Tut 4: Logistic Regression (cont)

Jan 2023

1. (Jan 2022 Final Q2(a)) Given the following results from the analysis of credit card applications approval dataset using logistic regression model.

```
glm(formula=Approved~., family=binomial, data=d.f.train)
Deviance Residuals:
    Min
              1 Q
                    Median
                                 3Q
                                          Max
-2.6796
         -0.5477
                    0.2681
                             0.3316
                                       2.4501
Coefficients:
                Estimate Std. Error z value Pr(>|z|)
(Intercept)
               3.1379649
                           0.5744168
                                        5.463 4.68e-08 ***
               -0.1758676
                           0.3229541
                                       -0.545
Maleb
                                                0.5861
Age
               0.0001318
                           0.0142338
                                        0.009
                                                0.9926
Debt
               0.0042129
                           0.0298740
                                        0.141
                                                0.8879
YearsEmployed -0.1023132
                           0.0582368
                                       -1.757
                                                0.0789
                                               < 2e-16
PriorDefaultt -3.6614227
                           0.3659226 -10.006
Employedt
               -0.2500687
                           0.4013495
                                       -0.623
                                                0.5332
CreditScore
              -0.1098142
                           0.0644360
                                       -1.704
                                                0.0883
ZipCode
               0.0011958
                           0.0009540
                                       1.253
                                                0.2100
                                       -2.311
                                                0.0209 *
Income
               -0.0004544
                           0.0001966
          0 '*** 0.001 '** 0.01 '* 0.05 '. ' 0.1 ' 1
(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 625.90
                            on 454
                                     degrees of freedom
Residual deviance: 294.33
                            on 445
                                     degrees of freedom
  (27 observations deleted due to missingness)
AIC: 314.33
```

where the output Approved is either positive (represented as 0) and negative (represented as 1) and the features

- Male is categorical with a=Female, b=Male;
- PriorDefault is categorical with f=false, t=true;
- Employed is categorical with f=false, t=true;
- Age, Debt, YearsEmployed, CreditScore, ZipCode, Income are continuous variables.
- (a) Write down the mathematical expression of the logistic model for the given data with the coefficient values rounded to 4 decimal places. (4 marks)

```
Solution. The logistic model is \mathbb{P}(\texttt{Approved}=1|\bm{X})=\frac{1}{1+e^{-(3.1380+\bm{w}^T\bm{X})}} [1.5 mark]
```

```
\label{eq:wave_energy} \begin{split} \pmb{w}^T \pmb{X} &= -0.1759\, \texttt{Male} + 0.0001\, \texttt{Age} + 0.0042\, \texttt{Debt} - 0.1023\, \texttt{YearsEmployed} \\ &- 3.6614\, \texttt{PriorDefault} - 0.2501\, \texttt{Employed} - 0.1098\, \texttt{CreditScore} \quad [2.5\,\, \text{marks}] \\ &+ 0.0012\, \texttt{ZipCode} - 0.0005\, \texttt{Income} \end{split}
```

(b) By calculating the probability of the credit card application being approved for a male of age 22.08 with a debt of 0.83 unit who has been employed for 2.165 years with no prior default and is currently unemployed, has a credit score 0 and a zip code 128 with income 0, find the **probability** of credit card applications approval and determine if the approval is positive or negative (using the cut-off of 0.5). (7 marks)

Solution. First, we calculate $\boldsymbol{w}^T\boldsymbol{X} = -0.1759\,(1) + 0.0001\,(22.08) + 0.0042\,(0.83) - 0.1023\,(2.165) \\ -3.6614\,(0) - 0.2501\,(0) - 0.1098\,(0) \\ +0.0012\,(128) - 0.0005\,(0)$ [4 marks] = -0.2380855

The probability of getting diabetes is

$$\mathbb{P}(\texttt{Approved} = 1 | \mathbf{X}) = \frac{1}{1 + \exp(-(3.1380 - 0.2380855))} = 0.9478$$
 [2 marks]

Since the probability is more than 0.5, the approval is **negative**. [1 mark]

(c) Calculate the odds ratio for the approval being negative with the prior default to be true against the prior default to be false. Infer the likelihood of getting a negative approval based on the prior default.

(6 marks)

Solution. The odds ratio for the approval with respect to prior default is

$$\frac{\frac{\mathbb{P}(\texttt{Approved}=1|\texttt{PriorDefault}=t)}{1-\mathbb{P}(\texttt{Approved}=1|\texttt{PriorDefault}=t)}}{\frac{\mathbb{P}(\texttt{Approved}=1|\texttt{PriorDefault}=t)}{1-\mathbb{P}(\texttt{Approved}=1|\texttt{PriorDefault}=f)}} = \frac{\exp(-3.6614227\times 1)}{\exp(-3.6614227\times 0)} = 0.02569593 \quad [4 \text{ marks}]$$

Someone with a prior default has a lower likelihood to get a negative approval compare to someone without a prior default. [2 marks]

2. (May 2020 Final Q2(a)) The testing dataset of an insurance claim is given in Table 2.1. The variables "gender", "bmi", "age_bracket" and "previous_claim" are the predictors and the "claim" is the response.

Table 2.1: The testing data of an insurance claim (randomly sampled with repeated entry).

gender	bmi	age_bracket	previous_claim	claim
female	under_weight	18-30	0	no_claim
female	$under_weight$	18-30	0	no_claim
$_{\mathrm{male}}$	over_weight	31-50	0	no_claim
female	$under_weight$	50+	1	no_claim
$_{\mathrm{male}}$	$normal_weight$	18-30	0	no_claim
female	underweight	18-30	1	no_claim
$_{\mathrm{male}}$	over_weight	18-30	1	no_claim
$_{\mathrm{male}}$	over_weight	50+	1	claim
female	normal_weight	18-30	0	no_claim
female	obese	50+	0	claim

The "gender" is binary categorical data, the "bmi" is a four-value categorical data with values under_weight, normal_weight, over_weight and obese, the "age_bracket" is a three-value categorical data with value "18-30", "31-50" and "50+", the "previous_claim" is a binary categorical data with 0 indicating "no previous claim" and 1 indicating "having a previous claim". The "claim" is a binary response with values "no_claim" (negative class, with value 1) and "claim" (positive class, with value 0).

Suppose a logistic regression model is trained and the coefficients are stated in Figure 2.2.

Figure 2.2: The coefficients of the logistic regression based on an insurance claim data.

```
Coefficients:
                 Estimate Std. Error z value Pr(>|z|)
                   3.1361
                              0.2990
                                      10.489
                                              < 2e-16 ***
(Intercept)
                                      -1.908
gendermale
                  -0.3343
                              0.1753
                                              0.05644 .
                  -1.9495
                                       -6.910 4.86e-12 ***
bmiobese
                              0.2821
bmiover_weight
                  -1.0563
                              0.2629
                                       -4.017 5.89e-05 ***
bmiunder_weight
                  -0.8424
                              0.2606
                                       -3.232
                                              0.00123
                  -0.2875
                                               0.21382
age_bracket31-50
                              0.2313
                                       -1.243
age_bracket50+
                  -1.2133
                              0.2241
                                      -5.414 6.18e-08 ***
                  -0.9505
                                      -5.392 6.96e-08 ***
previous_claim1
                              0.1763
         0 '*** 0.001 '** 0.01 '* 0.05 '. '0.1 ' 1
```

Write down the **mathematical formula** of the logistic regression model and then use it to **predict** the "claim" of the insurance data in Table 2.1 as well as **evaluating** the performance of the model by calculating the confusion matrix, accuracy, sensitivity, specificity, PPV, NPV of the logistic model.

[Note: The default cut-off is 0.5] (4 marks)

Solution. Let X be all the dummy variables associated with the four predictors and Y be the response variable Y. The mathematical formula is

$$\mathbb{P}(Y=1|X) = \frac{1}{1 + \exp(-(3.1361 + \beta^T X))}$$
 [0.4 mark]

where

$$\beta^T X = -0.3343 \cdot \text{male} - 1.9495 \cdot \text{obese} - 1.0563 \cdot \text{overweight} - 0.8424 \cdot \text{underweight} \\ - 0.2875 \cdot \text{age} 31 - 1.2133 \cdot \text{age} 50 - 0.9505 \cdot \text{prv.claim.} 1$$

[0.6 mark]

The prediction of the testing data is given below:

male	obese	over.wt	under.wt	age31	age50	prv.claim.1	prob	\widehat{Y}	Y
0	0	0	1	0	0	0	0.9083545	1	no_claim
0	0	0	1	0	0	0	0.9083545	1	no_claim
1	0	1	0	1	0	0	0.8112102	1	no_claim
0	0	0	1	0	1	1	0.5324324	1	no_claim
1	0	0	0	0	0	0	0.9427711	1	no_claim
0	0	0	1	0	0	1	0.7930248	1	no_claim
1	0	1	0	0	0	1	0.6889022	1	no_claim
1	0	1	0	0	1	1	0.3969113	0	claim
0	0	0	0	0	0	0	0.9583570	1	no_claim
0	1	0	0	0	1	0	0.4933065	0	claim

......[2 marks]

The confusion matrix is as follows

	claim (0)	no_claim (1)
predict 0	2	0
predict 1	0	8

The performance metrics are

Accuracy: 1 Sensitivity: 1 Specificity: 1

Pos Pred Value: 1