Predicting Job Salary

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Introduction

This task is known as a regression problem, one where the response variable Y is continuous in nature. This problem interestingly only has categorical variables that are difficult to process. The main focus of this part will be in checking different features and methods of extraction to improve results. Two languages were used and contrasted for this task to create a linear model from the features. Two methods were explored: bag of words and aggregation. The data consists of the following information:
Id - A unique identifier for each job ad
Title - A freetext field supplied to us by the job advertiser as the Title of the job ad.
FullDescription - The full text of the job ad as provided by the job advertiser.
LocationRaw - The freetext location as provided by the job advertiser.
LocationNormalized - Adzuna's normalised location from within our own location tree,
ContractType - full_time or part_time, interpreted by Adzuna from description
ContractTime - permanent or contract, interpreted by Adzuna from description
Company - the name of the employer as supplied to us by the job advertiser.
Category - 30 standard job categories this ad fits into, inferred in a very messy way based on the source SalaryRaw - the freetext salary field we received in the job advert from the advertiser.
SalaryNormalised - the annualised salary interpreted by Adzuna from the raw salary.
SourceName - the name of the website or advertiser from whom we received the job advert.

```
library(plyr) ; library(stringr)
library(caret) ; library(car)
library(class) ; library(knitr)
library(MASS) ; library(e1071)
library(glmnet) ; library(pls) ; library(mice)
```

1.Reading data into r and converting some variables into factors

```
sdata=read.csv("https://raw.githubusercontent.com/vigneshjmurali/Statistical-Predictive-Modelling/
master/Datasets/Project%201_Dataset_1_salary_uk.csv")
table(sdata$Category)
##       Accounting & Finance Jobs                       Admin Jobs
##                             606                              151
##        Charity & Voluntary Jobs                Consultancy Jobs
##                              23                               80
##           Creative & Design Jobs          Customer Services Jobs
##                              22                              257
##     Domestic help & Cleaning Jobs          Energy, Oil & Gas Jobs
##                              10                               31
##                Engineering Jobs                   Graduate Jobs
##                            1152                               19
##       Healthcare & Nursing Jobs       Hospitality & Catering Jobs
##                            3149                              525
##            HR & Recruitment Jobs                         IT Jobs
##                             578                             1414
##                      Legal Jobs       Logistics & Warehouse Jobs
##                              88                              110
##                Maintenance Jobs               Manufacturing Jobs
##                              20                              106
##              Other/General Jobs PR, Advertising & Marketing Jobs
##                             236                               88
##                   Property Jobs                     Retail Jobs
##                              44                               93
##                      Sales Jobs               Scientific & QA Jobs
##                             426                              129
##                Social work Jobs                   Teaching Jobs
##                              53                              342
```

```
##        Trade & Construction Jobs                            Travel Jobs
##                              148                                    100
sdata$Title<- as.factor(sdata$Title)
sdata$FullDescription<- as.factor(sdata$FullDescription)
sdata$ContractType[sdata$ContractType=='']<-NA
sdata$ContractType <- as.factor(sdata$ContractType)
sdata$ContractTime[sdata$ContractTime=='']<-NA
sdata$ContractTime <- as.factor(sdata$ContractTime)
sdata$Category <- as.factor(sdata$Category)
sdata$SourceName <- as.factor(sdata$SourceName)
sdata$Company <- as.factor(sdata$Company)
sdata$LocationNormalized <- as.factor(sdata$LocationNormalized)
sdata<-subset(sdata,select = -c(SalaryRaw))  ##delete 'SalaryRaw'
```

2. Data Cleaning

Aggregating Titles into three levels: Senior, Mid-Level, Junior

```
sdata$Tlevel<-"Mid-Level"
for(i in 1:length(sdata$Title)){
  if(grepl('Director', sdata[i,3],ignore.case=TRUE)|grepl("Senior",sdata[i,2] , ignore.case = TRUE
)| grepl("Manager",sdata[i,2] , ignore.case = TRUE) | grepl("Head",sdata[i,2] , ignore.case = TRUE
) |
grepl("Chef",sdata[i,2] , ignore.case = TRUE) | grepl("Lead",sdata[i,2] , ignore.case = TRUE)){
    sdata$Tlevel [i]<- "Senior"
  }
  else if (grepl("Junior",sdata[i,2] ,ignore.case = TRUE) |
           grepl("Entry",sdata[i,2] , ignore.case = TRUE))
  {
    sdata$Tlevel[i]<- "Junior"
  }
  else{
    sdata$Tlevel[i]<- "Mid-Level"
  }
}
```

Diveding locations into two levels, London label as 1, others as 0

```
myurl<-'https://docs.google.com/spreadsheets/d/e/2PACX-1vQXzU41Zv3GwB5s_YJQsrLdSnMt2isMWj03ZZ910sL
el_vL9ZtsyROewGegGZDkmwgYYa1FMw2tWzKl/pub?gid=1568496122&single=true&output=csv'
tree1 <- read.csv(url(myurl),header = FALSE)
tree<-as.vector(tree1[,'V1'])
for (i in 1:nrow(sdata)) {
  # get city name
  loc <- sdata$LocationNormalized[i]
  # find the first line in the tree in which that city name appears
  line.id <- which(grepl(loc, tree))[1]
  # use regular expressions to pull out the broad location
  r <- regexpr("~.+?~", tree[line.id])
  match <- regmatches(tree[line.id], r)
  # store the broad location
  sdata$Location[i] <- gsub("~", "", match)  #Error: replacement has length zero
}
## Error in sdata$Location[i] <- gsub("~", "", match): replacement has length zero
sdata$Location <- as.factor(sdata$Location)
table(sdata$Location)
##            East Midlands          Eastern England                   London
##                      349                      598                     1928
##        North East England       North West England         Northern Ireland
##                      214                      561                      125
##                 Scotland       South East England         South West England
##                      443                     4500                      514
##                    Wales            West Midlands Yorkshire And The Humber
##                      173                      366                      229
```

```r
# label London as 1, non-London as 0
sdata$Location <- as.factor(ifelse(sdata$Location == "London", 1, 0))
```

Since there are so many different companies. I have no idea how to aggregate them into levles. I just label Top 50 companies as 1, others as 0.

```r
company.counts <- summary(sdata$Company)
top.company <- names(company.counts[order(company.counts, decreasing= TRUE)][1:50])
sdata$TopCom <- factor(sdata$Company, levels=top.company)
sdata$TopCom[sdata$TopCom == ""] <-NA
sdata$TopCom <- as.factor(ifelse(is.na(sdata$TopCom), 0, 1))
```

Creating an aggregate category: WhiteCollar=(Accounting, Engineering, Legal, IT, Cosultancy,HR)
WhiteCollar labels 1, others label 0

```r
sdata$WhiteCollar <- grepl('IT', sdata$Category) | grepl('Engineer', sdata$Category) |
grepl('Finance', sdata$Category) | grepl('Legal', sdata$Category) | grepl('Consult', sdata$Categor
y)|
grepl('HR', sdata$Category)
sdata$WhiteCollar <- as.factor(ifelse(sdata$WhiteCollar == "TRUE", 1, 0))
```

Dividing 'SourceName' into two levels, Top 5 Source lables 1, others label 0

```r
sources.counts <- summary(sdata$SourceName)
top5.sources <- names(sources.counts[order(sources.counts, decreasing= TRUE)][1:5])
sdata$Top5Source <- factor(sdata$Source, levels=top5.sources)
sdata$Top5Source <- as.factor(ifelse(is.na(sdata$Top5Source), 0, 1))
```

Dropping previously modified attributes and attributes that will not be used

```r
sdata1<-subset(sdata,select = -c(Id,Title,FullDescription,LocationRaw,LocationNormalized,
                                 Company,Category,SourceName))
```

Randomly dividing the clean data set into two sets of labels 1 (training data) and 2(test data). Here I used mice package to impute missing values to variable 'contractType' and 'contractTime' in these two sets seperately. I tried to impute the missing values for the whole data set but failed as the size of the data set is too large.

Baseline

Having a baseline and a method of classifying success is equally as important in a regression model as with classification. In this case, it was decided that the root mean squared error (RMSE) would provide the most meaningful insight into the quality of the model. The works by calculating the difference between the expected outcome and the predicted outcome, squaring it, averaging that quantity and taking the square root.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2}$$

```r
set.seed(2344) ; n=10000
idx=sample(1:2,n,repl=T)
ss1<-sdata1[idx==1,]
ss_mod1=mice(ss1[, !names(ss1) %in% "SalaryNormalized"],
             method = c("polyreg", "polyreg", "", "" , "", "", ""))
## Warning: Number of logged events: 51
ss11<-cbind(complete(ss_mod1),SalaryNormalized=ss1[,'SalaryNormalized'])
ss2<-sdata1[idx==2,]
ss_mod2=mice(ss2[, !names(ss2) %in% "SalaryNormalized"],
             method = c("polyreg", "polyreg", "", "" , "", "", ""))
## Warning: Number of logged events: 51
ss22<-cbind(complete(ss_mod2),SalaryNormalized=ss2[,'SalaryNormalized'])
set.seed(1234) ; n=10000
idx2=sample(1:2,n,repl=T)
sdata2=rbind(ss11,ss22)
sdata1.train<-sdata2[idx2==1,]  #training set
sdata1.test<-sdata2[idx2==2,]  #testing set
```

3.Linear regression

The primary method for developing this model hinges on linear regression and shaping the features such that the linear regression model can best fit them

```
# Load  function
sdata.lm = lm(formula = SalaryNormalized ~ ., data = sdata1.train)
summary(sdata.lm)
## Call:
## lm(formula = SalaryNormalized ~ ., data = sdata1.train)
## Residuals:
##    Min     1Q Median     3Q    Max
## -32921  -9192  -2743   4846 142092
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)              22736.0     2729.8   8.329  < 2e-16 ***
## ContractTypepart_time    -2219.5      675.5  -3.286  0.00102 **
## ContractTimepermanent    -3969.3      630.3  -6.298 3.28e-10 ***
## TlevelMid-Level           7972.5     2646.3   3.013  0.00260 **
## TlevelSenior             15502.9     2657.0   5.835 5.73e-09 ***
## Location1                 3532.0      547.5   6.451 1.22e-10 ***
## TopCom1                  -5580.9      495.9 -11.253  < 2e-16 ***
## WhiteCollar1              9872.8      470.1  20.999  < 2e-16 ***
## Top5Source1              -1368.7      476.7  -2.871  0.00411 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 15110 on 4981 degrees of freedom
## Multiple R-squared:  0.1554, Adjusted R-squared:  0.154
## F-statistic: 114.5 on 8 and 4981 DF,  p-value: < 2.2e-16
lm_full <- sdata.lm  # full model is the model just fitted
lm_null <- lm(SalaryNormalized ~ 1, data = sdata1.train)
# backward selection
step(lm_full, trace = F, scope = list(lower=formula(lm_null), upper=formula(lm_full)),
     direction = 'backward')
## Call:
## lm(formula = SalaryNormalized ~ ContractType + ContractTime +
##     Tlevel + Location + TopCom + WhiteCollar + Top5Source, data = sdata1.train)
## Coefficients:
##           (Intercept)  ContractTypepart_time  ContractTimepermanent
##                 22736                  -2220                  -3969
##       TlevelMid-Level           TlevelSenior              Location1
##                  7972                  15503                   3532
##               TopCom1           WhiteCollar1            Top5Source1
##                 -5581                   9873                  -1369
# forward selection
step(lm_null, trace = F, scope = list(lower=formula(lm_null), upper=formula(lm_full)),
     direction = 'forward')
## Call:
## lm(formula = SalaryNormalized ~ WhiteCollar + Tlevel + TopCom +
##     Location + ContractTime + ContractType + Top5Source, data = sdata1.train)
## Coefficients:
##           (Intercept)           WhiteCollar1        TlevelMid-Level
##                 22736                   9873                   7972
##          TlevelSenior                TopCom1              Location1
##                 15503                  -5581                   3532
## ContractTimepermanent  ContractTypepart_time            Top5Source1
##                 -3969                  -2220                  -1369
##Predict using the model
lm.pred <- predict(sdata.lm , newdata = sdata1.test)
lm.RMSE<-sqrt(mean((lm.pred - sdata1.test$SalaryNormalized)^2))  #RMSE value, the smaller the bett
```

```
er
lm.RMSE
## [1] 14644.16
```
Both backward and forward selection shows that no variables was dropped, so I used the full model to make the prediction. The result above shows that RMSE=14644.16.

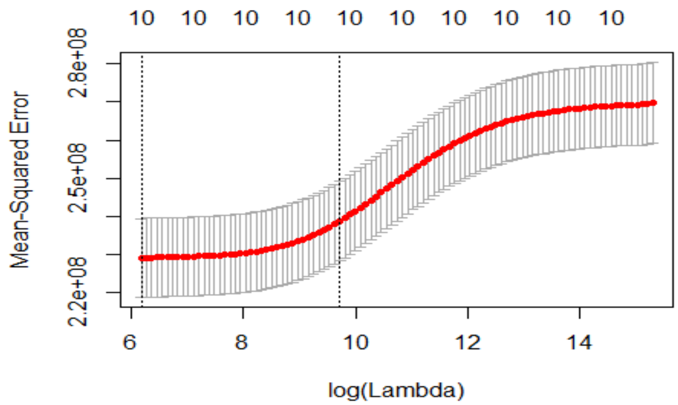
4.Trying modeling log-transformation of the response: log(SalaryNormalized)

```
log.lm <- lm(log(SalaryNormalized) ~., data=sdata1.train)
summary(log.lm)
## Call:
## lm(formula = log(SalaryNormalized) ~ ., data = sdata1.train)
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.60888 -0.27385 -0.01005  0.23389  1.89592
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)            9.92264    0.07432 133.518  < 2e-16 ***
## ContractTypepart_time -0.10134    0.01839  -5.511 3.75e-08 ***
## ContractTimepermanent -0.06286    0.01716  -3.663 0.000252 ***
## TlevelMid-Level        0.24133    0.07204   3.350 0.000815 ***
## TlevelSenior           0.48701    0.07233   6.733 1.85e-11 ***
## Location1              0.10195    0.01491   6.839 8.93e-12 ***
## TopCom1               -0.17090    0.01350 -12.657  < 2e-16 ***
## WhiteCollar1           0.29900    0.01280  23.360  < 2e-16 ***
## Top5Source1           -0.02449    0.01298  -1.887 0.059239 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4113 on 4981 degrees of freedom
## Multiple R-squared:  0.1945, Adjusted R-squared:  0.1932
## F-statistic: 150.4 on 8 and 4981 DF,  p-value: < 2.2e-16
log.pred <- predict(log.lm , newdata = sdata1.test)
log.RMSE<-sqrt(mean((exp(log.pred) - sdata1.test$SalaryNormalized)^2))  #RMSE value, the smaller t
he better
log.RMSE
## [1] 14857.66
```

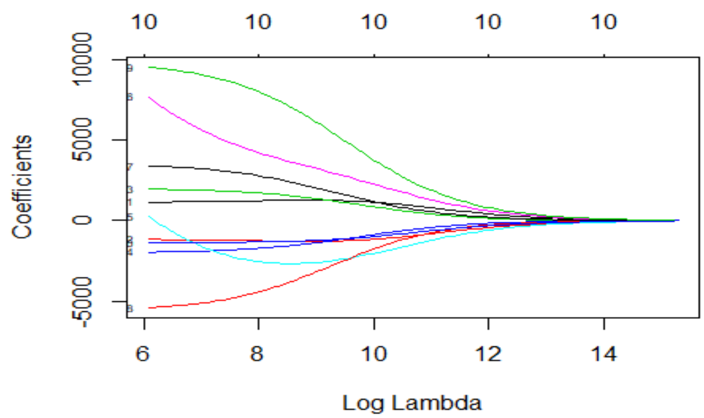
After log transformation to the response, the RMSE=14857.66 has increased compared to the model without transformation. This means that log transformation didn't help.

5.Ridge Regression

```
library(glmnet)
#training set
x.train <- model.matrix(SalaryNormalized ~., data = sdata1.train)[, -1]
y.train <- sdata1.train$SalaryNormalized
# test set
x.test <- model.matrix(SalaryNormalized ~., data = sdata1.test)[, -1]
y.test <- sdata1.test$SalaryNormalized
#  obtain best lambda
set.seed(1)
ri.lambda<- cv.glmnet(x.train, y.train, alpha = 0)
plot(ri.lambda)
```




```r
# predict test set using best lambda and calculate RMSE
ridge.fit <- glmnet(x.train, y.train, alpha = 0) ;plot(ridge.fit, xvar = "lambda", label = TRUE)
```

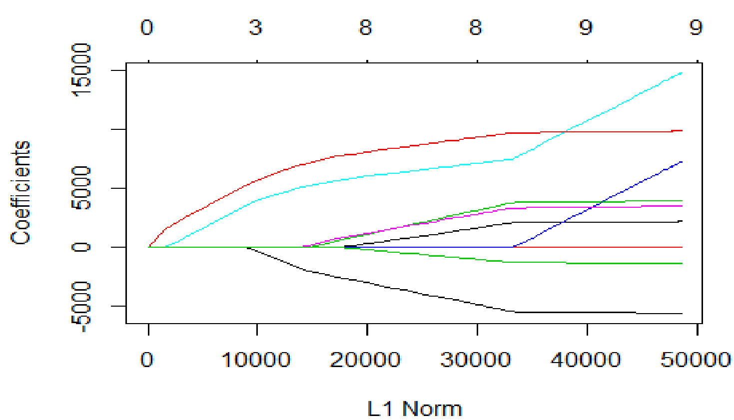



```r
ridge.pred <- predict(ridge.fit, s = ri.lambda$lambda.min, newx = x.test)
ridge.RMSE<-sqrt(mean((ridge.pred - y.test)^2))
```

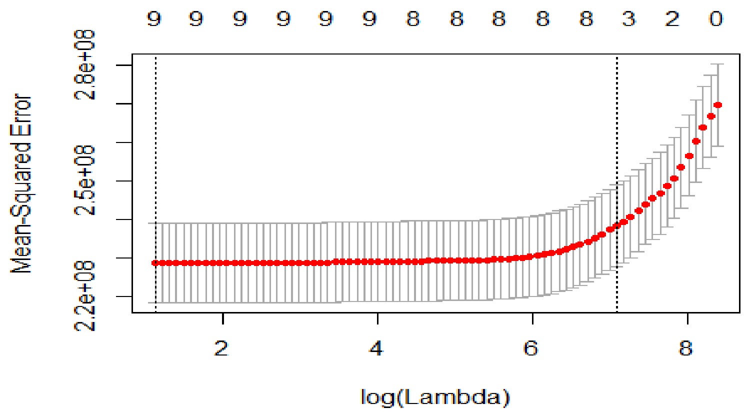
After using Ridge Regression to fit the data, we can see that RMSE= 14643.47 decreased a little bit compared to that of the linear regression.

6.The Lasso Regression

```r
set.seed(1) ; lasso.fit=glmnet(x.train,y.train,alpha=1) ;plot(lasso.fit)
```




```r
#  obtain best lambda
la.lambda=cv.glmnet(x.train,y.train,alpha=1) ;plot(la.lambda)
```

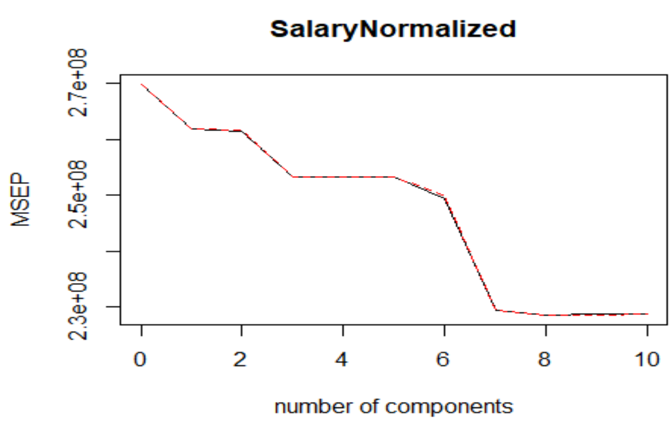



```r
# predict test set using best lambda and calculate RMSE
lasso.pred=predict(lasso.fit,s=la.lambda$lambda.min,newx=x.test)
lasso.RMSE<-sqrt(mean((lasso.pred - y.test)^2))
```

the result above showed us that RMSE= 14642.78 is very close to that of Ridge Regression.

7.Principal Components Regression

```r
set.seed(2) ; pcr.fit=pcr(SalaryNormalized~., data=sdata1.train,scale=TRUE, validation="CV")
summary(pcr.fit)
## Data:    X dimension: 4990 10
##  Y dimension: 4990 1
## Fit method: svdpc
## Number of components considered: 10
## VALIDATION: RMSEP
## Cross-validated using 10 random segments.
##        (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## CV           16427    16180    16172    15913    15914    15912    15792
## adjCV        16427    16179    16173    15912    15913    15911    15811
##        7 comps  8 comps  9 comps  10 comps
## CV       15148    15119    15122     15126
## adjCV    15147    15118    15119     15121
## TRAINING: % variance explained
##                   1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## X                  27.726   46.819   64.776   75.334   84.617   92.347
## SalaryNormalized    3.006    3.171    6.326    6.384    6.423    7.748
##                   7 comps  8 comps  9 comps  10 comps
## X                   99.86   100.00   100.00    100.00
## SalaryNormalized    15.20    15.54    15.55     15.55
validationplot(pcr.fit,val.type="MSEP")
```

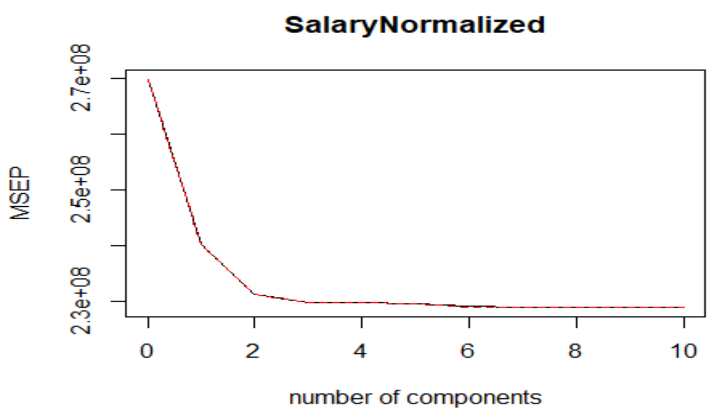



```r
set.seed(1) ; pcr.pred=predict(pcr.fit,x.test,ncomp=8) ;pcr.RMSE<-sqrt(mean((pcr.pred - y.test)^2))
# predict test set using M=8 and calculate RMSE
```

The lowest crossvalidation error occurs when there are M = 8 components; RMSE=14644.16, which means Principal Components Regression performed just like linear regression.

8.Partial Least Squares

```
set.seed(1)
pls.fit=plsr(SalaryNormalized~., data=sdata1.train,scale=TRUE, validation="CV") ;summary(pls.fit)
## Data:    X dimension: 4990 10
##  Y dimension: 4990 1
## Fit method: kernelpls
## Number of components considered: 10
## VALIDATION: RMSEP
## Cross-validated using 10 random segments.
##        (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## CV           16427    15502    15214    15164    15162    15155    15137
## adjCV        16427    15500    15211    15162    15160    15154    15135
##        7 comps  8 comps  9 comps  10 comps
## CV       15137    15137    15137     15137
## adjCV    15134    15134    15134     15134
## TRAINING: % variance explained
##                   1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## X                   22.41    37.73    53.29    65.90    78.15    82.77
## SalaryNormalized    11.36    14.73    15.22    15.24    15.33    15.53
##                   7 comps  8 comps  9 comps  10 comps
## X                   91.09   100.00   101.03    102.06
## SalaryNormalized    15.54    15.54    15.54     15.54
validationplot(pls.fit,val.type="MSEP")
```




```
#The lowest cross-validation error occurs when n = 7 partial least squares directions are used
pls.pred=predict(pls.fit,x.test,ncomp=7 ) ;pls.RMSE<-sqrt(mean((pls.pred - y.test)^2))
```

For Partial Least Squares,the lowest cross-validation error occurs when n = 7 partial least squares directions are used. RMSE=14644.56, which is approximately equal to that of linear regression.

9.Summary

```
# RMSE summary
RMSE <- rbind(lm.RMSE,log.RMSE,ridge.RMSE,lasso.RMSE,pcr.RMSE,pls.RMSE)
rownames(RMSE) <- (c('Linear Regression', 'Linear Regression(log transform)','Ridge Regression',
                     'The Lasso','Principal Components Regression','Partial Least Squares'))
colnames(RMSE) <- 'RMSE' ; round(RMSE, 4)
##                                      RMSE
## Linear Regression                14644.16
## Linear Regression(log transform) 14857.66
## Ridge Regression                 14643.47
## The Lasso                        14642.78
## Principal Components Regression  14644.16
## Partial Least Squares            14644.56
```

From the output above, we cann see that of all the methods that I used, Linear Regression with log transformation performed the worse, while The Lasso performed the best of all. And all the RMSE are pretty close.