

Logistic Regression

Consider the diabetes dataset. We will take Outcome as the response, the other variables as predictors. We will build a reasonably good” logistic regression model for these data.

- a) **Figure 1** shows the boxplots of Outcome as a function of other predictor variables. Based on the plots it can be observe that all the predictors will be helpfull when separating patients with diabeties and without diabeties as there is a difference between distributions of patients with diabeties and other for every predictor. Among them Pregnancy, Glucose, Insulin and Age will be really helpful.

```
library(car)
library(lmtest)
library(ggplot2)
library(ISLR)
library(MASS)
```

```
diab<-read.csv("diabetes.csv")
head(diab)
```

	Pregnancies..	Glucose..	BloodPressure..	SkinThickness..	Insulin..	BMI..
1	2	138	62	35	0	33.6
2	0	84	82	31	125	38.2
3	0	145	0	0	0	44.2
4	0	135	68	42	250	42.3
5	1	139	62	41	480	40.7
6	0	173	78	32	265	46.5

	DiabetesPedigreeFunction..	Age..	Outcome
1	0.127	47	1
2	0.233	23	0
3	0.630	31	1
4	0.365	24	1
5	0.536	21	0
6	1.159	58	0

```
diab$Outcome<-as.factor(diab$Outcome)
names(diab)<-c("Pregnancies","Glucose","BP","Thickness","Insulin","BMI","DPB","Age","Outcome")
str(diab)
```

```
'data.frame': 2000 obs. of 9 variables:
 $ Pregnancies: int 2 0 0 0 1 0 4 8 2 2 ...
 $ Glucose : int 138 84 145 135 139 173 99 194 83 89 ...
 $ BP : int 62 82 0 68 62 78 72 80 65 90 ...
 $ Thickness : int 35 31 0 42 41 32 17 0 28 30 ...
 $ Insulin : int 0 125 0 250 480 265 0 0 66 0 ...
 $ BMI : num 33.6 38.2 44.2 42.3 40.7 46.5 25.6 26.1 36.8 33.5 ...
 $ DPB : num 0.127 0.233 0.63 0.365 0.536 ...
 $ Age : int 47 23 31 24 21 58 28 67 24 42 ...
 $ Outcome : Factor w/ 2 levels "0","1": 2 1 2 2 1 1 1 1 1 1 ...
```

```
contrasts(diab$Outcome)
```

```
1
0 0
1 1
```

```
plot3a<-ggplot(diab, aes(x=Outcome, y=Pregnancies,fill=Outcome)) +
  geom_boxplot() + theme(legend.position = "none",axis.title.x = element_text(size=10), axis.title.y = element
```

```

plot3b<-ggplot(diab, aes(x=Outcome, y=Glucose,fill=Outcome)) +
  geom_boxplot() + theme(legend.position = "none",axis.title.x = element_text(size=10), axis.title.y = element_text(size=10))

plot3c<-ggplot(diab, aes(x=Outcome, y=BP,fill=Outcome)) +
  geom_boxplot() + ylab("Blood Pressure")+ theme(legend.position = "none",axis.title.x = element_text(size=10), axis.title.y = element_text(size=10))

plot3d<-ggplot(diab, aes(x=Outcome, y=Thickness,fill=Outcome)) +
  geom_boxplot() + ylab("Skin Thickness") + theme(legend.position = "none",axis.title.x = element_text(size=10), axis.title.y = element_text(size=10))

plot3e<-ggplot(diab, aes(x=Outcome, y=Insulin,fill=Outcome)) +
  geom_boxplot() + theme(legend.position = "none",axis.title.x = element_text(size=10), axis.title.y = element_text(size=10))

plot3f<-ggplot(diab, aes(x=Outcome, y=BMI,fill=Outcome)) +
  geom_boxplot() + theme(legend.position = "none",axis.title.x = element_text(size=10), axis.title.y = element_text(size=10))

plot3g<-ggplot(diab, aes(x=Outcome, y=DPB,fill=Outcome)) +
  geom_boxplot() + ylab("Diabetes Pedigree Function") + theme(legend.position = "none",axis.title.x = element_text(size=10), axis.title.y = element_text(size=10))

plot3h<-ggplot(diab, aes(x=Outcome, y=Age,fill=Outcome)) +
  geom_boxplot() + theme(legend.position = "none",axis.title.x = element_text(size=10), axis.title.y = element_text(size=10))

require(gridExtra)
grid.arrange(plot3a, plot3b, plot3c, plot3d, plot3e, plot3f, plot3g, plot3h, ncol=8)

```

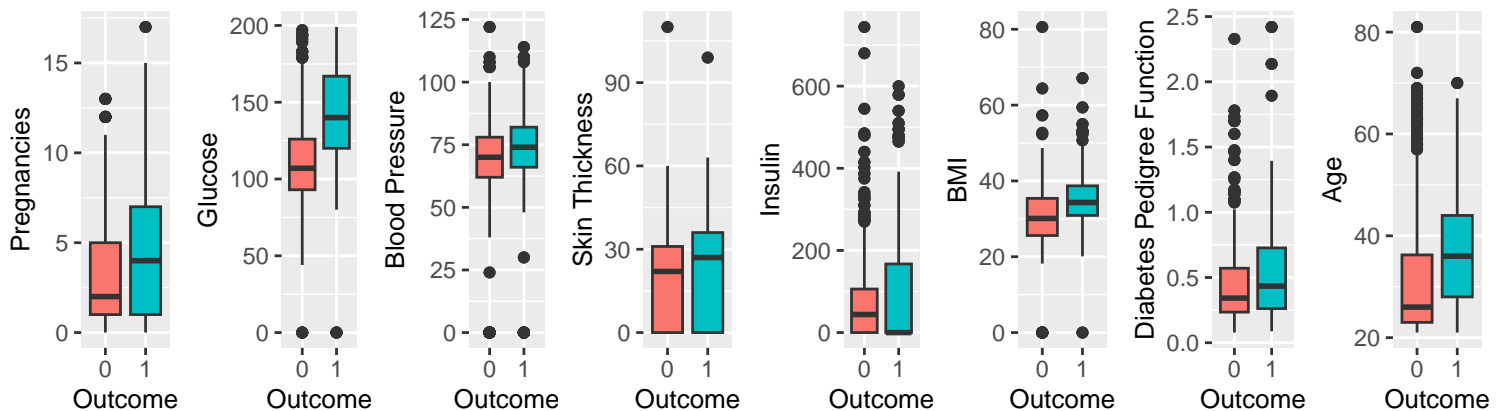


Figure 1: Class conditional distributions for the diabetes data.

```

#part b)
full.model <- glm(Outcome ~ Pregnancies + Glucose + BP + Thickness + Insulin + BMI + DPB + Age, family = binomial)
summary(full.model)

```

Call:

```

glm(formula = Outcome ~ Pregnancies + Glucose + BP + Thickness +
    Insulin + BMI + DPB + Age, family = binomial, data = diab)

```

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-8.0264511	0.4306345	-18.639	< 2e-16 ***
Pregnancies	0.1263845	0.0199997	6.319	2.63e-10 ***
Glucose	0.0337202	0.0022258	15.150	< 2e-16 ***
BP	-0.0096446	0.0032441	-2.973	0.00295 **
Thickness	0.0005185	0.0042301	0.123	0.90244
Insulin	-0.0012426	0.0005786	-2.148	0.03175 *
BMI	0.0775549	0.0088819	8.732	< 2e-16 ***
DPB	0.8877583	0.1860275	4.772	1.82e-06 ***

```
Age          0.0129414  0.0057020  2.270  0.02323 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(Dispersion parameter for binomial family taken to be 1)

```
Null deviance: 2569.4  on 1999  degrees of freedom
Residual deviance: 1914.3  on 1991  degrees of freedom
AIC: 1932.3
```

Number of Fisher Scoring iterations: 5

```
red.model <- glm(Outcome ~ Pregnancies + Glucose + BP + Insulin + BMI + DPB + Age, family = binomial, data = diab)
summary(red.model)
```

```
Call:
glm(formula = Outcome ~ Pregnancies + Glucose + BP + Insulin +
    BMI + DPB + Age, family = binomial, data = diab)
```

```
Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -8.0273146  0.4306244 -18.641  < 2e-16 ***
Pregnancies  0.1263707  0.0199944   6.320 2.61e-10 ***
Glucose      0.0336810  0.0022020  15.296  < 2e-16 ***
BP           -0.0095806  0.0032013   -2.993  0.00276 **
Insulin      -0.0012123  0.0005228   -2.319  0.02042 *
BMI           0.0778743  0.0084946   9.167  < 2e-16 ***
DPB           0.8894946  0.1855205   4.795 1.63e-06 ***
Age           0.0128944  0.0056879   2.267  0.02339 *
```

```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(Dispersion parameter for binomial family taken to be 1)

```
Null deviance: 2569.4  on 1999  degrees of freedom
Residual deviance: 1914.3  on 1992  degrees of freedom
AIC: 1930.3
```

Number of Fisher Scoring iterations: 5

```
anova(red.model, full.model, test = "Chisq")
```

Analysis of Deviance Table

```
Model 1: Outcome ~ Pregnancies + Glucose + BP + Insulin + BMI + DPB +
Age
Model 2: Outcome ~ Pregnancies + Glucose + BP + Thickness + Insulin +
BMI + DPB + Age
  Resid. Df Resid. Dev Df Deviance Pr(>Chi)
1      1992      1914.3
2      1991      1914.3  1 0.015033  0.9024
```

```
null.model <- glm(Outcome ~ 1, family = binomial, data = diab)
anova(null.model, red.model, test = "Chisq")
```

Analysis of Deviance Table

```
Model 1: Outcome ~ 1
Model 2: Outcome ~ Pregnancies + Glucose + BP + Insulin + BMI + DPB +
Age
  Resid. Df Resid. Dev Df Deviance  Pr(>Chi)
```

```

1      1999      2569.4
2      1992      1914.3  7    655.06 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

b)

- First, built a **model 1** by taking **Outcome** as response variable and all other variable as predictors. When testing the significance of j^{th} coefficient: i.e $H_0 : \beta_j = 0$ vs $H_0 : \beta_j \neq 0$, we do not reject the null hypothesis for predictors **Thickness** as its p value is $0.90244 > 0.05$. Thus we can conclude that predictor **Thickness** is not associated with response **Outcome** after adjusting for the other predictors.
- Then built a **model 2** by removing **Thickness** from the **model 1**. To compare two nested models - full(**model 1**) and reduced(**model 2**), change in deviance statistic is calculated and p value for chisquare test is $0.9024 > 0.05$. Therefore, we do not reject null hypothesis ($H_0 : \text{full model} = \text{reduced model}$) and conclude that **model 2** is pretty much good as the **model 1**.
- Finally test of model significance for **model 2** was carried by taking null model(model which has a common intercept and no predictors) as the reduced model and **model 2** as the full model. Change in deviance statistic is calculated and p value for chisquare test is $2.2 \times 10^{-16} < 0.05$. Therefore, we can reject null hypothesis ($H_0 : \text{full model} = \text{reduce model}$) and conclude that **model 2** is significant.

c) Let p be probability of success (probability of getting diabetes). Then the final model:

$$\begin{aligned} \text{logit}(p) = & -8.0273 + 0.1264\text{Pregnancies} + 0.0337\text{Glucose} - 0.0096\text{BP} - 0.0012\text{Insulin} \\ & + 0.0779\text{BMI} + 0.8895\text{BPP} + 0.0129\text{Age} \end{aligned}$$

- $\exp(0.1264) = 1.13470$. Therefore we expect to see about 13.5% increase in the odds of having diabeties, for a one-unit increase in Pregnancies given that other variables held constant..
- $\exp(0.0337) = 1.0342$. Therefore we expect to see about 3% increase in the odds of having diabeties, for a one-unit increase in Glucose given that other variables held constant.
- Training error rate for the model is 0.216

```

#part c)
CI<-confint(red.model)
rownames(CI)<-NULL
std.coef<-coef(summary(red.model))[, "Std. Error"]
names(std.coef)<-NULL
est<-cbind(coef(red.model),std.coef,CI)
colnames(est)<-c("Estimate","Std.Error","2.5%","97.5%")

library(xtable)
xtab<-xtable(est,caption="summary of estimates of the regression
coefficients")
digits(xtab)<-c(0,4,4,4,4)
print(xtab,table.placement="H")

```

% latex table generated in R 4.3.0 by xtable 1.8-4 package % Sat Nov 18 00:17:21 2023

	Estimate	Std.Error	2.5%	97.5%
(Intercept)	-8.0273	0.4306	-8.8896	-7.2009
Pregnancies	0.1264	0.0200	0.0874	0.1659
Glucose	0.0337	0.0022	0.0294	0.0381
BP	-0.0096	0.0032	-0.0159	-0.0033
Insulin	-0.0012	0.0005	-0.0022	-0.0002
BMI	0.0779	0.0085	0.0615	0.0948
DPB	0.8895	0.1855	0.5275	1.2549
Age	0.0129	0.0057	0.0017	0.0240

Table 1: summary of estimates of the regression coefficients

```
exp(coef(red.model))
```

```
(Intercept)  Pregnancies      Glucose          BP      Insulin          BMI
0.0003264236 1.1347027661 1.0342546108 0.9904651313 0.9987884571 1.0809867255
      DPB          Age
2.4338993683 1.0129778520
```

```
pred.prob.diab <- predict(red.model,diab, type = "response")
pred.diab <- ifelse(pred.prob.diab >= 0.5, "1", "0")
err.rate = 1 - mean(pred.diab == diab[, "Outcome"])
```