Analysis of Low Birth Weight of Newly Born Babies in Sunyani Municipality

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Abstract: Birth weight is one of the key indicators of the health and viability of the newborn infant and a person’s personality. It is desired that birth weight should be in the range of 2.5kg and 4.0kg. According to the World Health Organization (WHO) Low Birth Weight is as defined at birth less than 2.5kg. Low birth weight is major determinant of morbidity, mortality and disability in infancy and childhood. This is a very important indicator of a person’s health status, but little information known is about its causes and effects among mothers’ in Ghana. This is also risk factors for long-term impact on health outcomes in adult life. A study on some selected social and maternal factors pertaining to Low Birth Weight was conducted in Sunyani Municipal Hospital, Ghana. Records of 100 live births in a period of one year (16th January, 2016 to 29th December, 2016) were analyzed. This paper deploys singular value decomposition and multiple linear regression to identify the significant factors influencing the weight of the Low birth weight babies. The results obtained showed that all the selected maternal factors are the factors causing Low Birth Weight with mother’s haemoglobin concentration level being the most significant in all cases. We also conclude that pregnant women should take in additional nutritional food to increase haemoglobin concentration to avoid Low Birth Weight.

Keywords: Low Birth Weight, Birth weight, Haemoglobin concentration, Maternal Weight, Maternal height, Singular Value Decomposition (SVD), Multiple Linear Regression

1. Introduction

Birth weight is the single most important criterion for determining the neonatal and infant survival. Babies with a birth weight of less than 2.5kg irrespective of the period of their gestation are termed as Low Birth Weight (LBW) babies.

In Ghana, the issue of birth weight and factors influencing it has not received the much needed attention. This should not be the case given the importance of birth weight as an indicator of an individual baby’s survival and a person’s personality. W.H.O and UNICEF (2006), Ghana recorded higher Low Birth Weight cases of 16% compared to the 14% for sub-Saharan Africa. Low Birth Weight babies in Ghana was 10.70% as of 2011. Its highest value over the past 18 years was 16.10% in 2003, while its lowest value was 9.10% in 2006.

The purpose of this paper is to identify the factors that contribute to Low birth weight and to suggest some intervention strategies to improve the survival of the low birth weight babies.

The study will apply Singular Value Decomposition (SVD) and Regression Model to identify significant factors associated with Low Birth Weight babies. The data was analysed using the MATLAB and R softwares.

1.1 Background of Study

Sunyani is a city and the capital town of the Brong-Ahafo Region and the Sunyani Municipal of Ghana. Sunyani had a population of 248,496 at the 2012 census.
infection, baby’s sex using data from a District Hospital in the Ashanti Region of Ghana in 2013. Their results revealed that the significant factors were fetal infection, hemoglobin level, antenatal care and maternal age.

Mothers that have less than 12 years of education have an increased risk of delivering a low birth weight baby, while 12 or more years of education reduces that risk (Batech et al., 2013).

There is a 33% protection effect against LBW for women that have a higher education and a 9% higher probability of having a LBW child if the mother has not finished high school (Silvestrine et al., 2013). Therefore, an increase in education is vital for better access to necessary healthcare to ensure a healthy and safe delivery.

In terms of the other factors which influence birth weight, (Dearden et al. 2011) find that length of gestation is one of the most important predictors.

(Delaney et al. 2011) use a dramatic shift in public health which occurred in Ireland in the 1940s, and show that the children who benefited from improvements in early life experienced better health conditions went on to be healthier and stronger adults. Almond and Currie (2011) provide a recent summary of the causal evidence.

3. Methodology

3.1 Singular Value Decomposition

In linear algebra, the singular value decomposition (SVD) is a factorization of a real or complex matrix. It is the generalization of the eigen decomposition of a positive semidefinite normal matrix (for example, a symmetric matrix with positive eigen values) to any matrix via an extension of polar decomposition. It has many useful applications in signal processing and statistics.

The singular value decomposition of a matrix A is the factorization of A into the product of three matrices $A = UDV^T$ where the columns of U and V are orthonormal and the matrix D is diagonal with positive real entries.

$A = UDV^T$ which can be fully expressed as:

$$
\begin{bmatrix}
A_{11} & A_{12} & \cdots & A_{1n} \\
A_{21} & A_{22} & \cdots & A_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
A_{m1} & A_{m2} & \cdots & A_{mn}
\end{bmatrix} =
\begin{bmatrix}
U_{11} & U_{12} & \cdots & U_{1n} \\
U_{21} & U_{22} & \cdots & U_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
U_{m1} & U_{m2} & \cdots & U_{mn}
\end{bmatrix}
\begin{bmatrix}
D_{11} & 0 & \cdots & 0 \\
0 & D_{22} & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & D_{nn}
\end{bmatrix}
\begin{bmatrix}
V_{11} & V_{12} & \cdots & V_{1n} \\
V_{21} & V_{22} & \cdots & V_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
V_{m1} & V_{m2} & \cdots & V_{mn}
\end{bmatrix}
$$

Where
- $U$ is an orthogonal matrix
- $D$ is a diagonal matrix with non-negative real numbers and all its entries are singular values of $A$.
- $V^T$ is transpose of an orthogonal matrix $V$ (real or complex unitary matrix, if $V$ is real).

In contrast, the columns of $V$ in the singular value decomposition, called the right singular vectors of $A$, always form an orthogonal set with no assumptions on $A$. The columns of $U$ are called the left singular vectors and they form an orthogonal set. A simple consequence of the orthogonality is that for a square and invertible matrix $A$, the inverse of $A$ is $VD^{-1}U^T$, as the reader can verify.

3.2 Multiple Linear Regression

Multiple linear regression is a statistical technique that predicts values of one variable on the basis of two or more other variables. It is also generic term for any statistical technique used to analyze data from more than one variable. Regression models involve the following variables:
- The unknown parameters, denoted as $\beta$, which may represent a scalar or a vector.
- The independent variables $X$.
- The dependent variable, $Y$.

In various fields of application, different terminologies are used in place of dependent and independent variables.
Individual level variables were selected. These mainly consisted of maternal variables that may influence the birth weight of a baby. The selection of these variables, was further informed by the review of related literature to enable comparison of findings. The independent variables included: age of mother, ever attended school, blood pressure level, Haemoglobin concentration, location and weight of the mother.

4. Data Collection and Analysis

The study was conducted at Sunyani municipal Hospital, which is currently the Municipal Hospital, located in the Sunyani. The hospital offers public health services to the people in the entire Sunyani municipality and beyond. It also serves as a referral hospital in the region. The target population was newly born babies.

The relevant data on Low Birth Weight infants admitted to the Sunyani Municipal Hospital (SMH) from January 2016 to December 2016 was extracted from patient hospital records. Antenatal history were also extracted. From these, all with Low Birth Weight babies were identified by registration numbers.

The data was tabulated according to the various maternal factors included in the study and was analyzed using MATLAB and R software.

4.1 Dependent variable

The dependent variable for the study was recorded birth weights of newly born babies. The responses were grouped as low birth weight and normal birth weight. Babies with low birth weight were those weights less than 2.5 kilograms and those with weight of 2.5 kilograms.

4.2 Independent variable

Individual level variables were selected. These mainly consisted of maternal variables that may influence the birth weight of a baby. The selection of these variables, was

\[ \beta_i = \beta_0 + \beta_1 x_i \]

\[ \beta = \frac{\sum_{i=1}^{n} x_i y_i - n \overline{x} \overline{y}}{\sum_{i=1}^{n} (x_i - \overline{x})^2} \]

where \( \overline{x} \) is the mean of the \( x_i \)'s.

\[ \overline{y} \]

is the mean of the \( y_i \)'s.

4.3 Data grouping

Data was collected from the Sunyani Municipal Hospital and grouped for further analysis. The location of the mother was based on mother’s availability and easy to hospital and antenatal care. 1,2,3,4 and 5 were used to represent the grouped locations and defined as follows;

1, 2, 3, 4 :Represents mothers who have difficulty in accessing health and antenatal care because of their location.

5: Represents those from areas who have easy access to hospital and antenatal care because of their location.

The data was grouped according to the mother’s level of education and defined as follows :N: Represents mothers who have no education.

P: Represents mothers who have only primary education.

J: Represents mothers who have only junior high school education.

S: Represents mothers who have only secondary school education.

T: Represents mothers who have only tertiary education.

Baby weight \( Y \) is taken as the dependent variable and other maternal variables are treated as independent variables \( X_1,X_2,X_3,X_4,X_5,X_6,X_7,X_8,X_9,X_{10},X_{11},X_{12},X_{13},X_{14}, \)

where

\[ Y ': \] Baby weight

\[ X_1: \] Mother’s Age

\[ X_2: \] Mother’s Haemoglobin concentration

\[ X_3: \] Mother’s Blood Pressure

\[ X_4: \] Mother’s weight

\[ X_5: \] Mother’s with no educational background

\[ X_6: \] Mother’s with Primary school educational level

\[ X_7: \] Mother’s with Junior High school educational level

\[ X_8: \] Mother’s with Senior high school educational level

\[ X_9: \] Mother’s with Tertiary school educational level

\[ X_{10}: \] Mothers located at 1

\[ X_{11}: \] Mothers located at 2

\[ X_{12}: \] Mothers located at 3

\[ X_{13}: \] Mothers located at 4

\[ X_{14}: \] Mothers located at 5

4.4 Analysis with Singular Value Decomposition

Group one which includes the age from Age: 13-20 is shown in Table 1.

<table>
<thead>
<tr>
<th>Baby Weight</th>
<th>N0 (No)</th>
<th>Haemoglobin</th>
<th>Level of education</th>
<th>Location</th>
<th>BP</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;2</td>
<td>6</td>
<td>10.8</td>
<td>N</td>
<td>1</td>
<td>108.3</td>
<td>54.8</td>
</tr>
<tr>
<td>2&lt;=W&lt;2.5</td>
<td>9</td>
<td>10.64</td>
<td>P</td>
<td>2</td>
<td>115.5</td>
<td>53.1</td>
</tr>
<tr>
<td>&gt;=2.5</td>
<td>0</td>
<td>0</td>
<td>S</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

From Table 1:

\[ A = \begin{bmatrix} 6 & 10.8 & 108.3 & 54.8 & 0 & 0 & 5 & 1 & 0 & 1 & 1 & 2 & 1 \\ 9 & 10.64 & 115.5 & 53.1 & 1 & 2 & 5 & 1 & 0 & 3 & 0 & 5 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \]
Group two which includes the age from Age: 21-28 is shown in Table 2.

<table>
<thead>
<tr>
<th>Baby Weight</th>
<th>No:</th>
<th>Haemo globin</th>
<th>Level of education</th>
<th>Location</th>
<th>BP</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;2</td>
<td>7</td>
<td>10.1</td>
<td>2 0 1 1 3</td>
<td>1 0 5 1 0</td>
<td>130</td>
<td>64.7</td>
</tr>
<tr>
<td>2&lt;=W&lt;2.5</td>
<td>25</td>
<td>9.4</td>
<td>6 2 6 7 4</td>
<td>3 1 14 2 1</td>
<td>120.2</td>
<td>47.3</td>
</tr>
<tr>
<td>&gt;=2.5</td>
<td>7</td>
<td>11.9</td>
<td>2 0 2 3 0</td>
<td>1 1 3 0 2</td>
<td>149.7</td>
<td>66.2</td>
</tr>
</tbody>
</table>

From table 2:

\[ B = \begin{bmatrix} 7 & 10.1 & 130 & 64.7 & 2 & 0 & 1 & 1 & 3 & 1 & 0 & 5 & 1 & 0 \\ 25 & 9.4 & 120.2 & 47.3 & 6 & 2 & 6 & 7 & 4 & 3 & 1 & 14 & 2 & 1 \\ 7 & 11.9 & 149.7 & 66.2 & 2 & 0 & 2 & 3 & 0 & 1 & 1 & 3 & 0 & 2 \end{bmatrix} \]

Group three which includes the age from Age: 29-36 is shown in Table 3.

<table>
<thead>
<tr>
<th>Baby Weight</th>
<th>No:</th>
<th>Haemo globin</th>
<th>Level of education</th>
<th>Location</th>
<th>BP</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;2</td>
<td>14</td>
<td>11.9</td>
<td>0 1 4 1 4</td>
<td>0 2 8 2 1</td>
<td>128.8</td>
<td>70.6</td>
</tr>
<tr>
<td>2&lt;=W&lt;2.5</td>
<td>23</td>
<td>12.6</td>
<td>5 1 12 0 2</td>
<td>4 1 9 7 2</td>
<td>118.6</td>
<td>75.3</td>
</tr>
<tr>
<td>&gt;=2.5</td>
<td>4</td>
<td>10.6</td>
<td>1 0 3 0 0</td>
<td>0 1 2 1 0</td>
<td>117.5</td>
<td>71</td>
</tr>
</tbody>
</table>

From table 3:

\[ C = \begin{bmatrix} 14 & 11.9 & 128.8 & 70.6 & 0 & 1 & 4 & 1 & 4 & 0 & 2 & 8 & 2 & 2 \\ 23 & 12.6 & 118.6 & 75.3 & 1 & 5 & 12 & 0 & 2 & 4 & 1 & 9 & 7 & 2 \\ 4 & 10.6 & 117.5 & 71 & 1 & 0 & 3 & 0 & 0 & 1 & 2 & 1 & 0 \end{bmatrix} \]

Group one which includes the age from Age: 37-44 is shown in Table 4.

<table>
<thead>
<tr>
<th>Baby’s weight</th>
<th>No:</th>
<th>Haemo globin</th>
<th>Level of education</th>
<th>Location</th>
<th>BP</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;2</td>
<td>3</td>
<td>9.67</td>
<td>0 0 1 2 0 2 0 1 0</td>
<td>0 0 1 0 0</td>
<td>106</td>
<td>68.4</td>
</tr>
<tr>
<td>2&lt;=W&lt;2.5</td>
<td>5</td>
<td>12.6</td>
<td>1 1 3 0 0</td>
<td>0 1 0 2 1</td>
<td>136</td>
<td>69.5</td>
</tr>
<tr>
<td>&gt;=2.5</td>
<td>3</td>
<td>10.8</td>
<td>0 0 3 0 0</td>
<td>0 2 0 0 1</td>
<td>113.3</td>
<td>80.4</td>
</tr>
</tbody>
</table>

From table 4:

\[ D = \begin{bmatrix} 3 & 9.67 & 106 & 68.4 & 0 & 0 & 1 & 2 & 0 & 2 & 0 & 1 & 0 \\ 5 & 12.6 & 136 & 69.5 & 1 & 1 & 3 & 0 & 0 & 1 & 2 & 1 & 0 \\ 3 & 10.8 & 113.3 & 80.4 & 0 & 0 & 3 & 0 & 2 & 0 & 0 & 0 & 1 \end{bmatrix} \]

The MATLAB command >> [U,D,V] = svd(A,0) is used to decompose the matrices A,B,C and D above into three matrices.

To get the new coordinate of vectors in a reduced space we apply the iterative steps below to get the new set of coordinate vectors.

\[
Y = Y^T U_K D_K^{-1} \quad (1)
\]

\[
X_K = X^T U_K D_K^{-1} \quad (2)
\]

We will then use cosine similarity to find the vector determination values and then rank the results in decreasing order:

\[
Sim(a,b) = \frac{a \cdot b}{|a||b|} \quad (3)
\]

The results from the decomposed matrices A, B, C, D is shown in table 5 below:

**Table 5: Vector coordinates**

<table>
<thead>
<tr>
<th></th>
<th>Group One</th>
<th>Group Two</th>
<th>Group Three</th>
<th>Group Four</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y</td>
<td>[-0.0170 0.0195]</td>
<td>[-0.0140 -0.0217]</td>
<td>[-0.0157 0.0094]</td>
<td>[-0.0161 0.0202]</td>
</tr>
<tr>
<td>X_1</td>
<td>[-0.0602 0.3474]</td>
<td>[-0.0834 -0.7559]</td>
<td>[-0.0965 -0.7573]</td>
<td>[-0.0266 -0.0782]</td>
</tr>
<tr>
<td>X_2</td>
<td>[-0.0856 -0.0889]</td>
<td>[-0.0712 -0.0009]</td>
<td>[-0.0819 -0.0648]</td>
<td>[-0.8506 -0.5090]</td>
</tr>
<tr>
<td>X_3</td>
<td>[-0.8948 0.2393]</td>
<td>[-0.9056 -0.0405]</td>
<td>[-0.8507 0.2064]</td>
<td>[-0.5186 0.8456]</td>
</tr>
<tr>
<td>X_4</td>
<td>[-0.4309 -0.5653]</td>
<td>[-0.4047 0.3340]</td>
<td>[-0.5051 -0.1119]</td>
<td>[-0.0792 -0.0370]</td>
</tr>
<tr>
<td>X_5</td>
<td>[-0.0041 0.1284]</td>
<td>[-0.0215 -0.1706]</td>
<td>[-0.0139 -0.1901]</td>
<td>[-0.0026 -0.0482]</td>
</tr>
<tr>
<td>X_6</td>
<td>[-0.0082 0.2569]</td>
<td>[-0.0040 -0.0794]</td>
<td>[-0.0047 -0.0354]</td>
<td>[-0.0026 -0.0482]</td>
</tr>
<tr>
<td>X_7</td>
<td>[-0.0400 -0.0317]</td>
<td>[-0.0193 -0.1872]</td>
<td>[-0.0444 -0.3945]</td>
<td>[-0.0171 -0.0096]</td>
</tr>
<tr>
<td>X_8</td>
<td>[-0.0080 -0.0063]</td>
<td>[-0.0238 -0.2097]</td>
<td>[-0.0024 -0.0099]</td>
<td>[-0.0043 0.0278]</td>
</tr>
<tr>
<td>X_9</td>
<td>[0]</td>
<td>[-0.0147 -0.1090]</td>
<td>[-0.0143 -0.0510]</td>
<td>[0]</td>
</tr>
<tr>
<td>X_10</td>
<td>[-0.0162 0.2506]</td>
<td>[-0.0108 -0.0853]</td>
<td>[-0.0093 -0.1814]</td>
<td>[-0.0116 0.0603]</td>
</tr>
</tbody>
</table>

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The results from the cosine similarity is shown in table 6 below:

<table>
<thead>
<tr>
<th>x_{11}</th>
<th>-0.0039 - 0.1348</th>
<th>-0.0045 - 0.0225</th>
</tr>
</thead>
<tbody>
<tr>
<td>x_{12}</td>
<td>-0.0244 - 0.5075</td>
<td>-0.0468 - 0.4212</td>
</tr>
<tr>
<td>x_{13}</td>
<td>-0.0078 - 0.2696</td>
<td>-0.0062 - 0.0628</td>
</tr>
<tr>
<td>x_{14}</td>
<td>-0.0080 - 0.0063</td>
<td>-0.0070 - 0.0053</td>
</tr>
</tbody>
</table>

Hence from table 6 above:

- **GROUP ONE**:
  \[ x_1 > x_2 > x_3 > x_4 > x_5 > x_6 > x_7 > x_8 > x_9 > x_10 > x_11 > x_12 > x_13 \]

- **GROUP TWO**:
  \[ x_11 > x_9 > x_10 > x_5 > x_6 > x_7 > x_12 > x_1 > x_13 > x_6 > x_14 > x_7 > x_8 > x_11 > x_3 > x_4 \]

- **GROUP THREE**:
  \[ x_7 > x_11 > x_9 > x_8 > x_6 > x_7 > x_12 > x_14 > x_6 > x_1 > x_7 > x_13 > x_10 > x_5 \]

- **GROUP FOUR**:
  \[ x_2 > x_10 > x_4 > x_2 > x_1 > x_12 > x_7 > x_14 > x_1 > x_7 > x_12 > x_7 > x_9 > x_3 > x_13 > x_14 \]

Since Y is dependent on
\[ x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14}. \]

- **GROUP ONE**: It shows low birth weight in this category is closely related to the Age of the mother.
- **GROUP TWO**: It shows low birth weight in this category is closely related to mothers who are located in location 2.
- **GROUP THREE**: It shows low birth weight in this category is closely related to the mother’s blood pressure level.
- **GROUP FOUR**: It shows low birth weight in this category is closely related to the mother’s haemoglobin concentration level.

### 4.5 Analysis with Multiple Linear Regression

The results from R is shown in table 7 below:

| (Intercept) | Estimate | Std. Error | t value | Pr(>|t|) |
|-------------|----------|------------|---------|----------|
| 0.249238    | 0.060699 | 0.411      | 0.68257 |
| L           | -0.21447 | 0.045146   | -4.751  | 7.35e-06 *** |
| BP          | 0.008636 | 0.002261   | -3.819  | 0.002241 *** |
| H           | 0.158613 | 0.053734   | 2.952   | 0.03998 ** |
| MW          | -0.02287 | 0.005732   | -3.799  | 0.001326 *** |
| MA          | 0.040553 | 0.006165   | 6.578   | 2.76e-09 *** |
| ME          | 0.226975 | 0.047672   | -4.761  | 7.05e-06 *** |

Residual standard error: 0.3642 on 93 degrees of freedom 
Multiple R-squared: 0.4649. Adjusted R-squared: 0.4304
F-statistic: 13.47 on 6 and 93 DF, p-value: 6.163e-11

### 4.5.1 Multiple regression model

\[ y = \beta_0 + \beta_1L + \beta_2BP + \beta_3H + \beta_4MA + \beta_5ME + \epsilon \]
where \( \beta_0=0.249238, \beta_1=-0.214470, \beta_2=0.008636, \beta_3=0.158613, \beta_4=-0.022870, \beta_5=0.040553, \epsilon=0.226975 \)

Therefore the fitted model will be

\[ y' = 0.249238 - 0.214470L + 0.008636BP + 0.158613H - 0.022870MW + 0.040553ME \]

### Conclusions

The study results highlight some factors that are significantly associated with Low Birth Weight.

The results from the singular value decomposition analysis of Low Birth Weight with some predictor variables that influence low birth of newly born babies are mother’s age, mother’s location in location 2, blood pressure level and mother’s haemoglobin concentration level.

From the Multiple linear Regression model, it shows that all our maternal variables are significant.

That is the predictor variables mother’s age, mother’s location, mother’s weight, mother’s blood pressure, mother’s haemoglobin concentration and mother’s educational level were all statistically significant.

Now comparing the singular value decomposition analysis and the Multiple linear Regression analysis, we conclude the mother’s haemoglobin concentration level in this category is a more significant factor affecting the weight of babies.

Based on the findings from this study, the following recommendations are made to reduce the risk of an infant getting low birth weight.

Some actions taken before birth to avoid low birth weight are: regular checkup, appropriate nutrition intake, check haemoglobin status, taking of iron. The mother’s inability to gain weight should be identified, corrected and deleted early to avoid problems. Such actions should be taken before birth.

### References


