# DSS Prototype Analysis

Alvin Murphy

## Table of contents

# 1 DSS Installation as a Docker Container

https://github.com/jupyter/docker-stacks
https://hub.docker.com/r/jupyter/r-notebook/tags/

*(optional) docker pull jupyter/r-notebook:latest*

We want the Jupyter container to mount the DDS Prototype ~/analysis/ directory to provide access to scripts and data. Use the following to mount the analysis directory (i.e. current working directory) as a volume in the Juypter container. Note that the directory needed to be added as a valid mount point via the Docker Desktop Dashboard on Mac.

*docker run -it –rm -d -p 10000:8888 -v ${PWD}:/home/jovyan/work –name notebook jupyter/r-notebook:latest*

To find the token from the container:
*docker exec -it notebook jupyter server list*
or
*docker logs notebook*

Navigate to the container UI and enter the token: http://localhost:10000

# 2 DSS System Context

Figure 1 depicts the context for the DSS. The DSS operator interacts with the DSS Prototype for decision assitance. The DSS relies on a aircraft database to gather real-time flight data to review in decision support algorithms.

## 2.1 DSS Container Architecture

Nine containers are instantiated as part of the DSS architecuture (see Figure 2). Six provide the DSS implementation while the additional 3 support collection and calculation of metrics. Each application container was designed around the 12-Factor Application "Single Responsibility Principle"; e.g. each app has one purpose to enable rapid insertion of new capabilities with low cohesion to other functionality. At this time, all responses are canned without underlying calculations to focus on meeting the 500 ms hypothesis pryor to burdening the application with calculation latency.

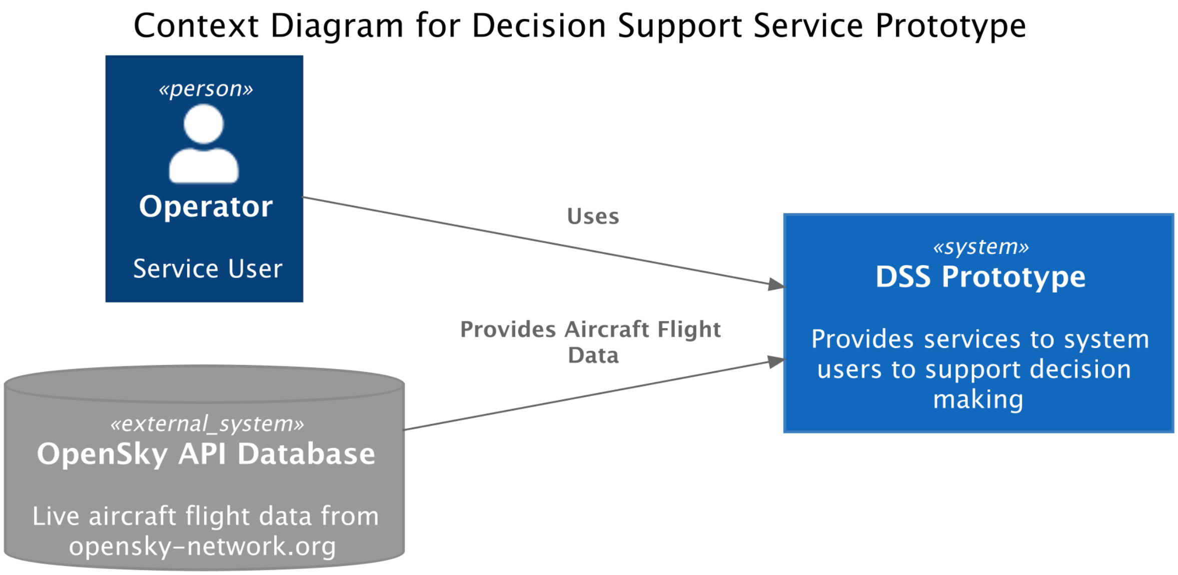



Figure 1: DSS Context Diagram

### 2.1.1 DSS Applications

- opensky-int: Provides the OpenSky API for flight data. The app provides data about aircraft within 60 NM of Richmond (RIC) or Dulles (IAD) airports.
- tm-server: Provides sensor track data (e.g. OpenSky) and system tracks to support DSS services. System tracks represent the system-wide common understanding of track object states used for decision support.
- wa-app: The Weapon Assessment Application determines which weapons are capable to successfully engage a target. The wa-app uses the tm-server api to get track data.
- te-app: The Trail Engage Application predicts the success probability of an engagement with a specific weapon target pairing. The predicted track kinematic data at engagement time is provided; therefore, the current track kinematics from the tm-server are not queried prior to providing a response.
- test-app: Provides an ability to initiate automated tests. the test-app uses the dss-ui to call dss-ui endpoint to replicate operator interactions with the DSS Prototype.
- dss-ui: Provides a simple graphical interface to launch DSS services.

### 2.1.2 DSS Tools

- telem-jaeger: The open source Jaeger containter collects "span" data from the DSS applications. Spans collect duration data for service calls amongst containers; e.g. latency. This the fundamental data that is being analysed here.

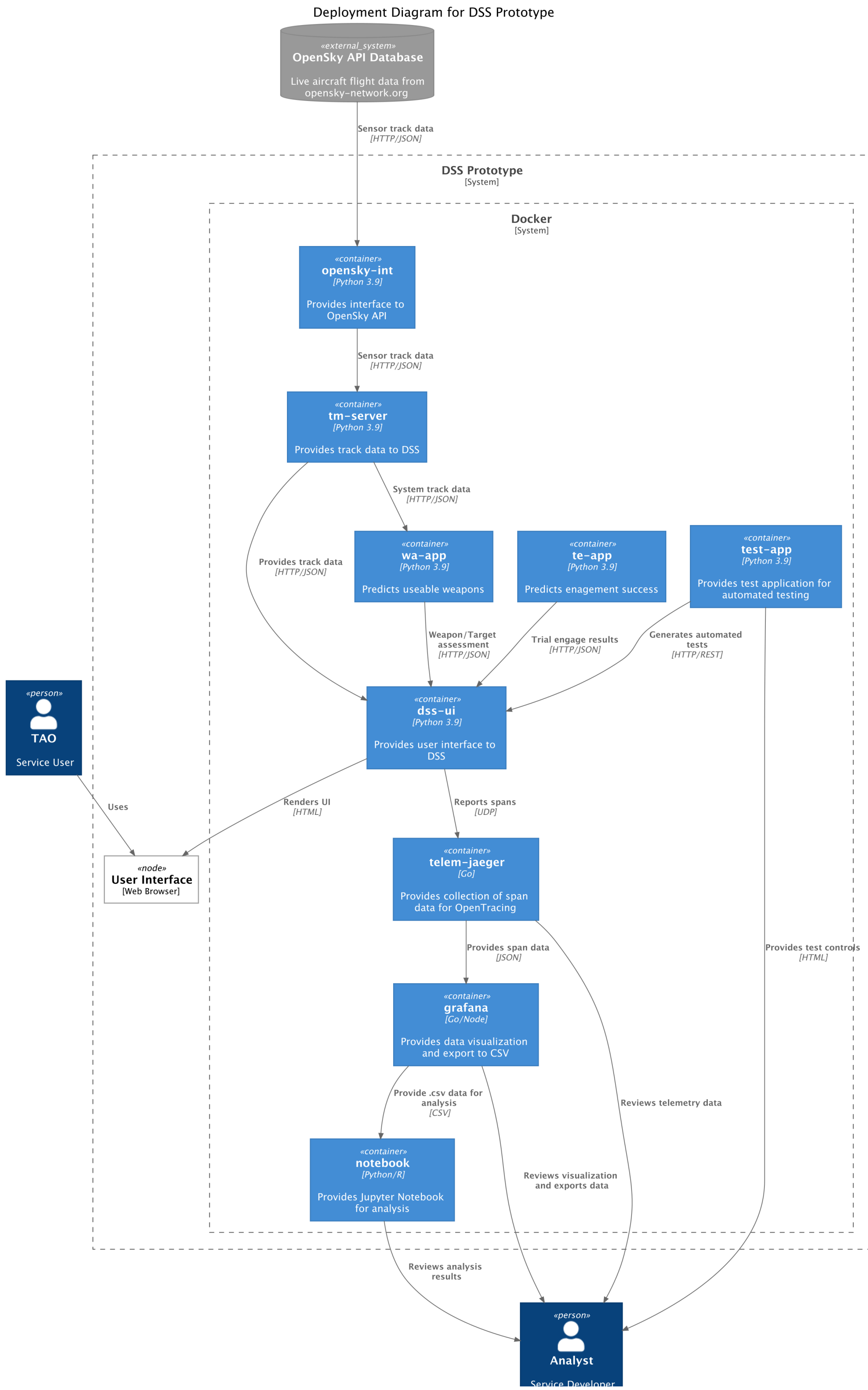



Figure 2: DSS Deployment Diagram

- grafana: The open source Grafana container connects to the telem-jaeger container to create visualization dashboards. Also, Grafana faciliates the export of data as a .csv file for analysis.
- notebook: The Jupyter Notebook container supports analysis of the data recorded by Jaeger and exported by Grafana. An embedded R software library is used for analysis.

### 2.2 Hypothesis

Hypotheses are "innocent until proven guilty." We'll assume that SpaceX and others have proven that DevSecOps tech can meet hard-real-time requirements but nothing available in the body of knowledge documents this.

**Hypothesis:** Modern DevSecOps architectures can be designed to meet hard-real-time latency ($\mu$) requirements using modern computing environments and computing infrastructure.

$H_0 : \mu \leq 500ms$ with jitter within latency bounds
$H_a : \mu > 500ms$ with jitter exceeding latency bounds

*Murphy, Alvin C. and Moreland Jr, James D. 'Integrating AI Microservices into Hard-Real-Time SoS to Ensure Trustworthiness of Digital Enterprise Using Mission Engineering'. 1 Jan. 2021 : 38 – 54.*

## 3 Exploratory Data Analysis

```
  Trace.ID           Trace.name          Start.time          Duration
 Length:100         Length:100         Length:100         Length:100
 Class :character   Class :character   Class :character   Class :character
 Mode  :character   Mode  :character   Mode  :character   Mode  :character
```

A data.frame: 6 × 2

| | Trace.ID <chr> | Trace.name <chr> |
|---|---|---|
| 1 | 9ee3577fb1b427bc4fc17fecc5154d7d | dss-prototype: /TE |
| 2 | f05ddc4dc13aff5c3098011b2a402401 | dss-prototype: /tracks |
| 3 | 2bd901fbbfc9ee8dfa7c9629d93a1567 | dss-prototype: /IAD |
| 4 | 69a48381a14e79da08aaa2353f7db4b2 | dss-prototype: /RIC |
| 5 | e83037dcb9438c04dc12fba373b5502f | dss-prototype: /WA |
| 6 | 7e381cd880adb670bb9627ca47020938 | dss-prototype: /TE |

A data.frame: 6 × 2

| | Start.time <chr> | Duration <chr> |
|---|---|---|
| 1 | 2022-05-02 10:25:01.366 | 36.0 ms |
| 2 | 2022-05-02 10:25:00.309 | 43.3 ms |
| 3 | 2022-05-02 10:24:58.818 | 464 ms |
| 4 | 2022-05-02 10:24:57.307 | 494 ms |
| 5 | 2022-05-02 10:24:56.128 | 139 ms |
| 6 | 2022-05-02 10:24:55.081 | 30.3 ms |

### 3.1 Convert Data into Useable Metrics

To make the data more usable and easier to understand we apply conversions from text to numeric and add additional columns with supporting information. A **useCase** column is added to identify specific DSS request use cases; e.g. Get Dulles Airport Data. The data also indicates whether the request is managed internally or a connection to an external service is required to provided a response (i.e., https://opensky-network.org). A **numContainers** column is added to indicate the number of containers involved in providing a use case response (e.g. independent variable). An **extNetworkHops** column is added to include network hops for external requests as an additional independent variable.

```
   Trace.ID            Trace.name           Start.time           Duration
 Length:100          Length:100          Min.   :1.651e+09   Min.   :0.01390
 Class :character    Class :character    1st Qu.:1.651e+09   1st Qu.:0.03275
 Mode  :character    Mode  :character    Median :1.651e+09   Median :0.07375
                                         Mean   :1.651e+09   Mean   :0.25404
                                         3rd Qu.:1.651e+09   3rd Qu.:0.48450
                                         Max.   :1.651e+09   Max.   :2.00000
   useCase           numContainers extNetworkHops
 Length:100          Min.   :2.0   Min.   : 0.0
 Class :character    1st Qu.:2.0   1st Qu.: 0.0
 Mode  :character    Median :3.0   Median : 0.0
                     Mean   :2.6   Mean   : 5.6
                     3rd Qu.:3.0   3rd Qu.:14.0
                     Max.   :3.0   Max.   :14.0
```

A data.frame: 6 × 3

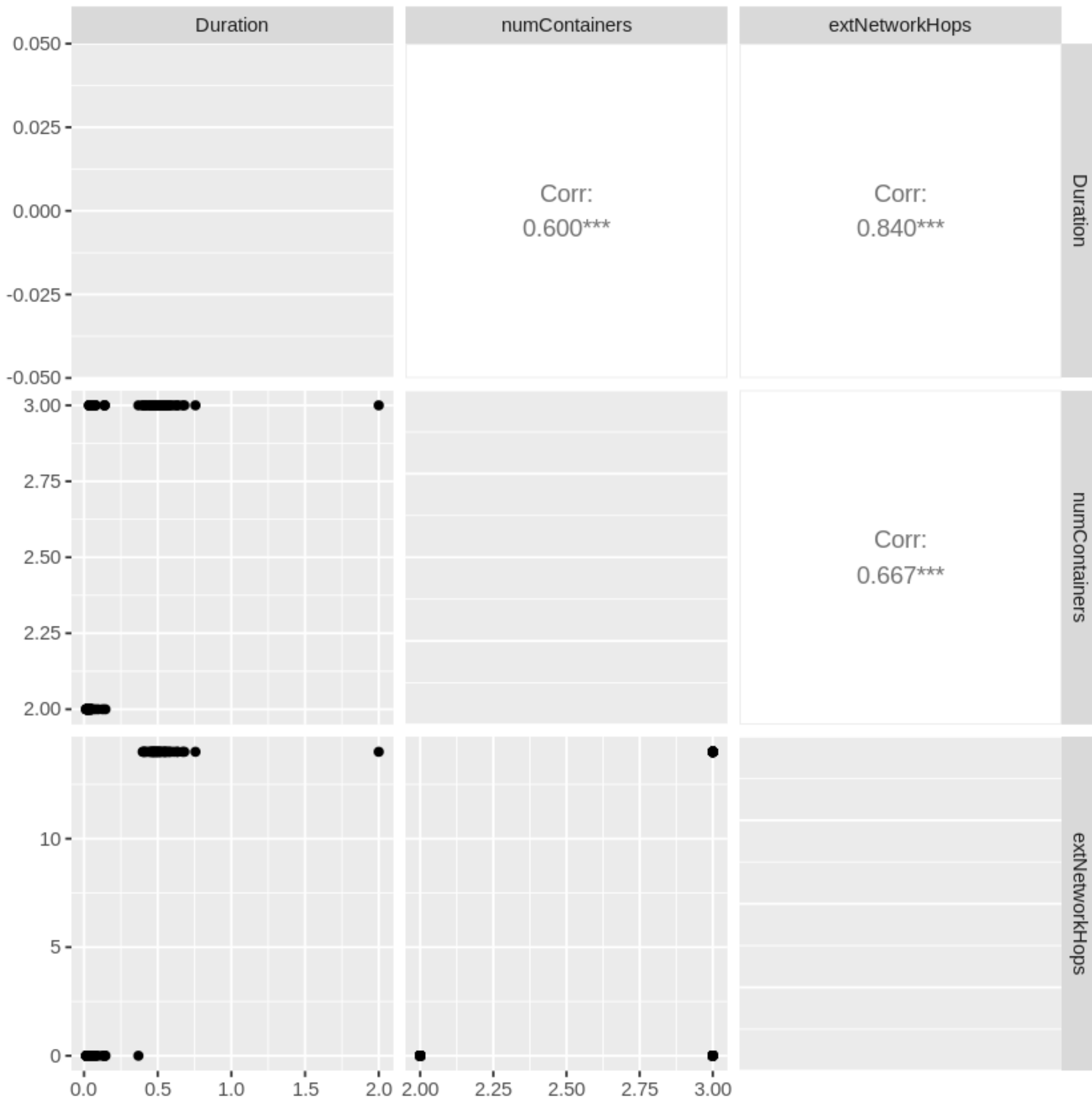
| | Trace.ID <chr> | Trace.name <chr> | Start.time <dbl> |
|---|---|---|---|
| 1 | 9ee3 | /TE | 1651487101 |
| 2 | f05d | /tracks | 1651487100 |
| 3 | 2bd9 | /IAD | 1651487098 |

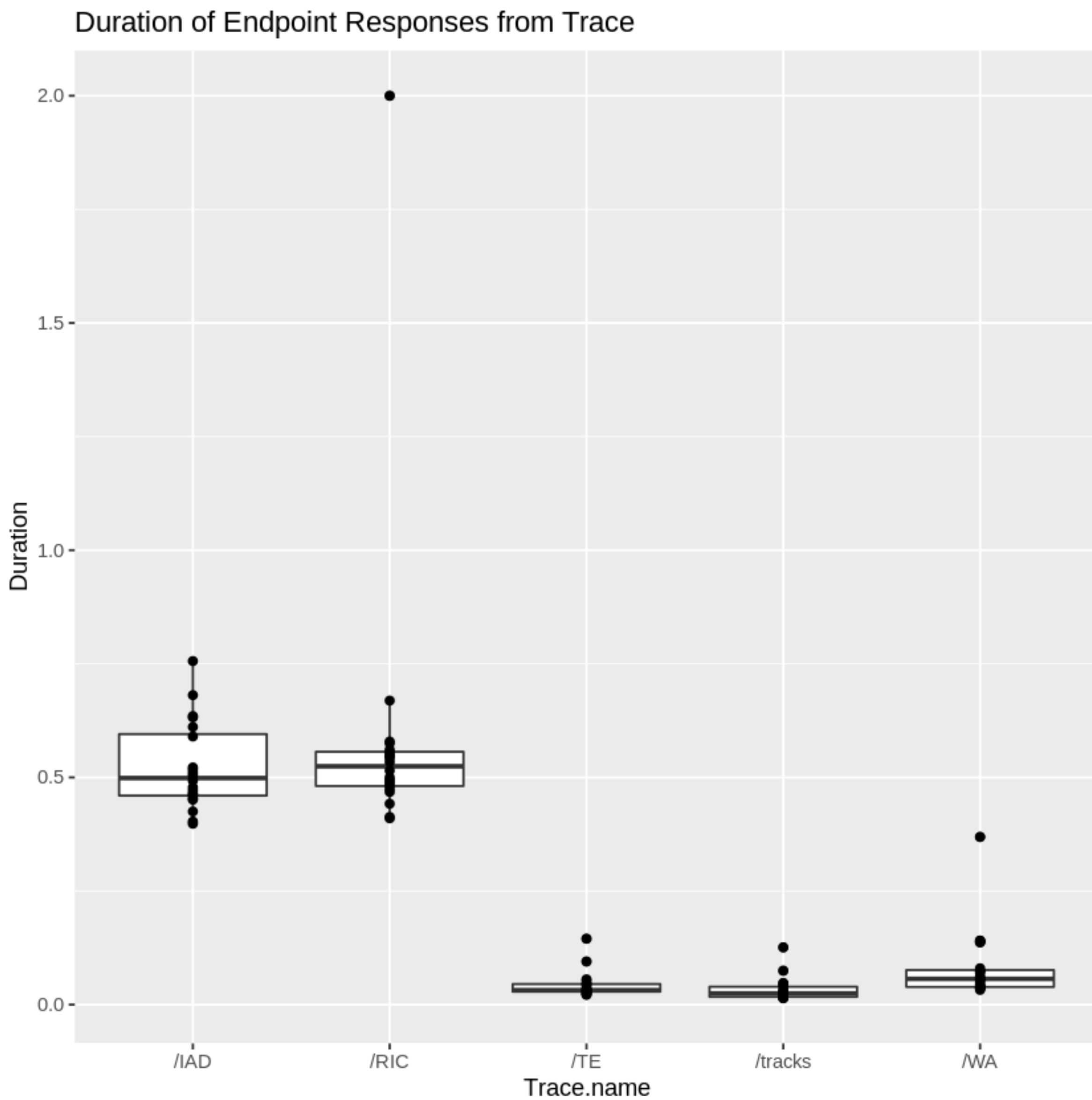
| | Trace.ID <chr> | Trace.name <chr> | Start.time <dbl> |
|---|---|---|---|
| 4 | 69a4 | /RIC | 1651487097 |
| 5 | e830 | /WA | 1651487096 |
| 6 | 7e38 | /TE | 1651487095 |

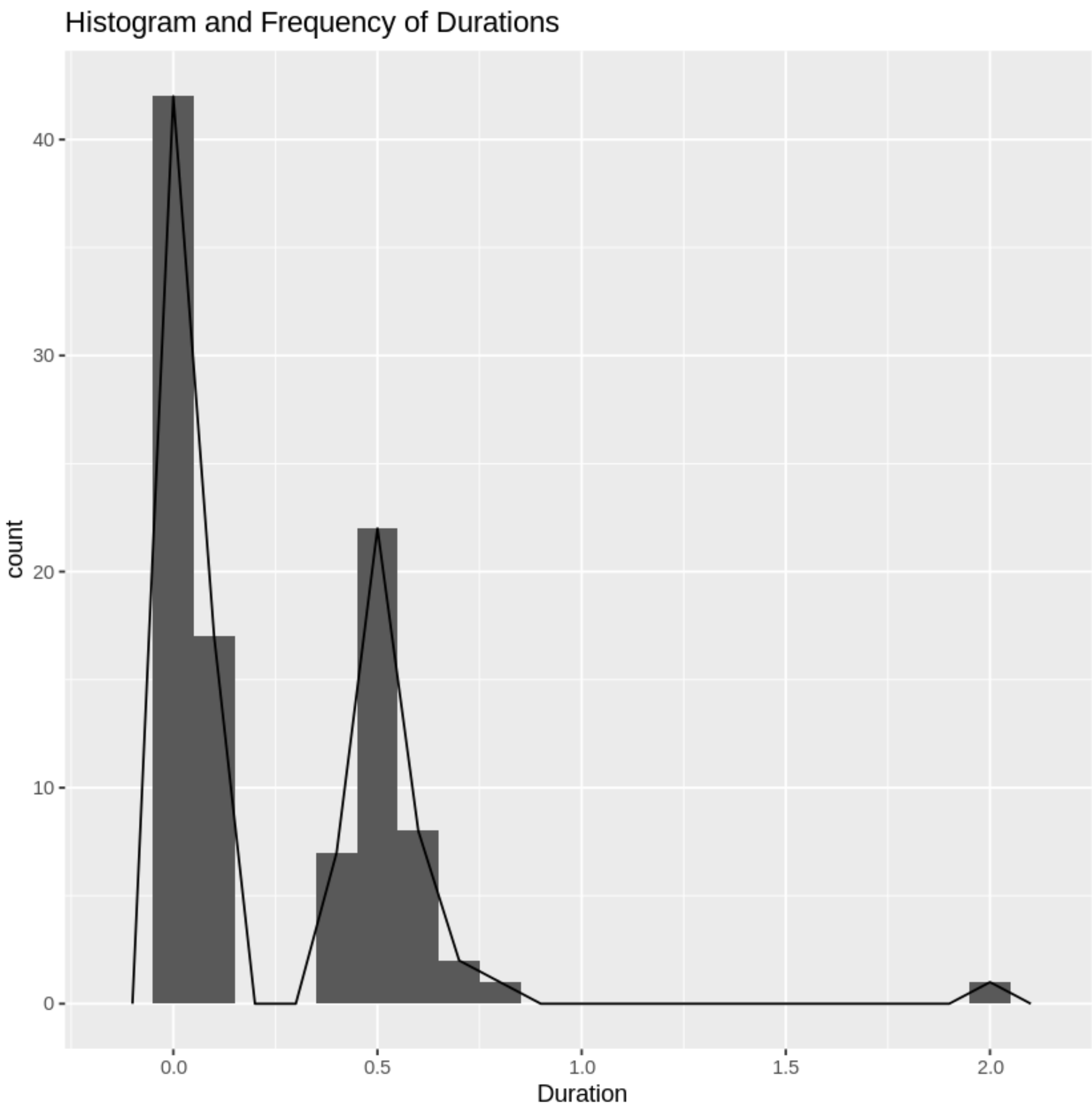
A data.frame: 6 × 4

| | Duration <dbl> | useCase <chr> | numContainers <dbl> | extNetworkHops <dbl> |
|---|---|---|---|---|
| 1 | 0.0360 | Trial Engage (Internal) | 2 | 0 |
| 2 | 0.0433 | Get Stored Local DSS Tracks (Internal) | 2 | 0 |
| 3 | 0.4640 | Get Dulles Airport Data (External) | 3 | 14 |
| 4 | 0.4940 | Get Richmond Airport Data (External) | 3 | 14 |
| 5 | 0.1390 | Assess Weapons (Internal) | 3 | 0 |
| 6 | 0.0303 | Trial Engage (Internal) | 2 | 0 |

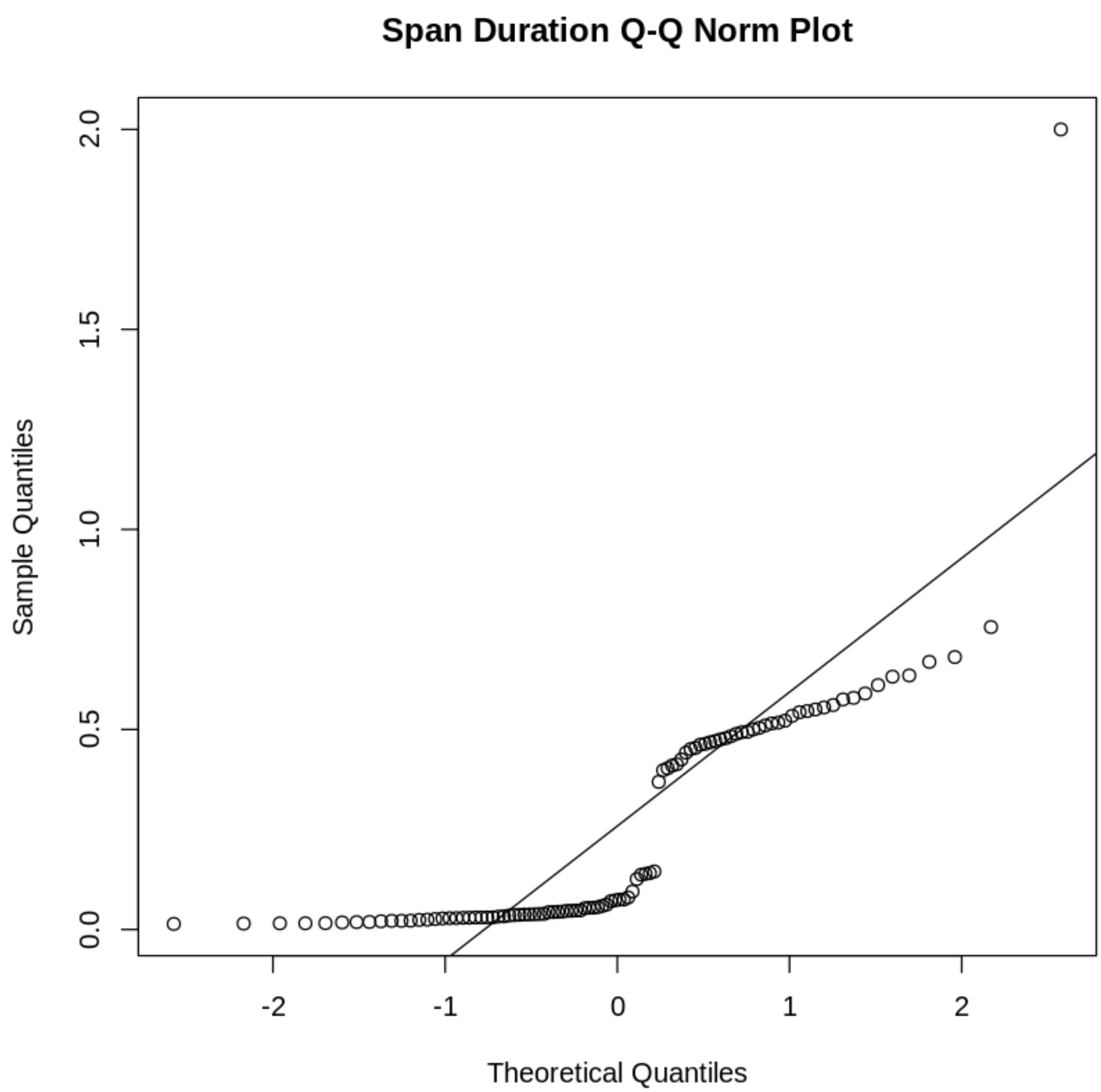
## 3.2 Exploratory Analysis Plots




Duration of Endpoint Responses from Trace
Duration
2.0
1.5
1.0
0.5
0.0
/IAD
/RIC
/TE
/tracks
/WA
Trace.name


Histogram and Frequency of Durations
count
40
30
20
10
0
0.0
0.5
1.0
1.5
2.0
Duration

### 3.3 Q-Q Normality Test

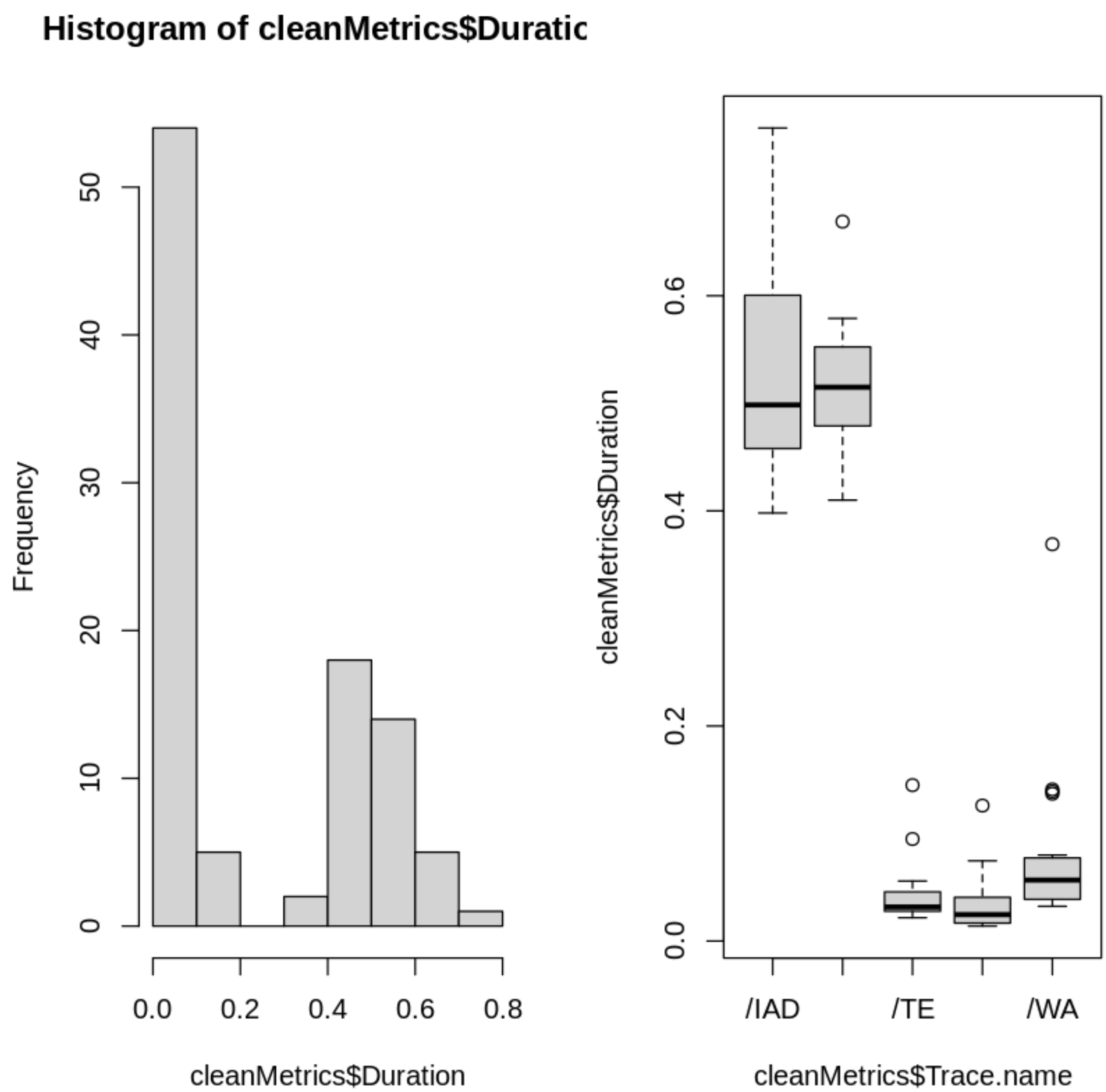


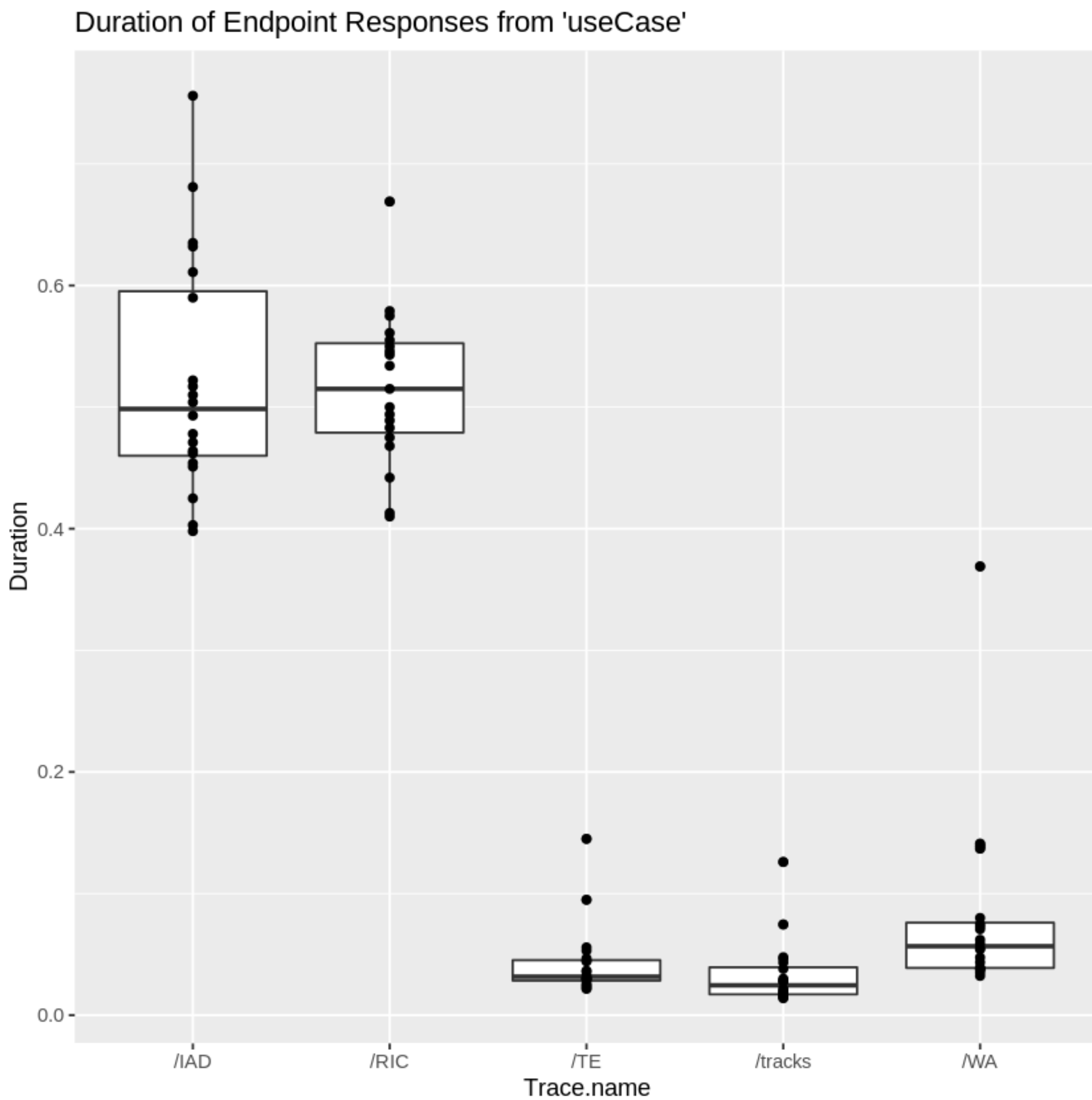

A transformation is needed to apply statistical analysis.

# 4 Clean the Data

## 4.1 Search for Outliers

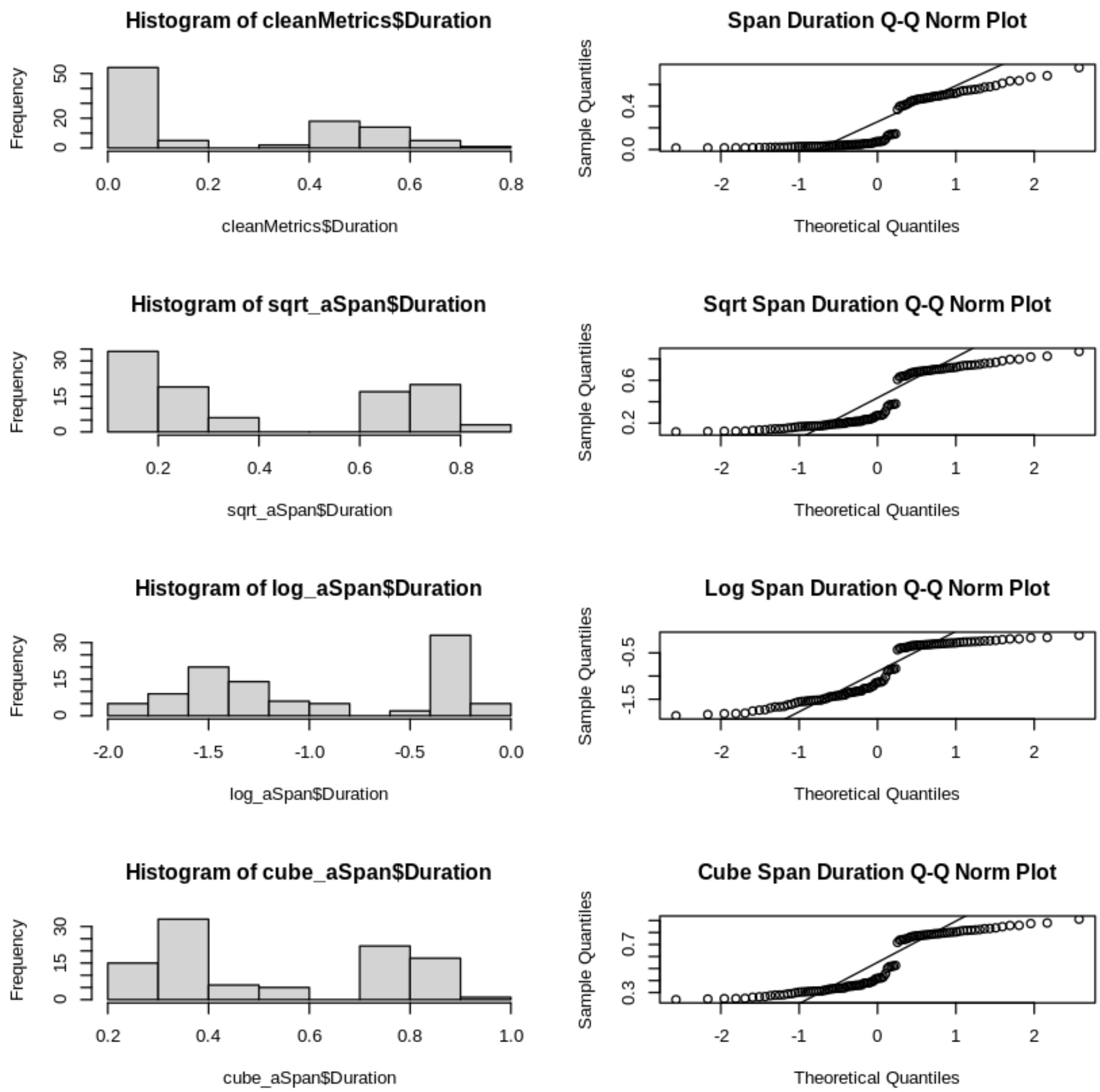
2




Duration of Endpoint Responses from 'useCase'
Duration
0.0
0.2
0.4
0.6
/IAD
/RIC
/TE
/tracks
/WA
Trace.name

## 4.2 Transformation of Clean Metrics

### 4.2.1 Sqrt, Log, and Cube Transformations




None of these transformation yield distributions that would be considered normal. Most likely due to access to external and internal services with differing latency. Lets try another transformation.

### 4.2.2 Box-Cox Transformation

Box and Cox (1964) developed a family of transformations designed to reduce nonnormality of the errors in a linear model. Applying this transform often reduces non-linearity as well, and heteroscedascity.

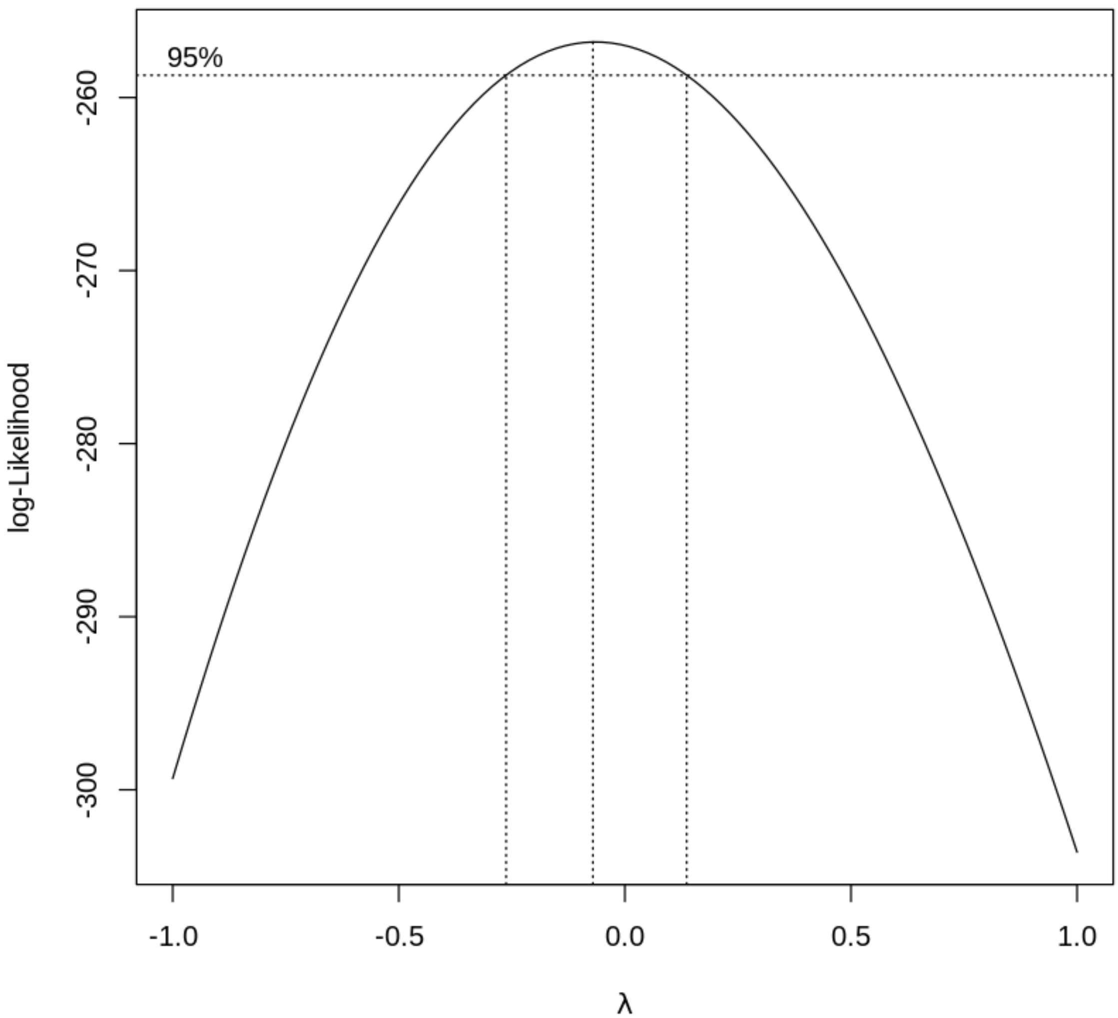
The idea is to transform the response variable $Y$ to a replacement response variable $Y_i^{(\lambda)}$, leaving the right-hand side of the regression model unchanged, so that the regression residuals become normally-distributed. Note that the regression coefficients will also change, because the response variable has changed; therefore, the regression coefficients must be interpreted with respect to the transformed variable. Also, any predictions made with the model have to be back-transformed, to be interpreted in the original units.

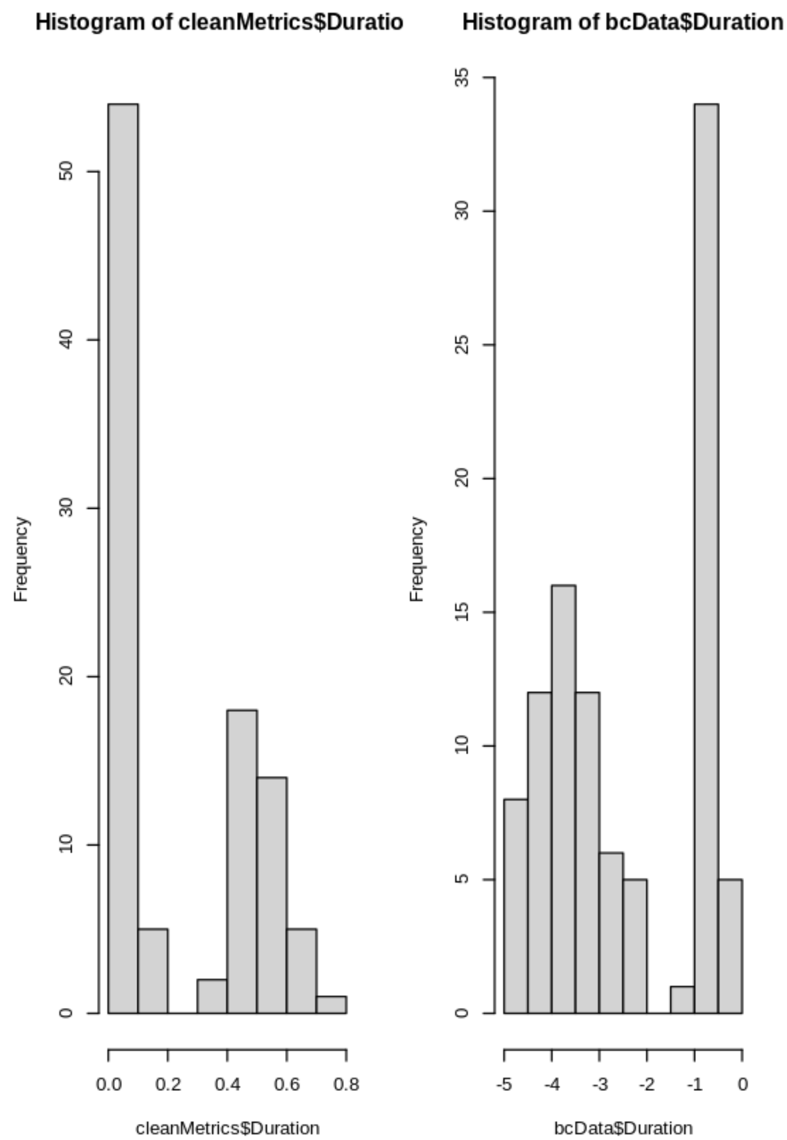
The standard (simple) Box-Cox transform is:

$$Y_i^{(\lambda)} = \begin{cases} \frac{Y_i^{\lambda}-1}{\lambda}, & (\lambda \neq 0) \\ log(Y_i), & (\lambda = 0) \end{cases}$$

*Box, G. E. P., & Cox, D. R. (1964). An Analysis of Transformations. Journal of the Royal Statistical Society, Series B (Metholodogical), 26(2), 211-252.*

http://www.css.cornell.edu/faculty/dgr2/_static/files/R_html/Transformations.html


95%
-260
-270
-280
-290
-300
log-Likelihood
-1.0
-0.5
0.0
0.5
1.0
λ




## 4.3 Normality Testing of the Trasformation

### 4.3.1 Shapiro-Wilk

The null-hypothesis of this test is that the population is normally distributed. Thus, if the p value is less than the chosen alpha level, then the null hypothesis is rejected and there is evidence that the data tested are not normally distributed. On the other hand, if the p value is greater than the chosen alpha level, then the null hypothesis (that the data came from a normally distributed population) can not be rejected (e.g., for an alpha level of .05, a data set with a p value of less than .05 rejects the null hypothesis that the data are from a normally distributed population).

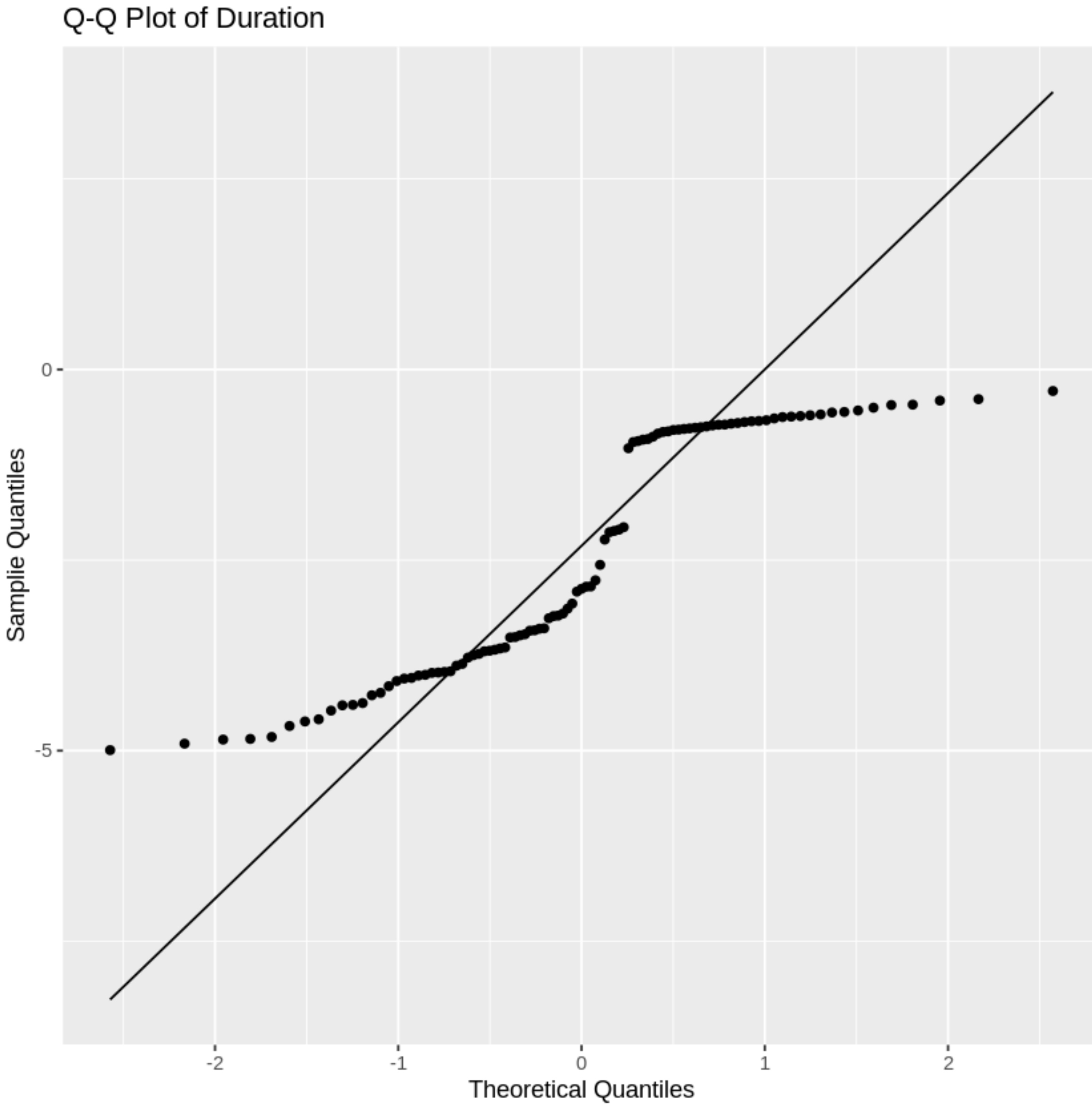
https://en.wikipedia.org/wiki/Shapiro–Wilk_test

```
    Shapiro-Wilk normality test

data:  bcData$Duration
W = 0.85873, p-value = 2.852e-08
```

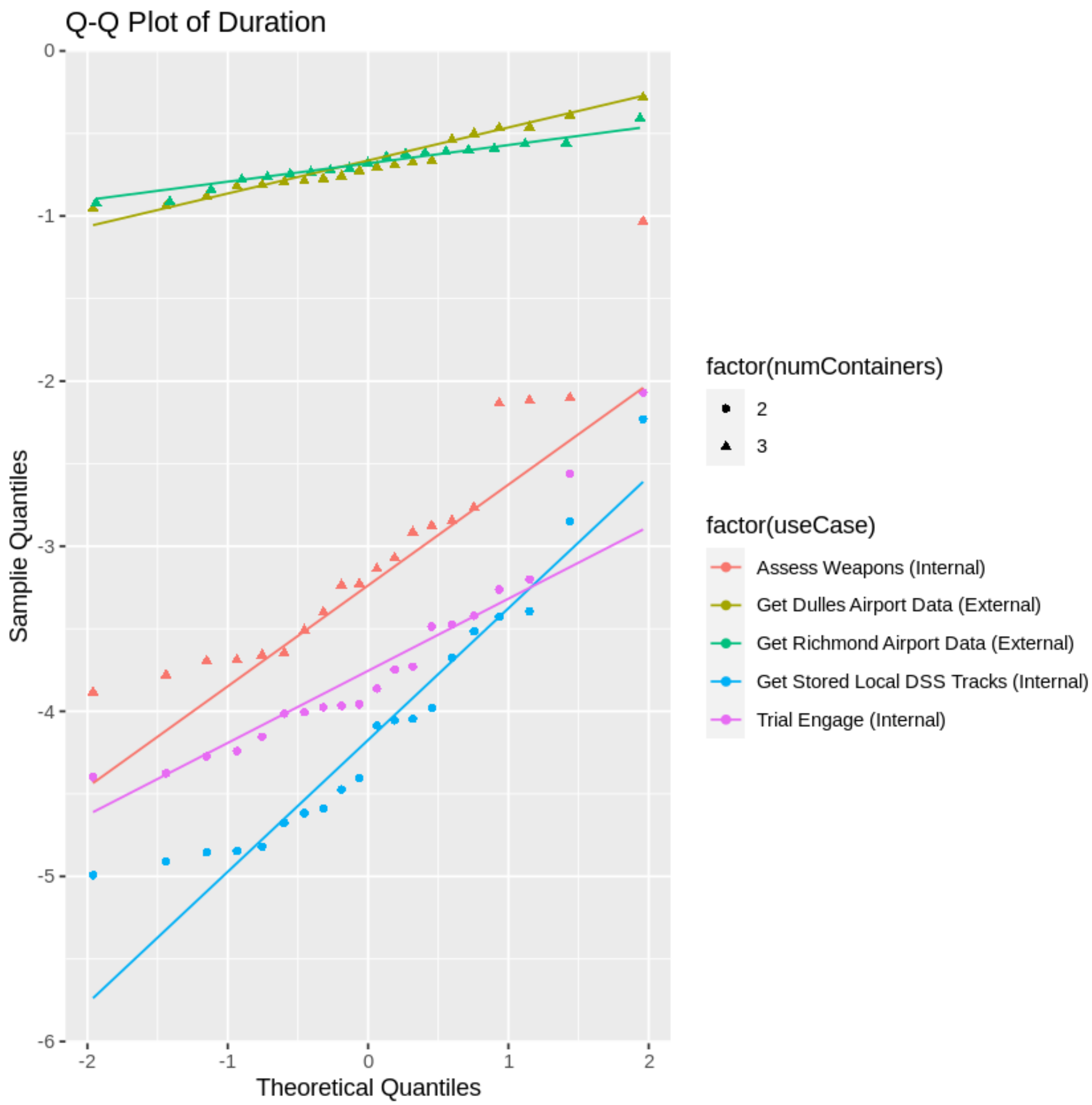
With p-value of 2.852e-08 $< 0.05$ we reject the null hypothesis that the data are from a normally distributed population. But we'll also do a Q-Q Norm plot to visually see the results.

*"if the p value is greater than the chosen alpha level, then the null hypothesis (that the data came from a normally distributed population) can not be rejected"*

### 4.3.2 Q-Q Norm



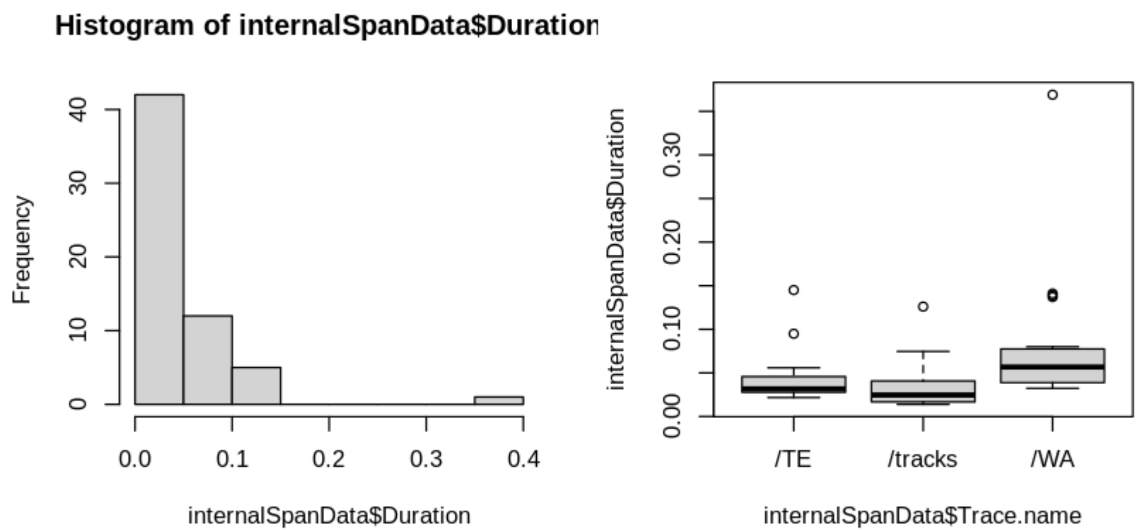
Q-Q Plot of Duration
Samplie Quantiles
Theoretical Quantiles
0
-5
-2
-1
0
1
2

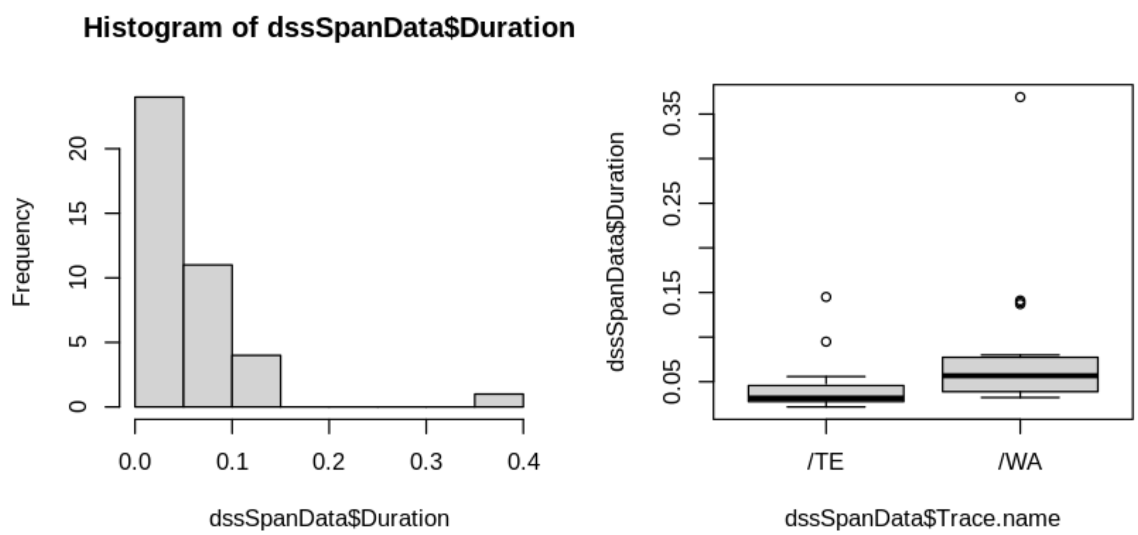



Our assumption here is that the separation of **Sample Quantiles** is from the difference between internal and external span durations (e.g. latency). Let's see what happens when we split the samples.

# 5 Separating "Original" Internal from External Data

## 5.1 Internal Data

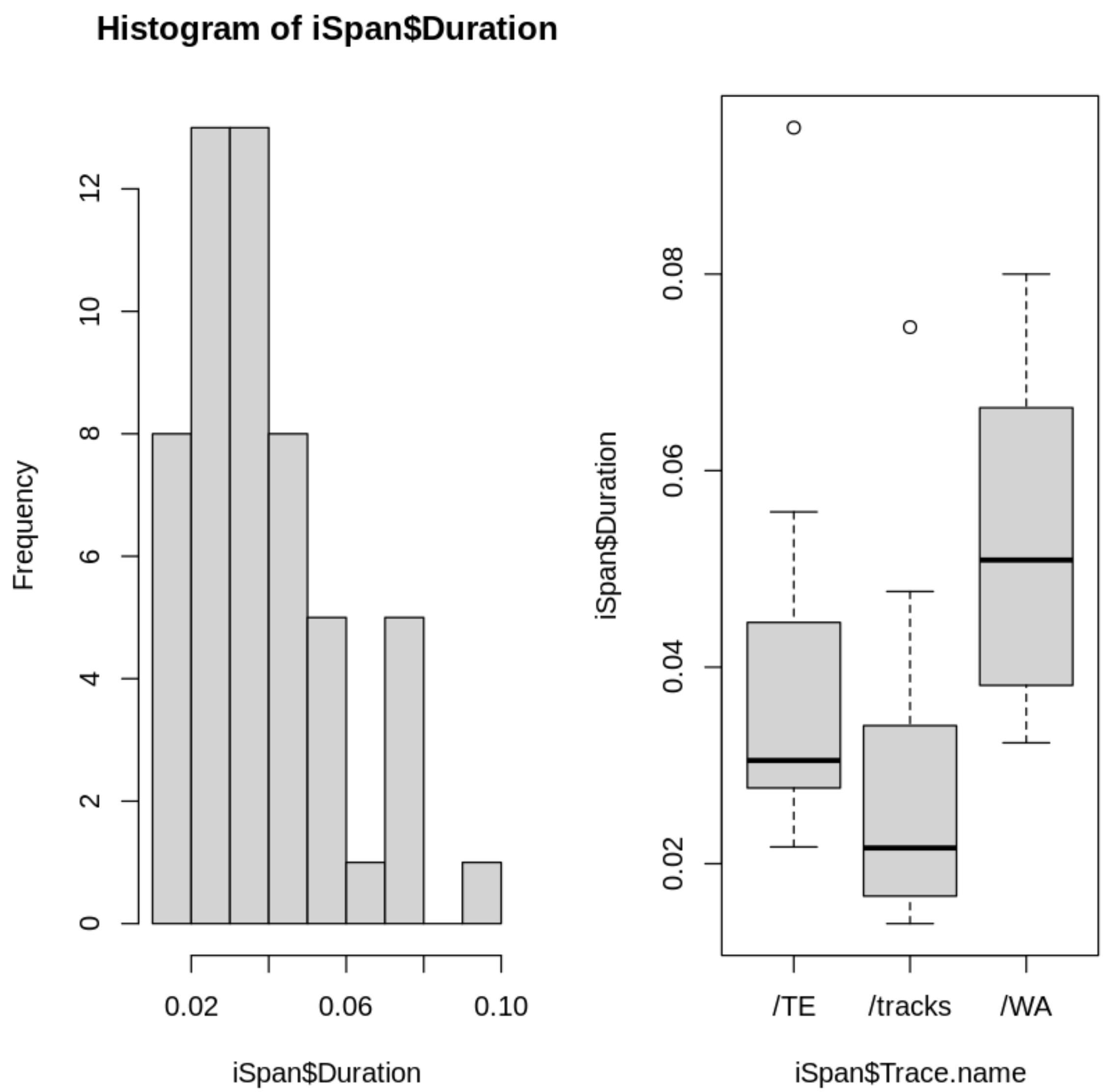



This result looks much better. However, we'll remove internal span outliers.

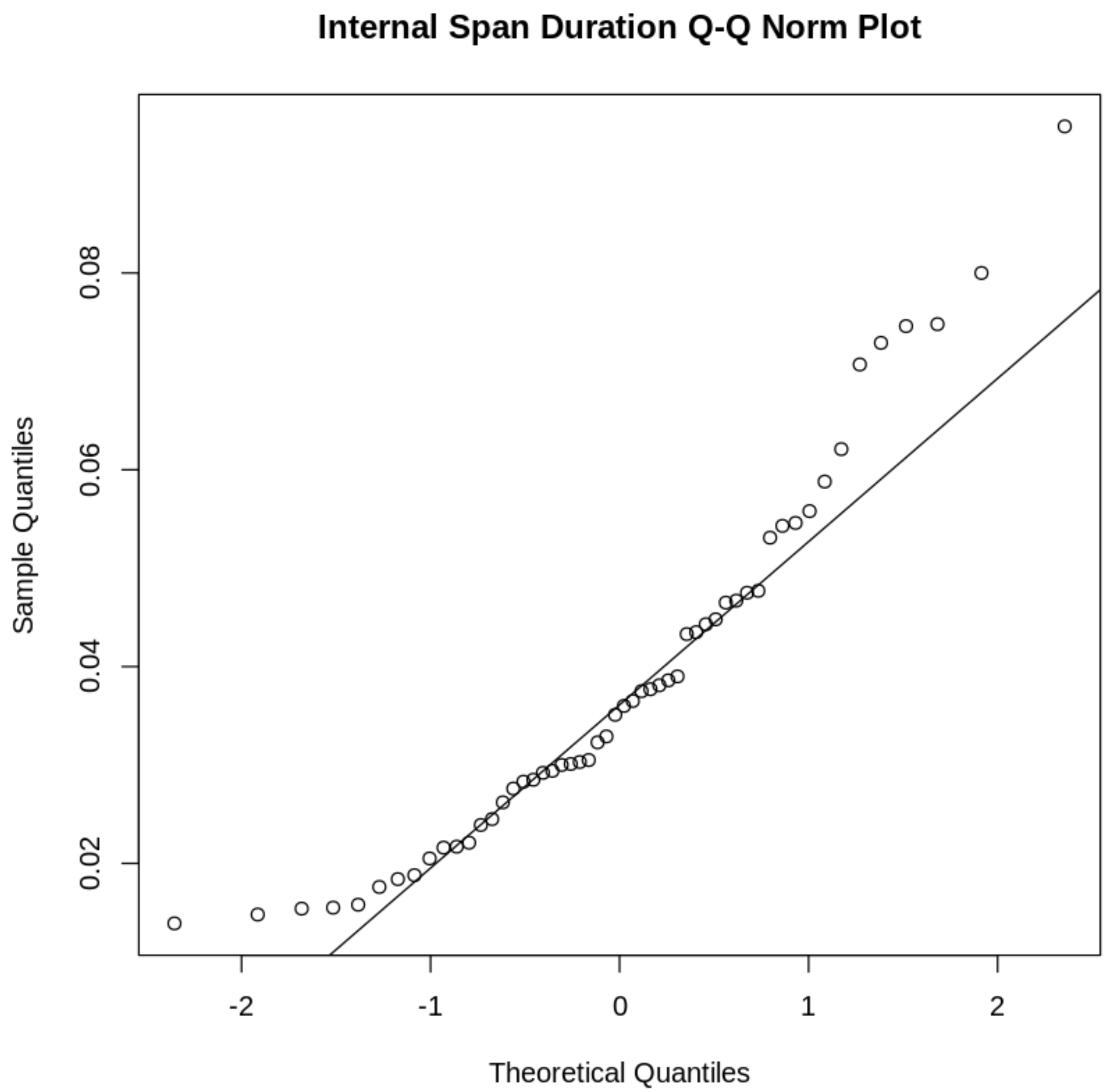
1. 0.126
2. 0.145
3. 0.139

4. 0.369
5. 0.137
6. 0.141



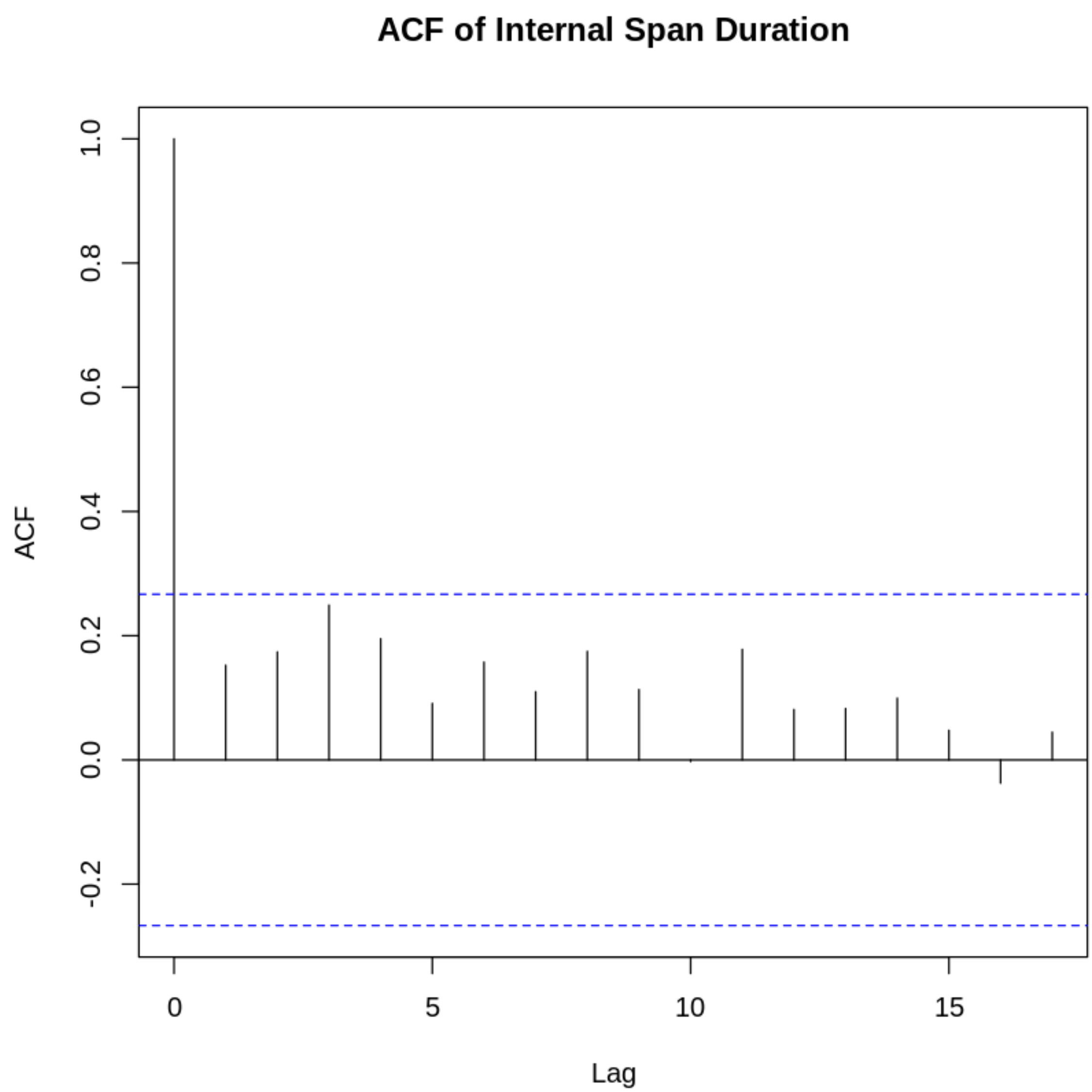

### 5.1.1 Q-Q Norm Plot of "Clean" Internal Span Data

We'll look a the Q-Q Norm Plot and Shapiro-Wilk Test




### 5.1.2 Autocorrelation

Autocorrelation plots are a commonly-used tool for checking randomness in a data set. This randomness is ascertained by computing autocorrelations for data values at varying time lags. If random, such autocorrelations should be near zero for any and all time-lag separations. If non-random, then one or more of the autocorrelations will be significantly non-zero.




#### 5.1.3 Shapiro-Wilk Normality Test

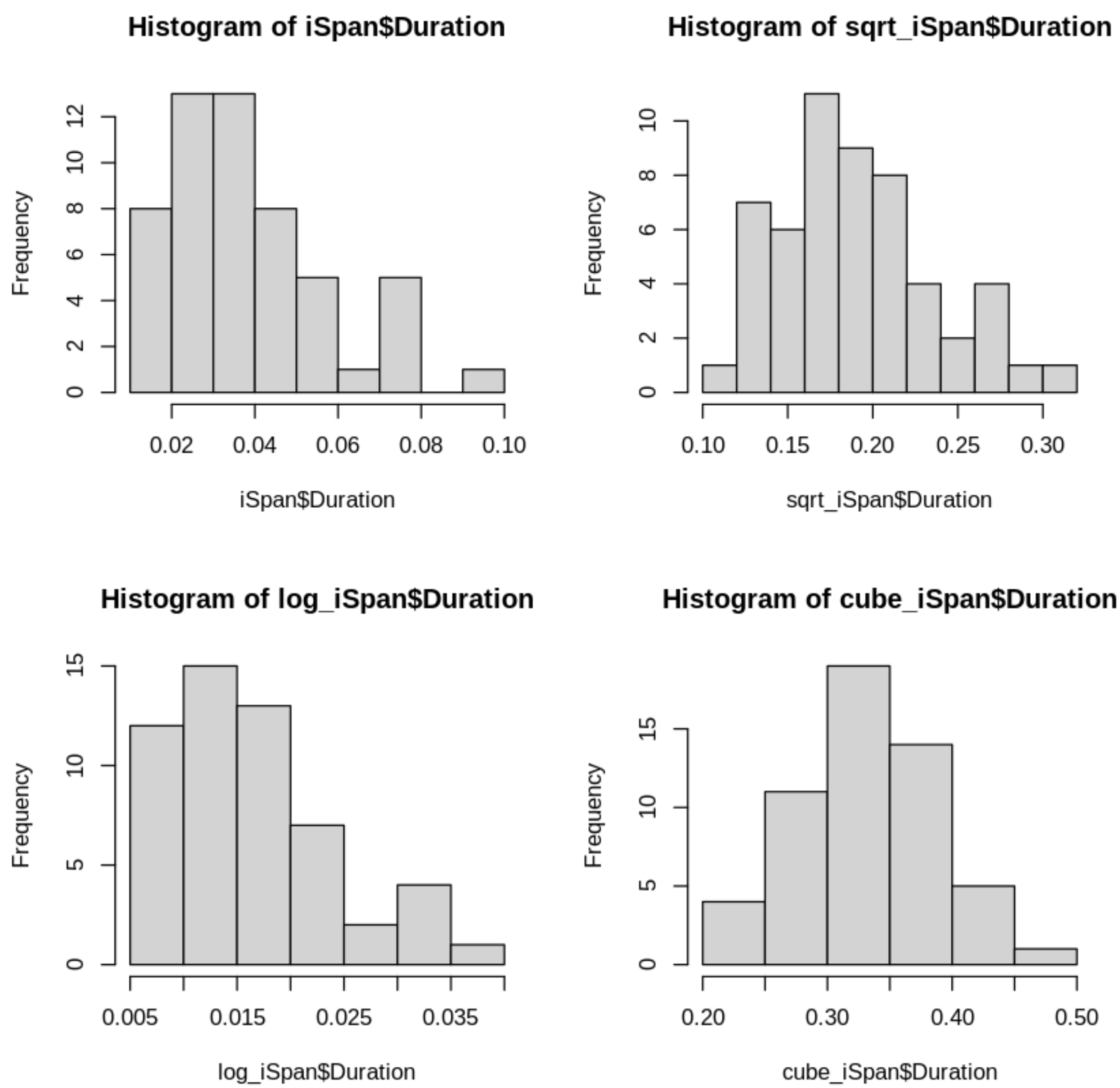
```
    Shapiro-Wilk normality test

data:  iSpan$Duration
W = 0.92499, p-value = 0.002321
```

With p-value of $0.002321 < 0.05$ we reject the null hypothesis that the data are from a normally distributed population.

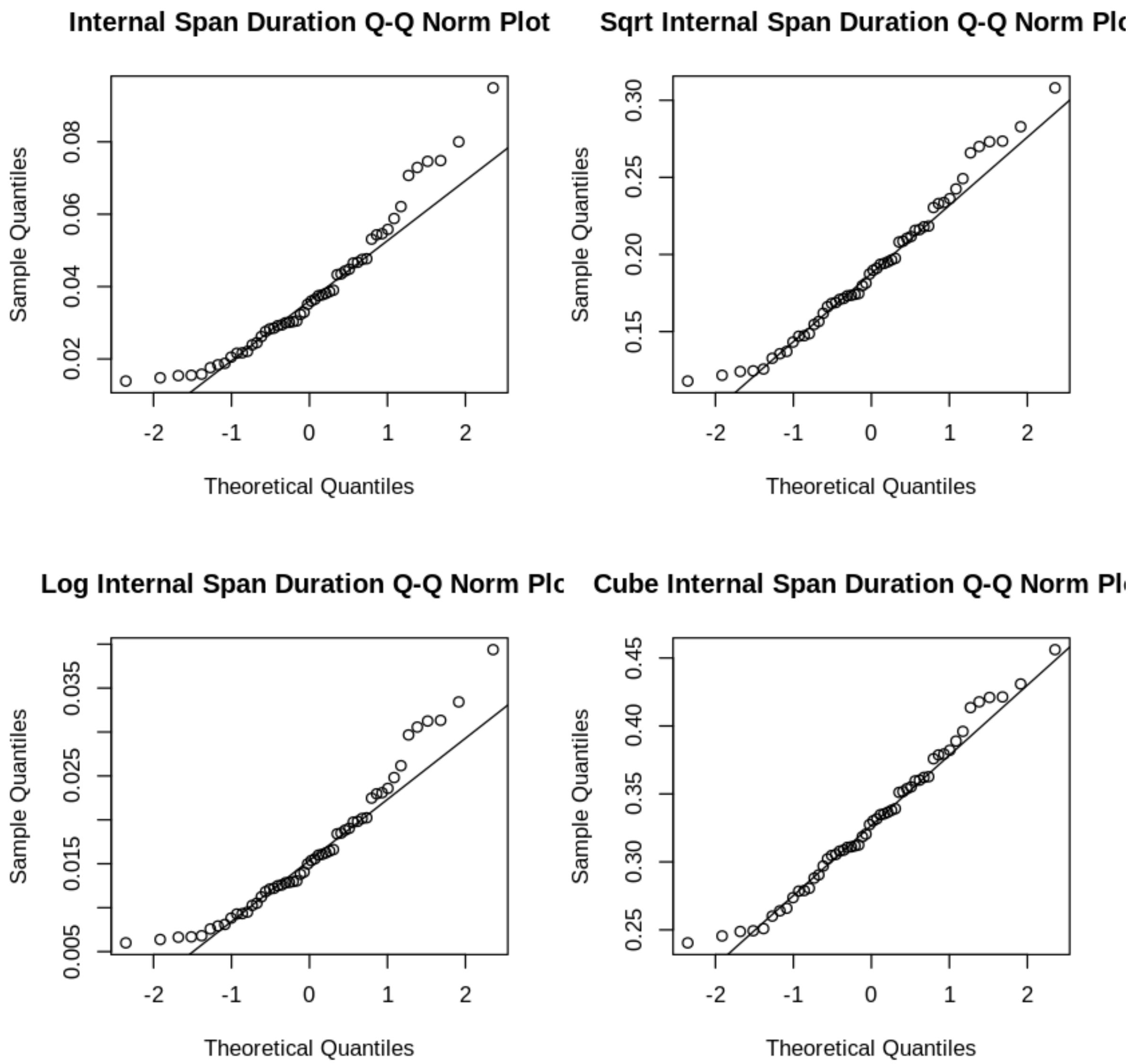
*"if the p value is greater than the chosen alpha level, then the null hypothesis (that the data came from a normally distributed population) can not be rejected"*

### 5.1.4 Data Transformations

#### 5.1.4.1 Sqrt-Log-Cube Transformations



### 5.1.4.2 Q-Q Norm Sqrt-Log-Cube




### 5.1.4.3 Shapiro-Wilk Testing Sqrt-Log-Cube

```
	Shapiro-Wilk normality test

data:  sqrt_iSpan$Duration
W = 0.9683, p-value = 0.1621
```

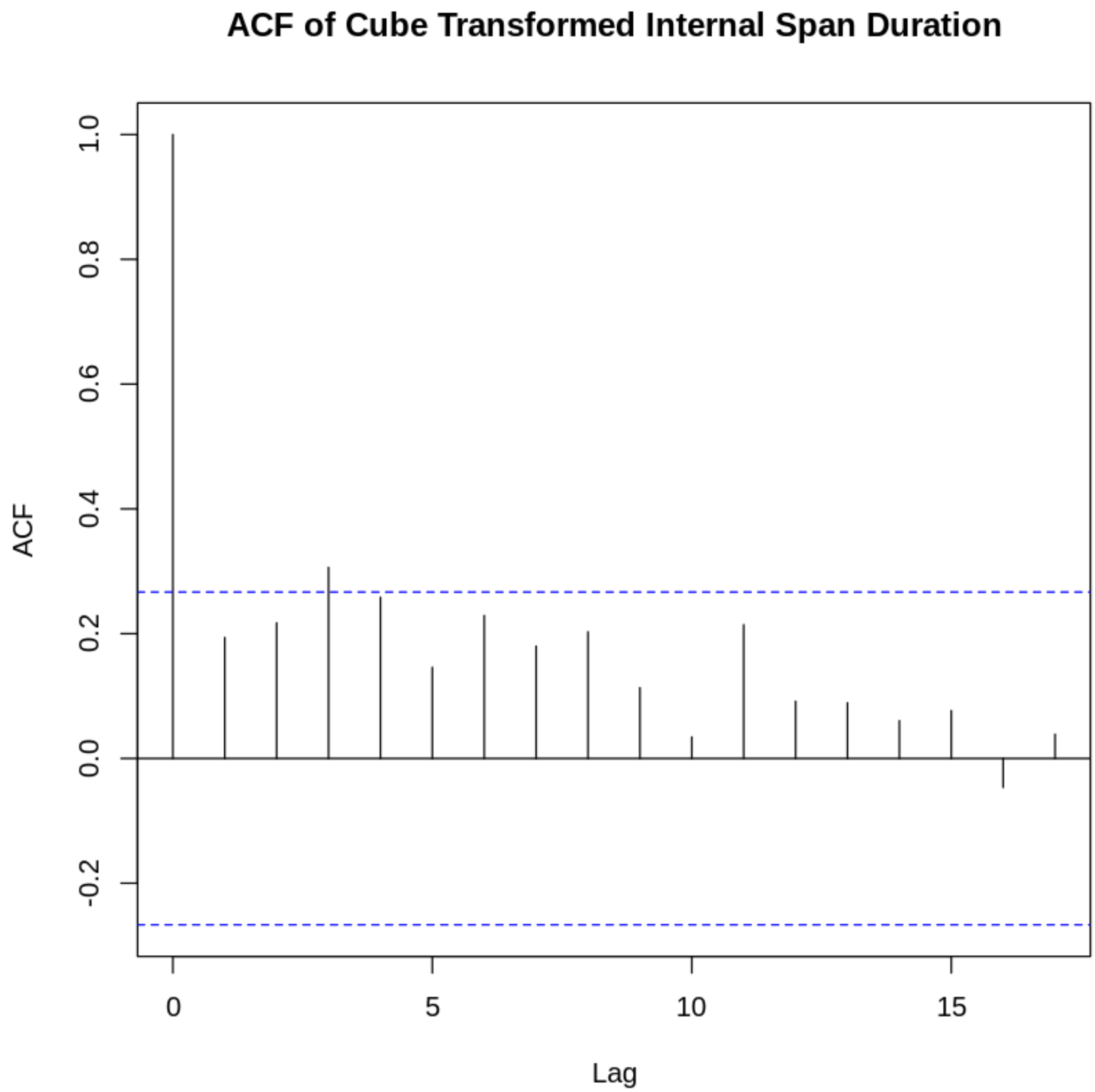
```
    Shapiro-Wilk normality test

data:  log_iSpan$Duration
W = 0.92922, p-value = 0.003398

    Shapiro-Wilk normality test

data:  cube_iSpan$Duration
W = 0.97633, p-value = 0.3593
```

The **cube transformation** seems to provide the best q-q plot fit. With a p-value of 0.3593 > 0.05 we fail to reject the null hypothesis and assume we now have a normal distribution.

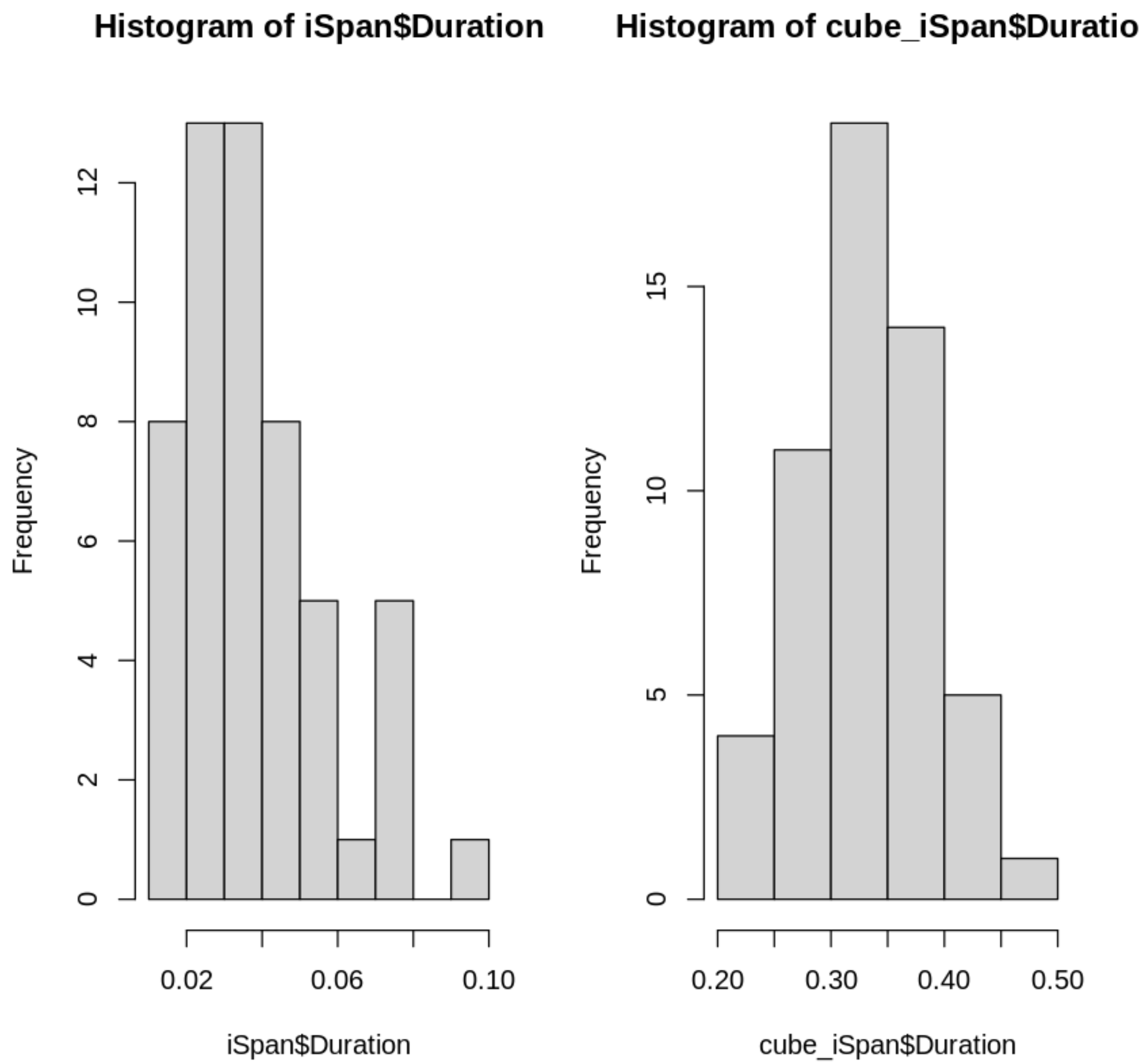
*"if the p value is greater than the chosen alpha level, then the null hypothesis (that the data came from a normally distributed population) can not be rejected"*

### 5.1.5 Autocorrelation

Autocorrelation plots are a commonly-used tool for checking randomness in a data set. This randomness is ascertained by computing autocorrelations for data values at varying time lags. If random, such autocorrelations should be near zero for any and all time-lag separations. If non-random, then one or more of the autocorrelations will be significantly non-zero.




The ACF indicates that the data is random since the results are near zero.




#### 5.1.6 Hypothesis Testing

We will use a Student's t-Test to test the hypothesis on **normal** internal span data. Our mean is 500 ms (e.g. $\mu = 0.5$ seconds) and our null hypthesis is less than 500 ms.

```
    One Sample t-test

data:  x
```

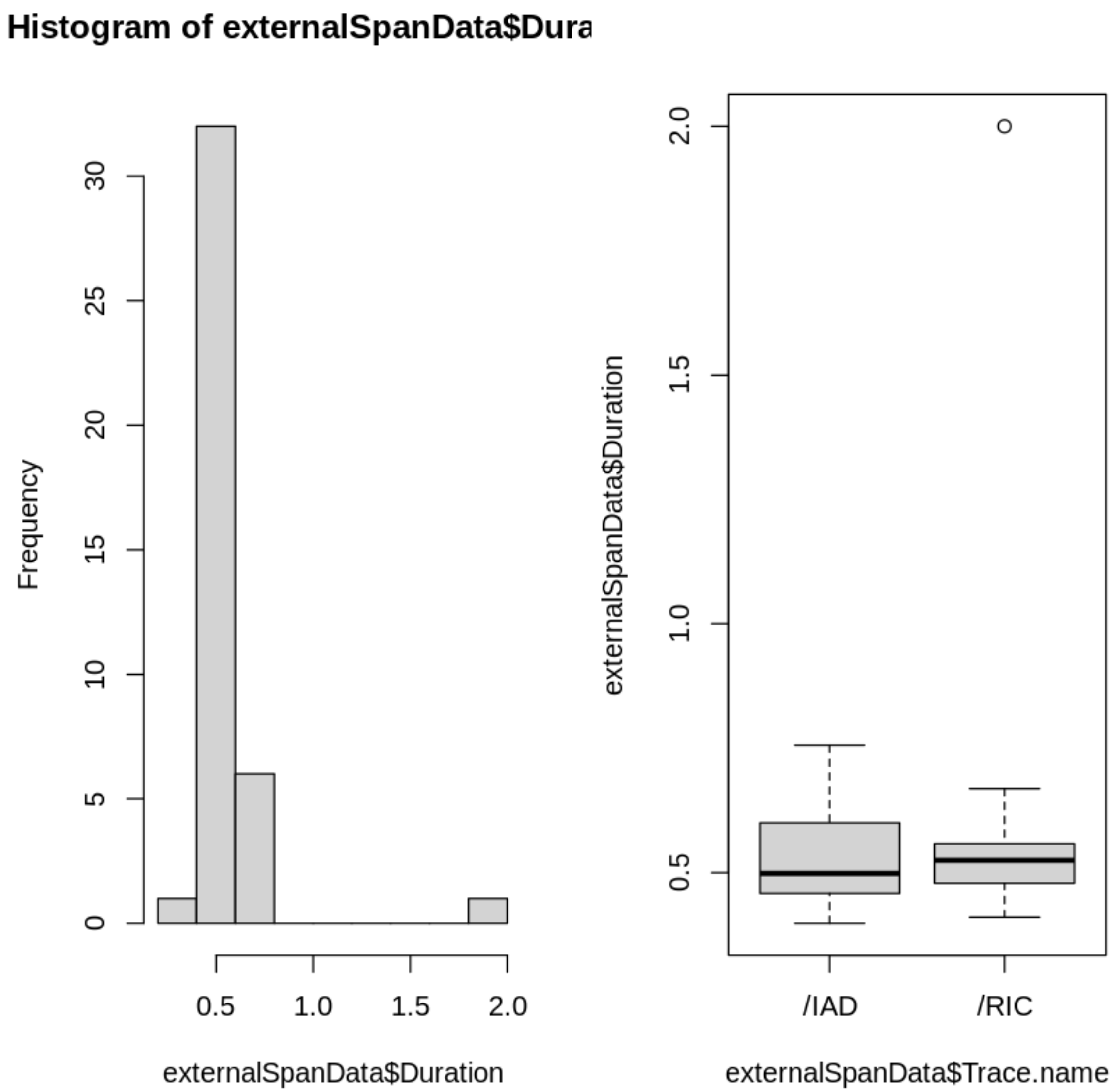
```
t = -64.323, df = 53, p-value = 1
alternative hypothesis: true mean is greater than 0.7937005
95 percent confidence interval:
 0.3178723       Inf
sample estimates:
mean of x
0.3299424


    One Sample t-test

data:  x
t = -180.44, df = 53, p-value = 1
alternative hypothesis: true mean is greater than 0.5
95 percent confidence interval:
 0.03440894        Inf
sample estimates:
 mean of x
0.03868889
```

With a original and transformation with a p-value of $1 > 0.05$ we fail to reject the null hypothesis, i.e. we assume that latency will be less than 500 ms.

*"If the p value is greater than the chosen alpha level, then the null hypothesis (that latency is $< 500$ ms) can not be rejected"*

## 5.2 External Data

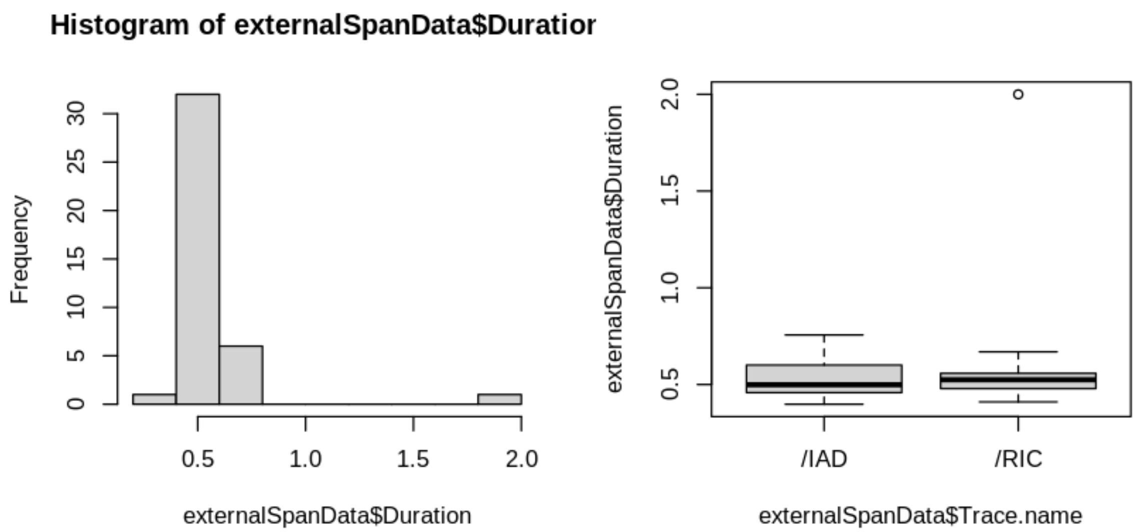
```
   Trace.ID           Trace.name           Start.time           Duration
 Length:40          Length:40          Min.   :1.651e+09   Min.   :0.3980
 Class :character   Class :character   1st Qu.:1.651e+09   1st Qu.:0.4670
 Mode  :character   Mode  :character   Median :1.651e+09   Median :0.5070
                                       Mean   :1.651e+09   Mean   :0.5565
                                       3rd Qu.:1.651e+09   3rd Qu.:0.5645
                                       Max.   :1.651e+09   Max.   :2.0000
   useCase          numContainers extNetworkHops
 Length:40          Min.   :3     Min.   :14
 Class :character   1st Qu.:3     1st Qu.:14
 Mode  :character   Median :3     Median :14
                    Mean   :3     Mean   :14
                    3rd Qu.:3     3rd Qu.:14
                    Max.   :3     Max.   :14
```

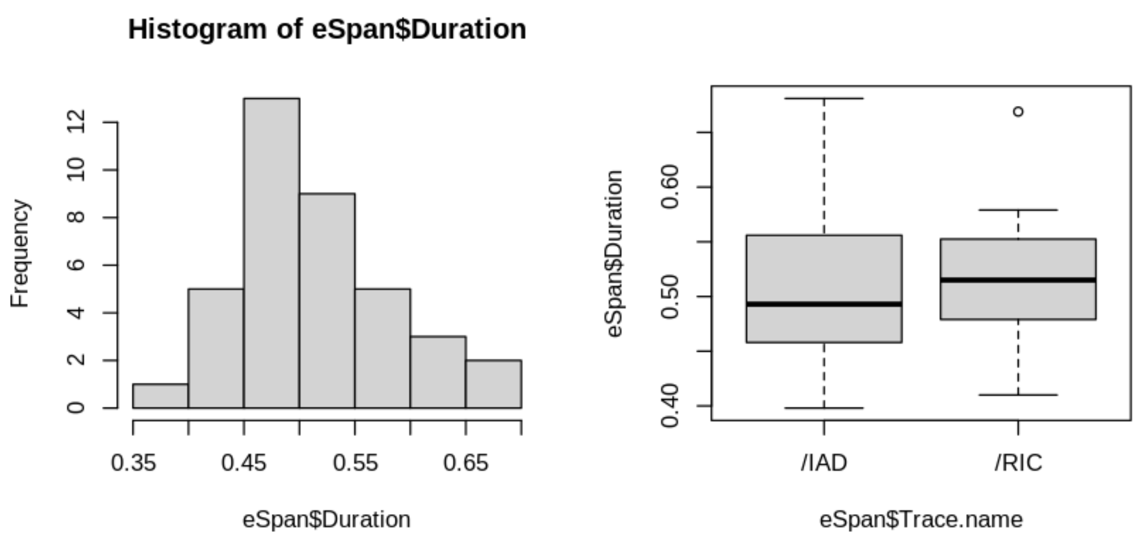



1. 2
2. 0.756

```
  Trace.ID           Trace.name          Start.time           Duration
 Length:38          Length:38          Min.   :1.651e+09   Min.   :0.3980
 Class :character   Class :character   1st Qu.:1.651e+09   1st Qu.:0.4650
 Mode  :character   Mode  :character   Median :1.651e+09   Median :0.5020
                                       Mean   :1.651e+09   Mean   :0.5132
                                       3rd Qu.:1.651e+09   3rd Qu.:0.5537
```

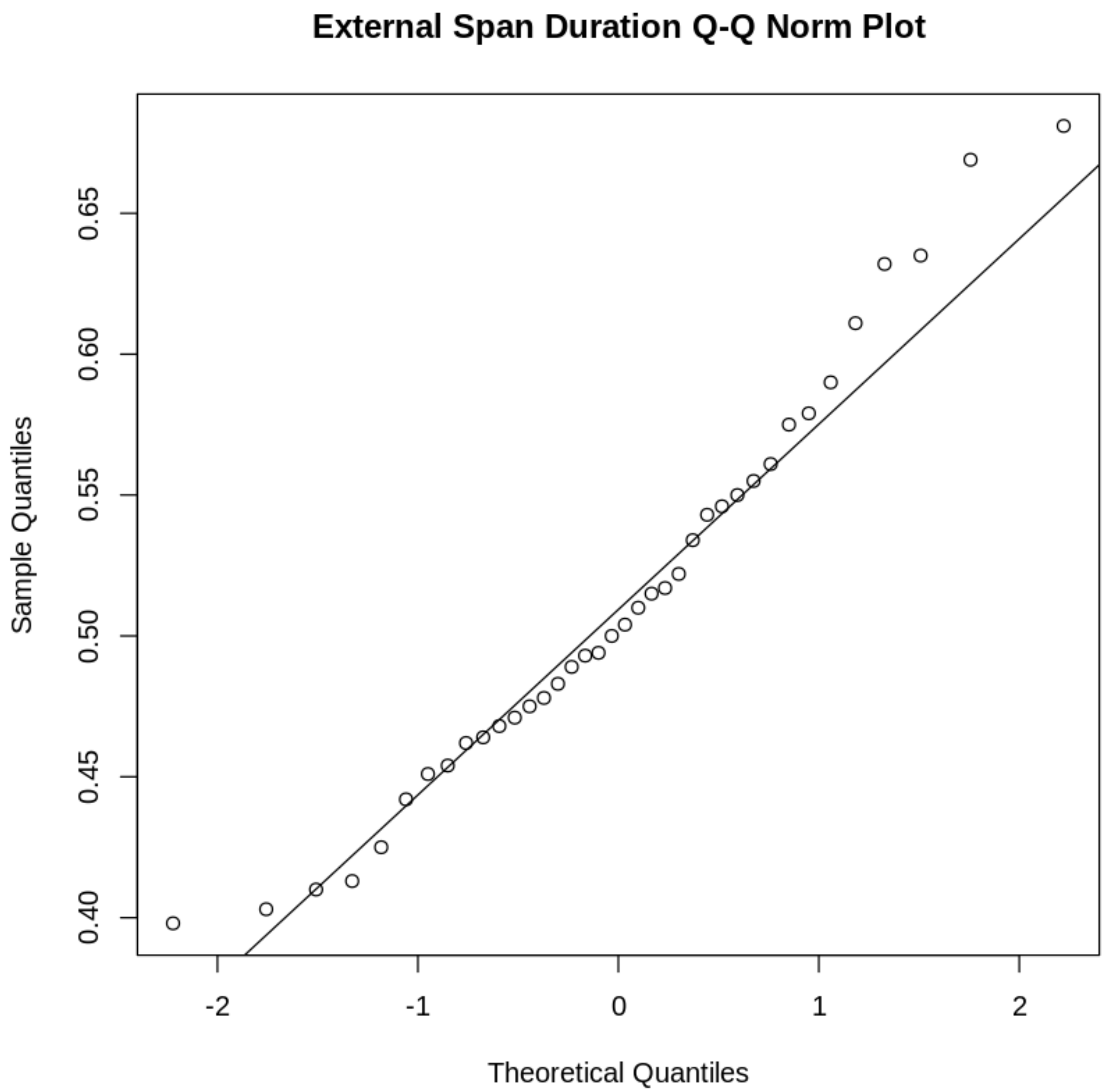
```
                                                   Max.   :1.651e+09   Max.   :0.6810
   useCase            numContainers extNetworkHops
 Length:38          Min.   :3     Min.   :14
 Class :character   1st Qu.:3     1st Qu.:14
 Mode  :character   Median :3     Median :14
                    Mean   :3     Mean   :14
                    3rd Qu.:3     3rd Qu.:14
                    Max.   :3     Max.   :14
```



### 5.2.1 Q-Q Norm Plot of "Clean" External Span Data

We'll look a the Q-Q Norm Plot and Shapiro-Wilk Test




### 5.2.2 Shapiro-Wilk Normality Test

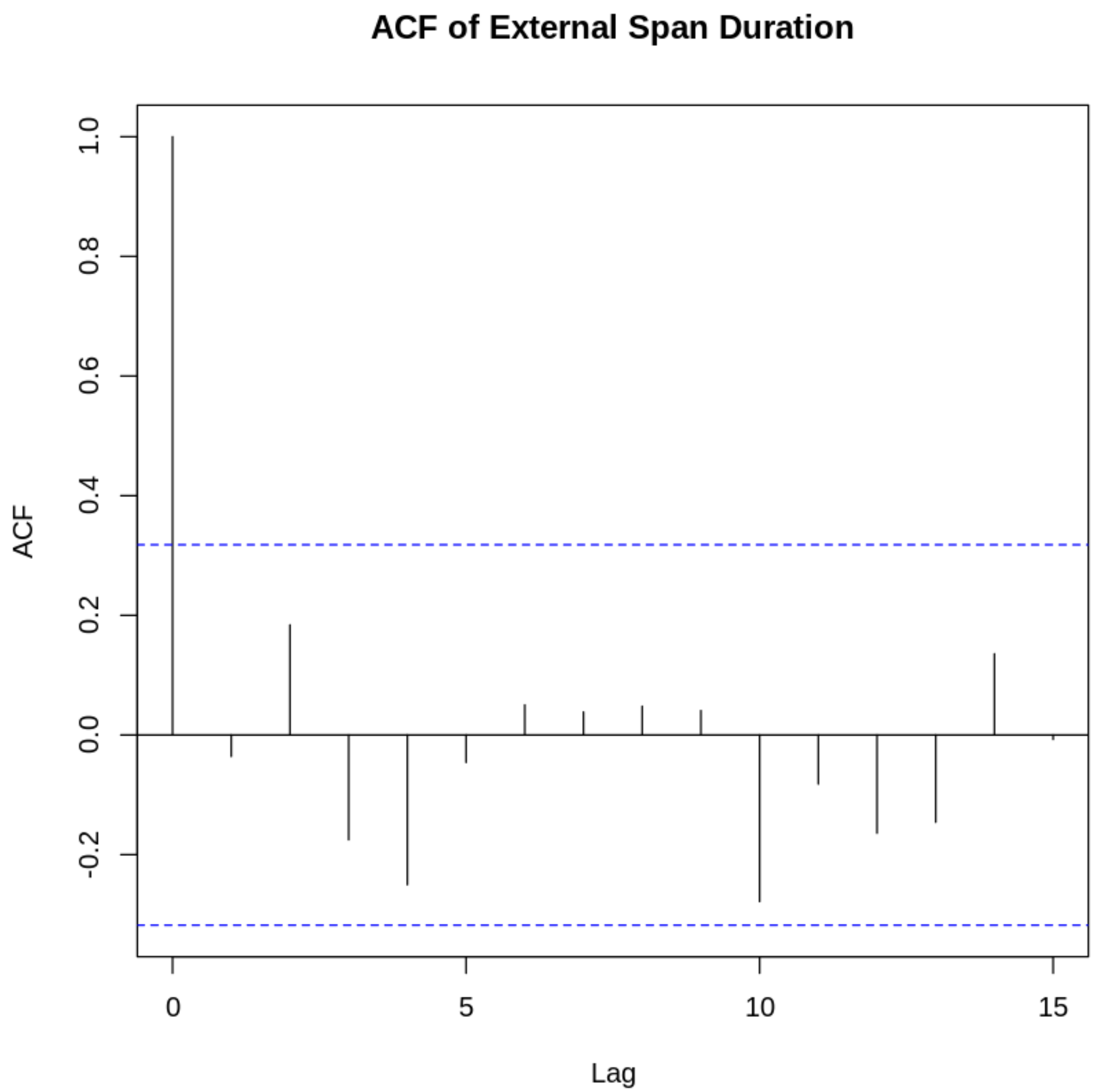
```
Shapiro-Wilk normality test
```

```
data:  eSpan$Duration
W = 0.96564, p-value = 0.2878
```

With a p-value of $0.2878 > 0.05$ we fail to reject the null hypothesis, i.e. we assume that we have a normal distribution.

*"if the p value is greater than the chosen alpha level, then the null hypothesis (that the data came from a normally distributed population) can not be rejected"*

### 5.2.3 Autocorrelation




The ACF indicates that the data is random since the results are near zero.

### 5.2.4 Hypothesis Testing

We will use a Student's t-Test to test the hypothesis on external span data. Our mean is 500 ms (e.g. $\mu = 0.5$ seconds) and our null hypthesis is less than 500 ms.

```
    One Sample t-test

data:  x
t = 1.1267, df = 37, p-value = 0.1336
alternative hypothesis: true mean is greater than 0.5
95 percent confidence interval:
 0.4934287       Inf
sample estimates:
mean of x
0.5132105
```

With a p-value of $0.1336 > 0.05$ we fail to reject the null hypothesis, i.e. we assume that 500 ms can be maintained for external service requests.

*"If the p value is greater than the chosen alpha level, then the null hypothesis (that latency is $<$ 500 ms) can not be rejected"*

# 6 Observations

## 6.1 General Discussion of Normality

It was required to separate external data from internal to establish normality of the data samples. The internal data set required transformation to establish normality, while the external data did not require a transformation.

## 6.2 Hypothesis Results

Hypothesis testing using the Student's t-Test indicates that latency constraints of 500 ms can be maintained internally and external. However, serveral external samples were greater than 500 ms. This is most likely due to the non-deterministic nature of internet (e.g. http) requests. Within the internal environment, data is directly routed between microservices within the Docker environment within a private network. The data shows that a container based microservice architecture can meet the requirement; however, care must be taken to manage processing per container that may increase container response times.