1.742e+01  6.726e+00   2.590 0.009818 **
## pytorch                        -1.378e+01  5.912e+00  -2.331 0.020045 *
## scikit                         -1.835e+00  4.840e+00  -0.379 0.704664
## tensor                          4.263e+00  5.319e+00   0.801 0.423202
## hadoop                          4.977e+00  3.408e+00   1.460 0.144682
## tableau                        -7.364e+00  3.148e+00  -2.340 0.019613 *
## bi                              6.228e+00  4.403e+00   1.414 0.157737
## flink                          -6.674e+00  8.994e+00  -0.742 0.458344
## mongo                           1.079e+01  5.002e+00   2.158 0.031294 *
## google_an                      -1.711e+01  9.020e+00  -1.897 0.058231 .
## job_title_simDA                -9.556e+01  8.003e+00 -11.942  < 2e-16 ***
## job_title_simDE                -6.541e+01  7.900e+00  -8.280 7.22e-16 ***
## job_title_simDS                -5.874e+01  7.474e+00  -7.860 1.63e-14 ***
## job_title_simM                 -7.507e+01  9.193e+00  -8.166 1.70e-15 ***
## job_title_simMLE               -4.311e+01  9.941e+00  -4.336 1.68e-05 ***
## job_title_simN                 -7.944e+01  7.588e+00 -10.469  < 2e-16 ***
## seniority_by_titleN            -1.176e+01  1.502e+01  -0.783 0.434088
## seniority_by_titleSR            1.507e+01  1.511e+01   0.997 0.319077
## degreeN                        -1.190e+00  2.378e+00  -0.500 0.617020
## degreeP                         1.588e+00  3.635e+00   0.437 0.662274
## desc_len                       -2.581e-04  7.173e-04  -0.360 0.719105
## num_comp                        1.721e+00  7.960e-01   2.162 0.030992 *
## size                           -2.140e+00  1.692e+00  -1.264 0.206519
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 23.73 on 640 degrees of freedom
## Multiple R-squared:  0.6538, Adjusted R-squared:  0.5992
## F-statistic: 11.97 on 101 and 640 DF,  p-value: < 2.2e-16
```

```r
## Compute variance inflation factors
library(car)
```

```
## Warning: package 'car' was built under R version 4.1.3
```

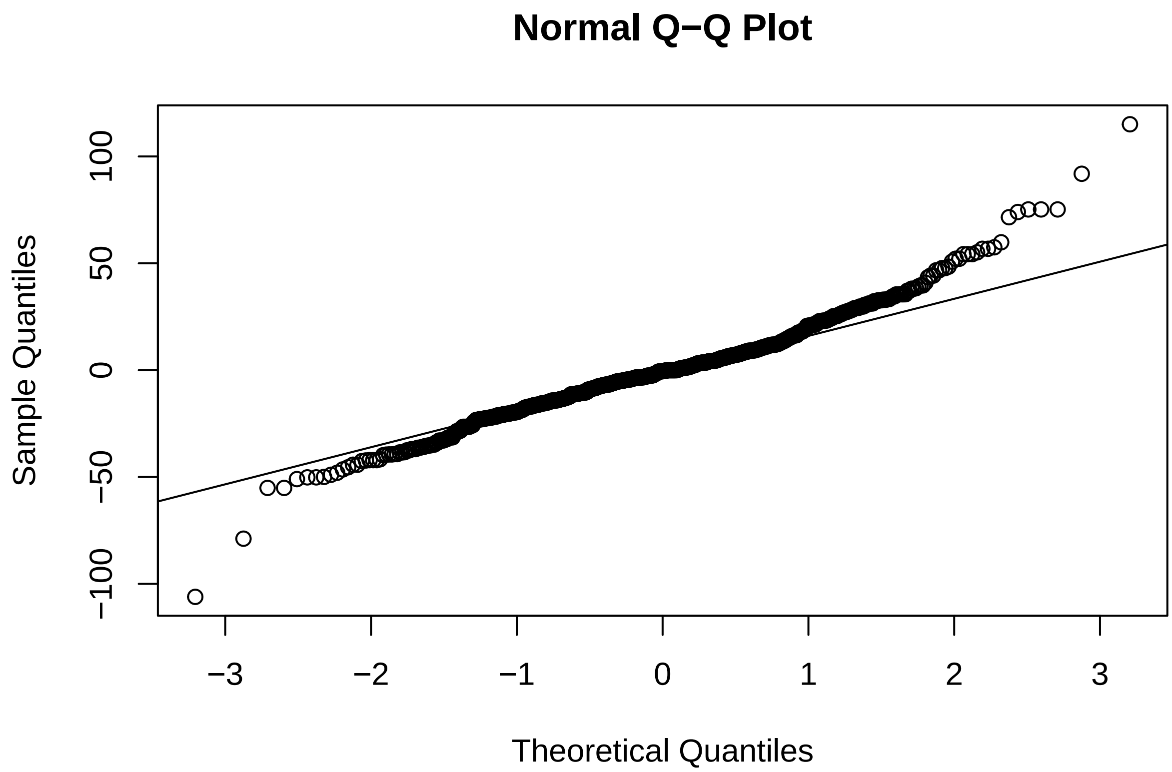
```
## Loading required package: carData
```

```
## Warning: package 'carData' was built under R version 4.1.3
```

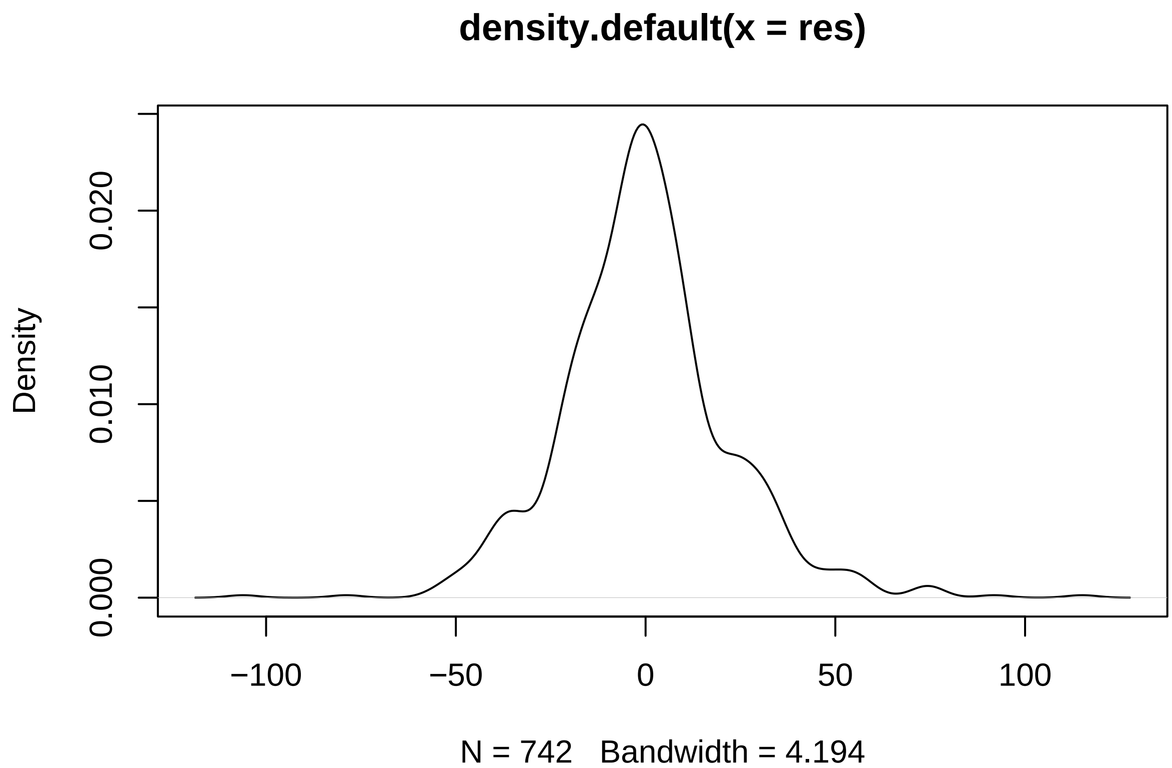
```r
vif(lm.fit)
```

```
##                            GVIF Df GVIF^(1/(2*Df))
## rating             2.511465e+00  1        1.584760
## type.of.ownership  3.699815e+02  7        1.525603
## sector             1.992028e+05 24        1.289443
## revenue            2.623077e+00  1        1.619592
## hourly             2.923337e+00  1        1.709777
## employer.provided  2.944862e+00  1        1.716060
## job.location       1.198876e+04 36        1.139330
## age                2.497064e+00  1        1.580210
## python             1.991172e+00  1        1.411089
## spark              2.387316e+00  1        1.545094
## aws                1.587134e+00  1        1.259815
## excel              1.441610e+00  1        1.200671
## sql                2.283700e+00  1        1.511192
## sas                1.634918e+00  1        1.278639
## keras              2.238703e+00  1        1.496230
## pytorch            2.293789e+00  1        1.514526
## scikit             2.083344e+00  1        1.443379
## tensor             3.266694e+00  1        1.807400
## hadoop             2.130541e+00  1        1.459637
## tableau            2.084797e+00  1        1.443883
## bi                 1.782754e+00  1        1.335198
## flink              1.417197e+00  1        1.190461
## mongo              1.562200e+00  1        1.249880
## google_an          1.984582e+00  1        1.408752
## job_title_sim      2.312312e+01  6        1.299184
## seniority_by_title 1.614244e+00  2        1.127177
## degree             2.892084e+00  2        1.304076
## desc_len           1.567474e+00  1        1.251988
## num_comp           1.597776e+00  1        1.264032
## size               2.903571e+00  1        1.703987
```

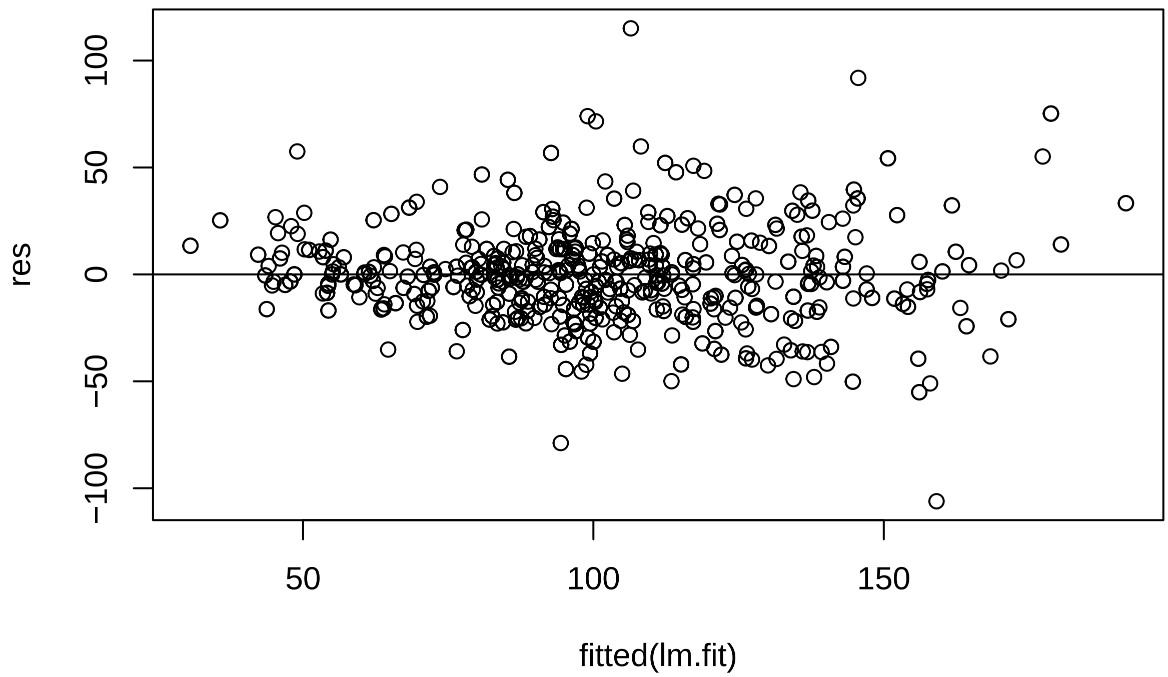
```r
# get list residual
res <- resid(lm.fit)

## normal distribution
### create a q-q plot
qqnorm(res)
qqline(res) # add a straight diagonal line to the plot
```




```r
plot(density(res))
```




```
####-> we can see that the density plot roughly follows the bell shape (normal distribution)

## produce residual vs.fitted plot to visualizing heteroskedasticity
plot(fitted(lm.fit), res)
abline(0,0)
```




```
#--> we can see the data showing heteroscedasticity. the residuals are observed to have unequal varianc
```

- we can see the data showing heteroscedasticity. the residuals are observed to have unequal variance

Lasso

- Now I will perform the lasso _ the techniques for shirinking the regression coefficients towards zero. By using this technique, hope the coefficiet estimates can significantly reduce their variance for a more accurate prediction.
- Now I will perform the lasso in order to predict salary on this data

```
# install.packages("glmnet")
library(glmnet)
```

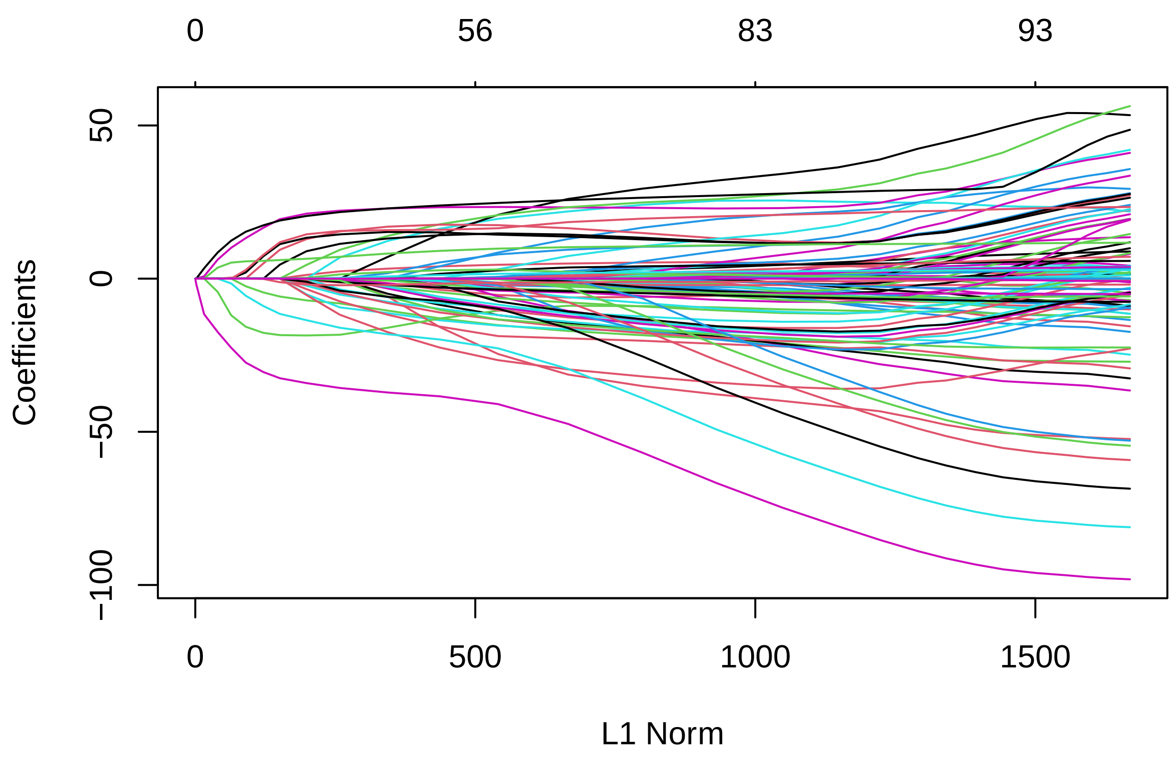
```
## Warning: package 'glmnet' was built under R version 4.1.3
```

```
## Loading required package: Matrix
```

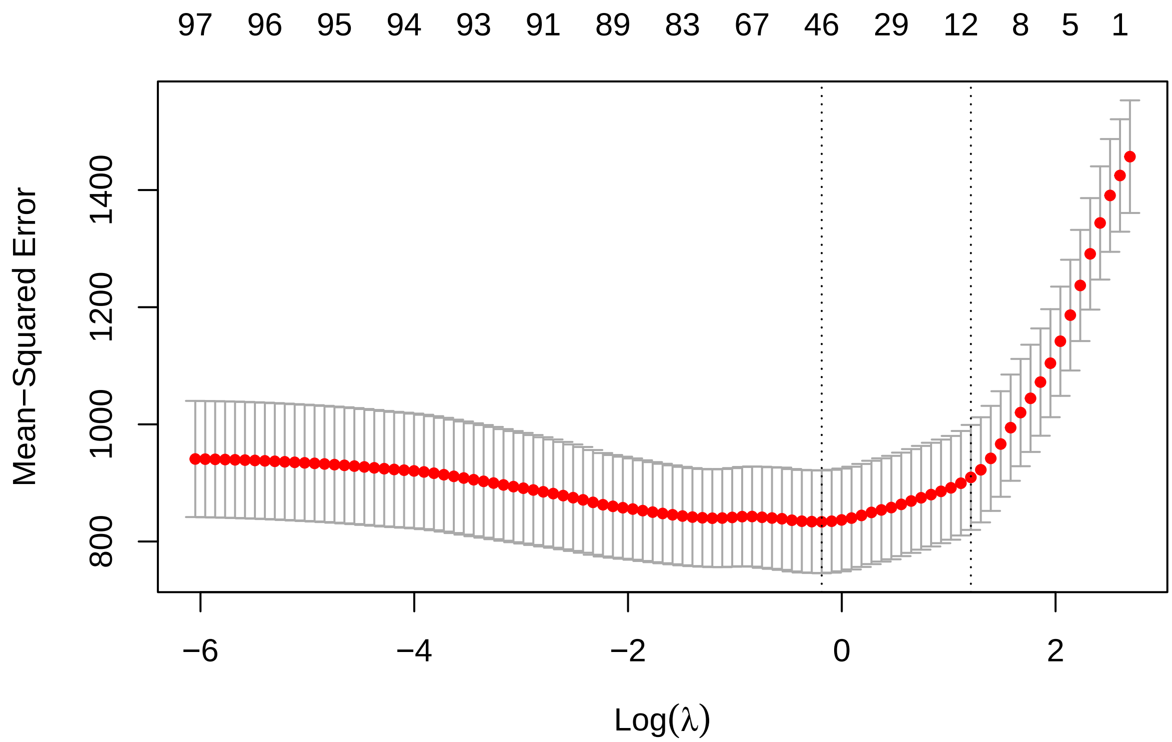
```
## Loaded glmnet 4.1-4
```

```r
x=model.matrix(salary~., data)[,-1] # automatically transforms any qualitative variables into dummy var
y=data$salary

# split the sample data into a training set and a test set in order to estimate the test error of the l
set.seed(1)
train=sample(1:nrow(x), nrow(x)/2)
test=(-train)
y.test=y[test]

# now we fit a lasso model
grid=10^seq(10,-2,length=100)
lasso.mod=glmnet(x[train,], y[train], alpha=1, lambda = grid)
plot(lasso.mod)
```

```
## Warning in regularize.values(x, y, ties, missing(ties), na.rm = na.rm):
## collapsing to unique 'x' values
```




```r
##-> we now see some of the coefficients will be exactly equal to zero

# perform cross-validation and compute the associated test error
set.seed(1)
cv.out=cv.glmnet(x[train,], y[train], alpha=1)
plot(cv.out)
```




```
bestlam=cv.out$lambda.min
lasso.pred=predict(lasso.mod, s=bestlam,newx=x[test,])
mean((lasso.pred-y.test)^2) # MSE = 762.544
```

```
## [1] 662.7368
```

```
##-> This is substantially lower than the test set MSE of least squares
```

- As expected, the lasso regression perform better than multiple linear regression compared MSE = 762.544 (mean square errors) in predicting the salary.

RandomForest

```
# install.packages("randomForest")
library(randomForest)
```

```
## Warning: package 'randomForest' was built under R version 4.1.3
```

```
## randomForest 4.7-1.1
```

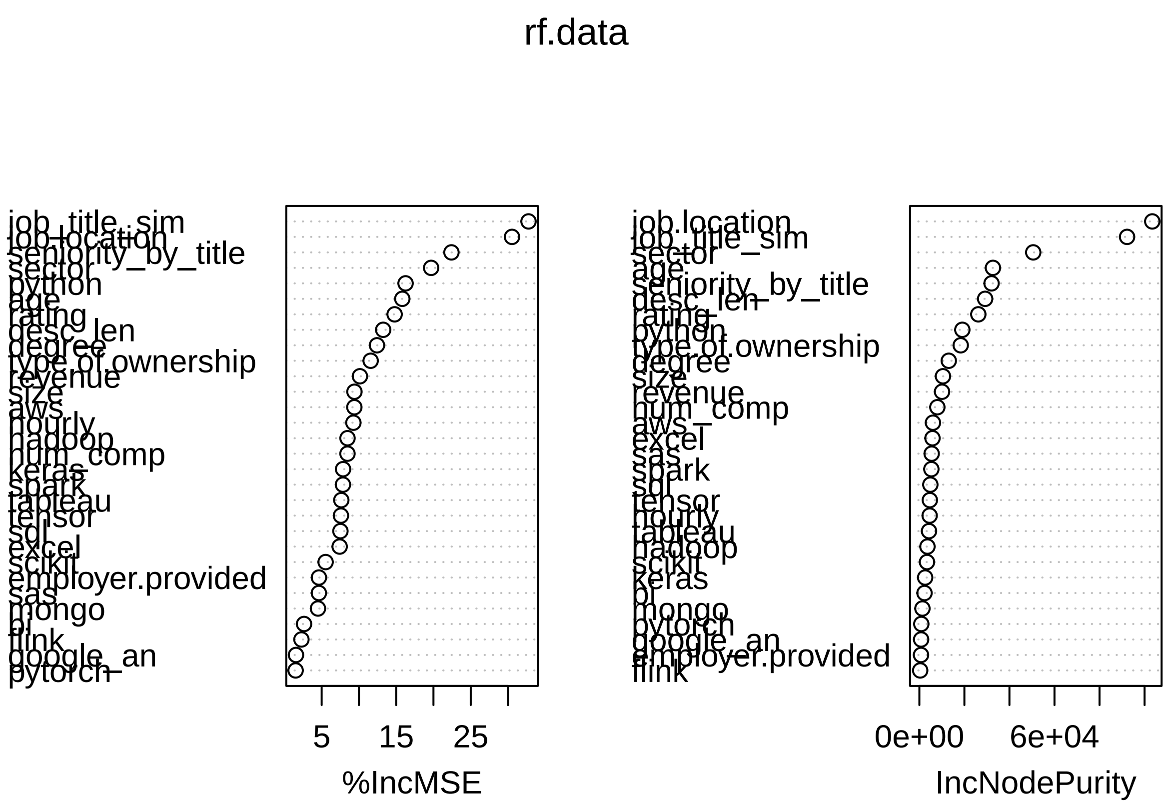
```
## Type rfNews() to see new features/changes/bug fixes.
```

```
##
## Attaching package: 'randomForest'

## The following object is masked from 'package:ggplot2':
##
##     margin
```

```r
set.seed(1)
train=sample(1:nrow(data), nrow(data)/2)
data.test=data[-train,"salary"]
rf.data=randomForest(salary~., data=data, subset=train, mtry=6, importance=TRUE)
yhat.rf= predict(rf.data, newdata=data[-train,])
mean((yhat.rf-data.test)^2) # 575.7547
```

```
## [1] 510.7222
```

```r
#plot of the importance measures
varImpPlot(rf.data)
```



- The results indicate that across all of the trees considerd in the random forest, the wealth level of the job title (job_title_sim) and job_location are by far the most important variables.
- The Random Forest model far outperformed the other approaches on the test and validation sets.