

What is the key to win a Formula One Grand Prix

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Dataset

Kaggle Dataset

- Real Formula One data
- Length, Turns, Temperature, Birth Year, and Team Value variables added manually

225 Rows & 18 columns

- Each observation is a winner of a Formula One Grand Prix

Summary Statistics:

Fastest Lap Speed (km/h)

Minimum	151.388
Q1	198.046
Median	209.915
Mean	210.137
Q3	224.752
Max	252.794

Wins from 2014-2024

Lewis Hamilton	82
Max Verstappen	62
Nico Rosberg	20
Sebastian Vettel	14
Valtteri Bottas	10
Daniel Ricciardo	8

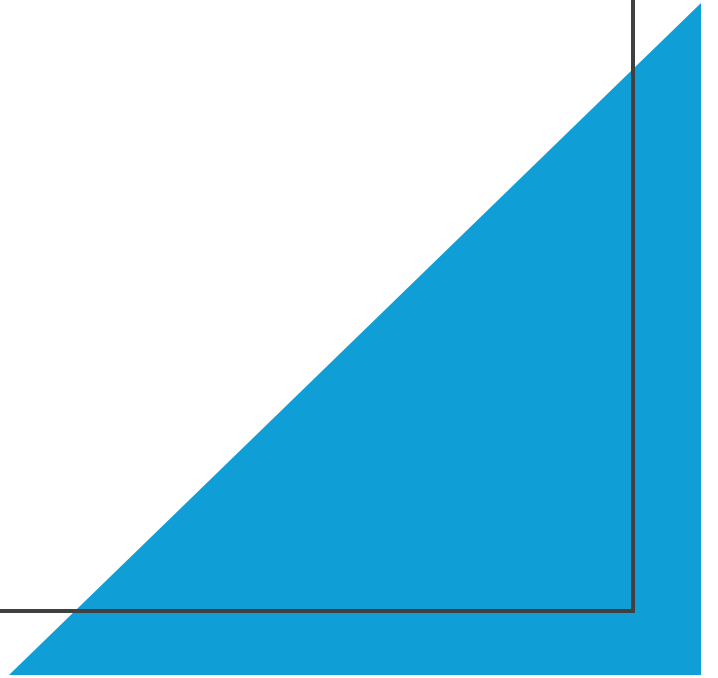
Time in Minutes

Minimum	73.686
Q1	87.776
Median	93.715
Mean	97.151
Q3	100.432
Max	181.733



First Research Question:

Can we predict the fastest speed when finishing their fastest lap?



1st Model – Extra Variables

avg_annual_temp – The average annual temperature for each country where a race is held

birth_year - The year of birth for each driver who wins a grand prix

team_value - The value of each team that wins a grand prix in billions of dollars

Description: df [6 × 2]

	circuit_name <chr>	avg_annual_temp <dbl>
1	70th Anniversary ...	48.63
2	Abu Dhabi Grand ...	82.71
3	Australian Grand ...	71.69
4	Austrian Grand Prix	45.39
5	Azerbaijan Grand ...	55.33
6	Bahrain Grand Prix	81.84

6 rows

Description: df [6 × 2]

	driver_ref <chr>	birth_year <dbl>
1	bottas	1989
2	gasly	1996
3	hamilton	1985
4	leclerc	1997
5	max_verstappen	1997
6	norris	1999

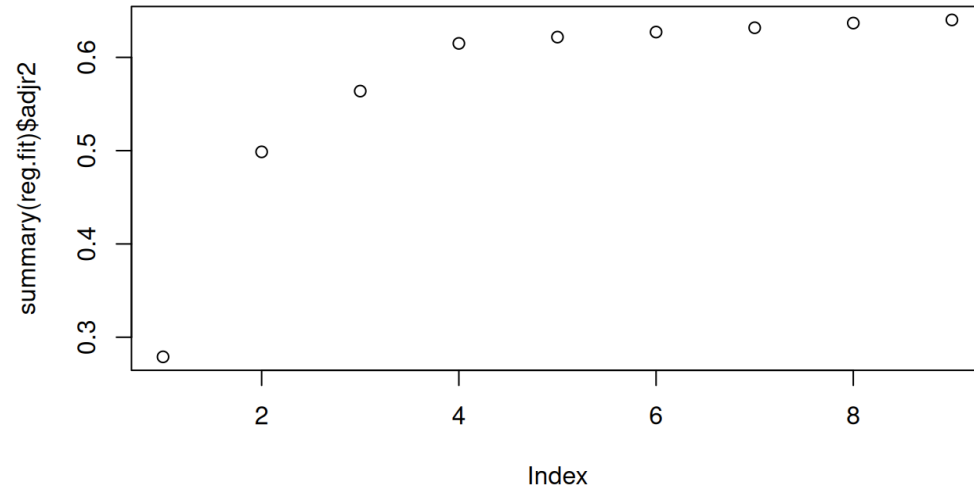
6 rows

Description: df [4 × 2]

	team_name <chr>	team_value <dbl>
1	Ferrari	6.50
2	McLaren	4.40
3	Mercedes	6.00
4	Red Bull	4.35

4 rows

1st Model – Finding Significant Predictors



Call:

```
lm(formula = fastest_lap_speed ~ year + time_minutes + Length +  
    Turn, data = f1_uid3)
```

Residuals:

Min	1Q	Median	3Q	Max
-30.336	-8.947	-0.383	7.008	52.334

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-3.074e+03	5.508e+02	-5.581	7.10e-08 ***
year	1.623e+00	2.727e-01	5.949	1.07e-08 ***
time_minutes	-3.084e-01	5.637e-02	-5.471	1.23e-07 ***
Length	1.572e+01	1.153e+00	13.639	< 2e-16 ***
Turn	-2.621e+00	2.809e-01	-9.329	< 2e-16 ***

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

Residual standard error: 12.95 on 217 degrees of freedom

Multiple R-squared: 0.6219, Adjusted R-squared: 0.6149

F-statistic: 89.23 on 4 and 217 DF, p-value: < 2.2e-16

1st Model – Assumptions

Shapiro-Wilk normality test

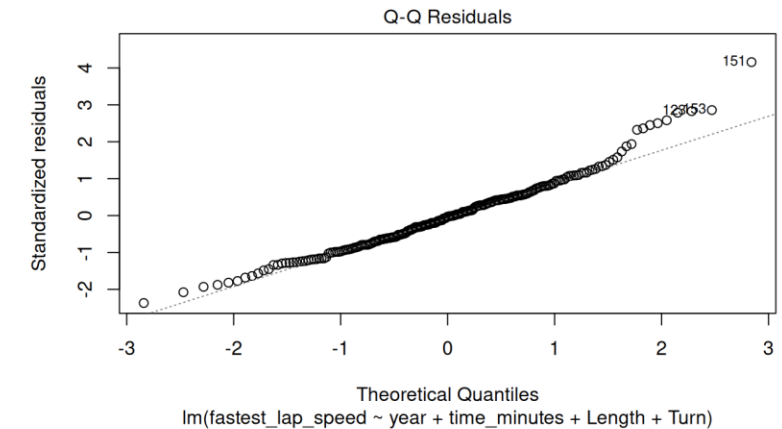
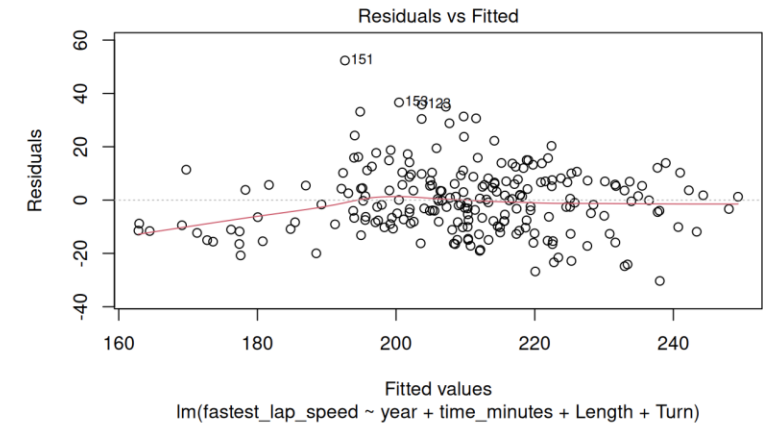
```
data: reduced.fit$residuals
```

```
W = 0.97401, p-value = 0.0004109
```

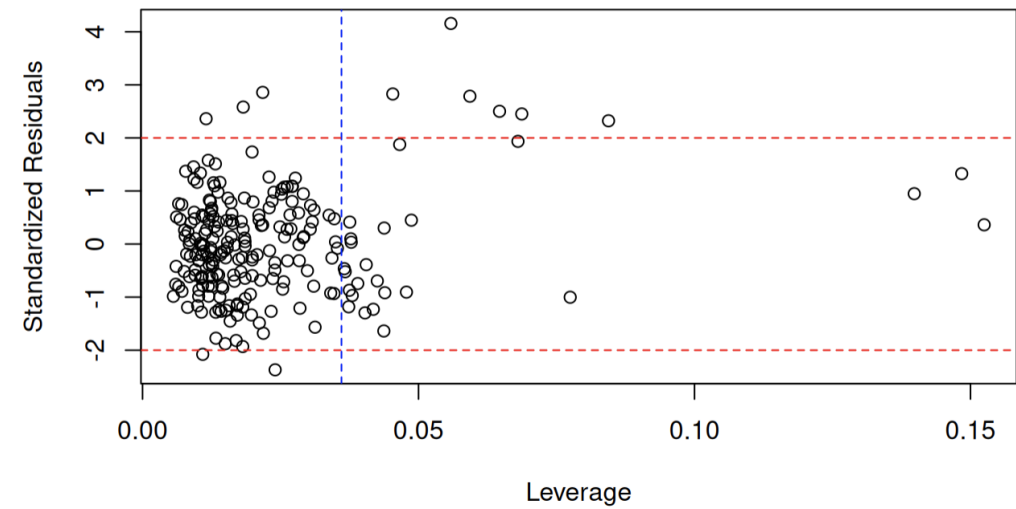
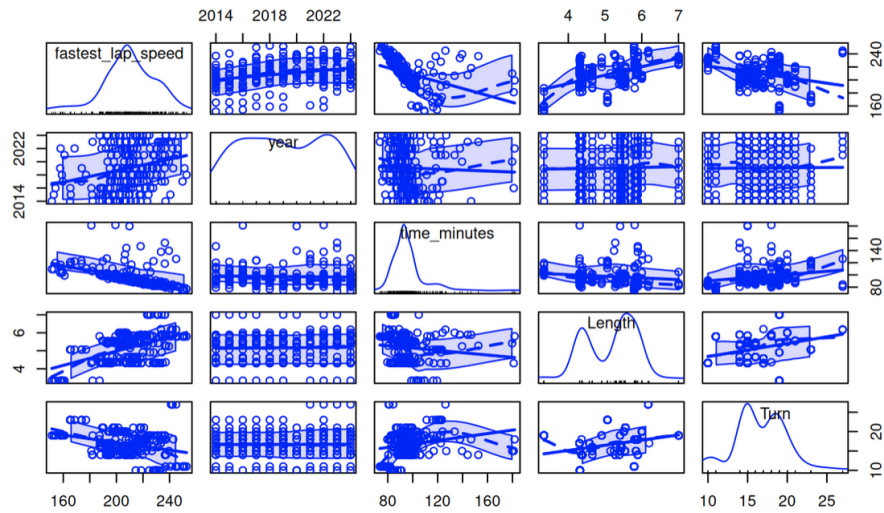
Non-constant Variance Score Test

Variance formula: $\sim$ fitted.values

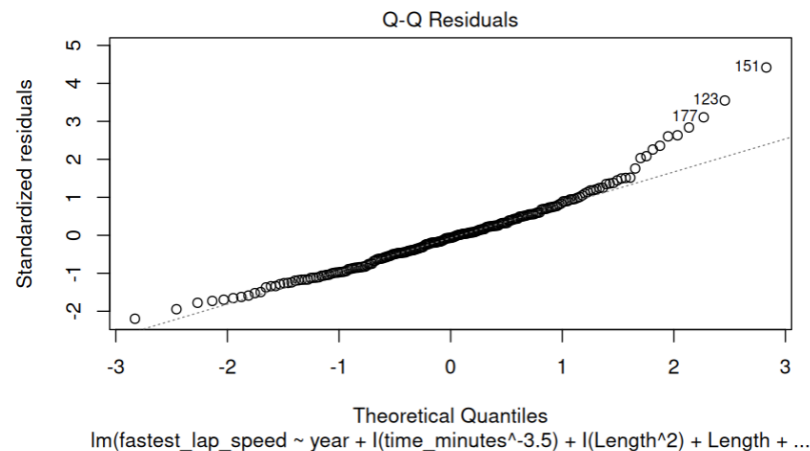
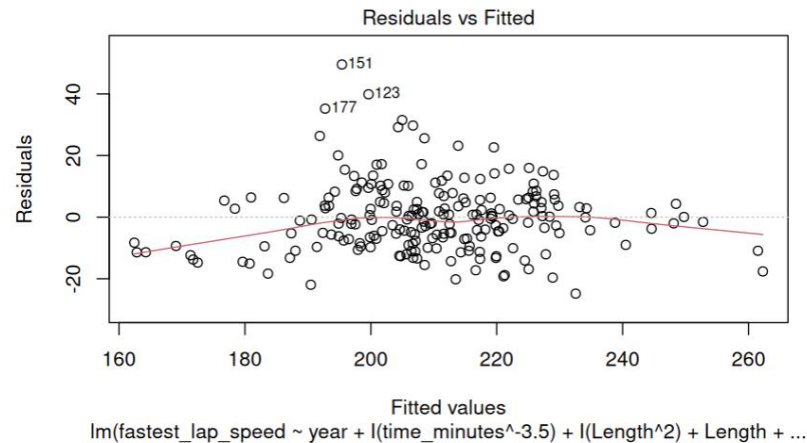
```
Chisquare = 1.80369, Df = 1, p = 0.17927
```



1st Model – Collinearity & Outliers



1st Model - Transformations



bcPower Transformations to Multinormality

	Est	Power	Rounded Pwr	Wald Lwr Bnd	Wald Up Bnd
year	2.9992	1.00		-93.6200	99.6183
time_minutes	-3.4810	-3.48		-4.2142	-2.7478
Length	1.6993	2.00		1.0245	2.3741
Turn	0.3967	0.00		-0.0862	0.8796

Likelihood ratio test that transformation parameters are equal to 0
(all log transformations)

Likelihood ratio test that no transformations are needed

bcPower Transformation to Normality

	Est	Power	Rounded Pwr	Wald Lwr Bnd	Wald Up Bnd
Y1	1.0459	1	0.1439	1.9478	

Call:

```
lm(formula = fastest_lap_speed ~ year + I(time_minutes^-3.5) +  
I(Length^2) + Length + log(Turn), data = f1_uid5)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-24.838	-7.488	-0.765	5.790	49.553

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-2.699e+03	5.024e+02	-5.371	2.08e-07 ***
year	1.421e+00	2.491e-01	5.706	3.94e-08 ***
I(time_minutes^-3.5)	1.652e+08	1.876e+07	8.807	5.09e-16 ***
I(Length^2)	-1.471e+00	9.549e-01	-1.541	0.12494
Length	2.737e+01	9.703e+00	2.821	0.00525 **
log(Turn)	-3.001e+01	4.593e+00	-6.535	4.82e-10 ***

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

Residual standard error: 11.46 on 208 degrees of freedom
Multiple R-squared: 0.6876, Adjusted R-squared: 0.6801
F-statistic: 91.56 on 5 and 208 DF, p-value: < 2.2e-16

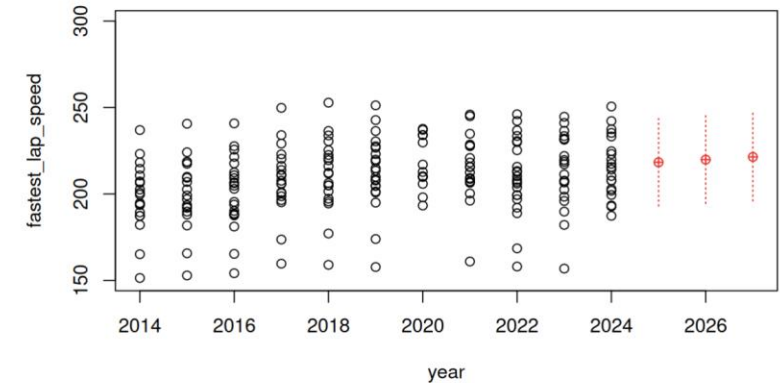
1st Model - Prediction

Prediction Plot

```
new_x <- data.frame(year=2027, time_minutes=97.290245, Length=5.166419, Turn=16.697674)
fastest_lap_speed_2027 <- predict(backtransformed.fit, newdata = new_x, interval =
"prediction")
plot(fastest_lap_speed ~ year, data = f1_uid6, xlim=c(2014, 2027), ylim=c(150, 300))
points(2025, fastest_lap_speed_2025[1,1], col="red", pch=10)
segments(x0 = 2025, y0 = fastest_lap_speed_2025[1,2], x1 = 2025, y1 =
fastest_lap_speed_2025[1,3], col = "red", lty = "dotted")
points(2026, fastest_lap_speed_2026[1,1], col="red", pch=10)
segments(x0 = 2026, y0 = fastest_lap_speed_2026[1,2], x1 = 2026, y1 =
fastest_lap_speed_2026[1,3], col = "red", lty = "dotted")
points(2027, fastest_lap_speed_2027[1,1], col="red", pch=10)
segments(x0 = 2027, y0 = fastest_lap_speed_2027[1,2], x1 = 2027, y1 =
fastest_lap_speed_2027[1,3], col = "red", lty = "dotted")
```

Prediction Intervals

```
print(fastest_lap_speed_2025)
print(fastest_lap_speed_2026)
print(fastest_lap_speed_2027)
```



	fit	lwr	upr
1	218.3001	193.0065	243.5937

	fit	lwr	upr
1	219.8589	194.4931	245.2247

	fit	lwr	upr
1	221.4177	195.9687	246.8667

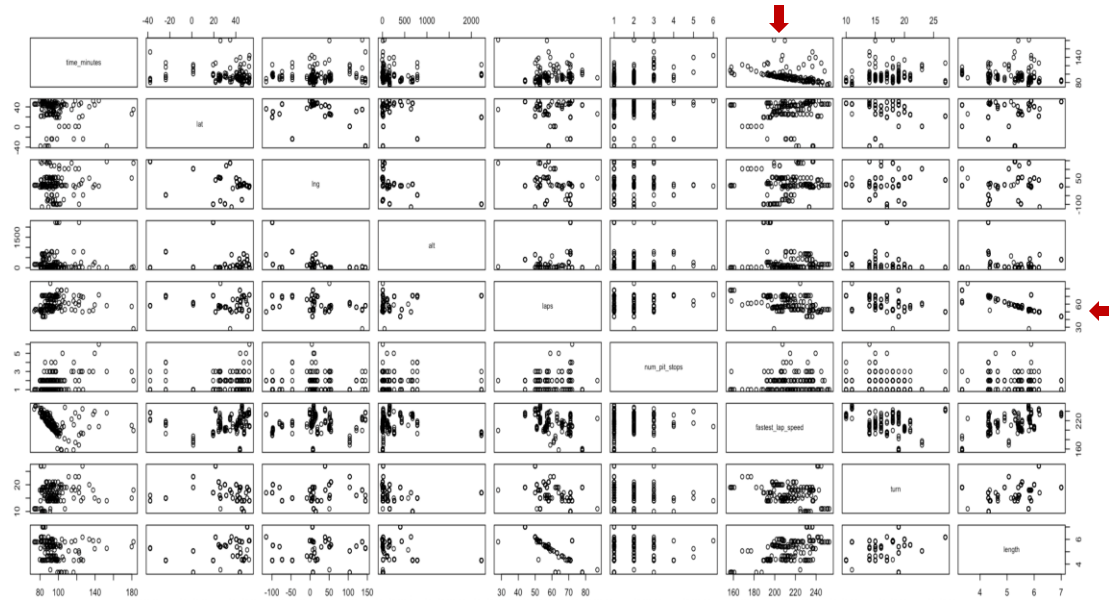
Second Research Question:

Can we predict the time it
takes to win a Grand Prix

After the addition of the halo on Formula One racecars (2018-2024)



Visualizing data:

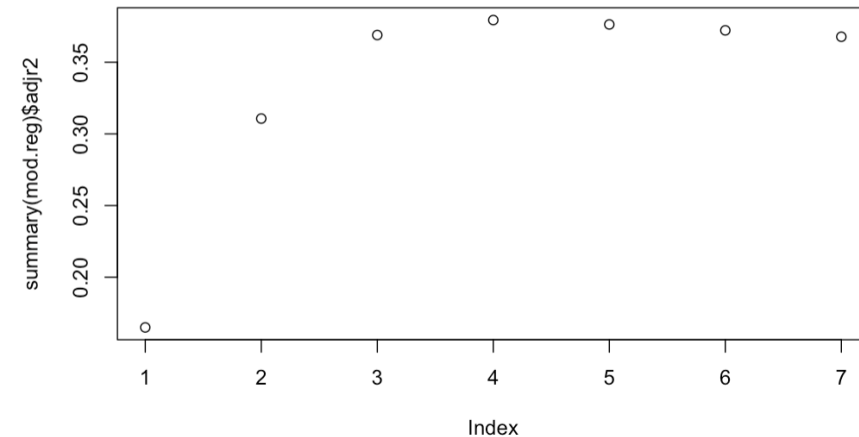
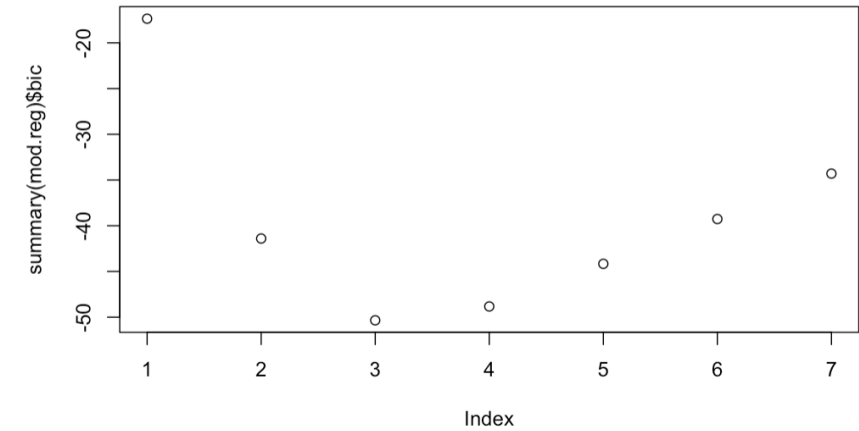


- Possible multicollinearity issues between `length` & `laps`
- Strong linear relationship between `time_minutes` & `fastest_lap_speed`

Variable Selection for Model with `regsubsets()`:

Significant predictors:

- `laps`: number of laps during grand prix
- `num_pit_stops`: Number of pit stops taken during the grand prix
- `fastest_lap_speed`: fastest speed during fastest lap (in kilometers per hour)



Testing for Multicollinearity with `vif()`:

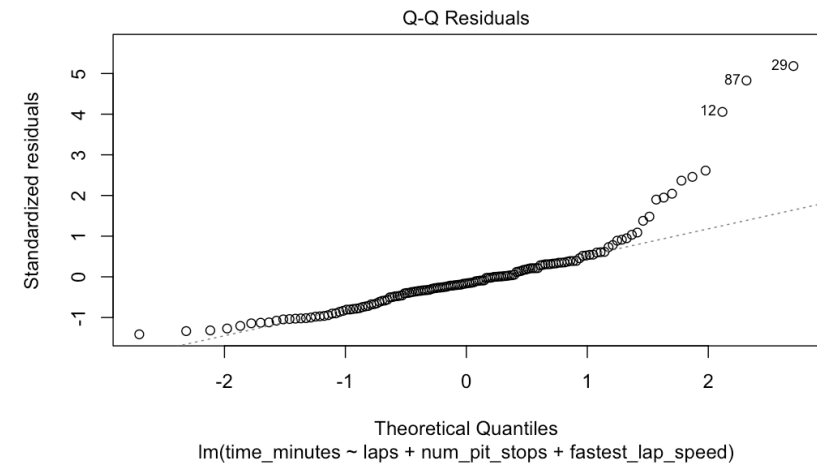
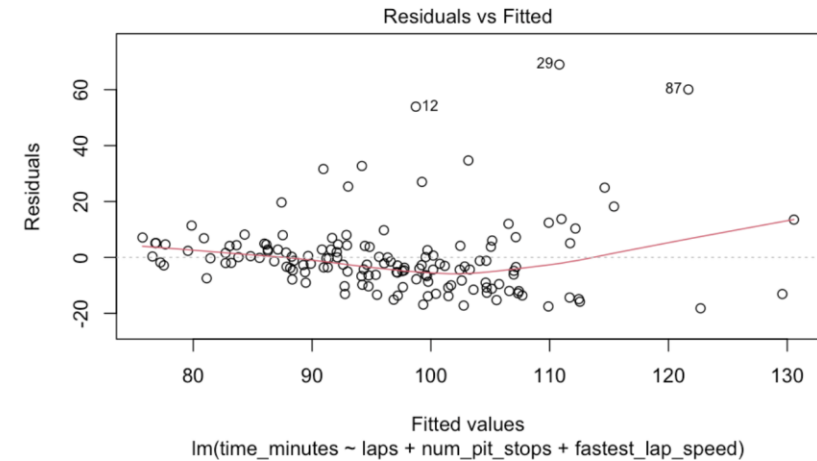
`laps: 1.33`

`num_pit_stops: 1.06`

`Fastest_lap_speed:
1.30`

Assumptions before Transformation:

- **Linearity:** No obvious pattern in fitted values v. residuals plot
- **Independence:** The observations are independent of each other
- **Normality:** The residuals do not appear to be normally distributed (Shapiro-Wilk: $5.148e-12$)
- **Equal variance:** The fitted values v. residuals plot shows datapoints are not randomly scattered around zero (ncvTest: $4.0825e-16$)



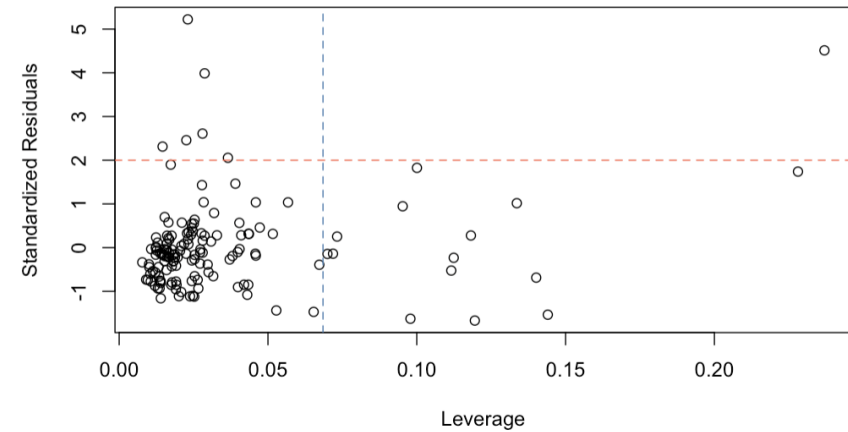
Outliers & bad leveraged datapoints

One bad leveraged datapoint:

- Max Verstappen: 2022 Japanese Grand Prix

Seven outliers:

- `time_minutes` over 120 minutes



Transformations using `powerTransform()`:

`time_minutes`

- Negative fourth power transformation

`laps`

- Log transformation

`num_pit_stops`

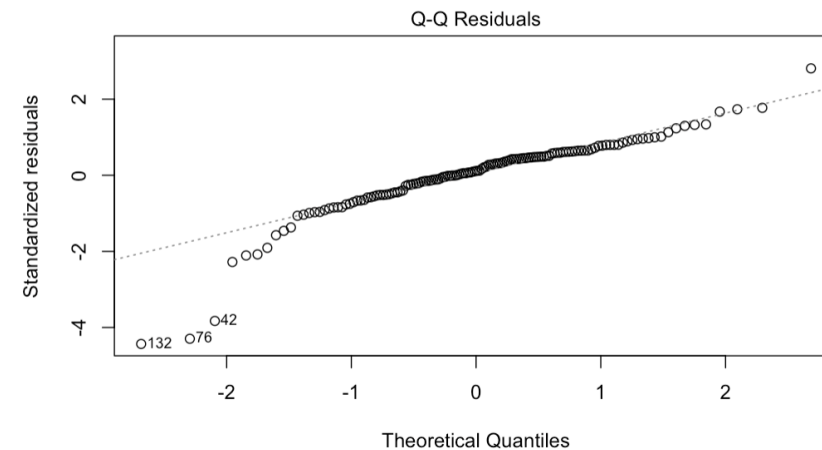
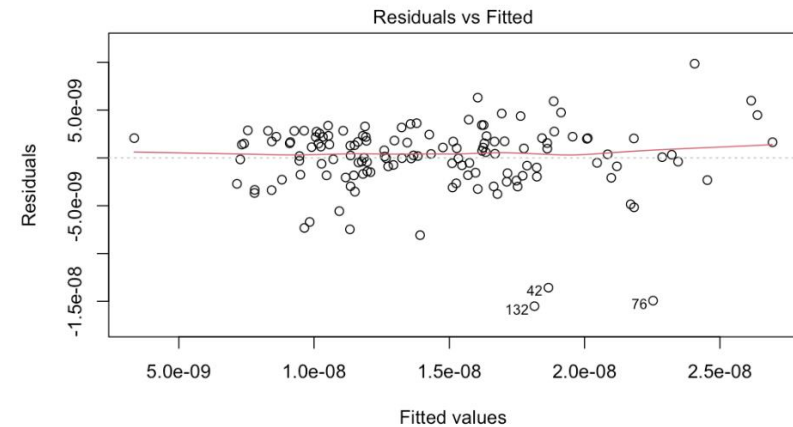
- Log transformation

`fastest_lap_speed`

- Square transformation

Assumptions after Transformation:

- **Linearity:** No obvious pattern in fitted values v. residuals plot
- **Independence:** The observations are independent of each other
- **Normality:** The residuals appear to be mostly normally distributed
- **Equal variance:** The fitted values v. residuals plot shows datapoints are mostly scattered randomly around zero



Final Model & Predictions

$$\widehat{\text{time_minutes}} = 1.67e^{-9} \log(\text{laps}) + 4.78e^{-9} \log(\text{num_pit_stops}) + 1.82e^{-12} (\text{fastest_lap_speed})^2 - 5.30e^{-10} (\text{fastest_lap_speed})$$

R^2_{adj} :

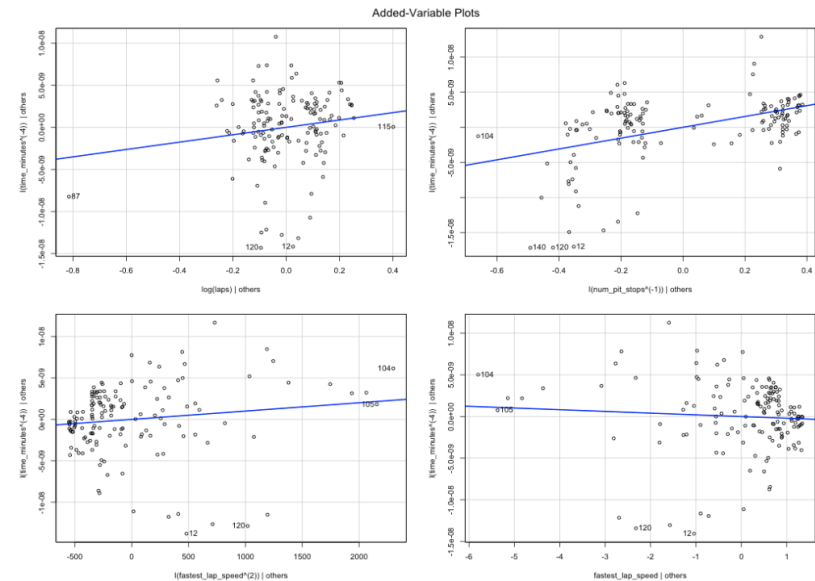
- 0.667 or 66.7%

Prediction:

- laps: 55
- num_pit_stops: 2
- fastest_lap_speed: 202

Result:

- 100.1285 minutes





QUESTIONS?