#### Exercise – Low birth weight

• Download the data set from Moodle:

Variable	Description	Data type	Level
ID	Identification code	Integer	
LOW	Low birth weight (Outcome)	Binary	0: Birth weight >= 2500g 1: Birth weight < 2500g
AGE	Age of the mother in years	Continuous	
LWT	Weight in pounds at the last menstrual period	Continuous	
RACE	Race	Categorical	1: White, 2: Black, 3: Other
SMOKE	Smoking status during pregnancy	Categorical	1: Yes, 0: No
PTL	History of premature labor	Integer	
HT	History of hypertension	Categorical	1: Yes, 0: No
UI	Presence of uterine irritability	Categorical	1: Yes, 0: No
FTV	Number of physician visits during the 1st trimester	Integer	
BWT	Birth weight in grams (Outcome)	Continuous	

• Source: Hosmer, D.W., Lemeshow, S. and Sturdivant, R.X. (2013) Applied Logistic Regression: Third Edition.

### Prepare data sets

```
LowBWT <- read.csv("{Path}/lowbwt.csv")

LowBWT$LOW <- factor(LowBWT$LOW)

LowBWT$RACE <- factor(LowBWT$RACE)

LowBWT$SMOKE <- factor(LowBWT$SMOKE)

LowBWT$HT <- factor(LowBWT$HT)

LowBWT$UI <- factor(LowBWT$UI)

library(glmnet)

# Fitting continuous outcome, variable "BWT"

x.con = model.matrix(BWT ~ . - 1 - ID - LOW, data = LowBWT)

y.con = LowBWT$BWT

# Fitting binary outcome, variable "LOW"

x.bin = model.matrix(LOW ~ . - 1 - ID - BWT, data = LowBWT)

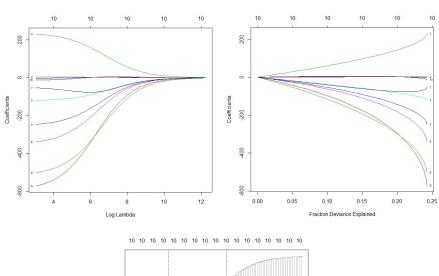
y.bin = LowBWT$LOW
```

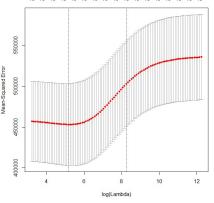
# Continuous outcome, Ridge regression

```
Ridge1 <- glmnet(x.con, y.con, alpha = 0)</pre>
plot(Ridge1, xvar="lambda", label=TRUE)
plot(Ridge1, xvar="dev", label=TRUE)
set.seed(56789)
Ridge1.cv = cv.glmnet(x.con, y.con, alpha = 0)
plot(Ridge1.cv)
coef(Ridge1, s = Ridge1.cv$lambda.1se)
(Intercept) 2847.7067859
AGE
                1.6026551
               0.7244883
LWT
RACE1
              50.8523714
RACE2
             -44.7463233
RACE 3
             -32.3425865
             -51.2953481
SMOKE1
             -34.7321317
PTL
             -80.3629268
НТ1
             -96.8631099
UI1
```

4.7682106

FTV

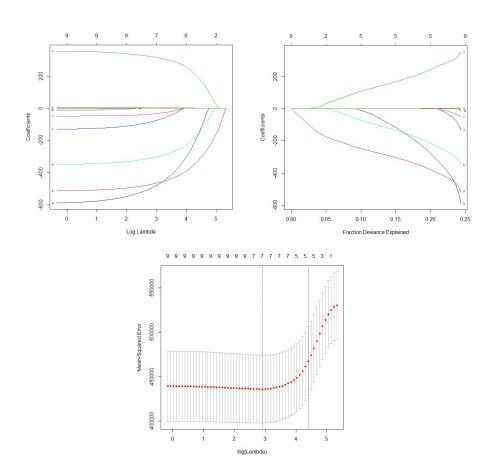




#### Continuous outcome, LASSO

```
LASSO1 <- glmnet(x.con, y.con, alpha = 1)
plot(LASSO1, xvar="lambda", label=TRUE)
plot(LASSO1, xvar="dev", label=TRUE)
set.seed(65432)
LASSO1.cv = cv.qlmnet(x.con, y.con, alpha = 1)
plot(LASSO1.cv)
coef(LASSO1, s = LASSO1.cv$lambda.1se)
(Intercept) 2919.9406351
AGE
               0.2770576
LWT
RACE1
             126.8831125
RACE2
RACE3
             -89.3331247
SMOKE1
PTL
             -29.7483233
НТ1
            -262.1262524
UI1
```

FTV



## Binary outcome, Ridge regression

```
Ridge2 <- glmnet(x.bin, y.bin, alpha = 0, family = "binomial")</pre>
plot(Ridge2, xvar="lambda", label=TRUE)
plot(Ridge2, xvar="dev", label=TRUE)
set.seed(56789)
Ridge2.cv = cv.glmnet(x.bin, y.bin, alpha = 0, family = "binomial")
plot(Ridge2.cv)
coef(Ridge2, s = Ridge2.cv$lambda.1se)
(Intercept) -0.560026873
AGE
             -0.005036865
LWT
             -0.001320565
RACE1
             -0.072877588
RACE2
              0.067682690
RACE 3
              0.044508306
SMOKE1
              0.082406149
PTL
              0.093369022
НТ1
              0.158414315
UI1
              0.110805589
                                                                      Fraction Deviance Explained
```

FTV

-0.012006530

# Binary outcome, LASSO

```
LASSO2 <- glmnet(x.bin, y.bin, alpha = 1, family = "binomial")
plot(LASSO2, xvar="lambda", label=TRUE)
plot(LASSO2, xvar="dev", label=TRUE)
set.seed(65432)
LASSO2.cv = cv.glmnet(x.bin, y.bin, alpha = 1, family = "binomial")
plot(LASSO2.cv)
coef(LASSO2, s = LASSO2.cv$lambda.1se)
(Intercept) -0.402500274
AGE
LWT
             -0.003655509
RACE1
             -0.248026319
RACE2
RACE3
              0.229056074
SMOKE1
              0.245427433
PTL
НТ1
              0.465913634
UI1
              0.214356081
FTV
                                                                       Fraction Deviance Explained
                                                                                                    log(Lambda)
```