

# final

Yuanyuan Wu

5/5/2019

1a

```
phenotypes <- read.csv("final2019_pheno.csv",  
                      stringsAsFactors = F, header = F)
```

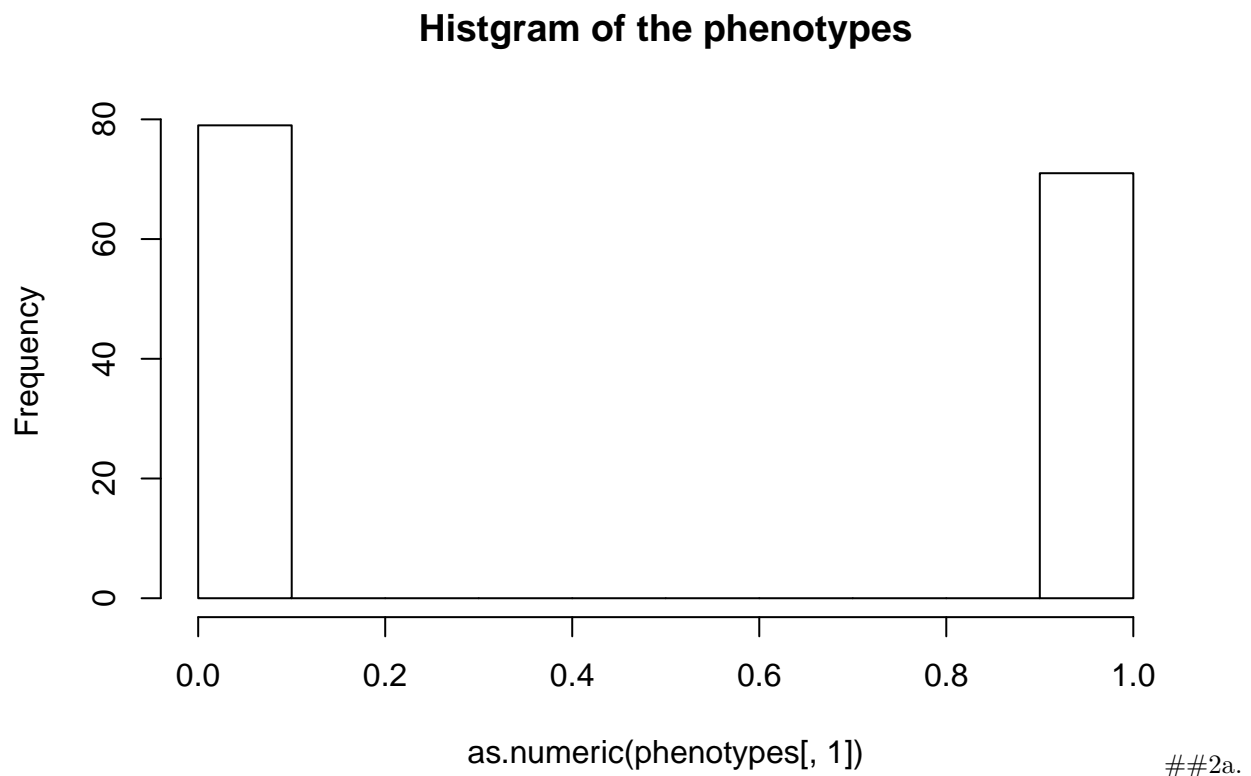
1b.

```
cat("The number of samples is: ",nrow(phenotypes),'\n')
```

```
## The number of samples is: 150
```

1c.

```
hist(as.numeric(phenotypes[,1]),main = 'Histogram of the phenotypes')
```



##2a.

```
genotypes <- read.csv("final2019_genotypes.csv",  
                     stringsAsFactors = F, header = F)
```

2b.

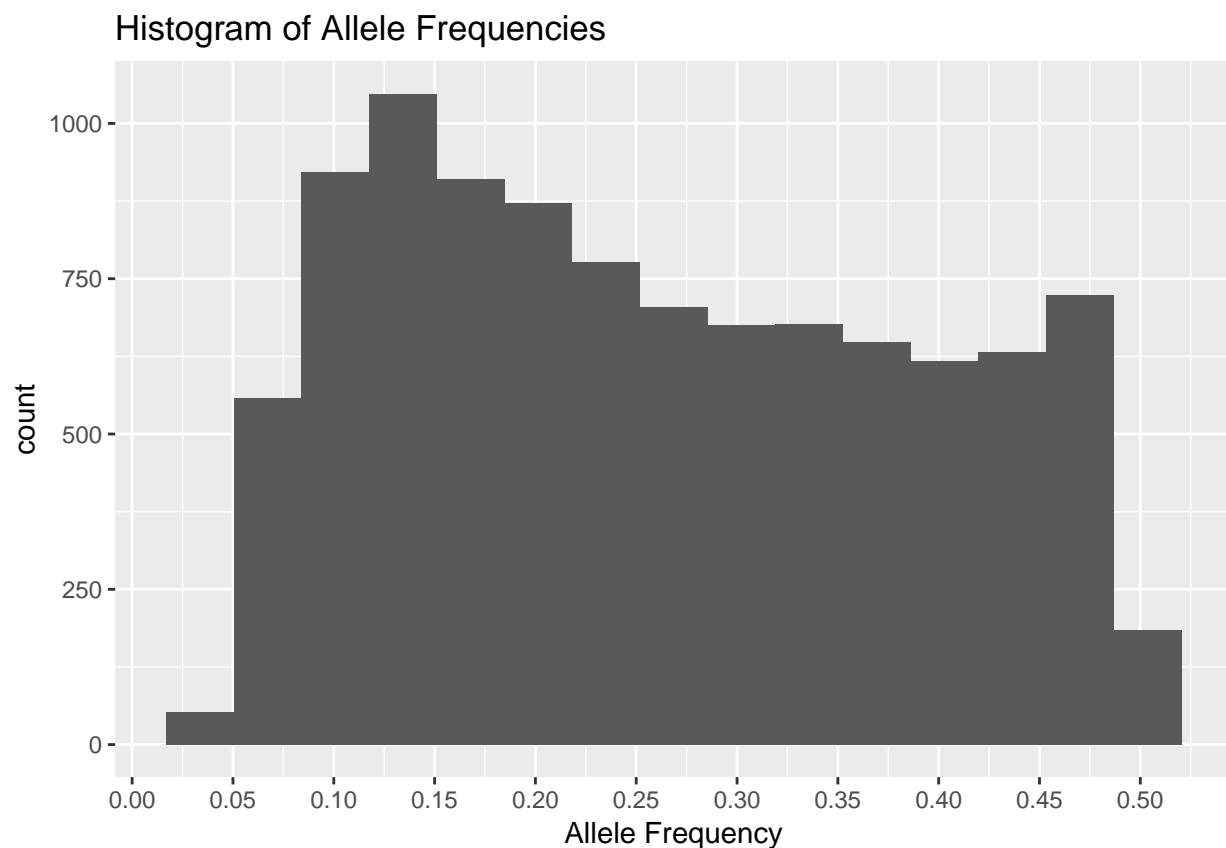
```
cat("The number of SNPs N is: ",ncol(genotypes),'\n')
```

```
## The number of SNPs N is: 10000
```

2c.

```
library(ggplot2)
maf_calc <- function(x){
  tab_x <- table(x)
  af <- 1-((2*max(tab_x[names(tab_x) %in% c(0,2)])+sum(x==1))/(2*nrow(genotypes)))
  return(af)
}
```

```
af <- apply(genotypes, 2, maf_calc)
ggplot(data.frame(af),aes(af))+geom_histogram(bins=15)+
  scale_x_continuous(breaks = seq(0,0.55,by=0.05))+
  labs(x="Allele Frequency", title="Histogram of Allele Frequencies")
```



3a.

```
#calculate p-val with IRLS
#most code are from Lab12
```

```

#recursion and apply functions are used for speed
gamma_inv_calc <- function(X_mx, beta_t){
  #initialize gamma
  # K is the part which goes into the exponent
  K <- X_mx %*% beta_t
  gamma_inv <- exp(K)/(1+exp(K))
  return(gamma_inv)
}

W_calc <- function(gamma_inv){
  W <- diag(as.vector(gamma_inv * (1- gamma_inv)))
  return(W)
}

beta_update <- function(X_mx, W, Y, gamma_inv, beta){
  beta_up <- beta + ginv(t(X_mx)%*%W)%*%X_mx)%*%t(X_mx)%*%(Y-gamma_inv)
  return(beta_up)
}

dev_calc <- function(Y, gamma_inv){
  deviance <- 2*( sum(Y[Y==1]*log(Y[Y==1]/gamma_inv[Y==1])) +
    sum((1-Y[Y==0])*log((1-Y[Y==0])/(1-gamma_inv[Y==0])))) )
  return(deviance)
}

loglik_calc <- function(Y, gamma_inv){
  loglik <- sum(Y*log(gamma_inv)+(1-Y)*log(1-gamma_inv))
  return(loglik)
}

logistic.IRLS.recursive <- function(Y, X_mx, beta_t, dpt1, gamma_inv, iter, d.stop.th = 1e-6, it.max = 100){
  # create empty matrix W
  W <- W_calc(gamma_inv)

  beta_t <- beta_update(X_mx, W, Y, gamma_inv, beta_t)

  #update gamma since it's a function of beta
  gamma_inv <- gamma_inv_calc(X_mx, beta_t)

  #calculate new deviance
  dt <- dev_calc(Y, gamma_inv)
  absD <- abs(dt - dpt1)

  if(absD < d.stop.th | iter > it.max) {
    #cat("Convergence at iteration:", i, "at threshold:", d.stop.th, "\n")
    logl <- loglik_calc(Y, gamma_inv)
    return(list(beta_t, logl))
  } else {
    return(logistic.IRLS.recursive(Y, X_mx, beta_t, dt, gamma_inv, iter+1, d.stop.th = 1e-6, it.max = 100))
  }
}

```

```

logistic.IRLS.pval.recursive <- function(Xa,Xd,Y, beta.initial.vec = c(0,0,0), d.stop.th = 1e-6, it.max
#Initialize
  beta_t <- beta.initial.vec
  dt <- 0

  X_mx <- cbind(rep(1,nrow(Y)), Xa, Xd)
  gamma_inv <- gamma_inv_calc(X_mx, beta_t)
  h1 <- logistic.IRLS.recursive(Y, X_mx, beta_t, dt, gamma_inv, 1, d.stop.th = 1e-6, it.max = 100)

  X_mx <- cbind(rep(1,nrow(Y)), rep(0,nrow(Y)),rep(0,nrow(Y)))
  gamma_inv <- gamma_inv_calc(X_mx, beta_t)
  h0 <- logistic.IRLS.recursive(Y, X_mx, beta_t, dt, gamma_inv, 1, d.stop.th = 1e-6, it.max = 100)

  LRT <- 2*h1[[2]]-2*h0[[2]] #likelihood ratio test statistic
  pval <- pchisq(LRT, 2, lower.tail = F)
  return(pval)
}

Y <- as.matrix(phenotypes)
colnames(Y) <- NULL
xa_matrix <- as.matrix(genotypes)-1

xd_matrix <- 1 - 2*abs(xa_matrix)

allPvals <- apply(rbind(xa_matrix,xd_matrix), 2, function(x) logistic.IRLS.pval.recursive(Xa=x[1:nrow(x)
log.allPval <- as.data.frame(-log10(allPvals),ncol=1)
adjusted_p <- -log10(0.05/ncol(genotypes))

```

### 3b

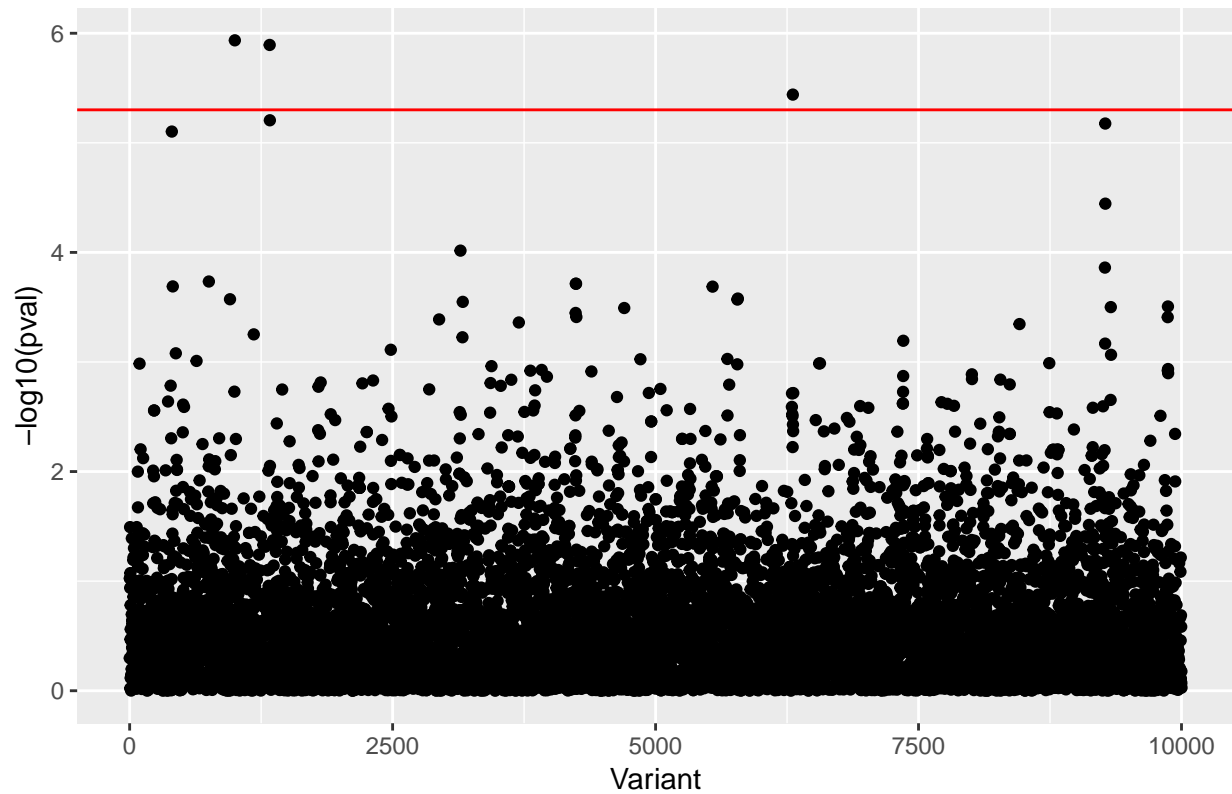
```

library(ggplot2)
log.allPval <- as.data.frame(-log10(allPvals),ncol=1)
adjusted_p <- -log10(0.05/ncol(genotypes))

ggplot(log.allPval,aes(1:nrow(log.allPval),log.allPval[,1])) +
  geom_point() +
  labs(x="Variant",y="-log10(pval)",title=c("Manhattan Plot"))+
  geom_hline(yintercept=adjusted_p,color = "red")

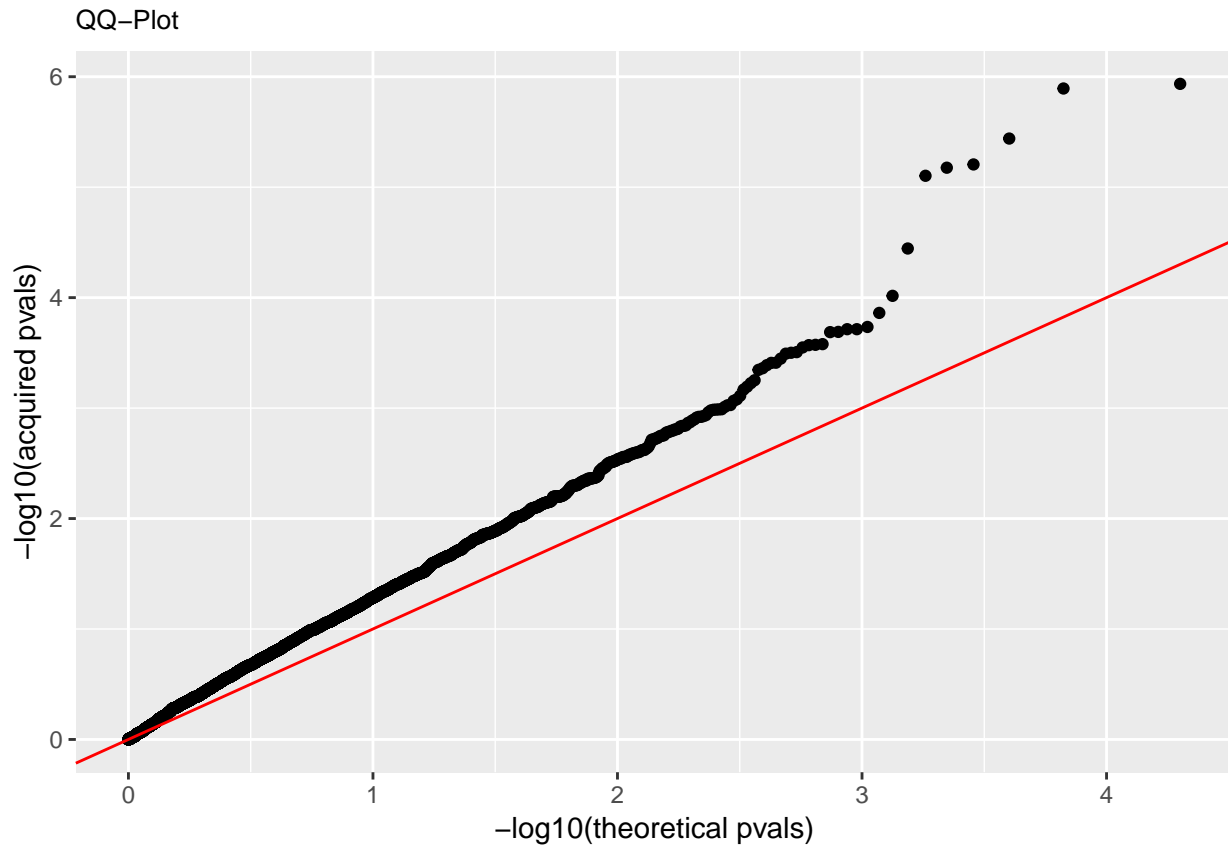
```

Manhattan Plot



##3c

```
qqDf1 <- data.frame(exp = sort(allPvals),theo = sort(qunif(ppoints(nrow(log.allPval)))))
ggplot(qqDf1,aes(-log10(theo), -log10(exp)))+geom_point()+
  geom_abline(slope = 1, color = "red")+
  labs(title="QQ-Plot",x="-log10(theoretical pvals)",y="-log10(acquired pvals)")+
  theme(plot.title = element_text(size=10))
```



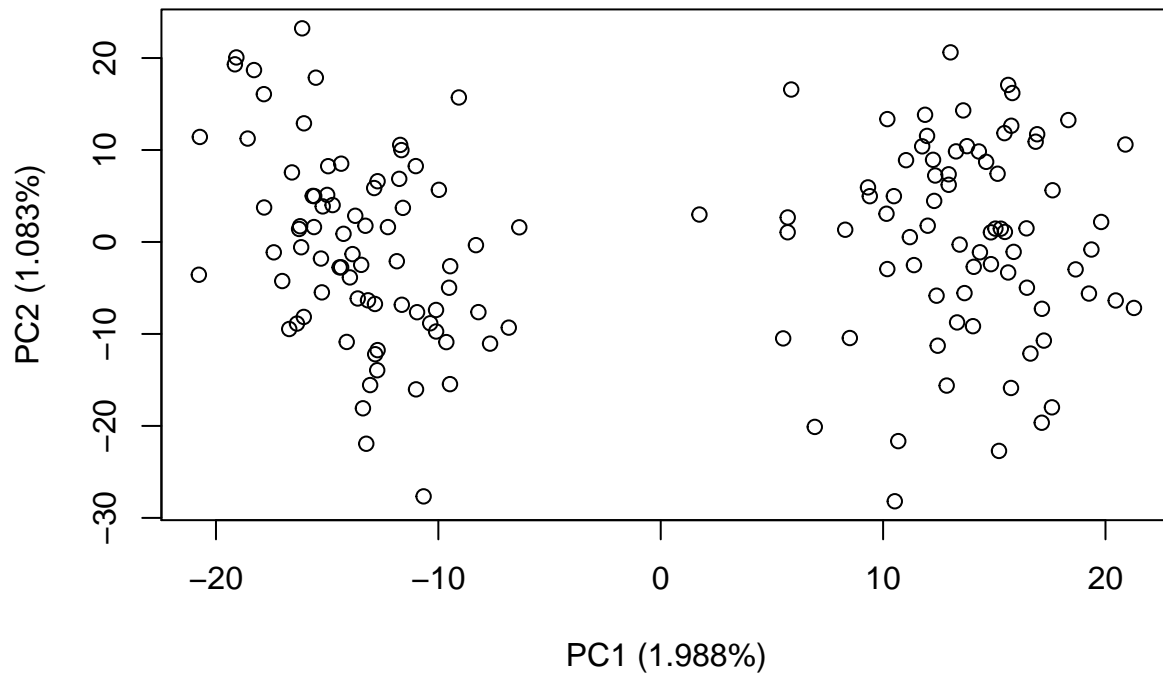
4a

```
#perform PCA
geno_pca <- prcomp(genotypes,scale = T)
```

4b

```
plot(geno_pca$x[,1],geno_pca$x[,2],main = "Genotype PCA",
     xlab = paste("PC1 (", 100*as.numeric(summary(geno_pca)$importance[, 1][2]), "%)", sep = ""),
     ylab = paste("PC2 (", 100*as.numeric(summary(geno_pca)$importance[, 2][2]), "%)", sep = ""))
```

## Genotype PCA



5a

```
#include PC1, 4 beta's
cov.logistic.IRLS.pval.recursive <- function(Xa,Xd,Y,PC1, beta.initial.vec = c(0,0,0,0), d.stop.th = 1e-6)
#Initialize
  beta_t <- beta.initial.vec
  dt <- 0

  X_mx <- cbind(rep(1,nrow(Y)), Xa, Xd,PC1)
  gamma_inv <- gamma_inv_calc(X_mx, beta_t)
  h1 <- logistic.IRLS.recursive(Y, X_mx, beta_t, dt, gamma_inv, 1, d.stop.th = 1e-6, it.max = 100)

  X_mx <- cbind(rep(1,nrow(Y)), rep(0,nrow(Y)),rep(0,nrow(Y)),PC1)
  gamma_inv <- gamma_inv_calc(X_mx, beta_t)
  h0 <- logistic.IRLS.recursive(Y, X_mx, beta_t, dt, gamma_inv, 1, d.stop.th = 1e-6, it.max = 100)

  LRT <- 2*h1[[2]]-2*h0[[2]] #likelihood ratio test statistic
  pval <- pchisq(LRT, 2, lower.tail = F)
  return(pval)
}

Y <- as.matrix(round(phenotypes) )
colnames(Y) <- NULL
xa_matrix <- as.matrix(genotypes)-1
xd_matrix <- 1 - 2*abs(xa_matrix)

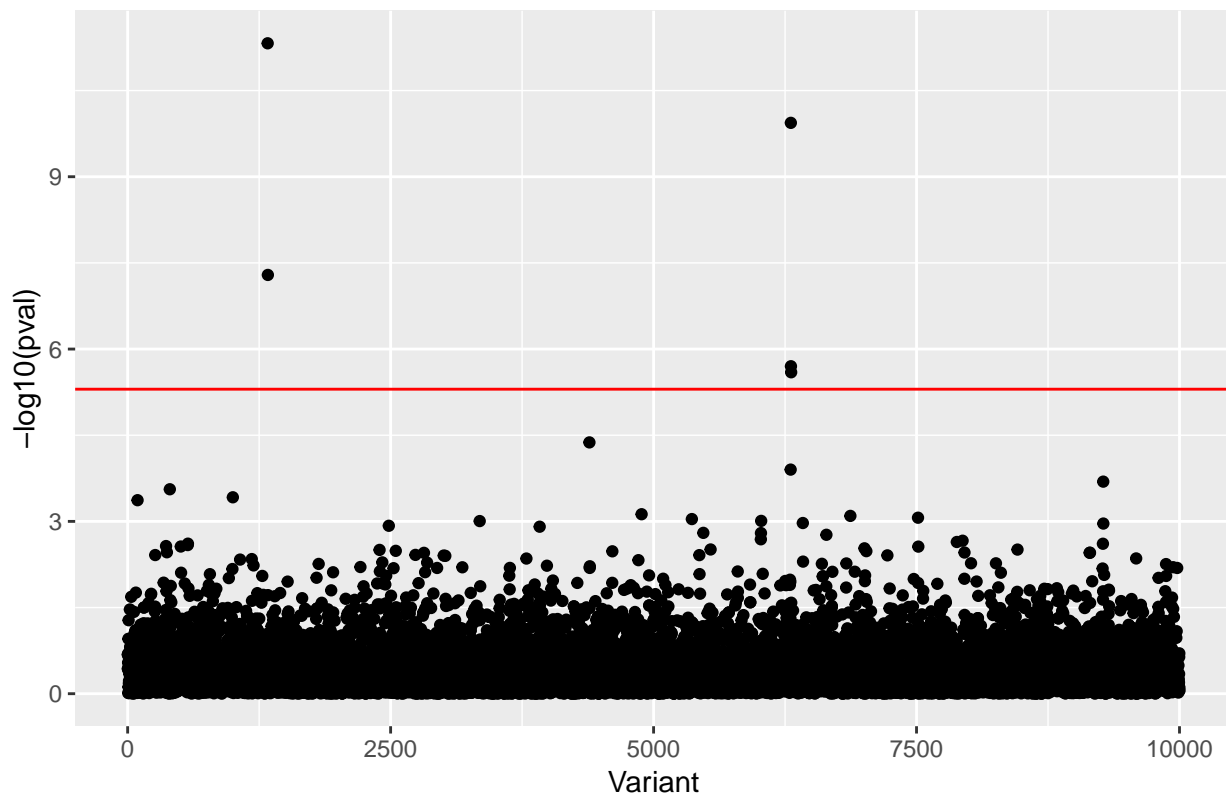
allPvals.PC1 <- apply(rbind(xa_matrix,xd_matrix), 2, function(x) cov.logistic.IRLS.pval.recursive(Xa=x[
```

5b

```
log.allPval.PC1 <- as.data.frame(-log10(allPvals.PC1),ncol=1)
adjusted_p <- -log10(0.05/ncol(genotypes))

ggplot(log.allPval.PC1,aes(1:nrow(log.allPval.PC1),log.allPval.PC1[,1])) +
  geom_point() +
  labs(x="Variant",y="-log10(pval)",title=c("Manhattan Plot"))+
  geom_hline(yintercept=adjusted_p,color = "red")
```

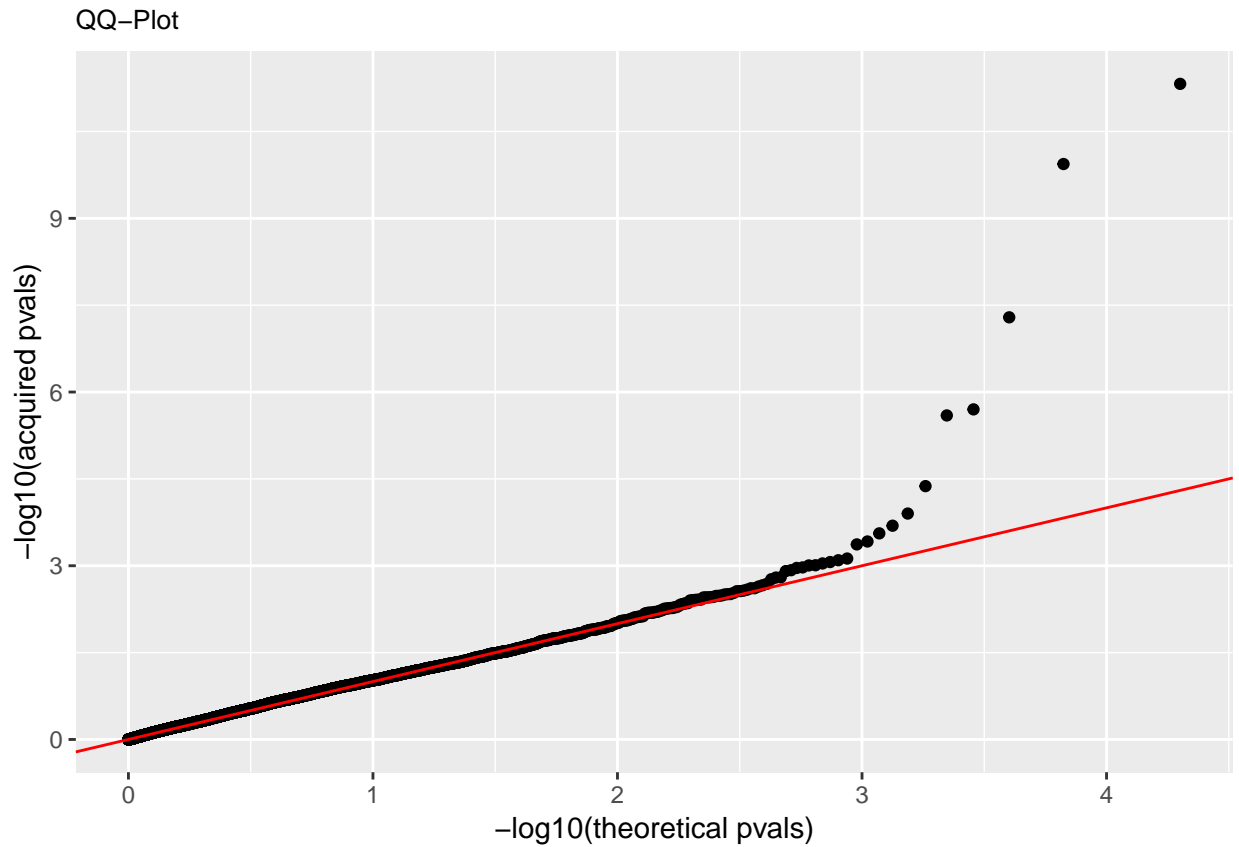
Manhattan Plot



5c.

```
qqDf1 <- data.frame(exp = sort(allPvals.PC1),theo = sort(qunif(ppoints(nrow(log.allPval)))))
ggplot(qqDf1,aes(-log10(theo), -log10(exp)))+geom_point()+
  geom_abline(slope = 1, color = "red")+
  labs(title="QQ-Plot",x="-log10(theoretical pvals)",y="-log10(acquired pvals)")+
  theme(plot.title = element_text(size=10))
```





6a.

```
#Bonferroni correction
adjusted_p <- 0.05/ncol(genotypes)
```

6b.

there are two peaks. They are separated by genotypes with p-values that fall below the cutoff.

7a.

(1,3) ##7b. (2,3) ##7c. (1,2)

8a

$$X_a \beta_\alpha = X_a \beta_a + X_d \beta_d + \beta'_u + \epsilon \quad \text{##8b 0}$$

9a

A1A1B1B1 A1A2B1B1 A2A2B1B1 A1A1B1B2 A1A2B1B2 A2A2B1B2 A1A1B2B2 A1A2B2B2 A2A2B2B2

**9b**

$$X_{a,1}, X_{d,1}, X_{a,2}, X_{d,2} = 1, -1, 1, -1$$

**9c**

$$\text{based on the interaction linear regression } y = \beta_u + \beta_{a,1} * X_{a,1} + \beta_{a,2} * X_{a,2} + \beta_{d,1} * X_{d,1} + \beta_{d,2} * X_{d,2} + \beta_{a_1a_2} * X_{a,1} * X_{a,2} + \beta_{a_1d_2} * X_{a,1} * X_{d,2} + \beta_{d_1a_2} * X_{d,1} * X_{a,2} + \beta_{d_1d_2} * X_{d,1} * X_{d,2} = 0.2 + 0.1 * 1 + 0.2 * (-1) + (-0.3) * 1 + 0.17 * (-1) + (-0.11) * 1 * 1 + 0.32 * 1 * (-1) + 0.08 * (-1) * 1 + (-0.03) * (-1) * (-1) = -0.91$$

**10a**

$$\{H, T\}$$

**10b**

$$\emptyset, \{H, T\}, \{H\}, \{T\},$$

**10c**

$$\text{in a fair game, } Pr(H) = Pr(T) = 0.5 \quad Pr(\emptyset) = 0 \quad Pr(H) = Pr(T) = 0.5 \quad Pr(H \cup T) = 1$$

**10d**

$$\text{define } X = 1 \text{ if Head, } X = 0 \text{ if tail}$$

**10e**

$$E(x) = Pr(X=1)1 + Pr(X=0)0 = 0.5$$

**10f**

$$X \text{ can be } 0, 1, 2, 3, \dots, 10 \text{ 11 possible outcomes}$$

**10g**

$$\text{An example of wrong estimator: } T = 1/N^2$$

**10h**

$$MLE(\hat{p}) = x/N, \text{ where } N \text{ is the number of total toss, } x \text{ is the heads}$$

**10i**

based on the static, there are 10 tests, hence:  $p = \text{choose}(10,8)/\text{choose}(10,5)$   
 $p = 0.178$

**10j**

$p > 0.05$ , fail to reject