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Statistical Estimation of Age at Death Using Adult Human Dental Age Indicators.

Original Article

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Abstract

Background: To illustrate a statistical method for age estimation in the field of forensic science where identification of human remains is beyond recognition.

Objective: The present investigation proposed a generalized linear model with the aim at finding an effective statistical model for human age estimation at death using solely dental indicators.

Materials and Method: The data used in the study are the same utilized by [1] and comprised measurements taken on 71 maxillary incisors from different individuals of known age at death. The study proposed a Gamma GLM model to predict the age at death. Model performance was assessed using diagnostic plots.

Results: The mean predicted age using the GLM model was 52.34 years compared with the actual mean age of 52.35 for the original data. The mean absolute error (a measure of average deviation of predicted age from known age) was found to be 5.78 years.

Conclusion: The Gamma GLM with identity link function does provide a reasonable model for dental age prediction using the data in [1].

Keywords: age estimation; dental age indicator; Generalized Linear Models; forensic science.

Introduction

Determination of age plays a significant role in Forensic Science in the identification of bodies as well as in relation to crime and accidents. Teeth are useful in determining age as they tend to stay intact especially in circumstances when the deceased has undergone such changes that identification of the deceased may be difficult by other means.

Many statistical methods have been employed in the past to estimate the age of a deceased individual using dental evidence. In these studies, like [2], regression techniques have been used in estimating human age using predictor variables such as attrition, secondary dentin apposition, periodontal recession, root resorption and root dentin translucency.

However, these methods have not been shown to be appropriate for categorical data which have been mostly been used in such studies [1]. A Bayesian prediction method was proposed for estimation of adult human age. However, this method was also shown to have its drawbacks including predictions that were sometimes inflated.

The present investigation utilizes the same data set (shown in Table A.3) utilized by [1] which comprise data collected for 71 second maxillary incisors. Similar to [2], a linear model is proposed in this investigation with the assumption of a Gamma distribution for the response variable. This is done in an effort to establish whether utilization of a Gamma model has any particular advantage in human age estimation.

2 Review of Literature

2.1 Importance of Age Estimation

Human age estimation has been shown to be important in the identification of individuals. This procedure has been utilized extensively in assessing the age of the living in cases where there is no record of birth date and can be used in many instances such as assessment of pensions at retirement, in the judicial system and in identification of individuals in crimes and accidents. It has also been used in the field of forensic science where identification of the deceased

individuals is necessary.

Aging techniques make the assumption that the factors that affect the aging of human skeleton are the same for all persons belonging to the same population and that biological age and chronological age are correlated [3]. Both of these measurements are different. Biological age looks at the speed at which a person ages and is based on bio-markers whereas

chronological age is calculated based on the date of birth of an individual. Exposure to environmental factors and genetics vary between individuals and so affect the way in which people age, causing a difference between biological age and chronological age. Evaluation of the age of an individual can be estimated by considering many different factors which include height, weight, changes which take place during puberty such as pelvic changes, hair growth and changes in hair colour, the appearance of ossification centres, bone development and dental aging [4]. The following section discusses the standard indicators of aging and age estimation.

2.2 Indicators of Aging

Scientists have studied aging of the human skeleton in an attempt to estimate age. The standard indicators of age include the following: examination of the pelvic bone such as pubic symphysis and auricular surface, degenerative joint disease, histological data, examination of sternal end of fourth rib and dental observations. Although pelvic bone was believed to be durable, it was found that there were discrepancies of age estimation using pelvic bone [5].

The rib cage of an individual usually was more efficient at age estimation when compared to data collected on pelvic bone as the rib cage does not usually undergo the same stress as that placed on the pelvic bone and is therefore more durable. However identification of this bone has proved

to be very difficult in cases where the skeleton is decomposed and the rib cage is fragmented [5]. Histological aging which consists of measurement of secondary osteon fragments and non-Haversian Canals [6] have also been shown to not be efficient at age estimation. In addition to this method, degenerative joint diseases such as osteoporosis and osteoarthritis have also been shown to have a linear relationship with age and have been used in the past for age estimation. However, this age indicator is also dependent on other factors such as genetics, obesity and gender so that use of this variable in age estimation is usually used as a last resort to estimating age when all other methods prove futile [5].

Another method of human age estimation involves the use of dental data. Methods using this indicator have been shown to be more effective at estimating age than other variables.

2.3 Dental Age Estimation and its Use in Forensic Science

Forensic Odontology is a branch of forensic science and odontology which is based on the observation and examination of teeth and presentation of dental evidence in the field of law [7]. In many instances, age estimation using teeth is the sole means of identification when the skull is all that remains of the human skeleton [8]. Teeth have been used for estimating age more than 170 years ago when emergence of teeth was first used for determining age in relation to child labour.

Skeletal age has been shown to be affected by malnutrition and other health factors and can therefore be used in evaluating an individual's biological age whereas dental age is better used for chronological age estimation [9].

By examination of different populations, it was observed that development of teeth varied amongst individuals of different ethnicities. Emergence of teeth was found to be less affected by external factors which made teeth a better candidate for age estimation.

In addition, the hardness and resiliency of dental tissue make teeth a valuable factor in age estimation as teeth are hardly affected by external conditions such as harsh temperatures, extreme humidity and in some cases even cremation, that sometimes even after such harsh external factors, the teeth can still be used in evaluation of age. In addition to physical changes of teeth such as lateral movement through jaw and eruption, teeth usually undergo many secondary changes which occur with increasing age. These include periodontal recession, attrition (tooth wear), cementum apposition, root resorption translucency, deposition of secondary dentin, changes in colour of teeth, change in root roughness [7]. The next section will therefore outline various techniques and statistical analyses employed in past studies that were used in age estimation based on dental observations.

2.4 Past Studies on Dental Age Estimation

Secondary changes in teeth were used to assist in estimating age [2]. The study used six variables which included: attrition, periodontal recession, secondary dentin, cementum apposition, root dentin translucency and root resorption. Scores were awarded using a four point scoring system based on the severity of change in the tooth. A linear regression method was used to link age to the sum of scores for each independent variable. One of the drawback of the method used is the assumptions on the residuals were not tested. This method was found to underestimate age in old persons and overestimate age in younger individuals.

There were many studies that used linear regression and various observational measurements taken on the teeth [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23]. The main problems from these papers included overestimation, underestimation and having predicted values of age that were way off the true value.

Computerized measurements were also made to minimise the subjectivity introduced in assessing the categories of teeth [24], [25], [26].

Most of the studies conducted in the past have utilized regression-based methods for estimating adult age. Results from these studies have produced models which were inappropriate for age estimation. The GLM method of age estimation which was conducted did however produce more favourable results than what was obtained by classical parametric regression techniques [27]. In this paper, we apply a GLM modelling technique to estimating age at death. We treat age as a positive continuous variable in an attempt at finding an effective model for human age estimation based solely on dental observations in the dataset.

3 Methodology

3.1 Data and Description of Covariates

We used the dataset from Table A.3 from [1]. Consent to use the data was sought from David Lucy, the main author of [1]. Following the leading author's advice, the paper has been appropriately referenced. The dataset consisted of data from 71 maxillary incisors which were obtained from different individuals with ages ranging from 17 - 86 years. The variables that were used were selected because of their strong correlation with age and included the following: periodontal recession, secondary dentin, apical translucency, root colour and root roughness of cementum. Periodontal recession, secondary dentin and translucency were measured using a seven point scoring system derived by [12] whereas colour estimate and root roughness were measured using a five point scoring method proposed by [18].

The variables in the data file were:

- Secondary Dentin - This is the dentin that is deposited throughout the wall of the pulp chamber and continuously throughout the lifetime of the individual. The scoring system is based on measurements of lengths of the pulp chamber [28].
- Apical Translucency (Transparency) - this variable is related to aging and describes how transparent the more dense part of the teeth appears in light. Translucency is caused by an increase in mineral deposits on the teeth which usually starts at the root tip and moves upward towards the crown of teeth [14].
- Root Roughness of Cementum - Cementum is the phrase used to describe tissue that covers the root of the tooth and is used to anchor the fibres to the root surface. The amount of cementum on the root surface increases throughout the life of the individual and usually triples between the ages of 11 and 76 years [14].
- Periodontal Recession - this is the term used to describe how much the roots of the teeth is exposed due to receding gums and is measured in millimetres (mm) by examining retraction of gums from root surface [29].
- Root Colour - this variable measures the degree of discoloration of the teeth which is related to increase in age ranging from a score of 1 referring to teeth with mild or no discoloration to a score of 5 referring to severely discoloured teeth [18].
- Age – this was the age at death of the individual measured in years.

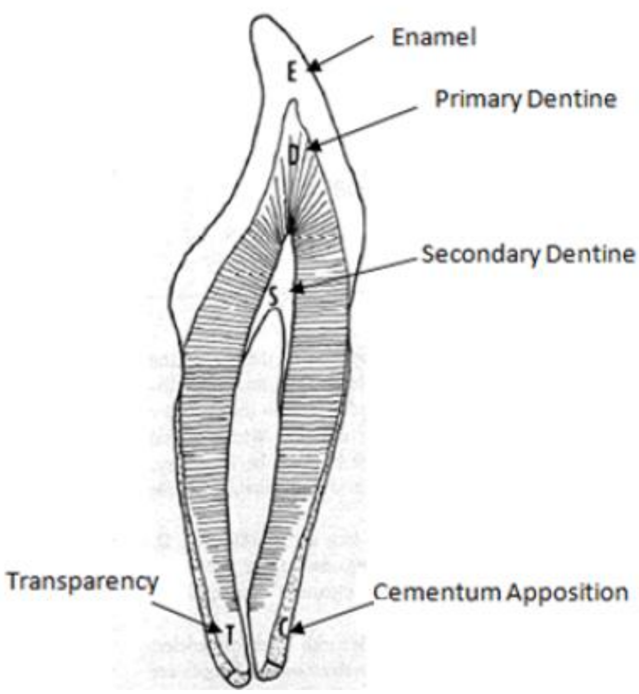

Figure 1: Sagittal section drawing of incisor

Source: [14]

3.2 Statistical Model-Generalized Linear Model

A Generalized Linear Model (GLM) encompasses a wide range of models which is used for analysing both quantitative and qualitative dependent variables and is based on the exponential family of distributions which include Normal, Binomial, Negative Binomial, Poisson, Inverse Gaussian, Geometric and Gamma. The exponential family offers more flexibility in that the variance structure of the response can be selected. By specifying a relationship between the linear predictors and the fit, relationships that originally were assumed to be non-linear can be "linearized" [30].

There are three components of a GLM:

- a random component which comprises of the response variable (Y_i) and its distribution.
- a linear predictor or systematic component which comprises of a linear combination of regressors.
- a link function that is used to link the linear predictors and explanatory variables with the parameters of the response variable.

3.2.1 Assumptions of a Generalized Linear Model

The standard multiple linear regression model is fit to data by maximum likelihood estimation or through the Ordinary Least Squares (OLS) method and has several restrictive assumptions such as normality of errors. The fit of a GLM model is assessed by method of maximum likelihood and uses the Iteratively Re-weighted Least Squares (IRWLS) approach. GLM's have less restrictive

assumptions than ordinary linear regression and involves independent observations and specification of the link function.

The response variable in this study is age which in this case is a positively skewed continuous variable. We modelled the response variable using a Gamma distribution. The Gamma distribution is extremely flexible and changing the parameters of the distribution results in varying shapes. This makes it very adaptive.

Results and Discussion:

In this study, the most significant factors of adult human age estimation are examined with the aim at finding the most effective model for age estimation. The proposed model utilized the same data set that was used by [1] which comprised of data on 71 maxillary incisors. All predictor variables in the study were treated as categorical variables where each variable was dummy coded in the analysis. The GLM analysis for the full data set was carried out and GLM modelling provided a linear equation which was used as a prediction model for age of subjects between the ages of 17 - 86 years. In order to get a parsimonious model, a stepwise procedure was run. This resulted in periodontal recession, translucency and colour estimate being kept in the GLM model. Statistical software R version 3.2.1 was used to perform these analyses.

A GLM was run using the gamma response specification. Table 1 shows the actual, predicted and 95% confidence intervals for the predicted age for each subject.

Table 1: Predicted Ages and 95% confidence intervals for predicted ages for Gamma GLM.

Actual Age	Predicted Value	Lower Limit	Upper Limit	Actual Age	Predicted Value	Lower Limit	Upper Limit
17	17.00	11.57	22.43	**48**	41.28	35.43	47.13
22	21.55	16.31	26.79	**50**	46.59	41.00	52.17
24	22.95	17.26	28.63	**52**	54.41	47.67	61.14
24	23.08	17.12	29.04	**53**	45.68	40.90	50.46
27	30.15	24.54	35.76	**55**	52.45	46.31	58.59
28	28.00	19.05	36.95	**57**	60.18	53.54	66.82
30	36.66	30.46	42.87	**57**	55.31	49.00	61.63
30	35.13	30.18	40.08	**58**	68.90	62.76	75.05
31	36.53	30.67	42.39	**58**	64.50	57.44	71.56
31	33.59	28.28	38.90	**59**	68.90	62.76	75.05
32	42.82	38.08	47.57	**59**	50.00	42.42	57.58
34	43.73	38.37	49.09	**65**	66.04	59.70	72.39
34	29.75	21.11	38.39	**66**	58.19	42.62	73.76
35	31.70	24.66	38.73	**66**	75.20	63.79	86.60
35	33.59	28.28	38.90	**68**	77.29	69.25	85.32
36	35.13	30.18	40.08	**68**	72.89	65.25	80.52
37	38.87	32.42	45.32	**68**	68.90	62.76	75.05
37	46.59	41.00	52.17	**72**	72.89	65.25	80.52
38	39.39	34.16	44.61	**73**	66.04	59.70	72.39
39	43.73	38.37	49.09	**73**	72.34	60.75	83.93

39	50.70	41.88	59.51	**74**	80.55	62.96	98.15
39	39.39	34.16	44.61	**74**	60.18	53.54	66.82
41	36.66	30.46	42.87	**74**	72.89	65.25	80.52
41	42.82	38.08	47.57	**75**	84.19	67.69	100.69
43	42.82	38.08	47.57	**75**	77.29	69.25	85.32
43	60.66	50.51	70.81	**76**	74.43	66.57	82.29
44	54.41	47.67	61.14	**76**	60.84	52.04	69.64
44	45.68	40.90	50.46	**77**	52.45	46.31	58.59
44	42.19	35.48	48.9	**79**	66.04	59.70	72.39
46	45.68	40.90	50.46	**79**	74.43	66.57	82.29
47	55.31	49.00	61.63	**79**	72.89	65.25	80.52
47	42.82	38.08	47.57	**79**	75.20	63.79	86.60
47	45.68	40.90	50.46	**80**	66.04	59.70	72.39
47	53.64	38.83	68.44	**80**	70.79	59.29	82.30
48	45.68	40.90	50.46	**86**	60.18	53.54	66.82
48	55.78	48.32	63.23				

Periodontal recession and colour estimate had strong positive relationships with age which replicates the finding reported by [22]. From the GLM model it can be deduced that periodontal recession with a score of 1 which represents less recessed gums have a negative association with age and was shown to not be significant in the analysis. The study also suggests that severely discoloured teeth have a greater association with age which is in agreement with findings of previous studies by [18], [22].

In the present study, the Gamma model predicted 39% of cases within 3 years of actual age and 55% within 5 years of actual age which were found to be improved estimates to those obtained by Gustafson who obtained predictions within 3.63 years in only 33% of cases [2].

The findings from the proposed model were also found to be improved predictions to those made in [31] where a predictive success of between 45 - 48% of cases were within 5 years of known age.

The mean predicted age for the model was 52.34 which was comparable with the average value for actual age of 52.35. The mean absolute error which is a measure of average deviation of predicted age from known age was found to be 5.78. This improved estimates in comparison to the findings of [25] who obtained a mean error on predictions of 8.9 ± 2.2.

The Gamma GLM model predicted 8% of the cases within 1 year of actual age for individuals less than 40. However the age of those older (over 75 years) seem to have been underestimated. This is consistent with findings of the study by [2]. Another study also underestimated age of older adults but over the age of 50 years [16].

One can argue that that the variables measured were very subjective in nature. However in underdeveloped countries, these may be the only variables that may be easily measured without incurring exorbitant costs.

Another limitation of this study is that predictions are only limited to individuals between the ages of 17 - 86 years. Another limitation is the initial plot of histogram of age revealed two distinct peaks in the data suggesting that it may be representative of bi-modally distributed data and hence further studies may need can be carried out exploring the possible application of mixture model GLMs.

Finally, the dataset used is relatively small and the number of individuals over 70 is also quite small. This may have resulted in an underestimation of those adults over 70 years.

Conclusions:

This study has revealed that periodontal recession, translucency and colour estimate were the most significant predictors of age using the Gamma GLM model. The predictive power of the model was strong. The data for the ages at the upper quantile were sparse and this resulted in the predictive power of the model being relatively poor when the ages were high (greater than 70). The goal of this paper was to illustrate the power of the GLM model in prediction age at death. Larger datasets would be have ideal in having a more comprehensive model.

Within the context of Forensic Science, age estimation continues to be a major area of research. The GLM is a predictive model that assumes the response variable need not ne normally distributed. This model corrects for the failure of the data to meet the assumptions of the linear regression model. It can be applied to other areas of Forensic Science where prediction is involved and the response variable falls into one of the common probability distributions. It should also be noted that no other study to our knowledge has used this dataset to predict ages besides [1].

Overall, the generalized linear model using a Gamma distributed response may be advantageous in modelling age at death based on dental data comprising simple subjective descriptive variables.

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