Artificial Neural Network to Modeling Zero-inflated Count Data: Application to Predicting Number of Return to Blood Donation

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ABSTRACT

Background: Traditional statistical models often are based on certain presuppositions and limitations that may not presence in actual data and lead to turbulence in estimation or prediction. In these situations, artificial neural networks (ANNs) could be suitable alternative rather than classical statistical methods.

Methods: The study was conducted in Shahrekord Blood Transfusion Center, Shahrekord, central Iran, on blood donors from 2008-2009. The accuracy of the proposed model to prediction of number of return to blood donations was compared with classical statistical models. A number of 864 donors who had a first-time successful donation were followed for five years. Number of return for blood donation was considered as response variable. Poisson regression (PR), negative binomial regression (NBR), zero-inflated Poisson regression (ZIPR) and zero-inflated negative binomial regression (ZINBR) as well as ANN model were fitted to data. MSE criterion was used to compare models. To fitting the models, STATISTICA 10 and, R 3.2.2 was used

Results: The MSE of PR, NBR, ZIPR, ZINBR and ANN models was obtained 2.71, 1.01, 1.54, 0.094 and 0.056 for the training and 4.05, 9.89, 3.99, 2.53 and 0.27 for the test data, respectively.

Conclusions: The ANN model had the least MSE in both training, and test data set and has a better performance than classic models. ANN could be a suitable alternative for modeling such data because of fewer restrictions.

Introduction

In regression models, when outcome is a count variable, Poisson Regression (PR) or negative binomial regression (NBR) is used for modeling. Poisson distribution is used if the mean and variance of the data on response variable are equal and negative binomial distribution is suitable if the variance is larger than the mean (count variable is largely dispersed). In real situations, during modeling count outcomes, we frequently face two issues namely overdispersion and excess zeroes in outcome values. Because of excess zeroes in response variable, mean and variance of response variable are not equal. Therefore, Poisson is not a suitable model for this type of data. In these specific situations, models such as zero-inflated Poisson regression (ZIPR), zero-inflated negative binomial regression (ZINBR), hurdle model, and generalized Poisson model have been recommended.

Generally, classical statistical models have some presuppositions and limitations, such as equal variances of errors, considering a default distribution for the response variables, and linear relationship between dependent as well as independent variables that in actual data may not be available. In addition, most of these approaches have not the capability of modeling sophisticated, non-linear relationships and high degree interactions. Sensitivity to missing values and outliers is another limitation of these models.

A potential approach that able to overcome the limitations of classical models could be artificial neural networks (ANNs). Multi-layer perceptron (MLP) is the most popular architecture in ANNs. Usually, back-propagation (BP) algorithm is used to learn MLP based on minimizing sum of squared errors. Generalizability of ANNs allows the model to provide an appropriate answer related to a new observation. Since the precise and accurate prediction is very important in medicine, so, using models with highest confidence is a priority and ANN model seems to be a suitable method for this purpose.

Blood, as a mysterious liquid, is part of the body’s vital system with special characteristics enabling it to save life of a patient or an individual in need through being donated. This issue is more important than one might think, as one per three individuals’ needs transfusion of blood and its products.

Despite all advances made in different medical fields, no artificial substitute has been yet found for blood to satisfy the needs of different patients and the only route to meeting the need for this vital substance is the blood donated or bought.

A human can donate blood several times during lifetime. Donors who donate blood at least once per six months are classified as constant donors. The number of blood donations by these donors is definite and their blood health is certain.
therefore it is more suitable for health system to enhance index of constancy as much as possible. Women can donate blood at most three times per year and men can do it once per three months[11,12]. Therefore, predicting the number of blood donations has a particular status and hence we should seek for an appropriate, highly accurate approach to predicting this number.

In this study, we proposed a new method with fewer restrictions based on ANN to model zero-inflated count responses, then, the accuracy of the proposed model was compared with common statistical and zero-inflated models to prediction of a number of returns to blood donations.

Methods

To compare ANN with classic models data from a longitudinal study was used. The study was designed as a follow-up study with a maximum of five years conducted in Shahrekord Blood Transfusion Center, Shahrekord, central Iran. At the beginning of the study, a list of registered donors in Negareh software system used by the Shahrekord Blood Transfusion Center, Iran. At the beginning of the study, a list of registered donors in Negareh software system used by the Shahrekord Blood Transfusion Center who had blood donations for the first time from 21 Mar 2008 until 20 Mar 2009 was prepared. The sampling method was systematic sampling and the sample size was calculated using previous information about percentage of donors return to blood donation for at least five times[10]. The number of return to blood donation until 20 Mar 2013 were extracted as response variable and sex, age, weight, marital status, education, job, blood group and Rh were considered as independent variables. Figure 1 shows the frequency of number of return to blood donation. Overall, 440 numbers (50.9%) of return to blood donation was zero. Therefore, zero-inflated models should be used for modeling data. For fitting models, 70% cases were used as training set, and 30% were used as test set.

That $p_i$ is proportion of extra zeroes than original Poisson or negative binomial in response variable and $Pr(Y_i=y_i)$ is probability of $Y_i=y_i$ in Poisson or negative binomial distribution. By replacing $\mu(\beta^Tx_i) = e^{\beta^Tx_i}$ in above formula, ZINPR model defined as:

$$Pr(Y_i=y_i) = \begin{cases} p_i+(1-p_i)\exp(-e^{\beta^Tx_i}) & \text{if } y_i=0 \\ (1-p_i)\ \frac{\exp(-e^{\beta^Tx_i})}{y_i!} & \text{if } y_i>0 \end{cases}$$

And ZINBR model can be written as:

$$Pr(Y_i=y_i) = \begin{cases} p_i+(1-p_i)(1+r\exp(\beta^Tx_i))^{-r} & \text{if } y_i=0 \\ (1-p_i)\ \frac{\Gamma(y_i+1)(r\exp(\beta^Tx_i))^{y_i}}{y_i!(r+1)(r\exp(\beta^Tx_i))^{y_i+r}} & \text{if } y_i>0 \end{cases}$$

That $r$ is overdispersion parameter.

For fitting of ANN model, MLP with one hidden layer was used. ANN adopts a set of input observations, $x_i$, and compute outputs $y_i$, using a specified number of layers. The architecture of ANN model can be written as:

$$y_i = \psi_o \left( \beta_0 + \sum_{j=1}^{M} \beta_j \psi_h \left( w_{j0} + \sum_{s=1}^{p} x_{is} w_{js} \right) \right)_{l=1,2,..,L-1}$$

$$y_i = \psi_h \left( \psi_o \right)_{l=L}$$

where $w_{lj}$ is the weight for input $x_{is}$ at the hidden node $j$. In addition, $\beta_i$ is the weight dependent to the hidden node $j$, and $w_{j0}$ and $\beta_0$ are the biases for the hidden and the output nodes respectively. In addition, $p$ and $M$ are number of covariates and number of nodes in hidden layer respectively. The function $\psi_h$ is activation functions of hidden layer and the function $\psi_o$ is activation functions of output layer.$^\text{7}$

The BP algorithm was used to learning MLP based on minimizing sum of squared errors. The BP algorithm has two computational paths; Forward path and backward path. For the k-th input, the equations on the forward path were as follows:

$$\hat y^k = x(k)$$

$$\hat y^{l+1}(k) = \hat y^l + \beta_l^{(l+1)}(k)\hat y^l + \beta_{l+1}^{(l+1)}(k) \quad l=1,2,..,L-1$$

$$\hat y = \hat y^L(k)$$

In forward path, the network parameters do not change during computing, and the activation functions applied on each neuron:

$$\hat y^{l+1}(n(k)) = \left[ \hat y^{l+1}(n_1(k)),...,\hat y^{l+1}(n_L(k)) \right]^T$$

In backward path, the sensitivity matrices from the last layer were returned to the first layer:

$$\delta^L(k) = \Delta k \hat e(k)$$

$$\delta^l(k) + \delta^{l+1} = \Delta k \hat e(k) \Delta^T$$

Finally, the weights and biases matrix were regulated by the following relationships:

$$\Delta^l = \Delta^l(k)$$

$$\Delta^L(k) = \Delta^L(k) - \alpha \delta^{L+1} \Delta^T$$

In recent formulas, $L$, $f$, $\theta^l$, $\alpha$, $\Delta^l$, $\Delta$, $\theta(k)$ and $\hat e(k)$ were referred to number of network layers, activation function, output in hidden layer, network learning rate, transformation

![Figure 1](https://example.com/figure1.png)

Figure 1: Frequency distribution of the number of return to blood donations

As discussed above, for count regression, models in the case of excess of zeroes in response variable, Poisson, and negative binomial models are inadequate and zero-inflated model is alternative way to model data. The probability density function for zero-inflated count data can be formulated as follows:

$$Pr(Y_i|\mu_i) = \begin{cases} p_i + (1-p_i) \ Pr(Y_i=0) & \text{if } y_i=0 \\ (1-p_i) \ Pr(Y_i=y_i) & \text{if } y_i>0 \end{cases}$$
Results

From 864 donors, 801 (92.7%) donors were male and 623 (72.1%) were married. Overall, 710 (82.2%) of donors lived in the city and 154 (17.8%) in the country. Mean ± standard deviation of age in donors at the first donation was 36.4±10.7 yr and the mean of body weight at the first donation was 77.8±11.7 kg. Number of return to blood donation was from 0 to 12 (Figure 1). Mean and standard deviation of number of return to blood donations was 1.41 and 2.16 respectively. Overall, 440 (50.9%) of donors did not return to donate blood. The frequency of successful return to blood donation with respect to blood type, donors’ Rh, marital status, stay, education level and job class is shown in Table 1.

For Akaike information criterion (AIC), NBR and ZINBR models have a similar performance, but MSE criterion is 0.96 for NBR and 1.03 for ZINBR (Table 2).

To find the best structure of ANN model, CG, BGD and BFGS training algorithms were compared and BFGS selected (Table 3). For BFGS algorithm, 4-8 neurons and four different activation functions in hidden layer with hyperbolic tangent activation function in the external layer were developed and compared (Table 4). Finally, regression and ANN models were compared with MSE criterion (Table 5).
network had better performance compared with statistical models for prediction.\(^1\)

In zero-inflated count data, the common methods in classic statistics suffer from some shortcomings. Their performances depend on the distribution of variables, size, and quality of data, etc. When relation between predictors and response variable is nonlinear, predictions will be confusing and will lack confidence. ANN can be considered as alternative techniques to overcome these problems.\(^2\)

Despite the advantages of ANN models, they have some limitations. They are neither capable to inference on the parameters nor to assess significance of relationship between the variables.\(^3\)

**Conclusion**

ANN model had the best performance of prediction of number of return to blood donation in both training and test data set compared with PR, NBR, ZIPR and ZINBR models. Therefore, considering the importance of precise prediction in medical studies and due to the restrictions of traditional statistical methods, the use of ANN model is a suitable alternative for analyzing such data.

**Conflict of interest statement**

The authors declare that there is no conflict of interest.

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**Highlights**

- ZINBR was the best model among classical statistical models to predicting number of return to blood donation
- The ANN model had the least MSE in both training and test data set
- ANN model had the best performance of prediction of number of return to blood donation in both training and test data set compared with PR, NBR, ZIPR and ZINBR models

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