

# Two-stage polytomous logistic regression tutorial

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Cancers are routinely classified into subtypes according to various features, including histopathological characteristics and molecular markers. Genomic investigations have reported heterogeneous association between loci and cancer subtypes. However, it is not evident what is the optimal modeling strategy for handling correlated tumor features, missing data, and increased degrees-of-freedom in the underlying tests of associations. In this tutorial, we proposed a two-stage polytomous regression framework to handle cancer data with multivariate tumor characteristics. In the first stage, a standard polytomous model is used to specify for all subtypes defined by the cross-classification of different markers. In the second stage, the subtype-specific case-control odds ratios are specified using a more parsimonious model based on the case-control odds ratio for a baseline subtype, and the case-case parameters associated with tumor markers. Further, to reduce the degrees-of-freedom, we allow to specify case-case parameters for additional markers using a random-effect model. We use the EM algorithm to account for missing data on tumor markers. The score-test distribution theory is developed by borrowing analogous techniques from group-based association tests. Through simulations across a range of realistic scenarios, we show the proposed methods outperforms alternative methods for identifying heterogeneous associations between risk loci and tumor subtypes.

*Keywords:* Two-stage polytomous model; Susceptibility variants; Cancer subtypes; EM algorithm; Score tests; Etiologic heterogeneity.

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## Overview

This vignette provides an introduction to the ‘TOP’ package. To load the package, users need to install package from CRAN and TOP from github. The package can be loaded with the following command:

```
# install.packages("devtools")
library(devtools)
#install_github("andrewhaoyu/TOP")
library(TOP)
```

## Two-stage polytomous model

In this vignette, we will demonstrate the methods with a breast cancer example. There are around 5,112 cases and 4,888 controls in the dataset. Four different tumor characteristics were included:

ER (positive vs negative), PR (positive vs negative), HER2 (positive vs negative), grade (ordinal 0, 1, 2).

For simplicity, we will first demonstrate the two-stage model with three binary tumor characteristics (ER, PR, and HER2). These three tumor characteristics could define 8 different breast cancer subtypes ( $8=2 \times 2 \times 2$ ). We included two covariates, one is a SNP that we are interested. The second one is the first principal component (PC1). Let  $D_i$  denote the disease status, taking values in  $\{0, 1, 2, \dots, 8\}$ , of the  $i$ th ( $i \in 1, \dots, 10,000$ ) subject in the study.  $D_i = 0$  represents a control, and  $D_i = m$  represent a subject with disease of subtype  $m$ . Let  $G_i$  be the genotype for  $i$ th subject and  $X_i$  be the PC1 for the  $i$ th subject. In the first-stage model, we use the standard “saturated” polytomous logistic regression model

$$Pr(D_i = m | G_i, X_i) = \frac{\exp(\beta_m G_i + \eta_m X_i)}{1 + \sum_{m=1}^8 \exp(\beta_m G_i + \eta_m X_i)}$$

where  $\beta_m$  and  $\eta_m$  is the regression coefficients for the SNP and PC1 for association with the  $m$ th subtype.

Because each cancer subtype  $m$  is defined through a unique combination of the 4 characteristics, we can always alternatively index the parameters  $\beta_m$  as  $\beta_{s_1 s_2 s_3}$ , where  $s_1, s_2, s_3 \in \{0, 1\}$  for the three binary tumor characteristics. Originally  $\beta_1$  could be the coefficient of cancer subtype ER-PR-HER2-. With the new index,  $\beta_1$  could be written as  $\beta_{000}$ , which means the ER, PR, HER2 are all negative. With this new index, we can represent the log odds ratio as

$$\beta_{s_1 s_2 s_3} = \theta^{(0)} + \theta_1^{(1)} s_1 + \theta_2^{(1)} s_2 + \theta_3^{(1)} s_3 + \theta_{12}^{(2)} s_1 s_2 + \theta_{13}^{(2)} s_1 s_3 + \theta_{23}^{(2)} s_2 s_3 + \theta_{123}^{(3)} (s_1 s_2 s_3).$$

Here  $\theta^{(0)}$  represents the standard case-control log odds ratio for a reference disease subtype compared to the control and  $\theta_k^{(1)}$  represents a case-case log odds ratio associated with the levels of  $k$ th tumor characteristics after adjusting for other tumor characteristics, and  $\theta_{k_1 k_2}^{(2)}$  represent case-case log odds ratios associated with pairwise interactions among the tumor characteristics and so on. This decomposition is equivalent with the first stage model. Since both the first stage and second stage have 8 parameters. We called this saturated model. The users could construct different two-stage model by assuming different second stage parameters to be 0. For example, the baseline only model:

$$\beta_{s_1 s_2 s_3} = \theta^{(0)}.$$

This model assumes all of the subtypes have the same log odds ratio. So it is equivalent to the standard logistic regression. We can also construct the additive two-stage model by assuming all of the second stage interactions parameters are 0, then the second stage decomposition becomes,

$$\beta_{s_1 s_2 s_3} = \theta^{(0)} + \theta_1^{(1)} s_1 + \theta_2^{(1)} s_2 + \theta_3^{(1)} s_3$$

Furthermore, we could construct the pairwise interaction two-stage model by assuming all of the second stage higher order interactions parameters are 0, then the second stage decomposition becomes,

$$\beta_{s_1 s_2 s_3} = \theta^{(0)} + \theta_1^{(1)} s_1 + \theta_2^{(1)} s_2 + \theta_3^{(1)} s_3 + \theta_{12}^{(2)} s_1 s_2 + \theta_{13}^{(2)} s_1 s_3 + \theta_{23}^{(2)} s_2 s_3$$

```
library(TOP)
#load in the breast cancer example
data(data, package="TOP")
```

```

#this is a simulated breast cancer example
#there are around 5000 breast cancer cases and 5000 controls disease
data[1:5,]
#four different tumor characteristics were included,
#ER (positive vs negative),
#PR (positive vs negative),
#HER2 (positive vs negative)
#the phenotype file
y <- data[,1:4]
#one SNP
#one Principal components (PC1) are the covariates
SNP <- data[,6,drop=F]
PC1 <- data[,7,drop=F]
#fit the additive two-stage model
model.1 <- TwoStageModel(y=y,additive=cbind(SNP,PC1),
                        missingTumorIndicator = 888)

```

```

#the model result is a list
#model.1[[4]] are the second stage odds ratio (95% CI)
#and p-value, the baseline effect is the case-control
#odds ratio of the reference subtype (ER-,PR-,HER2-,grade0).
#The main effect are the case-case odds ratio of the tumor characteristics.
(model.1[[4]])

```

##	Covariate	SecondStageEffect	OddsRatio	OddsRatio(95%CI low)
## 1	SNP	baseline effect	0.97	0.84
## 2	SNP	ER main effect	0.98	0.87
## 3	SNP	PR main effect	1.06	0.93
## 4	SNP	HER2 main effect	1.15	0.99
## 5	PC1	baseline effect	1.13	1.03
## 6	PC1	ER main effect	1.01	0.93
## 7	PC1	PR main effect	0.95	0.88
## 8	PC1	HER2 main effect	0.94	0.86
##	OddsRatio(95%CI high)	Pvalue		
## 1	1.13	0.69200		
## 2	1.11	0.76700		
## 3	1.20	0.37000		
## 4	1.33	0.06380		
## 5	1.24	0.00755		
## 6	1.08	0.87100		
## 7	1.03	0.21500		
## 8	1.03	0.17700		

```

#model.1[[5]] are the global association test and
#global heterogeneity test result of the covariates.
model.1[[5]]

```

```
## Covariate Global test for association Global test for heterogeneity
## 1 SNP 0.10100 0.248
## 2 PC1 0.00921 0.466
```

```
#model.1[[7]] are the case-control odds ratios
#for all of the subtypes.
head(model.1[[7]])
```

```
## Covariate Subtypes OddsRatio OddsRatio(95%CI low)
## 1 SNP EROPROHER20 0.97 0.84
## 2 PC1 EROPROHER20 1.13 1.03
## 3 SNP ER1PROHER20 0.95 0.81
## 4 PC1 ER1PROHER20 1.14 1.03
## 5 SNP EROPR1HER20 1.03 0.94
## 6 PC1 EROPR1HER20 1.08 1.02
## OddsRatio(95%CI high) Pvalue
## 1 1.13 0.69200
## 2 1.24 0.00755
## 3 1.12 0.55900
## 4 1.26 0.01010
## 5 1.12 0.52700
## 6 1.14 0.00623
```

```
#instead of additive model, you can also try
#different combinations. For example, for the PC1,
#we use the additive model, but for SNP,
#we use the baseline only model.
model.2 <- TwoStageModel(y=y,baselineonly = SNP,
                        additive=PC1,
                        missingTumorIndicator = 888)
```

The result is a list containing 9 elements. 1. the second stage parameters 2. the covariance matrix for the second stage parameters. 3. the second stage parameters organized for each covariate. 4. The case-control odds ratio and case-case odds ratios of tumor characteristics. 5. Global association test and global heterogeneity test result (Wald test based) 6. The first stage parameter organized for each covariate 7. First stage odds ratio of all the subtypes. 8. Likelihood 9. AIC

## Two-stage polytomous model self design second stage

Instead of using the hierarchical second stage decomposition we discussed in last section, the two-stage model also allows the user to self design the second stage matrix. For example, we could define five intrinsic breast cancer subtypes based on the four tumor characteristics: ER, PR, HER2, grade. The five intrinsic subtypes are: 1. (ER or PR)+, HER2-, grade 1 or 2; 2. (ER or PR)+, HER2+; 3. (ER or PR)+, HER2-, grade 3; 4. (ER & PR)-, HER2-; 5. ER-PR-HER2-. We are interested in estimating the case-control log odds ratios of these intrinsic subtypes.

```

library(TOP)
#load in the breast cancer example
data(data, package="TOP")
#this is a simulated breast cancer example
#there are around 5000 breast cancer cases and 5000 controls disease
data[1:5,]
#four different tumor characteristics were included,
#ER (positive vs negative),
#PR (positive vs negative),
#HER2 (positive vs negative)
#grade (ordinal 1,2,3)
#the phenotype file
y <- data[,1:5]
#generate the combinations of all the subtypes
#by default, we remove all the subtypes with less than 10 cases
z.standard <- GenerateZstandard(y)
M <- nrow(z.standard) #M is the total number of first stage subtypes

#initial a z.design matrix with M rows, and 5 columns
#each row represent a first stage subtype
#each column represent an aggregated subtype
z.design <- matrix(0,M,5)
#define names for the five intrinsic subtypes
colnames(z.design) <- c("HR+_HER2-_lowgrade",
                        "HR+_HER2+",
                        "HR+_HER2-_highgrade",
                        "HR-_HER2+",
                        "HR-_HER2-")

#To construct a self design second stage matrix,
#we need to find the corresponding first stage subtypes
#belonging to specific aggregated subtypes
#for first subtype HR+_HER2-_lowgrade
idx.1 <- which((z.standard[,1]==1|z.standard[,2]==1)
               &z.standard[,3]==0
               &(z.standard[,4]==1|z.standard[,4]==2))
z.design[idx.1,1] <- 1
#for second subtype HR+_HER2+
idx.2 <- which((z.standard[,1]==1|z.standard[,2]==1)
               &z.standard[,3]==1)
z.design[idx.2,2] <- 1
#for third subtype HR+_HER2-_highgrade
idx.3 <- which((z.standard[,1]==1|z.standard[,2]==1)
               &z.standard[,3]==0
               &z.standard[,4]==3)
z.design[idx.3,3] <- 1
#for third subtype HR-_HER2+
idx.4 <- which(z.standard[,1]==0&z.standard[,2]==0

```

```

        &z.standard[,3]==1)
z.design[idx.4,4] <- 1
#for third subtype HR-_HER2-
idx.5 <- which(z.standard[,1]==0&z.standard[,2]==0
               &z.standard[,3]==0)
z.design[idx.5,5] <- 1
#one SNP and one Principal components (PC1) are the covariates
SNP <- data[,6,drop=F]
PC1 <- data[,7,drop=F]

model.3 <- EMMvpolySelfDesign(y,
                              x.self.design = SNP,
                              z.design = z.design,
                              additive=PC1,
                              missingTumorIndicator = 888)

```

```

#model.3[[4]] are the second stage odds ratio (95% CI)
#and p-value of the intrinsic subtypes
(model.3[[4]])

```

##	Covariate	SecondStageEffect	OddsRatio	OddsRatio(95%CI low)
## 1	SNP	HR+_HER2-_lowgrade	1.02	0.93
## 2	SNP	HR+_HER2+	1.12	1.02
## 3	SNP	HR+_HER2-_highgrade	1.06	0.93
## 4	SNP	HR-_HER2+	1.03	0.73
## 5	SNP	HR-_HER2-	0.94	0.66
##	OddsRatio(95%CI high)	Pvalue		
## 1		1.12 0.7100		
## 2		1.22 0.0161		
## 3		1.22 0.3890		
## 4		1.44 0.8750		
## 5		1.36 0.7570		

```

#model.1[[5]] are the global association test and
#global heterogeneity test result of the covariates.
#Note global heterogeneity under self designed
#second stage matrix don't have interpretation
model.3[[5]]

```

##	Covariate	Global test for association	Global test for heterogeneity
## 1	SNP	0.251	0.16

```

#model.1[[7]] are the case-control odds ratios
#for all of the subtypes.
head(model.3[[7]])

```

##	Covariate	Subtypes	OddsRatio	OddsRatio(95%CI low)
## 1	SNP	ER1PROHER20grade1	1.02	0.93
## 2	SNP	ER0PR1HER20grade1	1.09	0.97
## 3	SNP	ER1PR1HER20grade1	1.02	0.93
## 4	SNP	ER0PROHER21grade1	1.04	0.97
## 5	SNP	ER1PROHER21grade1	1.02	0.93
## 6	SNP	ER0PR1HER21grade1	1.03	0.94

  

##	OddsRatio(95%CI high)	Pvalue
## 1	1.12	0.710
## 2	1.23	0.150
## 3	1.12	0.710
## 4	1.12	0.255
## 5	1.12	0.710
## 6	1.14	0.506

### Fixed effect two-stage model score test (FTOP)

To construct the score test for a fixed effect two stage model, we need two steps. First, we need to fit the model under the null hypothesis that the second stage parameters of SNP is 0. In other words, null of the subtypes is associated with the SNP. Second we need should compute the score and information matrix for each SNP. Based on the score and information matrix, we could construct the score test statistics for global association test

```
#fit the two-stage model under the null hypothesis
#that the second stage parameters of SNP is 0
#the model only has one covariate PC1
score.support.fixed <- ScoreTestSupportMixedModel(y=y,
                                                    additive=PC1,
                                                    missingTumorIndicator=888)

## [1] "EM Algorithm Converged"

#Generate the additive second stage design matrix
z.additive <- cbind(1,z.standard)
#compute the score and information matrix for SNP
score.test.fixed <- ScoreTestMixedModel(y=y,
                                         x=SNP,
                                         z.design = z.additive,
                                         score.test.support=score.support.fixed,
                                         missingTumorIndicator=888)

#the first element is the score
#the second element is the information matrix
score.fixed <- score.test.fixed[[1]]
infor.fixed <- score.test.fixed[[2]]
#compute the global association test p value
p.value.ftop <- DisplayFixedScoreTestResult(score.fixed,infor.fixed)
print(p.value.ftop)

## [1] 0.0539
```

## Mixed effect two-stage model score test (MTOP)

To construct the score test for a mixed effect two stage model, we need four steps. First, we need to fit the model under the null hypothesis that the second stage parameters of SNP is 0. In other words, null of the subtypes is associated with the SNP. Second, we need should compute the score and information matrix of fixed effect for each SNP. Then, we need to fit the model under the null that the variance of random effect is 0. Finally, we need to compute the score and information matrix of the random effect terms. With the score and information of fixed effect and random effect, we could construct the global association test for the mixed effect two-stage model.

```
#we are going to build a two-stage model with
#baseline parameter and ER case-case parameter as fixed
#We assume the PR, HER2, grade case-case parameter
#to be random
#fit the two-stage model under the null hypothesis
#that the second stage parameters of SNP is 0
#the model only has one covariate PC1
#Generate the z design matrix for fixed effect
z.design.fixed <- cbind(1,z.standard[,1])
#compute the score and information matrix for fixed effect
score.test.fixed <- ScoreTestMixedModel(y=y,
                                         x=SNP,
                                         z.design=z.design.fixed,
                                         score.test.support=score.support.fixed,
                                         missingTumorIndicator=888)

#the first element is the score
#the second element is the information matrix
score.fixed <- score.test.fixed[[1]]
infor.fixed <- score.test.fixed[[2]]

#fit the two-stage model under the null hypothesis
#that only the random effect is 0
#the model will have two covariates,
#PC1 and the fixed effect of SNP
score.support.random <- ScoreTestSupportMixedModelSelfDesign(y=y,
                                                                x.self.design = SNP,
                                                                z.design = z.design.fixed,
                                                                additive = PC1,
                                                                missingTumorIndicator = 888)
```

```
## [1] "EM Algorithm Converged"
```

```
#Generate the z design matrix for random effect
#PR, HER2 and grade is random effect
z.design.random <- z.standard[,2:4]

#compute the score and information matrix for random effect
score.test.random <- ScoreTestMixedModel(y=y,
```



```

x=SNP,
z.design=z.design.random,
score.test.support=score.support.random,
missingTumorIndicator=888)

#the first element is the score
#the second element is the information matrix
score.random <- score.test.random[[1]]
infor.random <- score.test.random[[2]]

#after we get the the fixed effect score, infor
#and random effect score, infor,
#we can combine them through the following function.
#two p value will be generated.
#the first p value for global association test.
#the second p value is for the null hypothesis
#that random effect is 0
#Under this situation, the second p value is NOT
#the global heterogeneity test p value since ER is fixed
p.value.mtop <- DisplayMixedScoreTestResult(
  score.fixed,
  infor.fixed,
  score.random,
  infor.random
)
print(p.value.mtop)

```

```
## [1] 0.09988282 0.14110544
```

## References

1. Zhang, H., Zhao, N., Ahearn, T.U, Wheeler W., García-Closas, M., Chatterjee, N., A mixed-model approach for powerful testing of genetic associations with cancer risk incorporating tumor characteristics (Submitted)