

# A Binary Logistic Regression with Threshold Values

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**Abstract:**-In this paper it was proposed to examine the suitability of binary regression for assessing the threshold values. A threshold effect indicates an association between a risk factor and a defined outcome above the threshold value but none below it. An important field of application is occupational medicine where, for a lot of chemical compounds and other agents which are non-carcinogenic health hazards, so called threshold limit values are specified. In this paper a model with threshold values within the frame work of logistic regression model was developed. A method for estimating and testing a threshold value is discussed. The method for assessing a threshold consists of an estimation procedure using the maximum likelihood technique and a test procedure based on the likelihood ratio statistic following under the hypothesis of no threshold, a quasi one sided chi-square distribution with one degree of freedom. A random sample of diabetic patients collected from King George Hospital, Visakhapatnam, were interviewed and the information on characteristics such as age, fasting blood glucose level, income, disease history, whether the patient has Blood Pressure (B.P), family history of the disease, type of disease, type of medicine were recorded for each patient. The relationship between B.P. and the explanatory variables was discussed with the help of the above model.

**Index Terms**—about four key words or phrases in alphabetical order, separated by commas.

## I. INTRODUCTION

A threshold effect indicates an association between a risk factor and a defined outcome above the threshold value but none below it. An important field of application is occupational medicine where, for a lot of chemical compounds and other agents which are non-carcinogenic health hazards, so called threshold limit values are specified. In this paper a model with threshold values within the framework of logistic regression model is presented. A method for estimating and testing a threshold value is described. In most available statistical packages the concept of a threshold is disregarded. The method for assessing a threshold consists of an estimation procedure using the maximum likelihood technique and a test procedure based on the likelihood ratio statistic which follows under the  $H_0$  the null hypothesis (no threshold) a quasi one –sided Chi-square distribution with one degree of freedom.

## II. BINARY REGRESSION

Suppose that for each individual or experimental unit the response  $Y_i$  can take only one of two possible values, denoted for convenience each by 0 and 1 respectively. Observations of this nature arise for example in medical trials where at the

end of the trial period the patient has either recovered ( $Y=1$ ) or has not ( $Y=0$ ) similarly, in this study a patient has blood pressure

( $Y=1$ ) or has not ( $Y=0$ ). We may write

$$P(Y_i=0) = 1 - \theta_i, \quad P(Y_i=1) = \theta_i$$

In most investigations, we have associated with each individual or experimental unit a vector of covariates or explanatory variables ( $X_1, X_2 \dots X_k$ ). The covariates may be qualitative, quantitative or a combination of both. The principal objective is to investigate the relationship between the response probability  $\theta$  and the explanatory variables  $X_1, X_2 \dots X_k$ . Often, otherwise, a subset of the  $X$ 's is of primary importance but due allowance must also be made for the effect of the remaining covariates.

The simplest empirical regression is to suppose that  $\theta_i$ , the value of  $\theta$  for the  $i^{\text{th}}$  individual, is linearly related to the explanatory variables, i.e., for the  $i^{\text{th}}$  individual

$$\theta_i = \beta_0 + \sum_{j=1}^k x_{ij} \beta_j \dots\dots\dots(2.1)$$

Where  $\beta_0$  is an unknown intercept and  $\beta_j$ 's are the unknown regression coefficients;  $x_{ij}$  is the value of the  $j^{\text{th}}$  explanatory variable on the  $i^{\text{th}}$  individual, with the condition

$$0 \leq \theta_i \leq 1 \dots\dots\dots(2.2)$$

A model in which (2.2) is automatically satisfied is the logistic distribution (Cox.D.R et al) with location  $\beta_0 + X \beta$  and unit scale

This has the cumulative distribution function

$$\frac{\exp(\mu - \beta_0 - X \beta)}{\{1 + \exp(\mu - \beta_0 - X \beta)\}} \quad , \text{so}$$

that

$$F(0; x) = \frac{1}{\{1 + \exp(\beta_0 + x\beta)\}} \quad ,$$

From which it follows that

$$\theta = p(Y = 1; x) = \frac{\exp(\beta_0 + x\beta)}{1 + \exp(\beta_0 + x\beta)}$$

$$1 - \theta = p(Y = 0; x) = \frac{1}{1 + \exp(\beta_0 + x\beta)}$$

Where  $X$  is the vector of explanatory variables and  $\beta$  is the vector of unknown regression coefficients.

This relation is linearized by the transformation

$$\ln\left(\frac{\theta}{1-\theta}\right) = \beta_0 + x\beta$$

.....(2.3)  
Which is called the logit function?

**III. LIKELIHOOD FUNCTION FOR BINARY DATA**

Let the responses  $y_1, y_2, \dots, y_N$  correspond to independent random variables  $Y_1, Y_2, \dots, Y_N$ . Where  $Y_i$  is assumed to be binomially distributed with index  $n_i$  and parameter  $\theta_i$ . Ungrouped data are considered with  $n_i=1$  ( $i=1, 2, \dots, N$ ). The log likelihood considered as a function of the vector  $\theta = (\theta_1, \dots, \theta_N)$  is

$$l(\theta; Y) = \sum_{i=1}^N \left[ y_i \ln\left(\frac{\theta_i}{1-\theta_i}\right) + n_i \ln(1-\theta_i) \right]$$

.....(3.1)  
In particular, if

$$\ln\left(\frac{\theta}{1-\theta}\right) = \beta_0 + x\beta$$

We have

$$l(\beta; Y) = \sum_i \sum_j y_i x_{ij} \beta_j - \dots(3.2)$$

The  $\beta$  vector of regression coefficients can be estimated by

maximizing (3.2). Many statistical packages have logistic regression as a module and  $\beta$  can be estimated directly.

**IV. BINARY LOGISTIC REGRESSION WITH THRESHOLD VALUES**

**Model:**

The dependent variable  $Y$  has two possible outcomes 0 for individuals without disease and 1 for those with disease and the explanatory variables are denoted by

$x_1, x_2, \dots, x_k$ . Consider a model with two explanatory variables. The logistic model is given by

$$\ln\left(\frac{\theta}{1-\theta}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$

..... (4.1)

Where  $\beta_0, \beta_1$  and  $\beta_2$  are constants.

If the explanatory variables  $x_1$  and  $x_2$  have thresholds denoted by  $t_1$ , and  $t_2$  respectively model (4.1) will be modified to

for  $x_1 \leq t_1, x_2 \leq t_2$   
for  $x_1 > t_1, x_2 > t_2$ .

or equivalently

$$\ln\left(\frac{\theta}{1-\theta}\right) = \beta_0 + \beta_1(x_1 - t_1)I(x_1 - t_1) + \beta_2(x_2 - t_2)I(x_2 - t_2)$$

with .. (4.2)  
 $I(x) = 0$  for  $x \leq 0$   
 $= 1$  for  $x > 0$

Usually the parameters  $\beta_0, \beta_1, \beta_2, t_1$ , and  $t_2$  are unknown and have to be estimated. But by contrast to  $\beta$  the parameters  $t_1$  and  $t_2$  are constrained by  $\min x_1 \leq t_1 \leq \max x_1$  and  $\min x_2 \leq t_2 \leq \max x_2$

**A. A THRESHOLD MOEL:**

In respect of the present study (4.2) can be extended to three explanatory variables with two explanatory variables having threshold values. The model for three variables where only two variables  $x_1$  and  $x_2$  have threshold values  $t_1$ , and  $t_2$  is given by

$$\ln\left(\frac{\theta}{1-\theta}\right) = \beta_0 + \beta_1(x_1 - t_1)I(x_1 - t_1) + \beta_2(x_2 - t_2)I(x_2 - t_2) + \beta_3 x_3$$

.....(4.1.1)

Where  $\ln\left(\frac{\theta}{1-\theta}\right)$  is called the logit

**B. ESTIMATION PROCEDURE:**

To estimate the parameters  $\beta_0, \beta_1, \beta_2, \beta_3$  and  $t_1$  and  $t_2$  of model (3.1.1), the likelihood function L or the log likelihood  $L = l(\beta_0, \beta_1, \beta_2, \beta_3, t_1, t_2; y)$  is maximized:

$$l(\beta_0, \beta_1, \beta_2, \beta_3, t_1, t_2; y) = \sum_{i=1}^N [y_i \ln \theta(x_i) + (1 - y_i) \ln(1 - \theta(x_i))] \quad (4.2.1)$$

where  $\ln\left(\frac{\theta(x_i)}{1 - \theta(x_i)}\right)$

is the logit for the  $i^{th}$  individual, and  $y_i$  is the binary response for the  $i^{th}$  individual.

In particular (4.2.1) becomes,

$$l(\beta, t; y) = \beta_0 \sum_{i=1}^N y_i + \beta_1 \sum_{i=1}^N (x_{1i} - t_1) y_i + \beta_2 \sum_{i=1}^N (x_{2i} - t_2) y_i + \beta_3 \sum_{i=1}^N y_i x_{3i} \quad (4.2.2)$$

where  $x_{ij}$  is the value of the explanatory variable  $x_j$  for subject  $i$  and  $N$  is the sample size, for  $j=1,2,3$  and  $\beta, t$  are the vectors of parameters.

$$E(Y_i) = n_i \theta_i \quad i=1,2,\dots,N$$

and the  $cov(y_1, y_2, \dots, y_N) = diag[n_i \theta_i (1 - \theta_i)]$ . Where  $y_i$  is assumed to be binomial with index  $n_i$  and parameter  $\theta_i$ . Ungrouped data can be treated with  $n_i=1$  for  $i=1,2,\dots,N$ .

Following an approximation by Hawkins.D.M (1977) one can calculate the log likelihood values  $l_i = l_i(\beta, t^{(i)}; y)$  assuming threshold,  $t^{(1)}$  has value  $t_{1i}$ , and  $t^{(2)}$  has value  $t_{2i}$ :

$$t^{(j)} = t_{ji} \quad i=1,2,\dots,N \quad j=1,2$$

where

$$t_{1i} = \min x_{1i} + \frac{\max \cdot x_{1i} - \min \cdot x_{1i}}{N - 1} (i - 1) \quad (3.2.3)$$

$$t_{2i} = \min \cdot x_{2i} + \frac{\max \cdot x_{2i} - \min \cdot x_{2i}}{N - 1} (i - 1) \quad (4.2.4)$$

for  $i=1,2,\dots,N$ .

If  $l_i$  is the maximum of all these values then the estimates

$\hat{t}_2$  will be between  $t^{(j-1)}$  and  $t^{(j+1)}$  for  $j=1,2$ .

**ESTIMATION OF  $\beta$  'S :**

$\beta$  's in (4.3.2) were estimated using Newton-Raphson iterative procedure (Rajaraman.V.2001). In general the  $k+1^{th}$  approximation for a  $\beta_j$  is obtained from  $k^{th}$  iteration as

$$\beta_j^{k+1} = \beta_j^k - \frac{l(\beta^k, t; y)}{\frac{\partial l}{\partial \beta_j}(\beta^k, t; y)} \quad \text{for } j=0,1,2,3. \quad (4.2.5)$$

The partial differential coefficients of the log likelihood function given by (4.3.2) with respect to  $\beta_0, \beta_1,$

$\beta_2,$  and  $\beta_3$  are obtained as follows :

$$\frac{\partial L}{\partial \beta_0} = \sum_{i=1}^N y_i - \frac{\sum_{i=1}^N \exp[\beta_0 + \beta_1(x_{1i} - t_1) + \beta_2(x_{2i} - t_2) + \beta_3 \sum_{i=1}^N y_i x_{3i}]}{1 + \exp[\beta_0 + \beta_1(x_{1i} - t_1) + \beta_2(x_{2i} - t_2) + \beta_3 \sum_{i=1}^N y_i x_{3i}]} \quad (4.2.6)$$

$$\frac{\partial L}{\partial \beta_1} = \sum_{i=1}^N y_i (x_{1i} - t_1) -$$

$$\frac{\sum_{i=1}^N \exp[\beta_0 + \beta_1(x_{1i} - t_1) + \beta_2(x_{2i} - t_2) + \beta_3 \sum_{i=1}^N y_i x_{3i}] (x_{1i} - t_1)}{1 + \exp[\beta_0 + \beta_1(x_{1i} - t_1) + \beta_2(x_{2i} - t_2) + \beta_3 \sum_{i=1}^N y_i x_{3i}]} \quad (4.2.7)$$

$$\frac{\partial L}{\partial \beta_2} = \sum_{i=1}^N y_i(x_{2i} - t_2) - \sum_{i=1}^N \frac{\exp[\beta_0 + \beta_1(x_{1i} - t_1) + \beta_2(x_{2i} - t_2) + \beta_3 \sum_{i=1}^N y_i x_{3i}](x_{2i} - t_2)}{1 + \exp[\beta_0 + \beta_1(x_{1i} - t_1) + \beta_2(x_{2i} - t_2) + \beta_3 \sum_{i=1}^N y_i x_{3i}]}$$

...

(4.2.8)

$$\frac{\partial L}{\partial \beta_3} = \sum_{i=1}^N y_i x_{3i} - \sum_{i=1}^N \frac{\exp[\beta_0 + \beta_1(x_{1i} - t_1) + \beta_2(x_{2i} - t_2) + \beta_3 \sum_{i=1}^N y_i x_{3i}]\sum_{i=1}^N y_i x_{3i}}{1 + \exp[\beta_0 + \beta_1(x_{1i} - t_1) + \beta_2(x_{2i} - t_2) + \beta_3 \sum_{i=1}^N y_i x_{3i}]}$$

...(4.2.9)

**V. DIABETES AND HYPERTENSION**

Diabetes is not a disease of the blood sugar alone. Diabetes affects the entire body from our mind to all organ systems. Therefore, controlling not only blood sugar but the factors controlling blood sugar as well, is important. High blood pressure is a worldwide condition of almost epidemic proportions. Yet because there are no tell-tale symptoms, it is often overlooked or treated casually. Although hypertension is more common among diabetics than among non-diabetics does not mean he or she will have hypertension. In some cases diabetics, high blood pressure, kidney diseases are linked closely. Diabetics who have kidney disease often develop high blood pressure as a result of the impaired function of their kidneys. Because the problems of diabetics, hypertension and kidney diseases are so closely interrelated preventing or controlling are helps reduce the complications of others. In this paper the dependence of the presence or absence of the response variable BP on the covariates AGE, DH, and TD was considered and discussed. The diabetic patients who were diagnosed for BP at a later date were coded as 1 and others as 0 for the purpose of analysis and treated as a binary response.

**A. FITTING OF A LOGISTIC REGRESSION:**

The data on the diabetic patients was used to estimate the relationship between the response probability  $\theta$  (where the dependent variable Y is whether a diabetic patient had B.P or not) and the relevant covariates. AGE, DH and TD. The calculations were performed using the statistical package STATISTIKA. By regressing B.P on the covariates AGE, DH, and TD obtained the following results.

Model; Logistic Regression  
 -2\*log (likelihood) = 235.4902.  
 Chi-square=5.7303, d.f. =3, p=. 135517  
 Ml estimates of the regression coefficients;

$$\hat{\beta}_0 = -1.7466, \hat{\beta}_1 = 0.0121, \hat{\beta}_2 = 0.0614, \hat{\beta}_3 = -0.2314$$

Thus the estimated logit function of (3.2.3) is given by

$$\log\left(\frac{\theta}{1-\theta}\right) = -1.7466 + 0.012 \text{ AGE} + 0.0614 \text{ DH} - 0.2314 \text{ TD} \dots\dots\dots(5.1.1)$$

Using (5.1.1) the chance that a diabetic patient will be diagnosed for B.P at a later date can be obtained. For instance the patient (s.no. =1) whose AGE = 30, DH = 1 and TD = 0 has the chance of 0.21 being diagnosed for BP at a later date. It can be noticed from (4.4.1) that DH and AGE are the contributors for the response probability. Of these two DH is the larger contributor with coefficient value of 0.0614. This indicates that the effect of DH is more on the fasting blood glucose (FG) levels as seen in the previous sections and on the chance that a diabetic patient is diagnosed for BP at a later date. So, DH must also be considered as a factor for being diagnosed for B.P. In such a situation, the problem of interest was to assess a threshold, if any, for the covariate DH. Since AGE and DH are the contributors for BP the above threshold model was considered.

Now considering  $x_1=AGE, x_2=DH, x_3=TD$ , in the model (4.2.2), we get

$$l(\beta, t; y) = \beta_0 + \beta_1 (AGE - t_1) + \beta_2 (DH - t_2) + \beta_3 TD \dots\dots\dots(4.1.2)$$

Using EXCEL and establishing the formulae from (4.2.3) to

(4.2.9) the m.l estimates of  $\beta$  's, the estimates for threshold values could be obtained. For the purpose of fitting the model given by (4.2.2) those patients whose disease history was more than one year were considered. The maximum of all  $l_i, i=1,2,\dots,N$  was obtained corresponding to  $\hat{t}_1=44.114$  and  $\hat{t}_2=3.97$ .

The initial values for all the  $\beta$  's were set to 0.1. The  $\beta$  's were converged with an accuracy of 0.01 and were found to be

$$\hat{\beta}_0 = -1.6713, \hat{\beta}_1 = 0.0115, \hat{\beta}_2 = 0.0617, \hat{\beta}_3 = -0.2615$$

And  $-2 \log l$  for the model given by (4.2.2) was found to be -75.5921.

Thus the fitted model can be seen to be

$$\ln\left(\frac{\theta}{1-\theta}\right) = -1.6713 + 0.0115(\text{AGE} - 44.114) + 0.0617(\text{DH} - 3.97) - 0.2615 \text{ TD} \dots\dots(5.1.3)$$

**B. HYPOTHESIS TESTING:**

The null hypothesis to be tested is whether the variables  $x_1$  and  $x_2$  here threshold  $t_1$  and  $t_2$  respectively:

$$H_0 : t_j \leq \min . x_j \quad \text{for } j=1,2.$$

The alternative hypothesis is

$$H_1 : t_j > \min x_j \quad \text{for } j=1,2$$

The likelihood ratio statistic as suggested by Cox.D.R. (1987) given by

$$r = -2[l(H_0) - l(H_1)]$$

follows a  $\chi^2$  distribution with one degree of freedom under  $H_0$ , where  $l(H_0)$  is the log likelihood under  $H_0$  and  $l(H_1)$  is the log likelihood under  $H_1$ . From the previous section the log likelihood of the model with no threshold was

$l(H_0) = -117.7451$ . Comparing this model with (4.1.3) for testing the hypothesis about possible threshold values for AGE and DH leads to a likelihood ratio of  $r = -2(-117.7451 + 75.5921) = 84.306$ .

Which is statistically significant ( $p < 0.05$ ). Thus the threshold effects  $\hat{t}_1$  and  $\hat{t}_2$  indicates an association between the risk factors AGE and DH and the response variable BP above the threshold values but none below them. Here there is a likelihood that a diabetic patient of age more than 44.14 years with a disease history of more than 3.97 years and a given TD will be diagnosed for BP at a later date.

**Data**

AGE	FG	DH	TD	BP
30	205	1	1	1
64	95	10	1	0
25	377	11	1	1
62	118	8	1	0
42	106	8	1	0
80	150	1	0	0
51	204	6	0	0
41	161	5	1	0
45	229	7	1	0
53	319	6	0	1
40	189	0	1	0
60	91	3	0	1
36	219	2	0	1
68	230	10	0	1
47	153	4	0	1
50	119	2	0	0
28	138	3	0	0
43	205	2	0	0
50	170	1	0	0
45	134	0	0	0
46	285	20	0	2

60	229	11	0	0
67	245	5	0	0
66	233	1	0	1
73	126	5	1	0
70	85	2	0	1
60	145	3	0	1
48	224	3	0	2
67	168	8	0	1
43	119	0	0	1
50	170	9	0	0
45	142	2	0	0
64	80	5	0	1
35	166	2	0	0
50	88	5	0	0
40	357	2	1	2
48	317	10	0	0
40	181	3	1	0
51	127	4	1	0
52	145	4	0	0
55	130	9	0	0
54	83	2	0	0
63	171	9	0	0
36	223	3	0	0
50	220	0	0	0
58	112	9	0	1
60	284	5	0	0
50	80	0	0	0
34	153	2	1	0
45	194	1	0	1
45	217	10	0	0
52	171	5	0	0
45	231	7	1	0
50	160	10	1	1
40	219	7	0	0
50	106	4	0	0
40	253	9	0	1
55	112	6	0	0
43	121	10	1	1
76	224	10	0	0
50	80	3	0	0
50	262	0	0	0
29	388	3	0	0
50	278	2	0	0
50	278	8	0	0
26	143	2	0	0
50	220	4	0	1
37	217	5	0	0
43	189	2	0	0
57	139	15	0	0
32	245	1	0	0
42	160	0	0	0
45	200	0	0	1
50	106	2	0	0



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60	200	6	0	1
55	202	5	0	1
51	102	4	0	0
60	80	10	0	0
50	86	0	0	1
45	184	2	0	0
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55	80	0	0	1
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67	117	6	0	0
50	120	8	1	1
83	85	8	0	0
45	80	1	0	1
62	86	10	0	0
50	88	1	0	0
29	98	1	1	0
48	110	6	1	0
64	90	4	0	1
40	80	2	1	0
63	110	6	1	0
65	297	25	0	1
56	149	5	0	0
40	167	2	0	0
42	265	4	1	0
40	147	6	1	0
45	244	6	0	0
50	284	2	0	0
33	154	0	0	0
80	215	12	0	0
52	279	8	0	0
58	346	8	0	1
50	210	2	0	0
62	108	2	0	1
50	150	2	0	0
50	195	5	1	1
57	152	2	1	1
46	172	7	1	1
48	342	3	1	0
50	124	7	0	0
40	345	4	0	0
50	123	1	0	0
50	130	3	0	0
59	121	7	1	1
50	213	0	0	0
45	145	1	0	0
50	124	7	0	0
32	300	1	0	0
52	176	2	0	0
56	203	5	1	0
64	113	10	0	0
42	185	1	0	0
65	234	7	1	0

61	102	1	0	0
40	163	1	0	1
42	125	8	0	1
51	141	3	0	0
60	89	1	0	0
40	132	2	1	0
45	256	30	0	1
60	152	15	0	1
60	242	6	0	0
38	236	0	0	1
45	233	4	0	0
50	213	10	0	0
48	151	6	0	0
63	220	10	0	0
50	310	6	0	0
36	178	4	1	0
57	103	4	0	0
29	92	1	0	0
54	253	2	0	1
70	127	5	0	0
45	160	5	0	0
54	168	12	0	1
72	153	7	0	1
44	135	1	0	0
45	218	0	0	0
73	165	2	0	0
60	213	2	0	0
44	131	4	1	1
65	125	1	0	1
47	98	10	0	0
40	100	1	1	0
52	237	4	1	1
65	204	3	0	1
45	253	4	0	1
75	167	10	0	1
60	132	3	0	0
73	60	1	0	0
44	256	1	0	1
66	119	15	1	1
55	140	5	0	1
40	133	2	1	0
50	244	2	0	0
64	171	16	1	0
50	346	7	0	0
50	331	8	0	0
48	268	1	0	0
55	120	5	0	1
70	97	1	0	0
56	80	3	0	1
35	199	3	0	1
41	103	3	0	0
38	96	0	0	0
58	168	5	0	0



56	188	20	1	0
65	220	4	0	0
50	191	4	0	0
32	169	0	1	0
53	65	1	0	1
50	215	1	1	0
64	242	10	0	0
55	199	0	0	0
83	128	9	0	1
53	179	2	1	0
50	219	2	0	0
30	125	0	0	0
35	353	0	1	0
45	213	4	0	1
45	115	2	0	0
42	76	0	0	0
58	113	5	0	1
39	154	0	1	0
35	118	4	1	0
44	239	3	1	0

Social Media Analytics, Sentiment Analytics, Telecom Churn, Segmentation, Forecasting etc

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