Multiple Regression Analysis of Body Fat Percent based on Siri Equation

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In this report, we will demonstrate that factors other than body density may be utilized to predict body fat percentage based on Siri equation "% Body Fat = (495 / Body Density)–450" (Siri 1961). Some predictive linear models were built using the research of correlations between the target variable, body fat percentage, and other independent variables that retained certain linearity. Model selection is implemented using a variety of techniques, including assumption test, forward and backward method selection, and 10-fold cross-validation. The conclusion is that body fat percentage and body density, together with age and abdomen as other independent variables, can establish a linear regression

Siri Equation | Linear regression | Model Selection

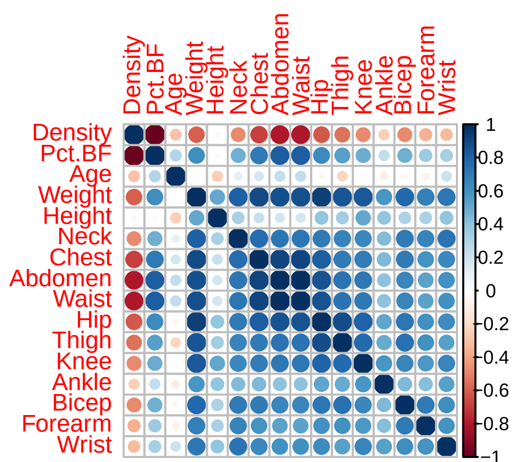
Introduction. Sociologists, biologists, and psychologists often study human performance in and across multiple characteristics to identify and analyze the underlying manifestations. The percentage of body fat is one of the key values that reflected the health and fitness of human beings. However, the accurate measurement of body fat percentage is difficult to handle and expensive. Hence, the application of calculations between other easily measurable attributes might be more effective. According to the Siri equation, body fat percentage could be calculated by body density directly. In this report, we will build and evaluate the regression models to find out whether the model could predict the target variable effectively and efficiently with certain attributes. People who are interested in predictive methods, human performance study, and fitness might be the stakeholders.

Data set. The data set was gathered by DASL (The Data and Story Library), an archive of hundreds of data files that provide a platform for statistics and data science study for students and teachers. The original source of this data set is BYU Human Performance Research Center. There were many methods used to collect and describe data including multiple regression, display of quantitative variables, hypothesis tests, partial regression plots, confidence intervals for proportions, sampling distribution, and so on. The dataset included 250 numerical observations within 16 variables. There were no missing or zero values and one outlier. The target variable is the percentage of body fat and other variables are described as physical characteristics involving density, age, weight, neck, chest, abdomen, waist, hip, thigh, knee, ankle, bicep, forearm, and wrist. To estimate the body density, the technique underwater would be used. The calculation of body volume is equal to the loss of weight in water with the temperature correction for the water's density, which is complicated. There was an unwanted outlier in the body fat percentage variable.

Analysis.

Dependent variable selection. Before choosing a model, we must choose the appropriate independent variable (x-value) and how many independent variables. The first is to contrast correlation coefficient plots to determine our independent variables, but it is challenging to select the correct variables from the naked eye. Thus, we decided to use forward and backward methods.

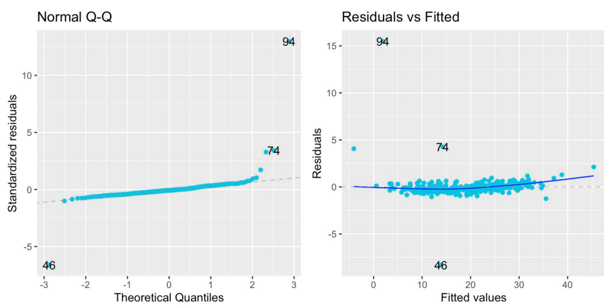
Forward & Backward Elimination. The specific operation steps: First, fit the model with the independent variable with the most significant correlation coefficient with the dependent variable y, carry out the significance test of the regression coefficient, and decide whether to introduce the independent variable into the model. (The value with the symbol *) By eliminating forward and backward, we derive the best three values for abdomen, density and age as dependent variables.



Model selection. Many models can predict our dependent variable, but we may not know which is the most suitable. At first, we used the most basic linear model to predict our PBF value by adding the three independent variables of density, age, and abdomen to form a linear model to see if it is suitable. Nevertheless, how do we go to see if it fits the modelling?

	Pct BF		log Pct BF		Pct BF		log Pct BF	
Predictors	*Estimates*	*p*	*Estimates*	*p*	*Estimates*	*p*	*Estimates*	*p*
(Intercept)	442.38	**<0.001**	58.55	**0.001**	423.69	**<0.001**	45.99	0.076
Density	-406.49	**<0.001**	-52.66	**<0.001**	-407.28	**<0.001**	-46.04	**0.002**
Age	0.01	0.074	-0.00	0.733				
Abdomen	0.06	**<0.001**	-0.00	0.974				
logAge					0.51	0.074	-0.28	0.625
logAbdomen					5.19	**<0.001**	1.40	0.577
Observations	250		250		250		250	
R^2 / R^2 adjusted	0.977 / 0.977		0.129 / 0.118		0.977 / 0.977		0.130 / 0.120	

Adjusted R-Squared. We can determine our model by comparing the size of the Adjusted R-Squared in each model. Rˆ2 shows how good terms (data points) fit a curve or line. Adjusted Rˆ2 indicates how well terms fit a curve or line but adjusts for the number of terms in a model. That is, valid variables added to the model will reduce the size of the R-squared, while invalid variables will only reduce its size and fit. So we performed several (Linear - Log, Log-linear, Log - Log) modelling to compare the size of the r-squared to select our model. However, because the model does not pass the assumption, we rejected the lowest two Adjusted r-squared models. linear-log would be our final model.



Assumption Check.

Linearity On the residuals and the fit plot. In the figure, we can see a clear pattern in the residual plot. And the pattern does not appear obvious shape. This would indicate that there is a linear relationship between the predictors and the outcome variable.

Independence From the source of the data set. We know that the variable in the data set is not related to the other variables. Secondly, we used Durbin-Watson test. The null hypothesis of the Durbin-Watson test says that they are independent. Our P-value is 0.272, we will not be able to reject the null hypothesis. This will provide us with enough evidence to show that our independence assumption is satisfied!

Homoskedasticity On the residuals and fit plots, we can see the spread looks relatively constant over the range of fitted values. And the residuals are uniformly distributed. So, this assumption is valid.

Normality It can be seen from the Q-Q plot that most points are in a straight line. Therefore, the assumption of normality of the residuals is well satisfied.

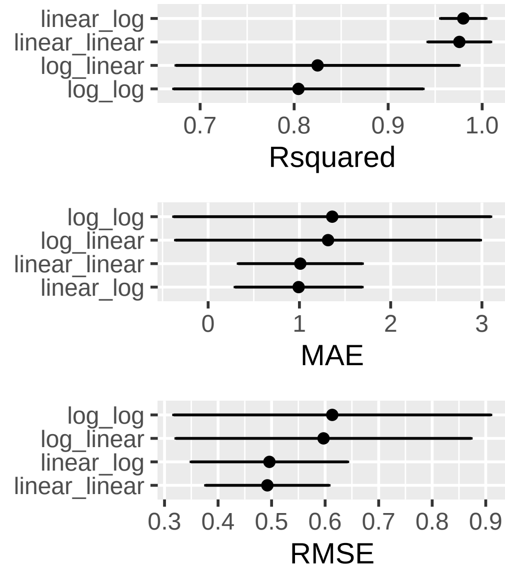
Results.

- Compare them to the observed values using the root mean square error:

$$RMSE = \sqrt{(\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n})}$$

- An alternative measure of performance, less influenced by outliers is the mean absolute error:

$$MAE = \frac{\sum_{i=1}^{m} |y_i - \hat{y}_i|}{m}$$



Linear-log Model has the biggest R-squared and smallest MAE and RMSE

$$Pct.BF = 423.7—407.3 \cdot Density + 0.5 \cdot \log(\overbrace{Age}) + 5.2 \cdot \log(\overbrace{Abdomen})$$

- A one year increase in Age results in a 0.5089% change in Pct.BF on average, holding Density and Abdomen constant.
- A one centimeter increase in Abdomen results in a 5.1896% change in Pct.BF on average, holding Age and Density
- A one unit decrease in Density results in a 407.2826 change in Pct.BF on average, holding Age and Abdomen constant

Discussion and Conclusion.

limitations. The report explores the linear relationship between **Density** and **Pct.BF** based on Siri equation.However the Siri equation is not just a simple linear regression.

For selection bias, there are only male above 22-year-old observations included which could not represent the whole population. The calculation of bodyfat percentage highly depends on the density, which might be considered as designed bias. Any human performance inferences are thus limited.

Future Research. In the future, we need to use different linear regression models (Lasso Regression, Ridge Regression) to improve the relationship between density and Pct.BF

This report only discusses a simple linear model. More different Machine Learning Model like K-Nearest Neighbors Model, Random Forest Model etc should be considered. Comparisons of limitations and uncertainties about the different Models is an important step that cannot to be ignored.

Conclusion. Body Density should be a factor which pay more attention to due to the huge direct effect of body density on percent body fat.

With age, percent body fat will also increase gradually, but we can effectively maintain a reasonable percent body fat by exercising the abdominal muscles.

A healthy amount of body fat is necessary for the body to function properly. While excess body fat is associated with an increased risk of heart disease,too little body fat is just as dangerous.

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