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A STATISCAL ANALYSIS OF DENTAL BRACKETS TYPES

Hazem ABBAS, Romeo NEGREA

Abstract

In paper we present a statistical analysis of a problem from real word, choose the adequate type of dental brackets for children in a dental clinic. A generalized regression model by Poisson type was used to analyzed two data group of children who use or used a dental brackets by different types. [1]

1 Introduction

Dental epidemiology involves studying and investigating the distribution and determinants of dental-related diseases in a specified population group to inform decisions in the management of health problems. In dental epidemiology studies, the hypothesis is typically followed by a cogent study design and data collection. Appropriate statistical analysis is essential to demonstrate the scientific association between the independent factors and the target variable. Analysis also helps to develop and build a statistical model. Poisson regression and its extensions have gained more attention in caries epidemiology than other working models such as logistic regression (see for example [1] , [2] ,[3])

[1]Mathematical Subject Classification (2010):*62P10, 62J12*
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2 Dental brackets

Dental braces (also known as brackets, orthodontic cases, or cases) are devices used in orthodontics that align and straighten teeth and help position them with regard to a person's bite, while also aiming to improve dental health. They are often used to correct underbites, as well as malocclusions, overbites, open bites, gaps, deep bites, cross bites, crooked teeth, and various other flaws of the teeth and jaw. Braces can be either cosmetic or structural. Dental braces are often used in conjunction with other orthodontic appliances to help widen the palate or jaws and to otherwise assist in shaping the teeth and jaws (see for example [4]).

Usually, the following types of dental appliances used in orthodontics are:

- Removable appliances – which can be taken out of the mouth by the patient;
- Functional appliances – which can be either removable or fixed;
- Fixed appliances – which are attached directly to the teeth.

Generally, removable appliances are used for simple tooth movement, such as individual tipping or limited expansion. They can also be used as an adjunct to fixed appliances, particularly during bite opening and molar distalization, or prior to functional appliance therapy to facilitate mandibular postural advancement. Functional appliances are used in the growing patient, often in conjunction with extra-oral force, to help correct both sagittal and vertical skeletal discrepancies, usually prior to the use of fixed appliances. Fixed appliances are the most popular form of appliance currently in use today because they can effect complex three-dimensional tooth movements in the management of many different types of malocclusion. Fixed devices can be made by different materials and it can be: aesthetic brackets or metal brackets.

2.1 Contemporary Metal Brackets

Metal brackets made from stainless steel are the most commonly used in orthodontic practice, but the color of the metal and its visibility may be objectionable to some adult patients. Manufacturers have tried to reduce the size of the bracket and hence its visibility by continuously redesigning the appliance. Another relatively recent introduction is a bracket made of titanium. A titanium bracket has the potential of working well in the small number of patients who experience nickel hypersensitivity from traditional metal brackets. Another variant of the

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metal bracket is a stainless steel bracket coated with a micro-thin layer of zirconianitride to impart a gold color. Along with this bracket, gold arch wires are available to complement the color (see [4], [5]). Brackets are either routinely cast or injection-molded from stainless steel, although to reduce the chance of allergic reaction, nickel-free brackets made from titanium or cobalt chromium are now available. Bonding techniques rely on a physical interaction being established between the bracket base and an etched enamel tooth surface. Bracket bases are therefore roughened or sandblasted to improve this bond and often curved in both the horizontal and vertical planes, which aids in bracket location and seating on the tooth crown. A significant disadvantage of metallic orthodontic brackets is their poor aesthetics. bracket systems that are transparent, or more closely resemble natural tooth colour, have therefore been developed.

2.2 Plastic Brackets

The early aesthetic brackets were made of acrylic and polycarbonate, which discoloured quite rapidly and were prone to both permanent deformation and failure. To overcome these problems, plastic brackets were made in polyurethane or polycarbonate reinforced with ceramic or fibreglass fillers. Plastic brackets to be bonded directly to enamel were initially made of polycarbonate and plastic molding powder (Plexiglas). Plexiglas brackets did not last long because of their discoloration, fragility, and breakage under stress. Also, much of the energy in the wire was expended in distorting the brackets because of the poor integrity of the arch wire slot, and therefore forces were not transmitted to the tooth. In recent years there have been several improvements to reinforce plastic brackets, such as precision-made stainless steel slot inserts and ceramic material fillers (15% to 30%). Metal slot reinforcement of plastic brackets appears to strengthen the matrix adequately so that torque can be applied at the same level as with metal brackets. Ceramic-reinforced composite brackets without a metal slot insert have been shown to have fairly low frictional characteristics compared with ceramic and metal brackets .18 Hence the newly introduced ceramic-reinforced plastic brackets are suitable for clinical use because they are color stable, have lower friction,"' and have the structural integrity to transmit orthodontic forces without distorting.

2.3 Ceramic Brackets

Ceramic brackets were introduced in the 1980s and provide higher strength, more resistance to wear and deformation, better colour stability and superior aesthetics. They are manufactured from aluminium oxide and are described as either

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monocrystalline or polycrystalline, depending upon whether they are made from one or many crystals. During the last decade, ceramic brackets have become the esthetic alternative to plastic brackets. The monocrystalline and polycrystalline ceramic materials used in manufacturing these brackets provide excellent color fidelity and stain resistance. However, clinicians may be inhibited from using ceramic brackets because of their reported fracture tendencies and, more importantly, their reported tendency to damage enamel during the debonding procedure. The manufacturers of these brackets have tried to improve bracket characteristics to facilitate easier debonding. These changes have included a shift from the purely chemical retention mechanism of resin bonding to the bracket base to a totally mechanical mode of bonding for the polycrystalline bracket. Investigations have found that debonding with sharp-edged pliers applies a bilateral force at the bracket base-adhesive interface and is the most effective method for debonding both polycrystalline and monocrystalline orthodontic brackets. Therefore forces applied at the interface rather than the bracket itself may prevent breakage on debonding. Brackets bonded by indirect techniques, which create a resin interlayer, facilitate debonding at the interface formed between this interlayer and the filled resin. Ceramic brackets may fracture during torsional and tipping movements, cause abrasion of opposing teeth, and have increased frictional resistance in sliding mechanics compared with plastic and metal brackets. Ceramic brackets have limitations and caution must be exercised in their use. Ceramic brackets should not be bonded to teeth that have cracks or signs of physical defects. A new design of the ceramic bracket is borrowed from the design of the metal reinforced plastic bracket. This bracket system incorporates a metal slot in the ceramic bracket, reducing the friction to levels experienced by stainless steel brackets. Another feature of this appliance is the ease of debonding via a vertical scribe line placed in the base of the bracket Despite these problems, adult patients often request ceramic brackets because of the improved aesthetics.

3 Preliminaries

3.1 Generalized linear regression models

Let $y_1, \ldots, y_n$ be a series of n observations on a characteristic Y from a statistical population. Of course, the (numerical) value y_i is only one of the possible realizations of the random variable Y_i. As we saw in the previous section, for linear models, we accept that all random variables Y_i are independent of each other and have a normal distribution of parameters the mean μ_i and the dispersion σ^2 i.e

$$Y_i \sim \mathcal{N}(\mu_i, \sigma^2)$$

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and we will assume that the mean (expected) value μ_i is a linear function of k predictors that take the (numerical) values $\overline{x}_i = (x_{i1}, \ldots, x_{ik})^t$ or

$$\mu_i = \overline{x}_i \cdot \beta$$

where β is the vector of parameters (unknown).

It is known that the above model can be generalized in two stages, the first refers to the stochastic component and the second to the systematic component of the model (linear). We will describe the generalized linear model as formulated by Nelder and Wedderburn in 1972 (see [6]).

Let's assume that all the observations come from a distribution from a family of exponential distributions with the probability density function

$$f(y_i) = \exp\{\frac{y_i \cdot \theta_i - b(\theta_i)}{a_i(\phi)} + c(y_i, \phi)\} \tag{1}$$

where θ_i and ϕ are the parameters and $a_i(\phi)$, $b(\theta_i)$ and $c(y_i, \phi)$ are known functions.

The parameters θ_i and ϕ are, in essence, the location and scale parameters.

The family of exponential distributions as defined includes, as special cases, the normal distribution, the binomial distribution, the Poisson distribution, the exponential distribution, the gamma distribution and the inverse Gaussian distributions.

The second possible generalization of the linear model is based on the fact that instead of modeling the average, as before, we will introduce a transformation, i.e. a continuous, differentiable and bijective function $g(y_i)$ thus 'incåt

$$\eta_i = g(\mu_i). \tag{2}$$

The function $g(\mu_i)$ is called *link function*. Examples of related functions can be: the identical function, the inverse (hyperbolic) function, the logarithmic function, etc.

We will assume that the transformed model follows a linear model, i.e

$$\eta_i = \overline{x_i}\beta. \tag{3}$$

The quantity η_i is called *linear predictor*. Since the link function is bijective, we can invert and we get

$$\mu_i = g^{-1}(\overline{x_i}\beta). \tag{4}$$

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We denote by $\hat{\mu_i}$ the values estimated (predicted) by the ω model and let $\hat{\theta}_i$ be the estimates corresponding to the canonical parameters. "similarly, we denote by $\tilde{\mu_i} = y_i$ 'and analogously $\tilde{\theta}_i$ for the canonical parameters under Ω.

The ratio criterion for comparing the two models in the family of exponential distributions is

$$-2\log\lambda = 2\sum_{i=1}^{n}\frac{y_i(\tilde{\theta}_i - \hat{\theta}_i - b(\tilde{\theta}_i) + b(\hat{\theta}_i)}{a_i(\phi)}.$$

The expression does not depend on the unknown parameters and it's called *deviation*

$$D(y,\hat{\mu}) = 2\sum_{i=1}^{n} p_i[y_i(\tilde{\theta}_i - \hat{\theta}_i) - b(\tilde{\theta}_i) + b(\hat{\theta}_i)] \tag{5}$$

The criterion of the likelihood ratio $-2\log L$ which represents the deviation divided by the scale parameter ϕ is called *scaled deviation*.

Let us return now to the comparison of two models ω_1, with p_1 parameters, and ω_2 with p_2 parameters, such that $\omega_1 \subset \omega_2$ 'and $p_2 > p_1$.

The logarithm of the ratio between the maximized likelihood functions for the two models can it is written as a difference of deviations, that is

$$-2\log\lambda = \frac{D(\omega_1) - D(\omega_2)}{\phi}. \tag{6}$$

The scale parameter is either known or estimated using a larger model ω_2.

The theory of large samples (law of large numbers) tells us that the asymptotic distribution of this criterion, under the usual regularity conditions is χ^2_ν with $\nu = p_2 - p_1$ degrees of freedom.

The problem of estimating the orders of linear models for data series was, for many mathematicians, an important object of study during the 1960s and 1970s. H. Akaike noticed that there is a similarity between choosing the number of factors in factorial analysis and determining the order of a linear model (that is, the number of predictor variables) (see [8]). . For example, in the case of a linear model, the idea of prediction is clear, but there is a problem that arises when parameters are estimated from the recorded data. In factorial analysis, the log-likelihoods are maximized and these maximizations are expected to be good models for the prediction distributions, but in this case the prediction no longer is a numerical value but a function that is estimated by the prediction distribution. The expected log-likelihood can be given by the Kullback-Leibler information.

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Selecting the minimum of Kullback-Leibler information, comes back to maximizing $M_f \log g(y)$.

We considered n observations of some i.i.d. random variables. $y_1, \ldots, y_n$ having an unknown probability density $f(y)$. We assume that we have a lot of alternative or candidate models of the type $g_m(.|\theta_m),\ m = 1, 2, \ldots, M$, where θ_m is the vector of density parameters g_m. We will want to estimate $I(f, g_m(.|\theta_m))$. We assume that the parameter vector θ_m is known. Then, from the law of large numbers, we have

$$M_f \log g_m(y|\theta_m) = \int_{-\infty}^{\infty} f(y) \log g_m(y|\theta_m) dy = \frac{1}{N} \sum_{n=1}^{N} \log g_m(y_n|\theta_m). \tag{7}$$

The vector of parameters θ_m for the densities $g_m(.|\theta_m)$ is unknown 'in practice'. Parameters must be estimated from the data and under the assumption that the model $g_m(|\theta_m)$ has been chosen. It is natural to use the maximum likelihood estimator $\hat{\theta}_m$ which maximizes the right member of (2.15). In this case, the law of large numbers no longer occurs when the vector of parameters is replaced with its estimates in the sense of maximum likelihood. so,

$$M\ M_f \log g_m(y|\hat{\theta}_m) \neq \frac{1}{N} M \sum_{n=1}^{N} \log g_m(y_n \hat{\theta}_m). \tag{8}$$

This happens because the same set of data was used twice, for parameter estimation and for log-likelihood estimation

The log-likelihood estimator in the case above is a shifted estimator. This displacement (bias) is approximately equal to the number of parameters estimated in the model. An approximate correction for this bias is given in the definition of Akaike's estimator denoted by AIC (*Akaike's Informational Criterion*):

$$\text{AIC}(g) = -2(\text{log-maximum likelihood of the model}) +$$

$$+2(\text{the number of estimated parameters of the model}) =$$

$$= -2 \sum_{n=1}^{N} \log g_m(y_n|\hat{\theta}_m) + 2|\hat{\theta}_m|$$

where $|.|$ represents the cardinality of the estimated parameters in the model.

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3.2 Poisson regression model

A random variable Y is said to have a Poisson distribution with parameter μ if a takes integer values $y = 0, 1, 2 \ldots$ with the probability

$$Pr[Y = y] = \frac{e^{-\mu}\mu^{y}}{y!} \tag{9}$$

for $\mu > 0$. The mean and variance are

$$M(Y) = Var(Y) = \mu$$

Since the mean is equal to the variance, any factor that affects one will affect the other. In other words, the usual assumption of homoscedasticity (equal variance) is not "fulfilled". for data with Poisson error (see [7]).

Suppose we have a sample with n observations $y_1, y_2, \ldots y_n$ which can be treated as realizations of independent Poisson random variables, with $Y_i \sim P(\mu_i)$, and suppose that we want the mean (and, therefore, the variance!) to depend on a vector of explanatory variables $\overline{x}_i$.

We could consider a simple linear shape model

$$\mu_i = \overline{x}_i \ \beta$$

but this model has the disadvantage that the linear predictor on the right can take any real value, while the Poisson mean on the left representing has a number of expectations, it must be non-negative.

A simple solution to this problem is to model the logarithm of the mean using a linear model. Thus, we calculated $\eta_i = \log(\mu_i)$ 'and we assume that the mean value of the transformation follows a linear model $\eta_i = \beta \ \overline{x}_i$. Thus, we will consider a generalized linear model with a (natural) logarithmic link function. Combine these two steps and we can write the log-linear model as

$$\log(\mu_i) = \overline{x}_i \ \beta. \tag{10}$$

We apply the exponential function to equation (4.2) and obtain a multiplicative model for the average:

$$\mu_i = \exp[\beta \ \overline{x}_i]$$

A measure of the discrepancy between the observed and estimated values is the statistical deviation. It is shown that for the Poisson responses the deviation is ia form

$$D = 2\sum\{y_i \log(\frac{y_i}{\hat{\mu}_i} - (y_i - \hat{\mu}_i)\}$$

The first term is identical to the binomial deviation. The second term, a sum of the differences between the observed and estimated values, is usually zero,

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because the maximum likelihood estimates in Poisson models have the property of reproducing the marginal distributions.

For large samples, the distribution of the deviation is approximately χ^2 with $n - p$ degrees of freedom, where n is the number of observations and p is the number of parameters.

4 Methods and results

4.1 Methods

In this descriptive study, the dental data of two groups of children with dental apparatus, the first group with "in use" brackets and the second groups "out use", i.e. children who have used a dental brackets. In both groups, the children were randomly selected from a list of of patients from a dental clinic. Overall, 665 samples were selected and their data for dental brackets was evaluated, 330 in the first group and 335 for the second group.

The response variable (denoted with Y_a and respectively Y_b) represent the type of dental brackets and the predictor variables were the age and the sex of patients (denoted with $X1_a$ and $X2_a$ and respectively $X1_b$ and $X2_b$).

In the first step, it was analyzed, using appropriate statistical tests, if there are significant statistical differences between the two groups. More precisely, the F-test (to check the equality in the variance) and the t-test (for the equality in the mean) were applied.

The next step, the generalized Poisson regression model was applied for the two predictors in both groups.

The last step consisted in optimizing the number of predictors using the "backward" selection procedure. Data analysis was performed using the R software (4.2.0).

4.2 Results

A primary descriptive statistics was made for the both groups. For the first group they are 8 types of dental brackets : "metalic clasic", "damon metalic", "safir", "damon clear", "aparat mobil" (i.e. mobile brackets) ,"genius", "metalic+safir" The simple histogram is represented in Graph 1.

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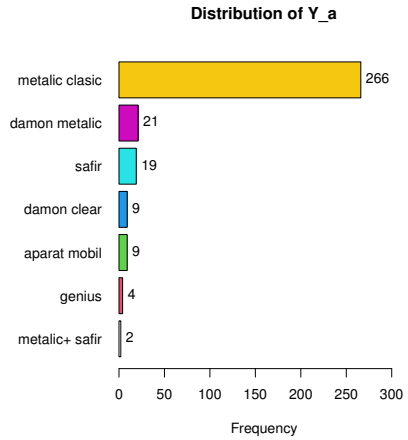


Figure 1: Distribution of brackets types for the first group

In analogous way, for the second group, where we have just 6 types, "metalic clasic", "safir", "damon metalic", "damon clear", "metalic+safir", "genius", the histogram is presented in Graph 2.

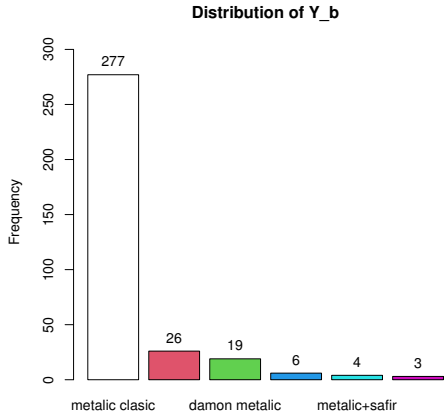


Figure 2: Distribution of brackets types for the second group

Using, successively, the F-test and the t-test, it was obtained that there are statistically significant differences between the two groups. Furthermore, the analysis using the regression method was performed separately, on each group of data (see Table 1 and Table 2, respectively).

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Table 1: Results form F-test for comparison of the groups.

F test to compare two variances	
data:	Y_a and Y_b
F = 1.6683, num df = 329, denom df = 334,	p-value = 3.594e-06
alternative hypothesis:	true ratio of variances is not equal to 1
95 percent confidence interval:	(1.344735, 2.069989)
sample estimates:	ratio of variances 1.668261

Table 2: Results form t-test for comparison of the groups.

Welch Two Sample t-test	
data:	Y_a and Y_b
t = 1.6449, df = 619.49,	p-value = 0.1005
alternative hypothesis:	true difference in means is not equal to 0
95 percent confidence interval:	(-0.02507669, 0.28378315)
mean of x	mean of y
1.466667	1.337313

Because, the both statistical test suggest a statistical difference between these two groups, we will make the regression analyze for the each data groups.

Table 3: Statistical details on the Poisson regression with both predictors.

glm(formula = Y_a ∼ X1_a + X2_a, family = poisson)				
Deviance Residuals:				
Min	1Q	Median	3Q	Max
-1.2272	-0.3640	-0.3040	-0.2205	2.9523
Coefficients:				
	Estimate	Std. Error	z value	Pr(> |z|)
(Intercept)	0.026840	0.189632	0.142	0.887
X1_a	0.026091	0.005944	4.389	1.14e-05 ***
X2_a	-0.076660	0.092703	-0.827	0.408
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
(Dispersion parameter for poisson family taken to be 1)				
Null deviance: 197.88 on 329 degrees of freedom				
Residual deviance: 180.04 on 327 degrees of freedom				
AIC: 912.73				
Number of Fisher Scoring iterations: 5				

First, we consider the Poisson regression model with both predictor variables, i.e. X1=Age (as a normal random variable) and X2=Sex (as binary random variable with two states "M" and "F" transformed in "1" and "2") for each data group (we denote as X1_a and X2_a for group 1, respectively, X1_b and X2_b for the group 2). The response variable is considered as categorial variable following a Poisson distribution

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(because de statistical mean value and variance value are almost the same , 1.466667 and 1.28308 for the first group and 1.337313 and 0.9691125 for the second group).

The results for the first group are presented in the Table 3.

Some detail about statistics indicators from above table.

- Coefficients and P-Values
  The coefficient estimate in the output indicate the average change in the log odds of the response variable associated with a one unit increase in each predictor variable.
  The standard error gives us an idea of the variability associated with the coefficient estimate. We then divide the coefficient estimate by the standard error to obtain a z value.
  The p-value $\Pr(> |z|)$ tells us the probability associated with a particular z value. This essentially tells us how well each predictor variable is able to predict the value of the response variable in the model.
- Null and Residual Deviance
  The null deviance in the output tells us how well the response variable can be predicted by a model with only an intercept term.
  The residual deviance tells us how well the response variable can be predicted by the specific model that we fit with p predictor variables. The lower the value, the better the model is able to predict the value of the response variable.
  To determine if a model is "useful" we can compute the Chi-Square statistic as: X^2 = Null deviance – Residual deviance with k degrees of freedom.
  We can then find the p-value associated with this Chi-Square statistic. The lower the p-value, the better the model is able to fit the dataset compared to a model with just an intercept term.
- AIC
  The Akaike information criterion (AIC) is a metric that is used to compare the fit of different regression models. The lower the value, the better the regression model is able to fit the data.

We observe that the predictor X2_a doesn't pass the z-test (the P-value is grater than alphs=0.05, i.e. there is a great probability such that the coefficient to be null from the statistical point of view), therefore, following the backward selection procedure, we can consider the regression model just with a single predictor, X1_a. The results are presented in the Table 4.

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Table 4: Statistical details on the Poisson regression with a single predictor (Age).

glm(formula = Y_a ∼ X1_a, family = poisson)				
Deviance Residuals:				
Min	1Q	Median	3Q	Max
-1.1568	-0.3689	-0.3109	-0.2539	3.0215
Coefficients:				
	Estimate	Std. Error	z value	Pr(> |z|)
(Intercept)	-0.09393	0.12229	-0.768	0.442
X1_a	0.02597	0.00596	4.357	1.32e-05 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
(Dispersion parameter for poisson family taken to be 1)				
Null deviance: 197.88 on 329 degrees of freedom Residual deviance: 180.72 on 328 degrees of freedom AIC: 911.41 Number of Fisher Scoring iterations: 5				

We can see that the intercept coefficient doesn't pass the z-test. Therefore we, consider the model with without intercept (this it is possible because we cannot put a dental bracket for a child of zero age). In the Table 5, is presented the statistical results for this model.

Table 5: Statistical details on the Poisson regression without intercept.

glm(formula = Y_a ∼ -1 + X1_a, family = poisson)				
Deviance Residuals:				
Min	1Q	Median	3Q	Max
-1.0428	-0.3927	-0.3439	-0.2958	2.9614
Coefficients:				
	Estimate	Std. Error	z value	Pr(> |z|)
X1_a	0.021682	0.002233	9.709	<2e-16 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
(Dispersion parameter for poisson family taken to be 1) Null deviance: 260.62 on 330 degrees of freedom Residual deviance: 181.31 on 329 degrees of freedom AIC: 910 Number of Fisher Scoring iterations: 5				

We can observe that this model is very good and the predictor "age" it is essential for the choosing of dental bracket of a child. In fact the model give as the parameter for Poisson distribution, i.e. mean value

$$\mu = e^{0.021682 * \text{age}}$$

and with this value we can compute the probability to choose the k type from the

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set of 8 types, using the formula

$$P(Y = y) = \frac{e^{-\mu}\mu^{y}}{y!}, \quad y = 0, 1, \ldots, 7$$

In an analogous way, we analyse the data from the second group. The statistical results are given in Table 6 (the Poisson regression model with both predictors), Table 7 (regression with a single predictor after the optimization using the backward selection procedure). We observe that for this group, the intercept coefficient pass the t-test.

Table 6: Statistical details on the Poisson regression with both predictors, for the second group.

glm(formula = Y_b ∼ X1_b + X2_b, family = poisson)				
Deviance Residuals:				
Min	1Q	Median	3Q	Max
-1.4534	-0.2302	-0.1423	-0.0816	3.1830
Coefficients:				
	Estimate	Std. Error	z value	Pr(> |z|)
(Intercept)	-0.541685	0.203198	-2.666	0.00768 **
X1_b	0.041367	0.006065	6.821	9.04e-12 ***
X2_b	0.030077	0.102890	0.292	0.77004
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
(Dispersion parameter for poisson family taken to be 1)				
Null deviance: 132.32 on 334 degrees of freedom Residual deviance: 93.14 on 332 degrees of freedom AIC: 822.43 Number of Fisher Scoring iterations: 4				

Table 7: Statistical details on the Poisson regression with a single predictors (Age), for the second group.

glm(formula = Y_b ∼ X2_b, family = poisson)				
Deviance Residuals:				
Min	1Q	Median	3Q	Max
-1.4518	-0.2192	-0.1311	-0.0879	3.1993
Coefficients:				
	Estimate	Std. Error	z value	Pr(> |z|)
(Intercept)	-0.495886	0.128849	-3.849	0.000119 ***
X2_b	0.041611	0.006008	6.925	4.35e-12 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
(Dispersion parameter for poisson family taken to be 1)				
Null deviance: 132.318 on 334 degrees of freedom Residual deviance: 93.226 on 333 degrees of freedom AIC: 820.52 Number of Fisher Scoring iterations: 4				

We can observe that this model is very good and the predictor "age" was essential for the choosing of dental bracket of a child. In this case the formula for

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Poisson parameter it is

$$\mu = e^{-0.495886+0.041611*\text{age}}$$

and with this value we can compute the probability to choose the k type from the set of 6 types, using the formula

$$P(Y = y) = \frac{e^{-\mu}\mu^y}{y!}, \quad y = 0, 1, \ldots, 5$$

5 Conclusions

We study the relation for the types of dental brackets and some records from patients files. A generalized regression model by Poisson type was proposed, based data from two different groups. In both cases, the mean value of the Poisson distribution depend by a single predictor – Age. These results are supported by dentists who note that the age of children is important for their teeth to support a certain type of bracket material. Our results give a simple computation for the probability of choosing a certain type of bracket based on the age of the children. Of course, there exists a little difference between the new group ("in use") and, somehow, the old group ("out of use") because there is a continuous development of new materials and new types for the dental brackets.

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Hasem ABBAS, Master student
Casa Denti–Dental Clinic
Str. Aurelianus 5A, 300551, Timişoara, România
E-mail: hazem6070@gmail.com

Romeo NEGREA
Department of Mathematics
Politehnica University of Timişoara
P-ta Victoriei 2, 300006, Timişoara, România
E-mail: romeo.negrea@upt.ro

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