

# DirectedStudiesAssignment1

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```
rm(list = ls())

# Loading packages
require(aplore3)

## Loading required package: aplore3

require(numDeriv)

## Loading required package: numDeriv

require(dplyr)

## Loading required package: dplyr

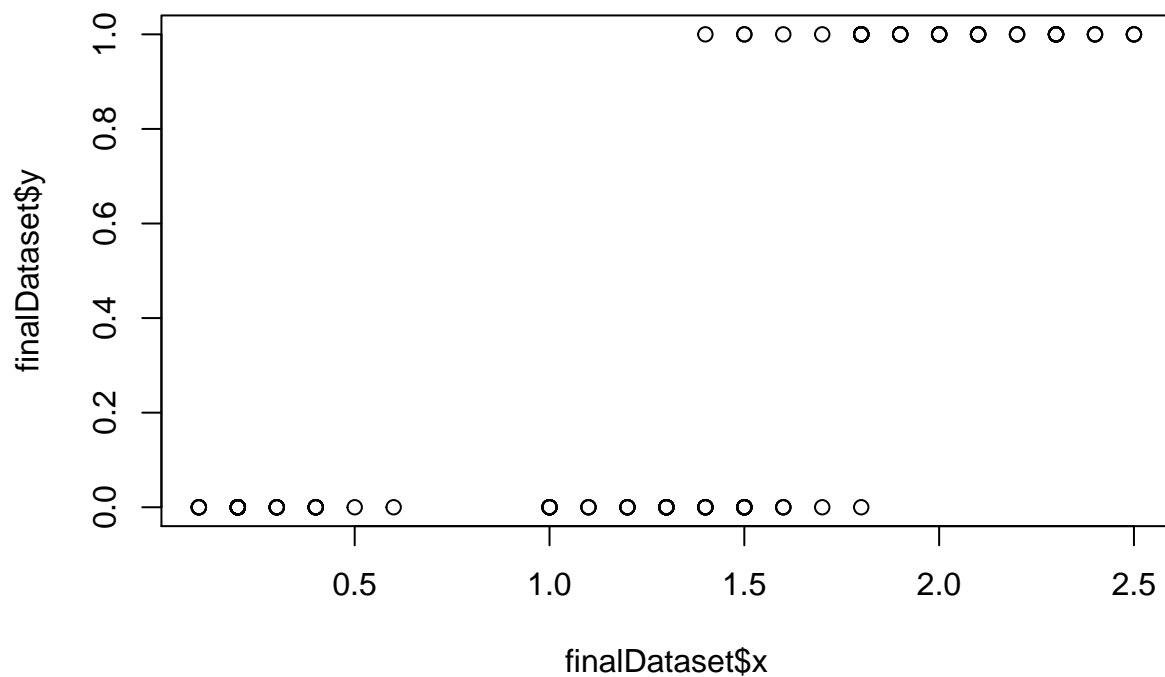
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##   filter, lag

## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union

?iris
df = iris
df1 <-data.frame(y = c(ifelse((df$Species)=='setosa',0,ifelse((df$Species)=='virginica',1,0))),
                x = (df$Petal.Width
                ))

finalDataset <- dplyr::filter(df1, y==0|y==1) ## "dplyr::" not required
plot(finalDataset$y~finalDataset$x)
```



## MLE

#Function MLE:

```
F1 <- function(data){
  B0 <- data[1]
  B1 <- data[2]
  y <- finalDataset$y
  x1 <- finalDataset$x
  X <- B0 + B1 * x1
  p <- exp(X) / (1 + exp(X))
  mle <- -sum(y * log(p) + (1 - y) * log(1 - p))
  # mle <- sum(log(pi)*(y) + (1-(y))*log(1-pi))

  (mle)
}
```

```
MLE <- optim(c(0.1,0.1),
            fn = F1,
            control = list(trace = 0),
            hessian = FALSE)
MLE
```

## \$par

```
## [1] -21.12900 12.94969
##
## $value
## [1] 16.7104
##
## $counts
## function gradient
##      95      NA
##
## $convergence
## [1] 0
##
## $message
## NULL
```

```
print("Paramters")
```

```
## [1] "Paramters"
```

```
print(MLE$par)
```

```
## [1] -21.12900 12.94969
```

```
paste("MLE", F1(MLE$par))
```

```
## [1] "MLE 16.7104045105802"
```

```
#In-Build GLM
```

```
glm_model <- glm(y ~ x ,
                 data = finalDataset,
                 family = binomial(link = "logit"))

coef(glm_model)
```

```
## (Intercept)          x
##   -21.12564    12.94751
```

```
#Newton Raphson Method
```

```
y <- finalDataset$y
x1 <- finalDataset$x

ZTP_MLE_NewtonRaphson <- function (x1,y, itr, B0=0,B1=0) {
  b0 <- rep(0,itr+1)
  b1 <- rep(0,itr+1)
  b0[1] <- B0
  b1[1] <- B1

  for (i in 1:itr){
```

```

e <- exp(b0[i] + b1[i] * x1)

#b0[i+1] =b0[i]-((sum(y)-sum(e/(1+e)))/-sum(e/e^2))
#b1[i+1]=b1[i]-((sum(x1*y)-sum(x1*e/(1+e)))/-sum(((x1^2)*e)/(e^2)))

b0[i+1]=b0[i]-((sum(y)-sum(e/(1+e)))/(-sum((e)/(e+1)^2)))
b1[i+1]=b1[i]-((sum(x1*y)-sum(x1*e/(1+e)))/(-sum(((x1^2)*e)/(e^2))))
}

data = c(b0,b1)
finaldf = data.frame (b0=b0,b1=b1, log.lik.value=F1(data))
finaldf

}

```

```

y <- finalDataset$y
x1 <- finalDataset$x

finalDF = ZTP_MLE_NewtonRaphson(x1,y,150)
finalDF

```

##		b0	b1	log.lik.value
## 1		0.0000000	0.0000000	127.3203
## 2		-0.6666667	0.03754176	127.3203
## 3		-0.7375138	0.10619167	127.3203
## 4		-0.8205170	0.17522489	127.3203
## 5		-0.9051525	0.24450281	127.3203
## 6		-0.9910310	0.31381530	127.3203
## 7		-1.0778961	0.38295220	127.3203
## 8		-1.1654819	0.45171016	127.3203
## 9		-1.2535186	0.51989734	127.3203
## 10		-1.3417390	0.58733731	127.3203
## 11		-1.4298844	0.65387196	127.3203
## 12		-1.5177107	0.71936343	127.3203
## 13		-1.6049917	0.78369498	127.3203
## 14		-1.6915230	0.84677097	127.3203
## 15		-1.7771235	0.90851611	127.3203
## 16		-1.8616361	0.96887412	127.3203
## 17		-1.9449277	1.02780602	127.3203
## 18		-2.0268884	1.08528823	127.3203
## 19		-2.1074296	1.14131055	127.3203
## 20		-2.1864828	1.19587416	127.3203
## 21		-2.2639972	1.24898979	127.3203
## 22		-2.3399376	1.30067593	127.3203
## 23		-2.4142829	1.35095733	127.3203
## 24		-2.4870233	1.39986361	127.3203
## 25		-2.5581595	1.44742810	127.3203
## 26		-2.6277003	1.49368680	127.3203
## 27		-2.6956613	1.53867756	127.3203
## 28		-2.7620638	1.58243940	127.3203
## 29		-2.8269338	1.62501191	127.3203
## 30		-2.8903005	1.66643479	127.3203
## 31		-2.9521960	1.70674750	127.3203

## 32	-3.0126542	1.74598898	127.3203
## 33	-3.0717107	1.78419740	127.3203
## 34	-3.1294017	1.82141001	127.3203
## 35	-3.1857641	1.85766302	127.3203
## 36	-3.2408349	1.89299152	127.3203
## 37	-3.2946512	1.92742940	127.3203
## 38	-3.3472495	1.96100937	127.3203
## 39	-3.3986659	1.99376288	127.3203
## 40	-3.4489361	2.02572018	127.3203
## 41	-3.4980947	2.05691030	127.3203
## 42	-3.5461758	2.08736109	127.3203
## 43	-3.5932125	2.11709923	127.3203
## 44	-3.6392369	2.14615030	127.3203
## 45	-3.6842804	2.17453877	127.3203
## 46	-3.7283733	2.20228808	127.3203
## 47	-3.7715450	2.22942065	127.3203
## 48	-3.8138237	2.25595794	127.3203
## 49	-3.8552371	2.28192049	127.3203
## 50	-3.8958115	2.30732794	127.3203
## 51	-3.9355728	2.33219911	127.3203
## 52	-3.9745455	2.35655199	127.3203
## 53	-4.0127534	2.38040380	127.3203
## 54	-4.0502198	2.40377104	127.3203
## 55	-4.0869666	2.42666952	127.3203
## 56	-4.1230153	2.44911436	127.3203
## 57	-4.1583865	2.47112006	127.3203
## 58	-4.1931001	2.49270052	127.3203
## 59	-4.2271752	2.51386907	127.3203
## 60	-4.2606304	2.53463847	127.3203
## 61	-4.2934834	2.55502099	127.3203
## 62	-4.3257513	2.57502838	127.3203
## 63	-4.3574509	2.59467195	127.3203
## 64	-4.3885979	2.61396252	127.3203
## 65	-4.4192078	2.63291052	127.3203
## 66	-4.4492955	2.65152595	127.3203
## 67	-4.4788753	2.66981843	127.3203
## 68	-4.5079609	2.68779721	127.3203
## 69	-4.5365658	2.70547118	127.3203
## 70	-4.5647028	2.72284890	127.3203
## 71	-4.5923844	2.73993862	127.3203
## 72	-4.6196224	2.75674826	127.3203
## 73	-4.6464286	2.77328546	127.3203
## 74	-4.6728141	2.78955759	127.3203
## 75	-4.6987898	2.80557173	127.3203
## 76	-4.7243660	2.82133472	127.3203
## 77	-4.7495529	2.83685316	127.3203
## 78	-4.7743602	2.85213342	127.3203
## 79	-4.7987975	2.86718162	127.3203
## 80	-4.8228737	2.88200369	127.3203
## 81	-4.8465979	2.89660535	127.3203
## 82	-4.8699784	2.91099214	127.3203
## 83	-4.8930237	2.92516937	127.3203
## 84	-4.9157417	2.93914223	127.3203
## 85	-4.9381401	2.95291568	127.3203

## 86	-4.9602265	2.96649456	127.3203
## 87	-4.9820081	2.97988353	127.3203
## 88	-5.0034920	2.99308709	127.3203
## 89	-5.0246851	3.00610961	127.3203
## 90	-5.0455939	3.01895533	127.3203
## 91	-5.0662249	3.03162833	127.3203
## 92	-5.0865843	3.04413257	127.3203
## 93	-5.1066782	3.05647190	127.3203
## 94	-5.1265123	3.06865003	127.3203
## 95	-5.1460924	3.08067058	127.3203
## 96	-5.1654241	3.09253703	127.3203
## 97	-5.1845125	3.10425278	127.3203
## 98	-5.2033631	3.11582111	127.3203
## 99	-5.2219807	3.12724521	127.3203
## 100	-5.2403704	3.13852818	127.3203
## 101	-5.2585369	3.14967303	127.3203
## 102	-5.2764847	3.16068267	127.3203
## 103	-5.2942185	3.17155993	127.3203
## 104	-5.3117426	3.18230756	127.3203
## 105	-5.3290612	3.19292824	127.3203
## 106	-5.3461784	3.20342456	127.3203
## 107	-5.3630984	3.21379905	127.3203
## 108	-5.3798250	3.22405416	127.3203
## 109	-5.3963620	3.23419227	127.3203
## 110	-5.4127131	3.24421571	127.3203
## 111	-5.4288820	3.25412673	127.3203
## 112	-5.4448721	3.26392753	127.3203
## 113	-5.4606868	3.27362025	127.3203
## 114	-5.4763296	3.28320695	127.3203
## 115	-5.4918036	3.29268968	127.3203
## 116	-5.5071120	3.30207039	127.3203
## 117	-5.5222578	3.31135101	127.3203
## 118	-5.5372441	3.32053341	127.3203
## 119	-5.5520738	3.32961940	127.3203
## 120	-5.5667498	3.33861076	127.3203
## 121	-5.5812748	3.34750923	127.3203
## 122	-5.5956515	3.35631648	127.3203
## 123	-5.6098826	3.36503416	127.3203
## 124	-5.6239706	3.37366387	127.3203
## 125	-5.6379182	3.38220717	127.3203
## 126	-5.6517276	3.39066559	127.3203
## 127	-5.6654014	3.39904062	127.3203
## 128	-5.6789418	3.40733369	127.3203
## 129	-5.6923512	3.41554624	127.3203
## 130	-5.7056317	3.42367964	127.3203
## 131	-5.7187856	3.43173523	127.3203
## 132	-5.7318149	3.43971434	127.3203
## 133	-5.7447218	3.44761826	127.3203
## 134	-5.7575083	3.45544822	127.3203
## 135	-5.7701763	3.46320547	127.3203
## 136	-5.7827278	3.47089121	127.3203
## 137	-5.7951647	3.47850659	127.3203
## 138	-5.8074889	3.48605276	127.3203
## 139	-5.8197021	3.49353085	127.3203

```
## 140 -5.8318061 3.50094194      127.3203
## 141 -5.8438026 3.50828711      127.3203
## 142 -5.8556934 3.51556739      127.3203
## 143 -5.8674800 3.52278382      127.3203
## 144 -5.8791642 3.52993738      127.3203
## 145 -5.8907474 3.53702905      127.3203
## 146 -5.9022313 3.54405979      127.3203
## 147 -5.9136173 3.55103054      127.3203
## 148 -5.9249070 3.55794221      127.3203
## 149 -5.9361017 3.56479569      127.3203
## 150 -5.9472030 3.57159186      127.3203
## 151 -5.9582122 3.57833159      127.3203
```

```
F2 <- function(p){
  y <- finalDataset$y
  p<-p/100
  if(any(p > 1) | any(p < 0)) {
    val <- 0
  } else {
    val <- -sum(y * log(p) + (1 - y) * log(1 - p))
  }
  val
}
uniroot(f = F2, interval=c(1,99),extendInt = "yes")
```

```
## $root
## [1] 101.97
##
## $f.root
## [1] 0
##
## $iter
## [1] 2
##
## $init.it
## [1] 2
##
## $estim.prec
## [1] 0
```

Comprison

```
print("In build GLM")
```

```
## [1] "In build GLM"
```

```
print((glm_model))
```

```
##
## Call: glm(formula = y ~ x, family = binomial(link = "logit"), data = finalDataset)
##
```

```

## Coefficients:
## (Intercept)          x
##      -21.13      12.95
##
## Degrees of Freedom: 149 Total (i.e. Null);  148 Residual
## Null Deviance:      191
## Residual Deviance: 33.42    AIC: 37.42

## [1] "Using Optim"

## [1] "b0 -21.1289971502894"

## [1] "b1 12.9496947420738"

## [1] "log.lik.value 16.7104045105802"

print("Using Newton Raphson")

## [1] "Using Newton Raphson"

last_row = tail(finalDF, n=1)
paste("b0",last_row[1])

## [1] "b0 -5.95821217724173"

paste("b1",last_row[2])

## [1] "b1 3.57833158893427"

paste("log.lik.value",last_row[3])

## [1] "log.lik.value 127.320265537562"

```