

A Look into Maternal Mortality Rate

Using a linear regression approach

Carlos Aguilar & Harrison Plate



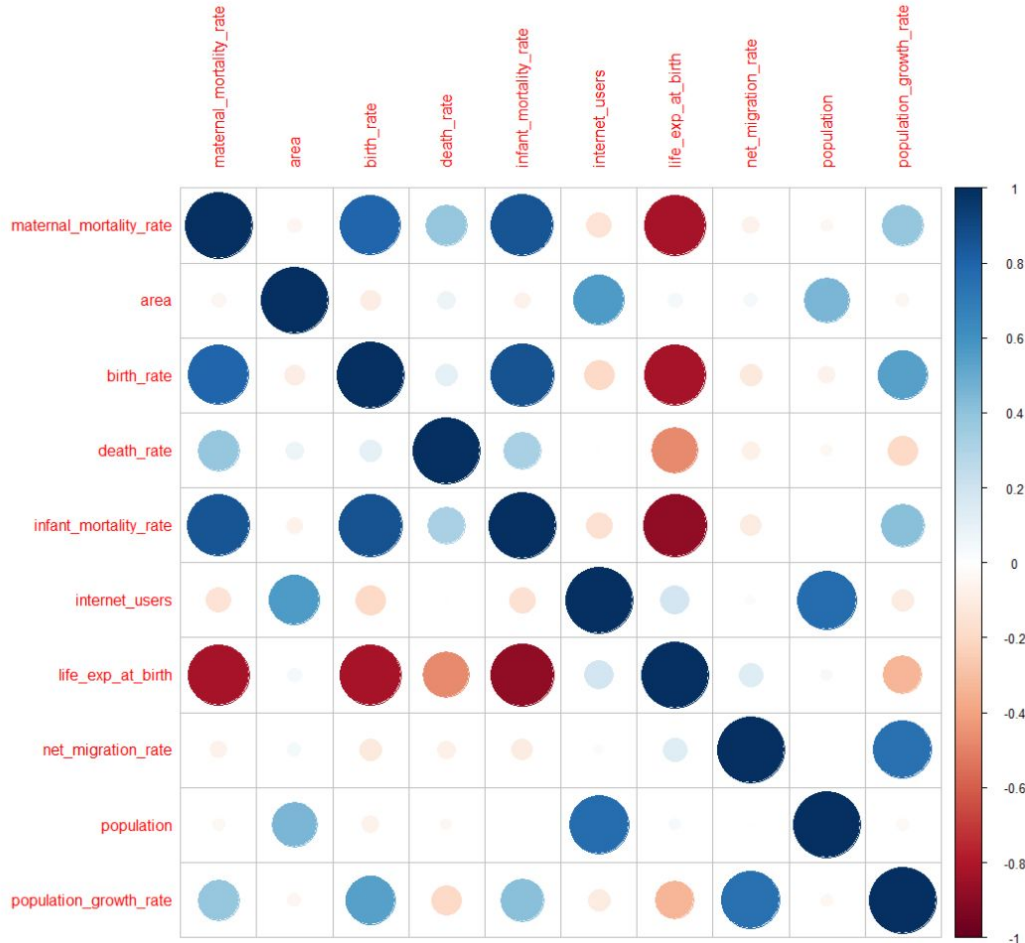
Data Description

- Country-level statistics from the US Central Intelligence Agency (CIA)
- Collected in 2017
- Data frame with 259 observations on 11 different variables

Goals

- Investigate what are the possible predictive variables in our data set that are linearly related to Maternal Mortality Rate?
- What are some of the inferences we can make with our data? What are some aspects we can improve to decrease maternal mortality rate?
- Try something new for our data set

CORRELATION MATRIX



Response Variable for Full Model
Maternal Mortality Rate

Predictive Variables for Full Model

Area

Birth Rate

Death Rate

Infant Mortality Rate

Life Expectancy at Birth

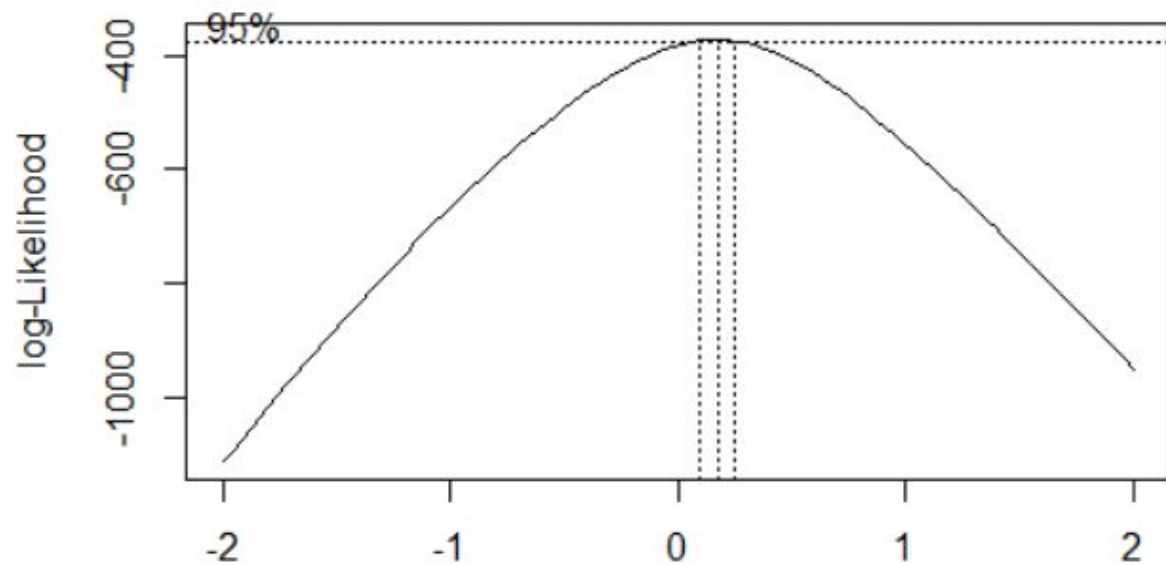
Net Migration Rate

Population

Population Growth Rate

$$H_0 : \beta_j = 0$$

$$H_A : \beta_j \neq 0 : \text{for at least 1 predictor}$$



BOX-COX

λ

bcPower Transformation to Normality

	Est	Power	Rounded	Pwr	wald	Lwr	Bnd	wald	upr	Bnd
y1	0.1738		0.17		0.0989		0.2487			

Likelihood ratio test that transformation parameter is equal to 0
(log transformation)

Likelihood ratio test that no transformation is needed

Summary of Transformed Full Model

```
Call:
lm(formula = (maternal_mortality_rate)^(1/5) ~ area + internet_users +
    death_rate + infant_mortality_rate + life_exp_at_birth +
    birth_rate + net_migration_rate + population + population_growth_rate,
    data = df_final)
```

Residuals:

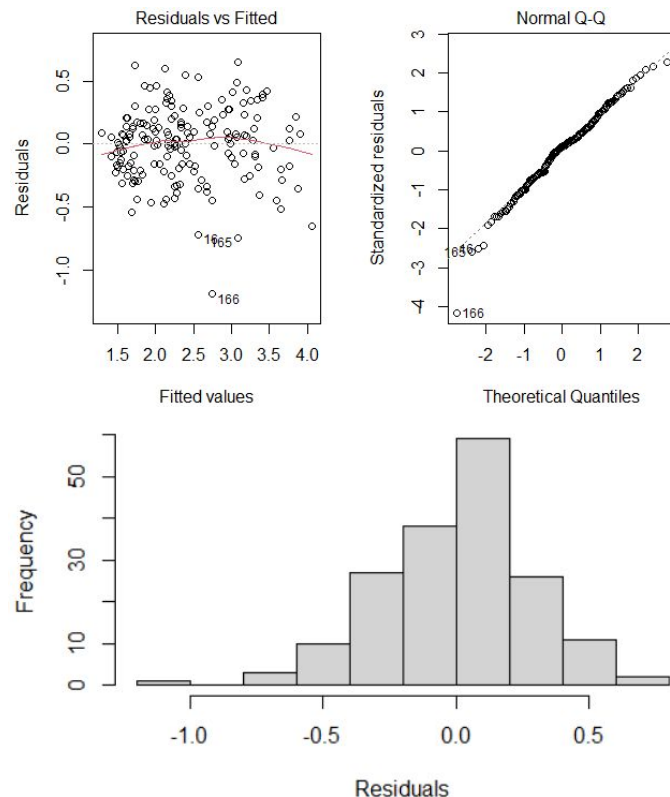
	Min	1Q	Median	3Q	Max
	-1.19200	-0.17924	0.02994	0.17049	0.65045

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	5.424e+00	6.300e-01	8.609	5.26e-15 ***
area	8.479e-09	1.344e-08	0.631	0.52908
internet_users	-6.503e-10	1.046e-09	-0.622	0.53497
death_rate	-1.465e-01	7.584e-01	-0.193	0.84703
infant_mortality_rate	8.605e-03	2.293e-03	3.754	0.00024 ***
life_exp_at_birth	-4.534e-02	6.976e-03	-6.499	8.93e-10 ***
birth_rate	1.175e-01	7.576e-01	0.155	0.87697
net_migration_rate	1.031e-01	7.579e-01	0.136	0.89195
population	2.473e-10	2.471e-10	1.001	0.31836
population_growth_rate	-1.048e+00	7.578e+00	-0.138	0.89019

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2902 on 167 degrees of freedom
Multiple R-squared: 0.8496, Adjusted R-squared: 0.8415
F-statistic: 104.8 on 9 and 167 DF, p-value: < 2.2e-16



Improving Our Model Step-by-Step

- Performed a step function in R to reduce our number of predictors being used from 9 to 4

```
Step:  AIC=-435.54  
(maternal_mortality_rate)^(1/5) ~ death_rate + infant_mortality_rate +  
  life_exp_at_birth + birth_rate
```

- Predictors are:
 - Birth Rate
 - Infant Mortality Rate
 - Death Rate
 - Life Expectancy at Birth

	Df	Sum of Sq	RSS	AIC
<none>			14.282	-435.54
- birth_rate	1	0.3830	14.665	-432.85
- infant_mortality_rate	1	1.2956	15.578	-422.17
- death_rate	1	1.6637	15.945	-418.03
- life_exp_at_birth	1	3.9079	18.190	-394.73

Done! Maybe..?

- 4 significant predictors
- Full model:
 - Adj. R²: 0.841506
 - AIC: 75.99666
- Stepped model:
 - Adj. R²: 0.8436858
 - AIC: 68.76710
- AOV p-value > 0.05 indicates that the 5 predictors can be dropped



```
Call:
lm(formula = (maternal_mortality_rate)^(1/5) ~ death_rate + infant_mortality_rate +
    life_exp_at_birth + birth_rate, data = df_final)
```

```
Residuals:
    Min       1Q   Median       3Q      Max
-1.2042 -0.1742  0.0360  0.1739  0.6626
```

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)    5.547843    0.614250   9.032 3.36e-16 ***
death_rate     -0.042858    0.009575  -4.476 1.38e-05 ***
infant_mortality_rate 0.008784    0.002224   3.950 0.000114 ***
life_exp_at_birth  -0.046587    0.006791  -6.860 1.19e-10 ***
birth_rate      0.011681    0.005439   2.148 0.033144 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 0.2882 on 172 degrees of freedom
Multiple R-squared:  0.8472,    Adjusted R-squared:  0.8437
F-statistic: 238.5 on 4 and 172 DF,  p-value: < 2.2e-16
```

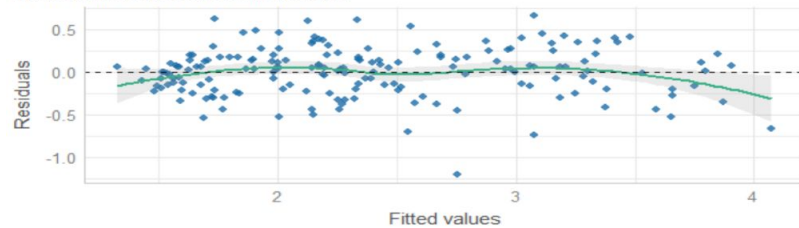
Analysis of Variance Table

```
Model 1: (maternal_mortality_rate)^(1/5) ~ death_rate + infant_mortality_rate +
    life_exp_at_birth + birth_rate
Model 2: (maternal_mortality_rate)^(1/5) ~ area + internet_users + death_rate +
    infant_mortality_rate + life_exp_at_birth + birth_rate +
    net_migration_rate + population + population_growth_rate
```

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	172	14.282				
2	167	14.060	5	0.2218	0.5269	0.7557

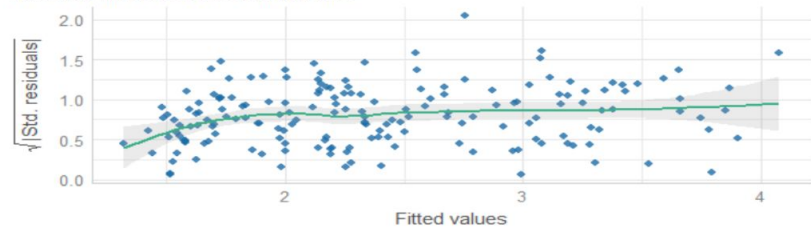
Linearity

Reference line should be flat and horizontal



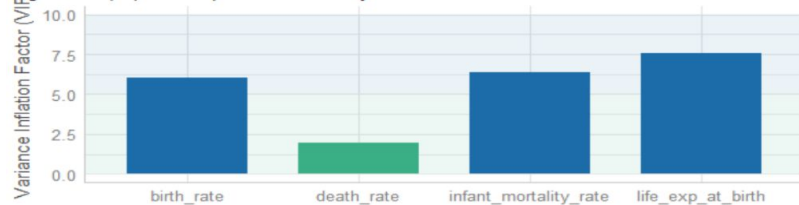
Homogeneity of Variance

Reference line should be flat and horizontal



Collinearity

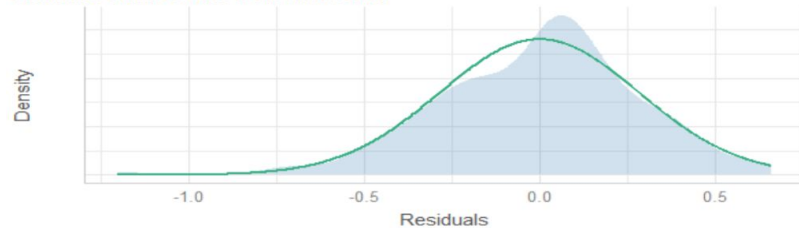
Higher bars (>5) indicate potential collinearity issues



low (< 5) moderate (< 10) high (>= 10)

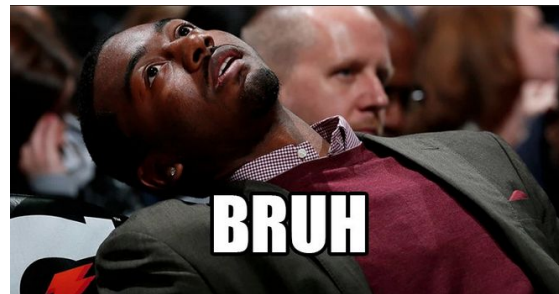
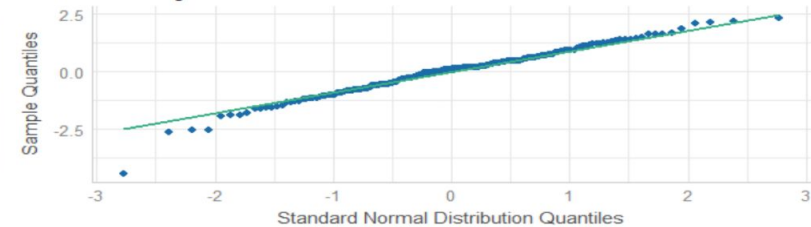
Normality of Residuals

Distribution should be close to the normal curve



Normality of Residuals

Dots should fall along the line



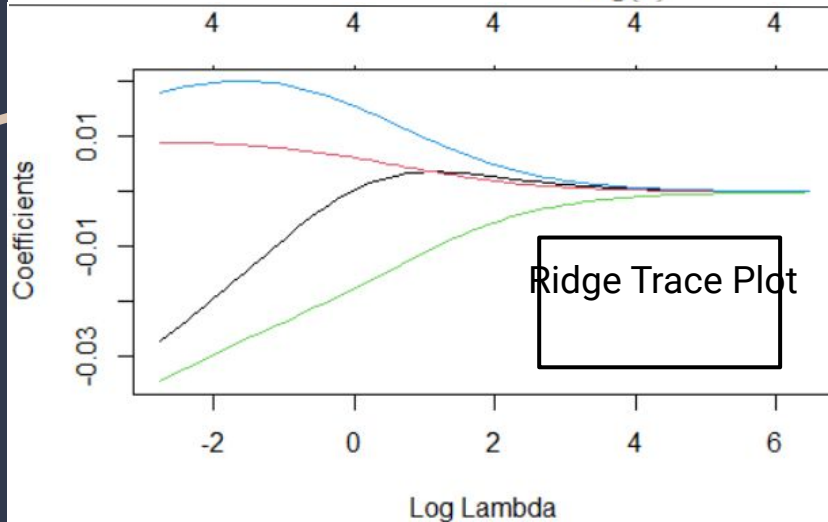
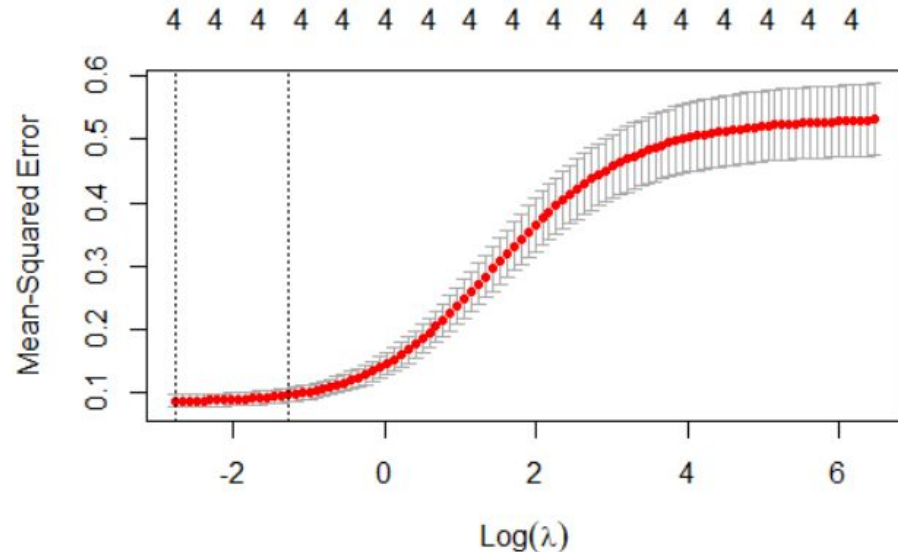
Collinearity Issue

Ridge Regression

- We want to find the best lambda that produces the lowest MSE
 - The lowest MSE produces the best model
- Best Lambda: 0.06342977
- The ridge regression signifies that life_exp_at_birth is the least important predictor

```
5 x 1 sparse Matrix of class "dgCMatrix"
              s0
(Intercept)    4.431683368
death_rate     -0.027119913
infant_mortality_rate 0.008939495
life_exp_at_birth -0.034548217
birth_rate      0.018178334
```

Black
Red
Green
Blue



Collinearity & Low p-value

Analysis of variance Table

Model 1: (maternal_mortality_rate)^(1/5) ~ death_rate + infant_mortality_rate + birth_rate

Model 2: (maternal_mortality_rate)^(1/5) ~ death_rate + infant_mortality_rate + life_exp_at_birth + birth_rate

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	173	18.190				
2	172	14.282	1	3.9079	47.063	1.189e-10 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

- The low p-value indicates that life_exp_at_birth is a significant predictor
 - We chose to drop it due to the results of the ridge regression
- Alternative option: stack the collinear data into 1 column

Insignificant Predictors: Round 2

- After removing life expectancy at birth, we find that death rate could also be removed
- Step #2
- Before 2nd Step:
 - Adj. R²: 0.8020654
 - AIC: 109.5773
- After 2nd Step:
 - Adj. R²: 0.8028622
 - AIC: 107.8835

```
Call:
lm(formula = (maternal_mortality_rate)^(1/5) ~ death_rate + infant_mortality_rate +
    birth_rate, data = df_final)
```

Residuals:

Min	1Q	Median	3Q	Max
-1.00872	-0.21522	0.02784	0.21176	0.83474

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.384471	0.106733	12.971	< 2e-16 ***
death_rate	-0.004806	0.008782	-0.547	0.585
infant_mortality_rate	0.015740	0.002227	7.068	3.71e-11 ***
birth_rate	0.029925	0.005339	5.605	8.08e-08 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3243 on 173 degrees of freedom
Multiple R-squared: 0.8054, Adjusted R-squared: 0.8021
F-statistic: 238.7 on 3 and 173 DF, p-value: < 2.2e-16

Start: AIC=-394.73
(maternal_mortality_rate)^(1/5) ~ death_rate + infant_mortality_rate + birth_rate

	Df	Sum of Sq	RSS	AIC
- death_rate	1	0.0315	18.221	-396.42
<none>			18.190	-394.73
- birth_rate	1	3.3032	21.493	-367.19
- infant_mortality_rate	1	5.2521	23.442	-351.83

Step: AIC=-396.42
(maternal_mortality_rate)^(1/5) ~ infant_mortality_rate + birth_rate

	Df	Sum of Sq	RSS	AIC
<none>			18.221	-396.42
- birth_rate	1	4.0569	22.278	-362.84
- infant_mortality_rate	1	6.1802	24.401	-346.73

Analysis of Variance Table

```
Model 1: (maternal_mortality_rate)^(1/5) ~ infant_mortality_rate + birth_rate
Model 2: (maternal_mortality_rate)^(1/5) ~ death_rate + infant_mortality_rate +
        birth_rate
      Res.Df    RSS Df Sum of Sq    F Pr(>F)
1       174 18.221
2       173 18.190   1   0.03149 0.2995 0.5849
```

Final Model : $\widehat{MaternalMortalityRate}^2 = \hat{\beta}_0 + \widehat{InfantMortalityRate}x_1 + \widehat{BirthRate}x_2 = 1.339008 + 0.015183x_1 + 0.030970x_2$

call:

```
lm(formula = (maternal_mortality_rate)^(1/5) ~ infant_mortality_rate +
    birth_rate, data = df_final)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-1.00088	-0.20711	0.02856	0.21028	0.81003

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.339008	0.066876	20.022	< 2e-16 ***
infant_mortality_rate	0.015183	0.001976	7.682	1.09e-12 ***
birth_rate	0.030970	0.004976	6.224	3.51e-09 ***

signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3236 on 174 degrees of freedom

Multiple R-squared: 0.8051, Adjusted R-squared: 0.8029

F-statistic: 359.4 on 2 and 174 DF, p-value: < 2.2e-16

Final Model Interpretation

A one unit increase in infant_mortality_rate (1 more death per 1,000 live births), with the other predictor (birth_rate) held fixed, is associated with an increase in maternal_mortality_rate by $(0.015183)^5$ units, which equals $8.06841002 \times 10^{-10}$ units, which can be interpreted as $8.06841002 \times 10^{-10}$ more deaths (where the death is related to pregnancy or birth) per 100,000 live births.

A one unit increase in birth_rate (1 birth per 1000 people), with the other predictor (infant_mortality_rate) held fixed, is associated with an increase in maternal_mortality_rate by $(0.030970)^5$ units, which equals $2.84908907 \times 10^{-8}$ units, which can be interpreted as $2.84908907 \times 10^{-8}$ more deaths (where the death is related to pregnancy or birth) per 100,000 live births.

Call:

```
lm(formula = (maternal_mortality_rate)^(1/5) ~ infant_mortality_rate +  
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```

Residuals:

Min	1Q	Median	3Q	Max
-1.00088	-0.20711	0.02856	0.21028	0.81003

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.339008	0.066876	20.022	< 2e-16 ***
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birth_rate	0.030970	0.004976	6.224	3.51e-09 ***

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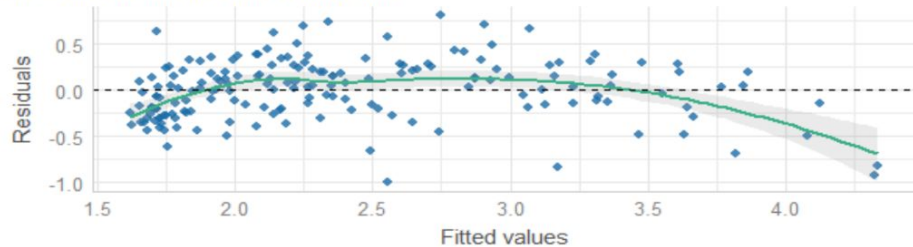
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Multiple R-squared: 0.8051, Adjusted R-squared: 0.8029

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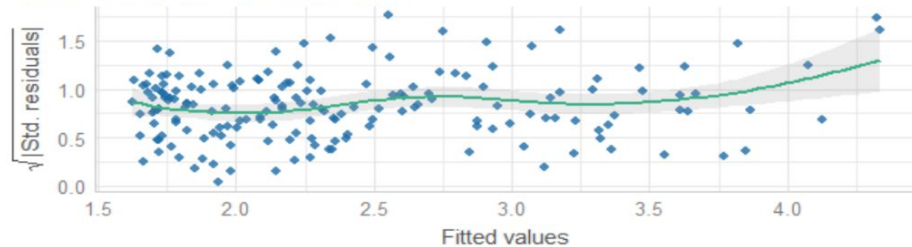
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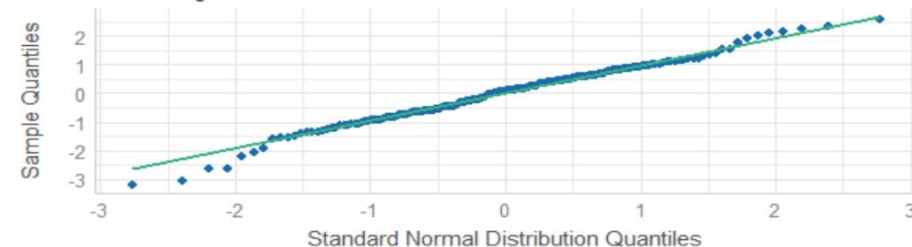
Collinearity

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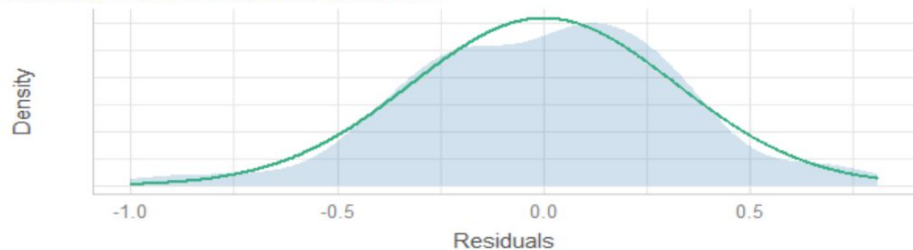
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Normality of Residuals

Distribution should be close to the normal curve



shapiro-wilk normality test

```
data: resid(lmlogstep_no_col2)
w = 0.99015, p-value = 0.2621
```



Outliers and Leverage Points

- 11 outliers
- 15 leverage points
 - ~ 0.033
- Final Step: investigate outliers

