HW3: PCA and PLS Regression

Avantika Diwadkar

10/6/2022

Libraries

```
library(glmnet)
library(dplyr)
library(reshape2)
library(tibble)
library(pander)
```

Read in the gene expression and genotyping datasets

```
#Read in the data
norm_expr <- read.table("~/Documents/Penn_State/Fall2022/HW1/Data/GEUVADIS_normalized_expression
genot_df <- read.table("~/Documents/Penn_State/Fall2022/HW1/Data/GEUVADIS_chr20_processed.traw</pre>
```

Clean the dataset

```
#Filter data for 1 gene
gene1_exp <- as.data.frame(norm_expr[1,])
gene1_vars <- genot_df %>%
    dplyr::filter(POS >= gene1_exp$start - 500000, POS <= gene1_exp$start + 500000) %>%
    dplyr::select(-CHR, -X.C.M, -POS, -COUNTED, -ALT)

#Wrangle data
gene1_exp <- gene1_exp %>% dplyr::select(-chromosome, -start, -end)
gene1_exp_df <- as.data.frame(t(gene1_exp))
gene1_exp_df <- gene1_exp_df[-1, ]
gene1_exp_df <- tibble::rownames_to_column(as.data.frame(gene1_exp_df), "Individuals")
names(gene1_exp_df) <- c("Individuals", "GeneExp")

gene1_var_df <- as.data.frame(t(gene1_vars))
names(gene1_var_df) <- as.vector(gene1_vars$SNP)</pre>
```

```
gene1_var_df <- gene1_var_df[-1, ]</pre>
gene1_var_df <- tibble::rownames_to_column(gene1_var_df, "Individuals")</pre>
gene1_var_df$Individuals <- gsub(".*_","", gene1_var_df$Individuals)</pre>
#Final dataframe merge
gene1_data <- merge(gene1_exp_df, gene1_var_df, by="Individuals")</pre>
gene1_data[1:4, 1:8]
##
     Individuals GeneExp 20_49051640_A_G_b37 20_49051816_T_TAA_b37
         HG00096 28.29987
## 1
                                                                      0
## 2
         HG00097 23.46323
                                               0
                                                                      0
## 3
         HG00099 17.72964
                                               1
                                                                      1
## 4
         HG00100 25.84449
##
     20_49052954_T_C_b37_20_49053450_C_T_b37_20_49053871_C_A_b37
## 1
                        1
## 2
                        2
                                              2
                                                                   2
                                                                   2
## 3
                        2
                                              2
## 4
                                              1
                                                                   1
     20_49054108_A_G_b37
## 1
## 2
                        2
## 3
                        2
## 4
                        2
```

Split data into training and testing

```
#training data
X_train <- data.matrix(sapply(gene1_data[1:268,3:2152], as.numeric))
Y_train <- data.matrix(as.numeric(gene1_data$GeneExp[1:268]))

#testing data
X_test <- data.matrix(sapply(gene1_data[269:358,3:2152], as.numeric))
Y_test <- data.matrix(as.numeric(gene1_data$GeneExp[269:358]))

#data
#the response
X <- data.matrix(sapply(gene1_data[,3:2152], as.numeric))
#the outcome
Y <- data.matrix(as.numeric(gene1_data$GeneExp))</pre>
```

Run LASSO with glmnet

```
#Run lasso regression (alpha=1)
fit1 <- glmnet(x=X_train, y=Y_train,alpha = 1, lambda = 0.01, standardize = TRUE)
glm_pred <- predict(fit1, newx=X_test, s=0.01)

#calculate RMSE
sqrt(mean((glm_pred - Y_test)^2))</pre>
## [1] 195.4083
```

Run Principal Component Regression

Step 1: Normalize and scale the data Step 2: Generate covariance matrix Step 3: Perform Single Value Decomposition

```
set.seed(1)
#standardize the data
X.scaled <- scale(X, center = T, scale = T)</pre>
Y.scaled <- scale(Y, center = T, scale = T)
#Single Value Decomposition of the scaled vector
Xsvd <- svd(X.scaled, nu = 0)</pre>
Xsvd$d <- Xsvd$d/sqrt(nrow(X.scaled) - 1)</pre>
#Add Principal component scores
Xsvd$scores <- X.scaled %*% Xsvd$v</pre>
#Add names to eigenvectors
dimnames(Xsvd$v) <- list(colnames(X.scaled), paste0("PC", seq_len(ncol(Xsvd$v))))
#View top 10 PCs with variance explained by each
#Xsvd$scores[,1:20] %>% head(1)
Xsvd$var <- Xsvd$d^2/sum(Xsvd$d^2)</pre>
pc_df <- data.frame("PCs" = paste0("PC", seq_len(ncol(Xsvd$v))), "Scores" = as.vector(Xsvd$scored)
pc_df %>% head(10)
##
       PCs
               Scores Variance_explained
## 1
       PC1 18.279164
                               0.06531712
```

```
## PCs Scores Variance_explained

## 1 PC1 18.279164 0.06531712

## 2 PC2 -8.424923 0.05422389

## 3 PC3 1.994324 0.04803224

## 4 PC4 -12.589615 0.04693614

## 5 PC5 9.645772 0.04216777
```

```
## 6
      PC6 -2.118952
                              0.04200894
## 7
      PC7
            9.729784
                              0.03413867
## 8
      PC8
            8.331388
                              0.03215538
## 9
      PC9 -5.814618
                              0.03144519
## 10 PC10
            7.438896
                              0.02807713
```

Run Regression with Principal Components

```
set.seed(1)
pcs <- as.data.frame(Xsvd$scores)</pre>
names(pcs) <- paste0("PC", seq_len(ncol(pcs)))</pre>
Y_pcr <- cbind(Y.scaled, pcs[,1:10])</pre>
pcrmodel <- lm(Y.scaled ~ ., data = Y_pcr)</pre>
summary(pcrmodel)
##
## Call:
## lm(formula = Y.scaled ~ ., data = Y_pcr)
##
## Residuals:
##
       Min
                  1Q
                       Median
                                    3Q
                                            Max
## -1.86320 -0.81684 -0.00276 0.80091 1.89206
##
## Coefficients:
##
                 Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.529e-16 5.319e-02
                                       0.000
                                                1.000
## PC1
              -2.260e-03 4.495e-03 -0.503
                                                0.615
## PC2
               4.234e-03 4.933e-03 0.858
                                                0.391
## PC3
               -1.692e-03 5.242e-03 -0.323
                                                0.747
## PC4
               -3.215e-03 5.303e-03 -0.606
                                               0.545
## PC5
               -1.257e-03 5.594e-03 -0.225
                                                0.822
## PC6
                                                0.235
               6.671e-03 5.605e-03
                                     1.190
## PC7
               -4.930e-03 6.218e-03 -0.793
                                                0.428
## PC8
               3.925e-03 6.406e-03
                                     0.613
                                                0.541
## PC9
               -2.891e-03 6.478e-03 -0.446
                                                0.656
## PC10
               7.824e-03 6.856e-03 1.141
                                                0.255
##
## Residual standard error: 1.006 on 347 degrees of freedom
                                   Adjusted R-squared:
## Multiple R-squared: 0.01542,
```

F-statistic: 0.5434 on 10 and 347 DF, p-value: 0.8589

Partial Least Square Regression

Y dimension: 358 1
Fit method: kernelpls

Step1 : Initialize Step 2 : Iteration to derive mth direction Zm and update Xm so it is orthogonal to Zm Step 3: Repeat for X1 .. Xp and use Z1.. Zp in lm model

```
p = ncol(as.data.frame(X_test))
dimnames(X_test) <- NULL</pre>
Z_list <- list()</pre>
for (j in seq(1, p)){
  Xj = as.matrix(X_test[,j])
  Xjm = matrix(0, ncol=11, nrow = nrow(X_test))
  Xjm[,1] \leftarrow Xj[,1]
  for (m in seq(1, 10)){ #10 pls components
    #initialize power
    if (m==1)\{f=m\} else \{f = m-1\}
    #initialize Xjm
    Xjf = Xjm[,f]
    #calculate phi
    phi = t(Xjf) %*% Y_test
    #vector for direction m
    Zm = phi %*% Xjf
    #update Xjf for k=f+1
    k=f+1
    Xjk = Xjf - ((t(Zm) %*% Xjf)/(t(Zm) %*% Zm))*as.vector(Zm)
    Xjm[,k] \leftarrow Xjk[,1]
  }
  #Save Z component
  Z_{list[[j]]} \leftarrow Z_{m}
}
```

As PLS function is giving error I will be using the pls package for regression

```
library(pls)
set.seed(777)
pls_df <- as.data.frame(cbind(sapply(gene1_data[,3:200], as.numeric),as.numeric(gene1_data$Gene1_df <- pls_df %>% dplyr::rename("Y"="V199")
pls.fit <- plsr(Y~.,data=pls_df,scale=T, ncomp=10)
summary(pls.fit)

## Data: X dimension: 358 198</pre>
```

```
## Number of components considered: 10
## TRAINING: % variance explained
     1 comps 2 comps 3 comps 4 comps 5 comps 6 comps 7 comps 8 comps
##
## X
      21.878
              41.191
                        46.186
                                59.028
                                         68.080
                                                  78.154
                                                           83.126
                                                                    86.99
## Y
       0.829
              1.646
                         5.888
                                 7.026
                                          7.873
                                                   8.619
                                                            9.718
                                                                    10.96
##
     9 comps 10 comps
## X
       89.53
                 91.79
## Y
       12.34
                 13.14
```