

# Does Size Matter? (Estimation of Banana Weight with a Regression Modeling Approach)

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## Summary

## Introduction

The purpose of this study was to determine the most effective regression model to predict the weight of a banana using external measurements. This study also demonstrated multiple techniques for developing regression models. These models were then examined to demonstrate their effectiveness at creating regression models.

## Data Collection

First a small sample set bananas were purchased from the Real Canadian Superstore. The weight, length, diameter and circumference were then calculated using a scale and a ruler.

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.0004513	0.4005	0.6352	0.5719	0.7617	0.9812

In order to determine the minimum sample size needed, random sample sizes of 10 were generated using radius and length as the predictors. The correlation of the random sample sizes were calculated and a matrix of the correlations were generated. The value of the squared population multiple correlation coefficients with two predictor variables was then calculated and determined to be approximately 0.5719. From this the minimum sample size required was then determined from the table from Gregory T. Knofczynski's Sample Size When Using Multiple Linear Regression for Prediction, the minimum sample size was determined to be between 15 and 35, therefore the minimum number of bananas required was finalized at 24 bananas.

## Analysis

To begin analysis a model using all predictor variables was created. In this case the density of the banana is assumed to be a constant.

Let:

$$W = \text{Weight (g)}, L = \text{Length (mm)}, R = \text{Radius (mm)}$$

Then:

$$\log(W) = \beta_0 + \beta_1 \log(L) + \beta_2 \log(R) + \beta_3 \log(C) \implies W = e^{\beta_0} \times L^{\beta_1} \times R^{\beta_2} \times C^{\beta_3}$$

In the second model the predictor variable, circumference, was removed. This is because  $C = 2\pi R$ .

$$\log(W) = \beta_0 + \beta_1 \log(L) + \beta_2 \log(R)$$

The third model considered the predictor, length.

$$\log(W) = \beta_0 + \beta_1 \log(L)$$

The fourth model considered only one predictor, radius.

$$\log(W) = \beta_0 + \beta_2 \log(R)$$

	Estimate	Std. Error	t value	Pr(> t )
<b>(Intercept)</b>	-0.6702	1.913	-0.3503	0.7296
<b>Radius_log</b>	1.77	0.5596	3.163	0.004684
<b>Length_log</b>	0.1223	0.1249	0.9787	0.3389

Table 3: Fitting linear model: Weight\_log ~ Radius\_log + Length\_log

Observations	Residual Std. Error	$R^2$	Adjusted $R^2$
24	0.09062	0.3262	0.2621

	Estimate	Std. Error	t value	Pr(> t )
<b>(Intercept)</b>	0.3046	1.632	0.1867	0.8536
<b>Radius_log</b>	1.669	0.5494	3.038	0.006043

Table 5: Fitting linear model: Weight\_log ~ Radius\_log

Observations	Residual Std. Error	$R^2$	Adjusted $R^2$
24	0.09054	0.2955	0.2635

	Estimate	Std. Error	t value	Pr(> t )
<b>(Intercept)</b>	4.99	0.8037	6.209	3e-06
<b>Length_log</b>	0.04917	0.1457	0.3374	0.739

Table 7: Fitting linear model: Weight\_log ~ Length\_log

Observations	Residual Std. Error	$R^2$	Adjusted $R^2$
24	0.1076	0.005146	-0.04007

Table 8: Analysis of Variance Table

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
21	0.1725	NA	NA	NA	NA
20	0.171	1	0.001429	0.1671	0.687

Table 9: Analysis of Variance Table

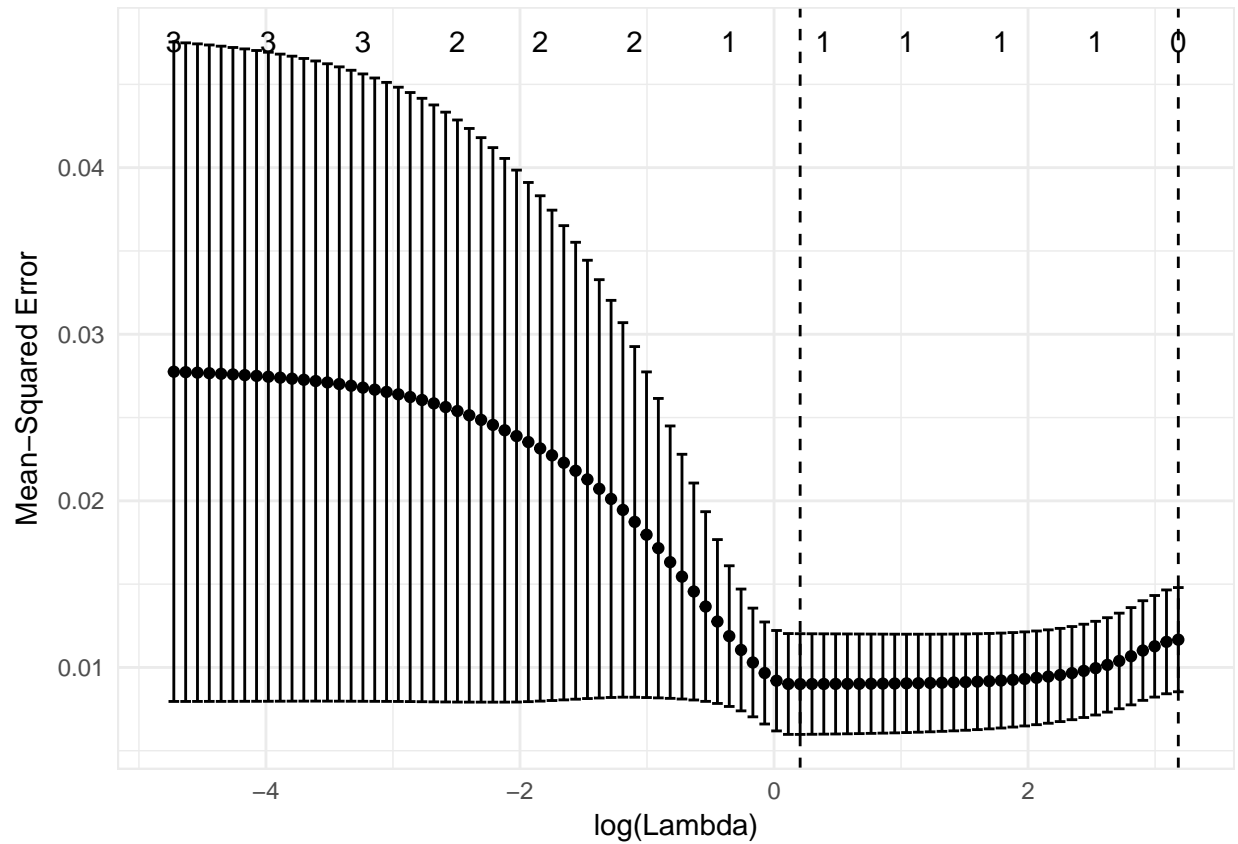
Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
22	0.1803	NA	NA	NA	NA
20	0.171	2	0.009296	0.5435	0.5891

Table 10: Analysis of Variance Table

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
22	0.1803	NA	NA	NA	NA
21	0.1725	1	0.007867	0.9578	0.3389

```
## Warning: Option grouped=FALSE enforced in cv.glmnet, since < 3 observations
## per fold
```

```
## Warning: Option grouped=FALSE enforced in cv.glmnet, since < 3 observations
## per fold
```



	1
(Intercept)	0.55713
Length	0.00000
Radius	0.00000
Circumference	0.00000

---

	1
Length_log	0.00000
Radius_log	1.58392
Circumference_log	0.00000

---

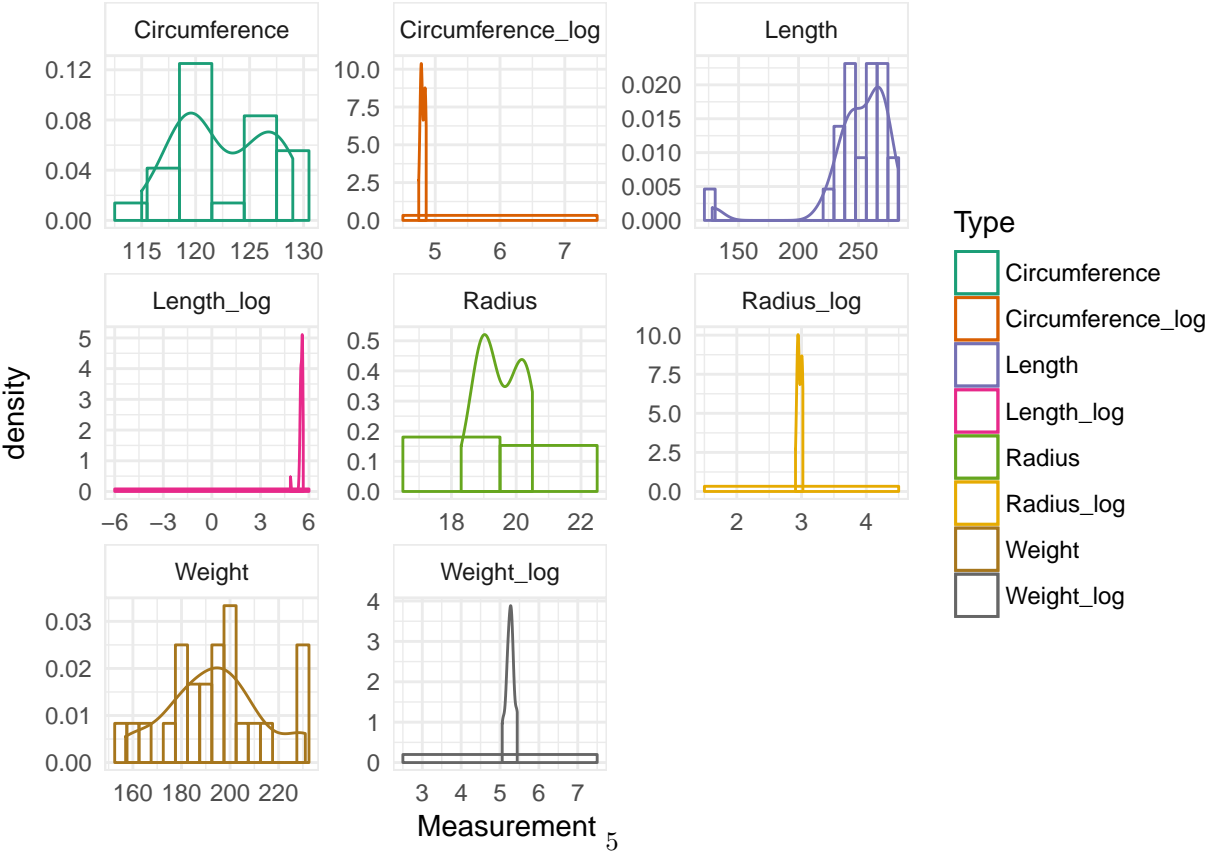
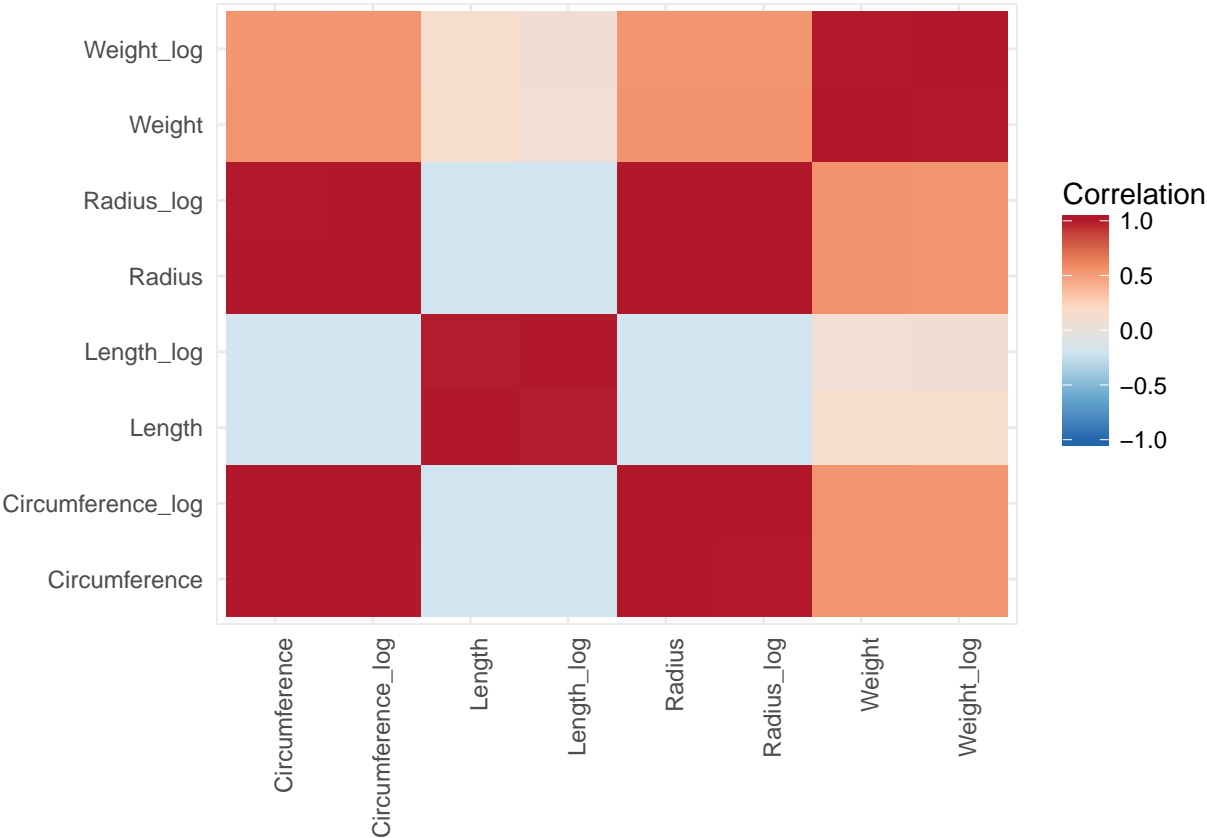


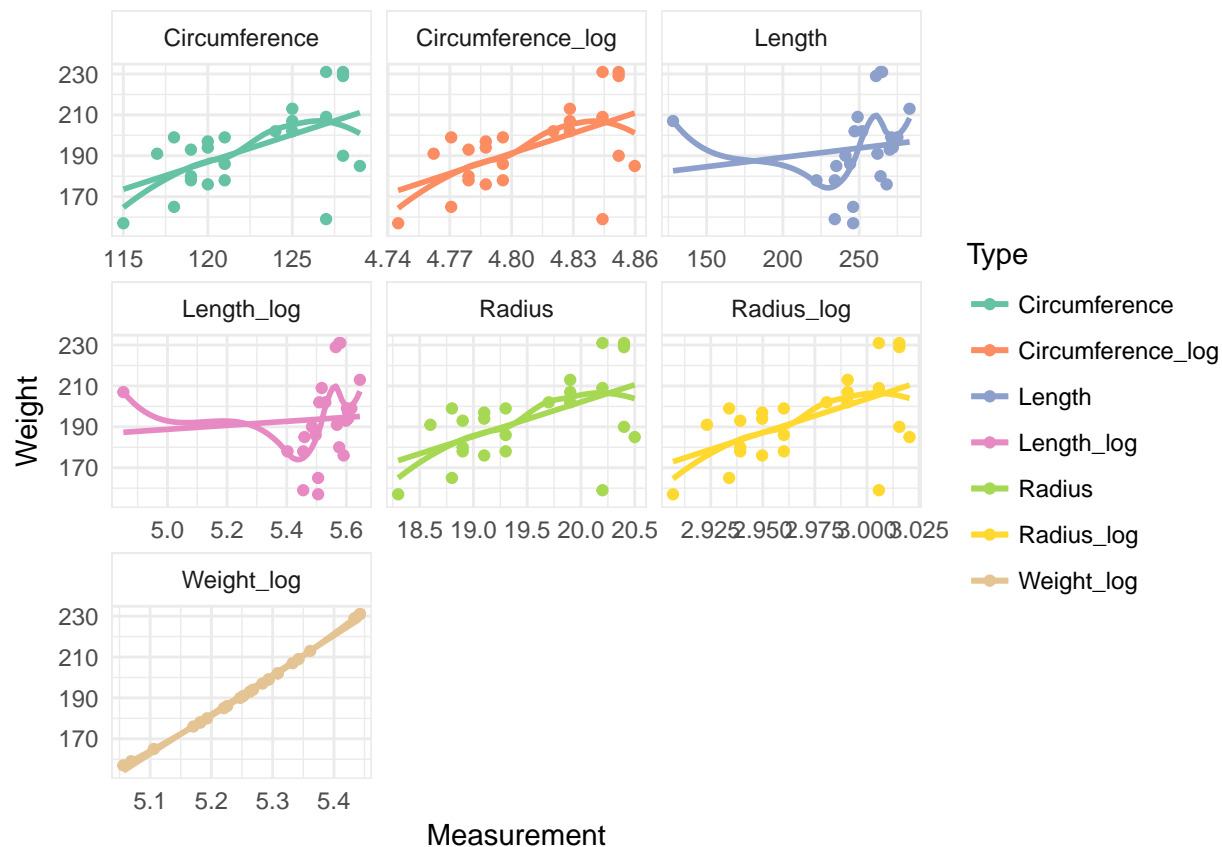
---

	1
(Intercept)	5.261471
Length	0.000000
Radius	0.000000
Circumference	0.000000
Length_log	0.000000
Radius_log	0.000000
Circumference_log	0.000000

---

Appendix





## Cross Validation

```
## Analysis of Variance Table
##
## Response: Weight_log
##           Df Sum Sq Mean Sq F value Pr(>F)
## Length_log  1  0.0013   0.0013    0.16 0.6928
## Radius_log  1  0.0822   0.0822   10.01 0.0047 **
## Residuals   21  0.1725   0.0082
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## fold 1
## Observations in test set: 8
##           [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8]
## Predicted  5.2368 5.2368 5.196 5.1998 5.3143 5.2304 5.344 5.215
## cvpred     5.2428 5.2428 5.207 5.2131 5.3184 5.2464 5.358 5.222
## Weight_log  5.2832 5.2679 5.106 5.1818 5.3613 5.1818 5.220 5.193
## CV residual 0.0404 0.0251 -0.101 -0.0314 0.0429 -0.0646 -0.137 -0.029
##
## Sum of squares = 0.04    Mean square = 0    n = 8
##
## fold 2
```

```

## Observations in test set: 8
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8]
## Predicted  5.24195 5.348 5.333 5.2350 5.2548 5.3386 5.1853 5.3251
## cvpred     5.23389 5.324 5.310 5.2248 5.2417 5.3184 5.1822 5.3056
## Weight_log 5.22575 5.434 5.442 5.1705 5.2933 5.2470 5.2523 5.3423
## CV residual -0.00814 0.109 0.132 -0.0543 0.0516 -0.0714 0.0701 0.0367
##
## Sum of squares = 0.05      Mean square = 0.01      n = 8
##
## fold 3
## Observations in test set: 8
##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8]
## Predicted  5.22 5.318 5.1488 5.3497 5.2822 5.2976 5.2173 5.2101
## cvpred     4.78 5.267 5.1137 5.3771 5.2744 5.2788 5.2464 5.2500
## Weight_log 5.33 5.069 5.0562 5.4424 5.3083 5.3083 5.2627 5.2933
## CV residual 0.55 -0.198 -0.0574 0.0654 0.0339 0.0295 0.0163 0.0433
##
## Sum of squares = 0.35      Mean square = 0.04      n = 8
##
## Overall (Sum over all 8 folds)
##      ms
## 0.0183

## # A tibble: 24 x 13
##      ID Weight Radius Length Circumference Weight_log Radius_log
##      <int> <int> <dbl> <int>          <int>      <dbl>      <dbl>
## 1     1     197  19.1    272           120      5.28      2.95
## 2     2     194  19.1    272           120      5.27      2.95
## 3     3     165  18.8    246           118      5.11      2.93
## 4     4     186  19.3    244           121      5.23      2.96
## 5     5     178  18.9    234           119      5.18      2.94
## 6     6     207  19.9    128           125      5.33      2.99
## 7     7     213  19.9    283           125      5.36      2.99
## 8     8     178  19.3    222           121      5.18      2.96
## 9     9     229  20.4    261           128      5.43      3.02
## 10    10     231  20.2    265           127      5.44      3.01
## # ... with 14 more rows, and 6 more variables: Length_log <dbl>,
## #   Circumference_log <dbl>, Predicted <dbl>, cvpred <dbl>, `CV
## #   Residual` <dbl>, Residual <dbl>

```

## MAE

```

## # A tibble: 1 x 2
##      MAE  MPAE
##      <dbl> <dbl>
## 1  13.7 0.0722

```