Time Series Forecasting for SFO Air Passengers

2023-06-14

1. Load Packages

```
library(fpp3)
```

```
## ── Attaching packages ─────────────────────────────────────── fpp3
0.5 ──
```

```
## ✓ tibble      3.2.1     ✓ tsibble     1.1.3
## ✓ dplyr       1.1.2     ✓ tsibbledata 0.4.1
## ✓ tidyr       1.3.0     ✓ feasts      0.3.1
## ✓ lubridate   1.9.2     ✓ fable       0.3.3
## ✓ ggplot2     3.4.2     ✓ fabletools  0.3.3
```

```
## ── Conflicts ─────────────────────────────────────────── fpp3_confli
cts ──
## ✖ lubridate::date()    masks base::date()
## ✖ dplyr::filter()      masks stats::filter()
## ✖ tsibble::intersect() masks base::intersect()
## ✖ tsibble::interval()  masks lubridate::interval()
## ✖ dplyr::lag()         masks stats::lag()
## ✖ tsibble::setdiff()   masks base::setdiff()
## ✖ tsibble::union()     masks base::union()
```

```
library(tsibble)
library(readr)
library(tseries)
```

```
## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo
```

```
library(plotly)
```

```
##
## Attaching package: 'plotly'
```

```
## The following object is masked from 'package:ggplot2':
##
##     last_plot
```

```
## The following object is masked from 'package:stats':
##
##     filter
```

```
## The following object is masked from 'package:graphics':
##
##     layout

library(knitr)
library(officedown)
```

2. Load data from SFO air passenger .csv file

```
## Rows: 50,730
## Columns: 12
## $ operating_airline           <chr> "ATA Airlines", "ATA Airlines", "ATA A
irli…
## $ operating_airline_iata_code <chr> "TZ", "TZ", "TZ", "AC", "AC", "CA", "C
A", …
## $ published_airline           <chr> "ATA Airlines", "ATA Airlines", "ATA A
irli…
## $ published_airline_iata_code <chr> "TZ", "TZ", "TZ", "AC", "AC", "CA", "C
A", …
## $ geo_summary                 <chr> "Domestic", "Domestic", "Domestic", "I
nter…
## $ geo_region                  <chr> "US", "US", "US", "Canada", "Canada",
"Asi…
## $ activity_type_code          <chr> "Deplaned", "Enplaned", "Thru / Transi
t", …
## $ price_category_code         <chr> "Low Fare", "Low Fare", "Low Fare", "O
ther…
## $ terminal                    <chr> "Terminal 1", "Terminal 1", "Terminal
1", …
## $ boarding_area               <chr> "B", "B", "B", "B", "B", "G", "G", "A"
, "A…
## $ passenger_count             <dbl> 27271, 29131, 5415, 35156, 34090, 6263
, 55…
## $ year                        <date> 2005-07-01, 2005-07-01, 2005-07-01, 2
005-…
```

3. Data Exploration

3.1.1.1. Air Passengers Traffic at SFO

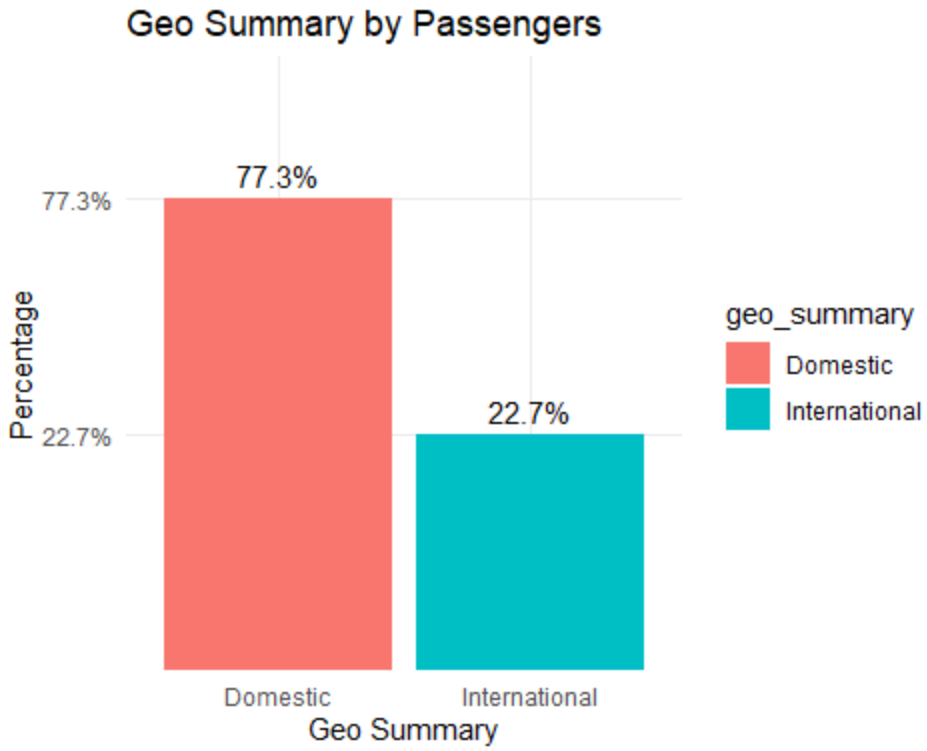
3.1.1.2. Air Passengers Traffic at SFO by Activity Type

3.1.1.3. Air Passengers Traffic at SFO by Geography

```
## Warning in RColorBrewer::brewer.pal(N, "Set2"): minimal value for n is 3,
returning requested palette with 3 different levels

## Warning in RColorBrewer::brewer.pal(N, "Set2"): minimal value for n is 3,
returning requested palette with 3 different levels
```

3.1.1.4. Geo Summary by Passengers




```
## Selecting by percent
```

3.1.1.5. Top 10 Operating Airlines by Percentage

Table 1: *sfo_top_passenger table*

operating_airline	total	percent
United Airlines	338.15071	30.1%
SkyWest Airlines	95.37713	8.5%
United Airlines - Pre 07/01/2013	89.15942	7.9%
American Airlines	80.36718	7.2%
Delta Air Lines	79.17331	7%
Southwest Airlines	73.45913	6.5%
Virgin America	66.76843	5.9%
Alaska Airlines	52.80735	4.7%
JetBlue Airways	30.02645	2.7%
US Airways	18.45011	1.6%

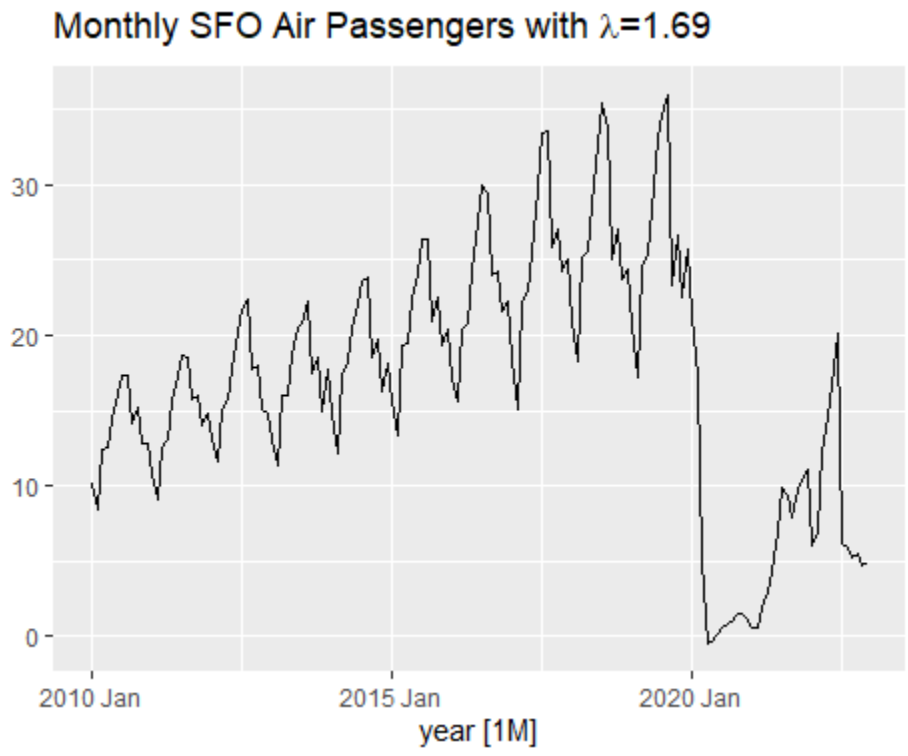
4. Data Transformation

4.1.1.1. Convert to tisbble format

Table 2: *sfo_passenger table*

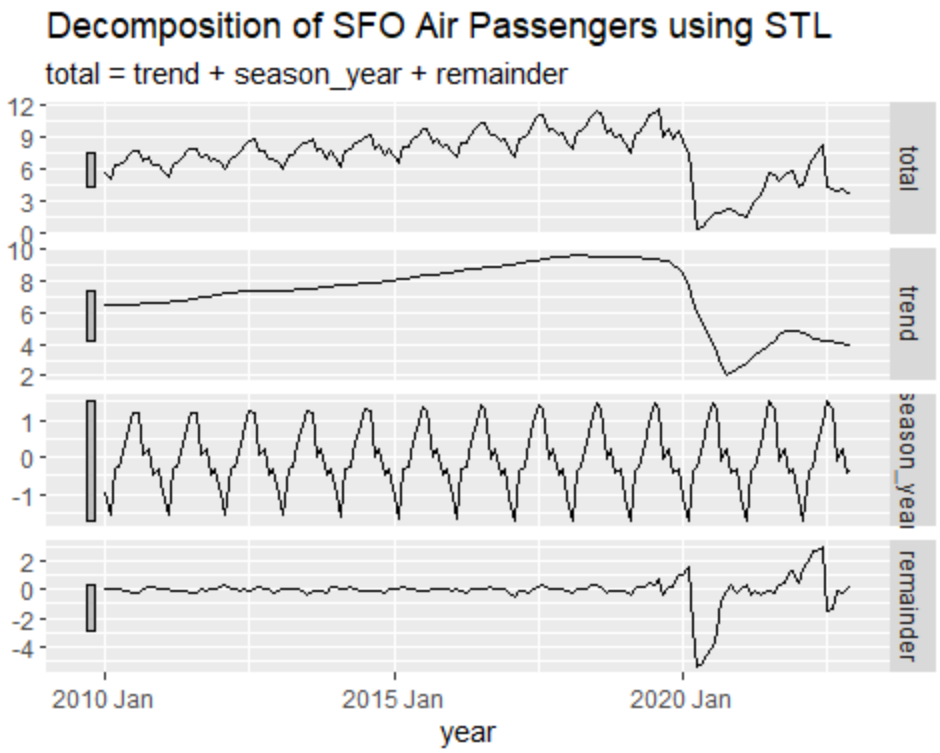
year	total
2010 Jan	5.570932
2010 Feb	5.030722
2010 Mar	6.211916
2010 Apr	6.278118
2010 May	6.760710
2010 Jun	7.225772

4.1.1.2. Box-Cox transformation for `lambda`



Note: We tried implementing Box-Cox transformation, but it did not have much impact on the final results, hence while applying final model fitting we used non transformed data.

4.1.1.3. Decomposition using STL



4.1.1.4. KPSS test for differencing

kpss_stat	kpss_pvalue
0.6012911	0.02251899

ndiffs

1

p-value (0.02) is significant. Reject null hypothesis. It indicate that the series is not stationary. Therefore a number difference required to make a time series stationary.

4.1.1.5. Dickey-Fuller test

```
## [1] 0.3541204
```

4.1.1.6. Split train and test set

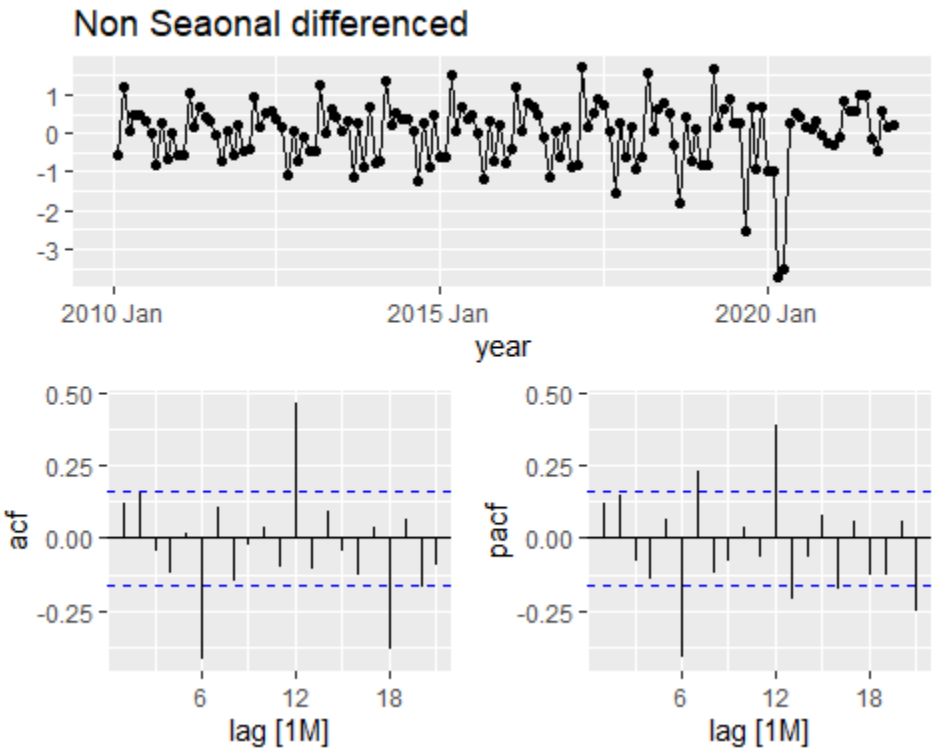
```
## [1] "Train Min:  2010 Jan  Train Max:  2021 Dec"

## [1] "Test Min:  2022 Jan  Test Max:  2022 Dec"
```

4.1.1.7. Examine ACF and PACF plots for the differenced

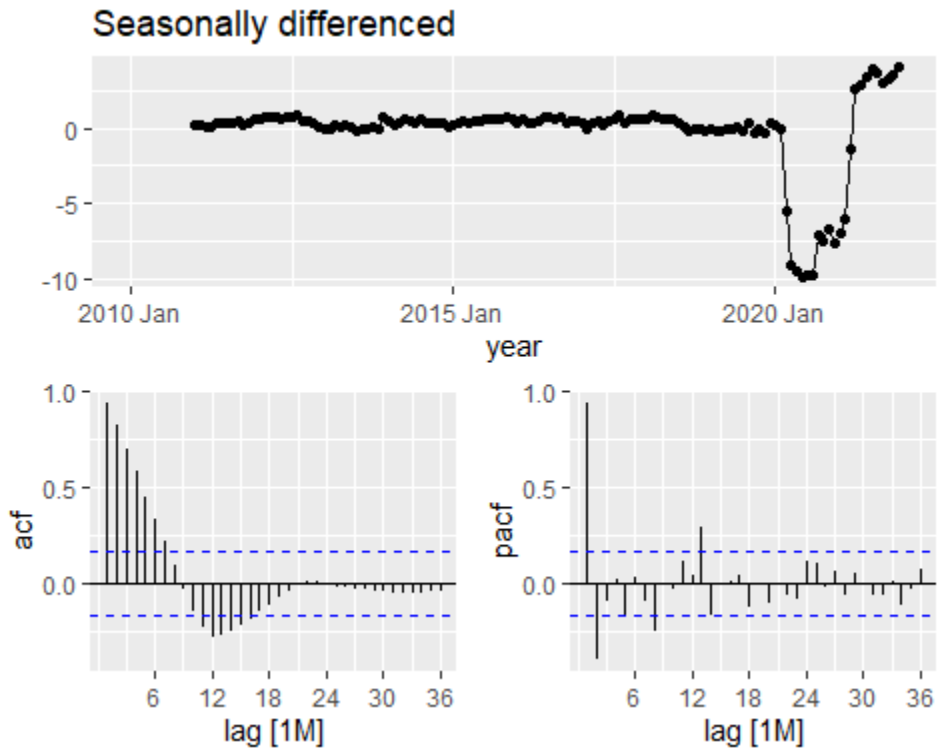
```
## Warning: Removed 1 row containing missing values (`geom_line()`).

## Warning: Removed 1 rows containing missing values (`geom_point()`).
```




```
## Warning: Removed 12 rows containing missing values (`geom_line()`).
```

```
## Warning: Removed 12 rows containing missing values (`geom_point()`).
```



5. Model Fitting

5.1.1.1. Fit the models (ets, arima)

Model name	Orders
Ets_auto	<ETS(A,Ad,A)>
Ets_ses	<ETS(A,A,N)>
Ets_hw_mul	<ETS(M,A,M)>
Ets_damped_add	<ETS(A,Ad,A)>
Ets_damped_mul	<ETS(A,Ad,M)>
Arima_stepwise	<ARIMA(1,0,2)(2,0,0)[12] w/ mean>
Arima_search	<ARIMA(1,0,2)(2,0,0)[12] w/ mean>
Arima_311	<ARIMA(3,1,1)(2,0,0)[12]>
Arima_410	<ARIMA(4,1,0)(0,0,2)[12]>
Arima_012	<ARIMA(0,1,2)(0,0,2)[12]>
Arima012011	<ARIMA(0,1,2)(0,1,1)[12]>

Model name	Orders
Arima210011	<ARIMA(2,1,0)(0,1,1)[12]>
Arima011011	<ARIMA(0,1,1)(0,1,1)[12]>
Arima212011	<ARIMA(2,1,2)(0,1,1)[12]>
Arima210111	<ARIMA(2,1,0)(1,1,1)[12]>

6. Model Evaluation Metrics

6.1.1.1. Accuracy measures of the forecast

```
## Warning: The future dataset is incomplete, incomplete out-of-sample data w
ill be treated as missing.
## 24 observations are missing between 2023 Jan and 2024 Dec
```

.model	.type	RMSE	MAE	MAPE
Ets_ses	Test	1.717613	1.634137	35.92445
Ets_damped_mul	Test	1.795588	1.673425	37.11414
Arima011011	Test	1.800386	1.659921	35.86206
Arima012011	Test	1.813586	1.674685	36.15545
Arima210011	Test	1.820583	1.679460	36.38118
Arima210111	Test	1.923835	1.738153	38.92653
Arima212011	Test	1.985007	1.800789	40.93028
Ets_auto	Test	2.191658	1.918942	44.33543
Ets_damped_add	Test	2.191658	1.918942	44.33543
Arima_012	Test	2.637478	1.853172	29.97824
Arima_410	Test	2.671977	1.882842	30.48522
Arima_search	Test	2.733989	1.847116	29.07042
Arima_stepwise	Test	2.733989	1.847116	29.07042
Arima_311	Test	3.079463	2.311271	39.14233
Ets_hw_mul	Test	3.311143	2.515613	63.20995

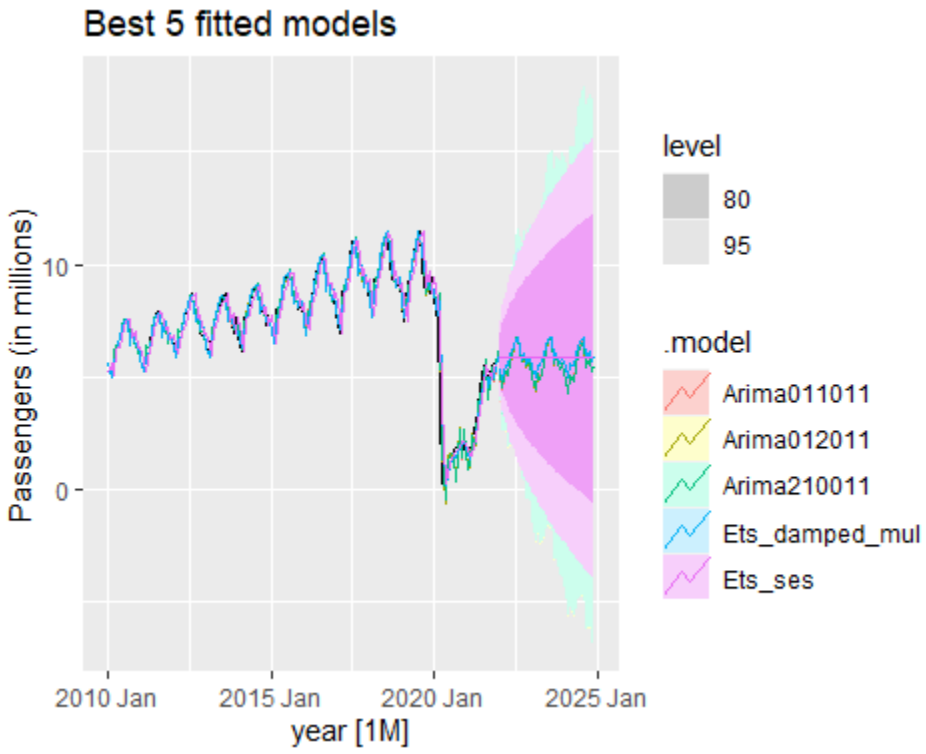
- RMSE (Root Mean Squared Error): measures the average difference between the forecasted and the actual values, taking into account the squared differences.
- The `lowest RMSE` indicates `better accuracy`.

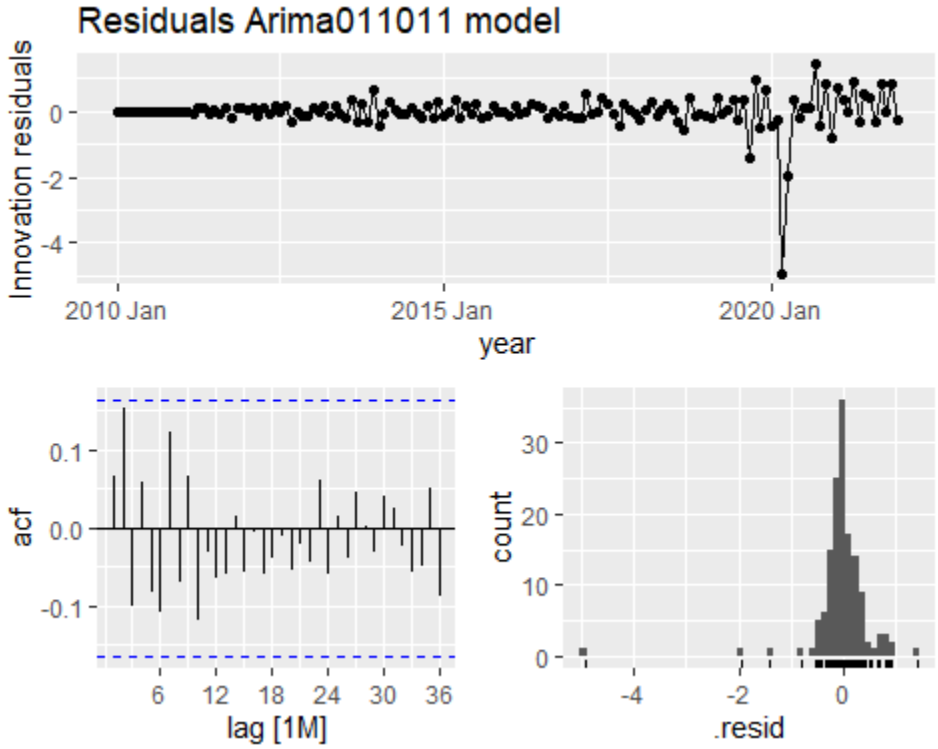
6.1.1.2. Summary report for fitted time series models

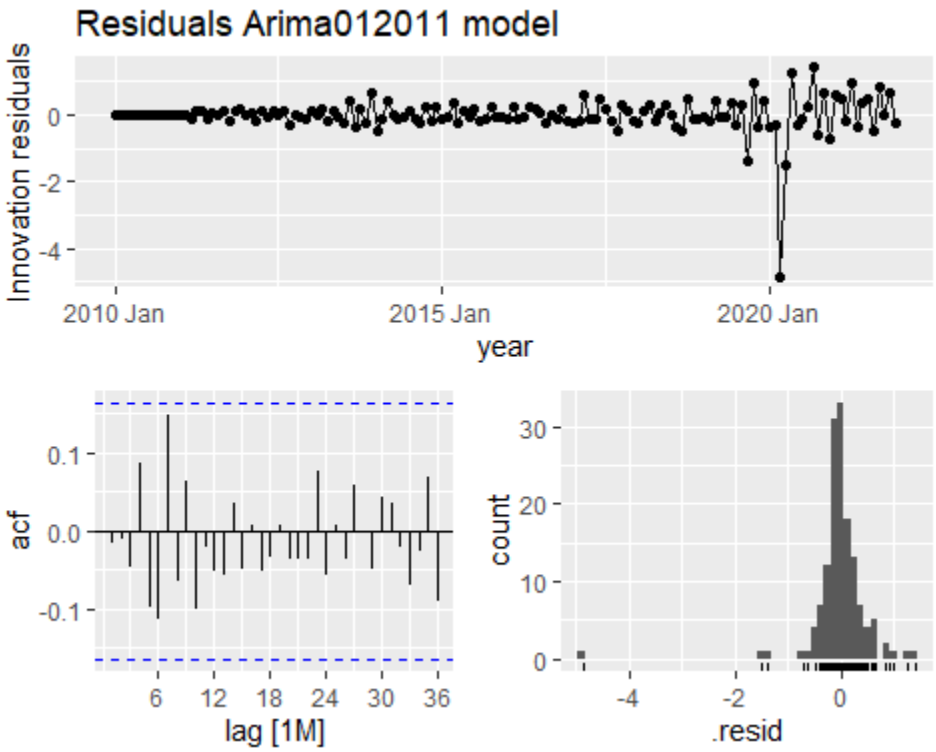
```
## Warning in report.mdl_df(selected_models): Model reporting is only support
ed
## for individual models, so a glance will be shown. To see the report for a
## specific model, use `select()` and `filter()` to identify a single model.
```

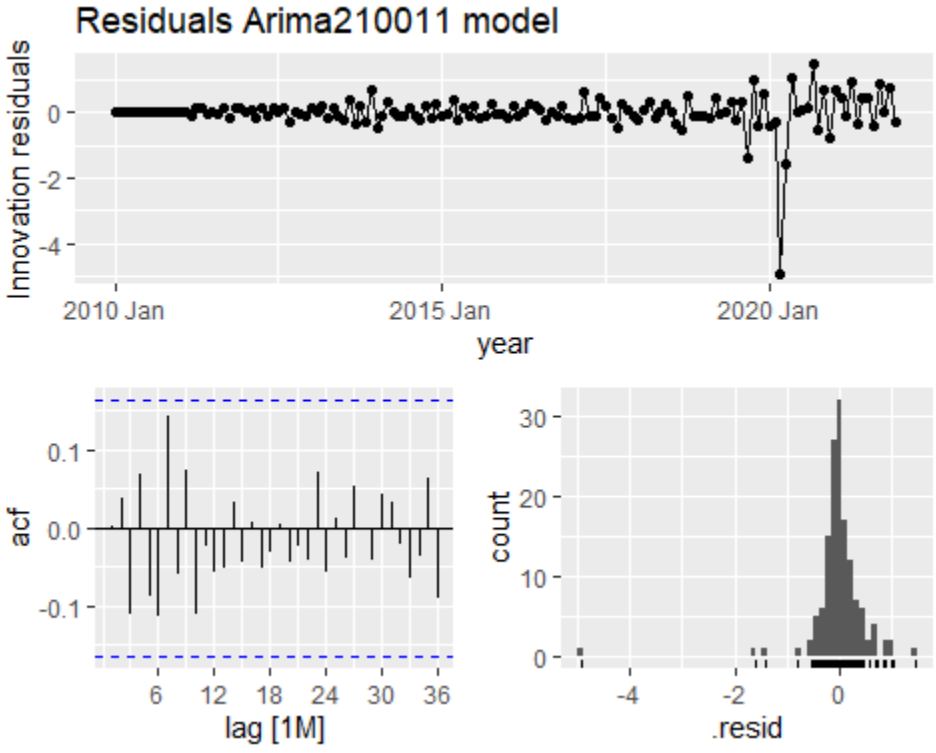
.model	AIC	AICc	BIC
Arima012011	250.7273	251.0448	262.2281
Arima210011	252.4017	252.7191	263.9025
Arima011011	253.9418	254.1308	262.5674
Ets_damped_mul	585.9072	591.3792	639.3638
Ets_ses	670.4162	670.8510	685.2653

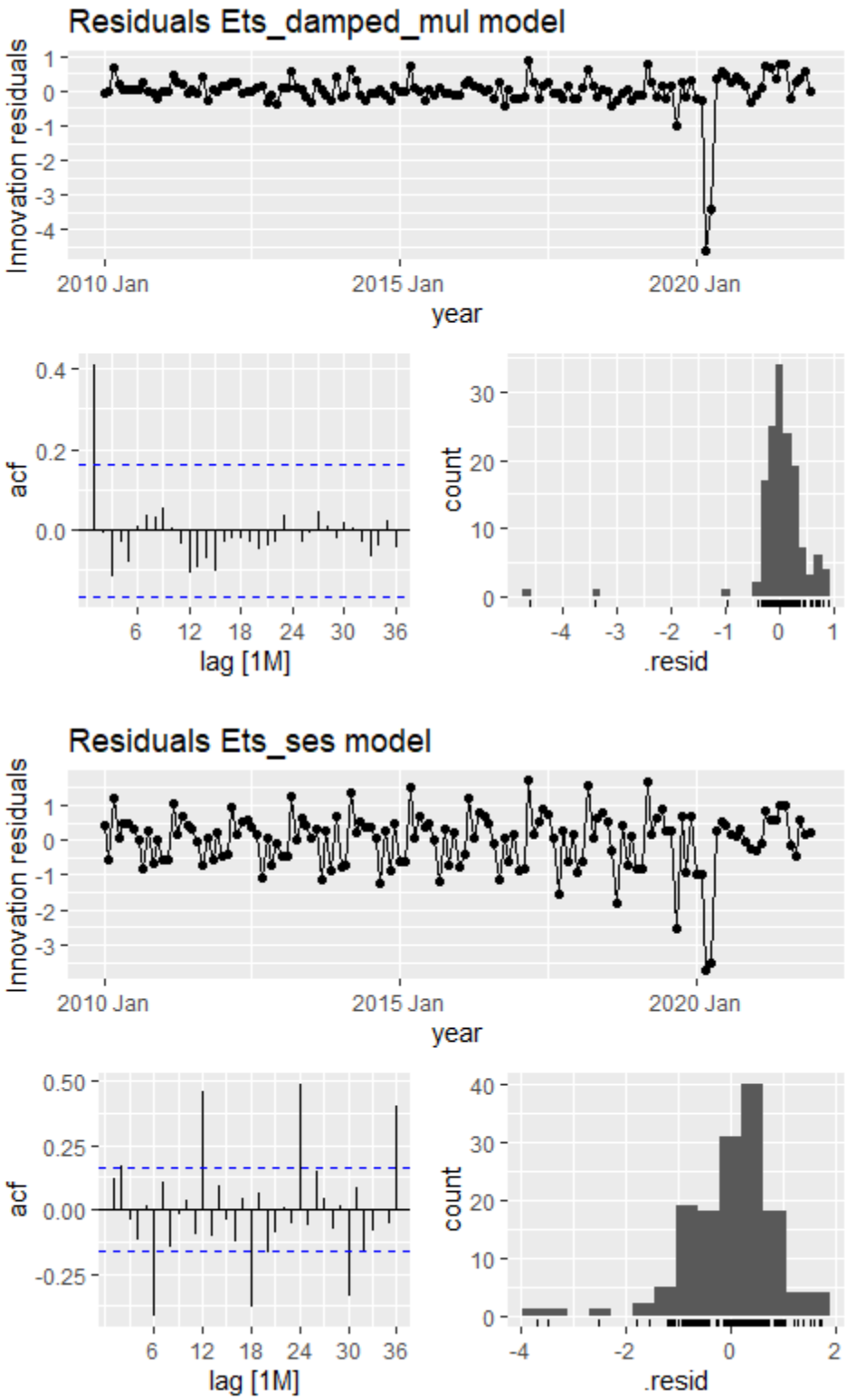
- AICc (Akaike Information Criterion corrected): a `lowest AICc` value indicates a `best-fitting model`.


Best 5 fitted models
Passengers (in millions)
10
0
2010 Jan
2015 Jan
2020 Jan
2025 Jan
year [1M]
level
80
95
.model
Arima011011
Arima012011
Arima210011
Ets_damped_mul
Ets_ses


Residuals Arima011011 model
Innovation residuals
0
-2
-4
2010 Jan
2015 Jan
2020 Jan
year
acf
0.1
0.0
-0.1
6
12
18
24
30
36
lag [1M]
count
30
20
10
0
-4
-2
0
.resid


Residuals Arima012011 model
Innovation residuals
0
-2
-4
2010 Jan
2015 Jan
2020 Jan
year
acf
0.1
0.0
-0.1
6
12
18
24
30
36
lag [1M]
count
30
20
10
0
-4
-2
0
.resid


Residuals Arima210011 model
Innovation residuals
0
-2
-4
2010 Jan
2015 Jan
2020 Jan
year
acf
0.1
0.0
-0.1
6
12
18
24
30
36
lag [1M]
count
30
20
10
0
-4
-2
0
.resid



6.1.1.3. Ljung-Box test

```
## Series: total
## Model: ARIMA(0,1,2)(0,1,1)[12]
##
```

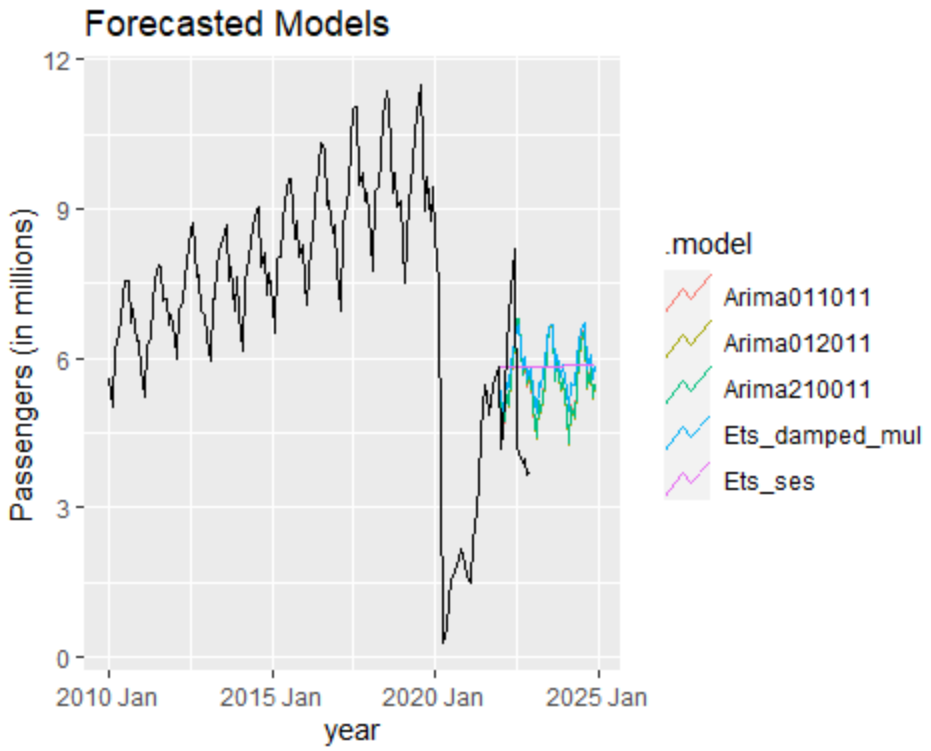
```
## Coefficients:
##          ma1     ma2     sma1
##       0.4213  0.1963  -0.8873
## s.e.  0.0927  0.0827   0.1489
##
## sigma^2 estimated as 0.3329:  log likelihood=-121.36
## AIC=250.73   AICc=251.04   BIC=262.23
```

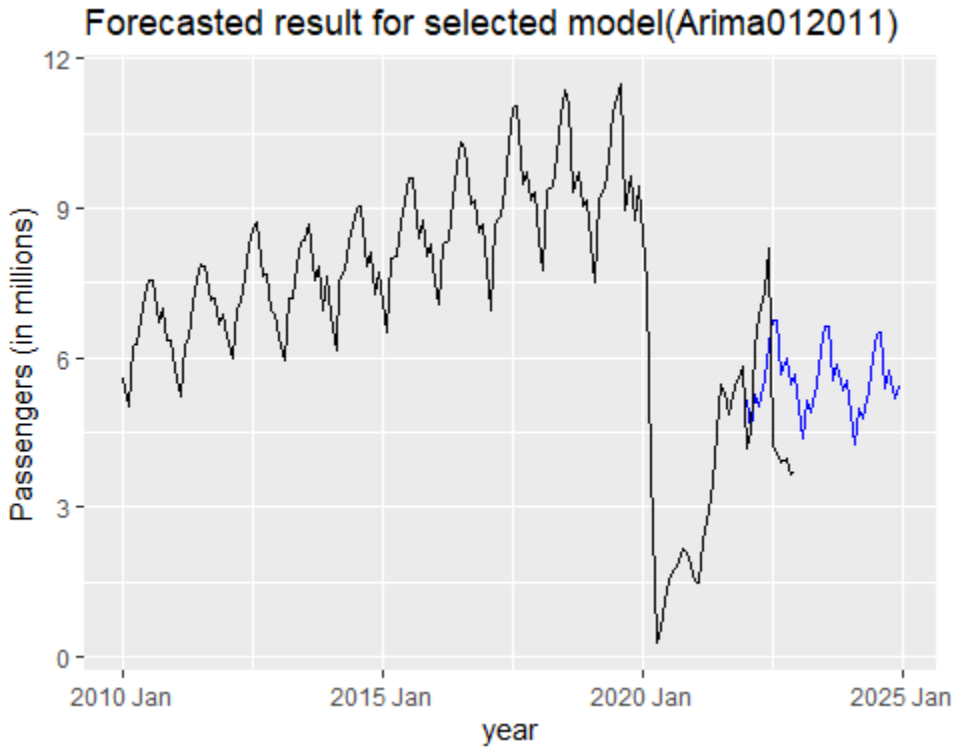
.model	lb_stat	lb_pvalue
Arima012011	11.14494	0.1324204

For non-seasonal component, ARIMA(0,1,2) has 2 MA terms, for seasonal ARIMA(0,1,1) has 0 MA term estimated. Therefore the degree of freedom should be 5.

Since the p-value > 5%, not reject H0 at a significant level. The residuals could be considered white noise series and the model has adequately captured the underlying data.

6.1.1.4. Model selection and forecast

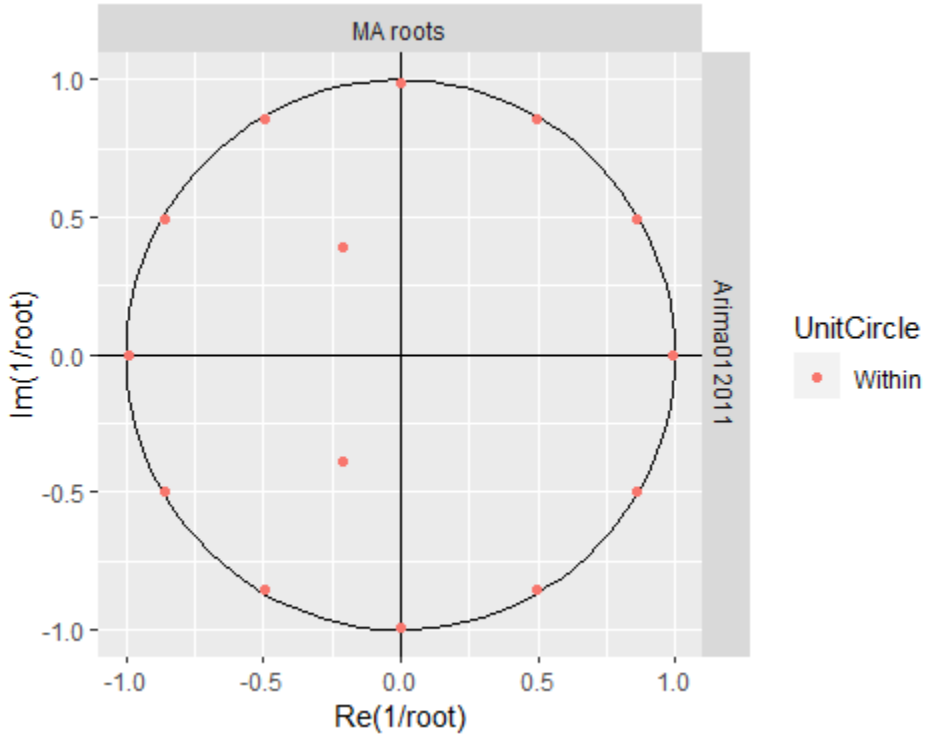





```
##  [1] 5.155015 4.517561 5.251238 5.018928 5.594702 6.259479 6.739579 6.7650
69
```

```
##  [9] 5.652866 5.992561 5.458187 5.673563 4.981288 4.387225 5.120902 4.8885
92
## [17] 5.464365 6.129142 6.609243 6.634733 5.522530 5.862225 5.327850 5.5432
26
## [25] 4.850952 4.256889 4.990566 4.758255 5.334029 5.998806 6.478907 6.5043
96
## [33] 5.392194 5.731889 5.197514 5.412890
```

6.1.1.5. Inverse root test



This inverse toot test implies that the model is stable and a good fit to the data. Also the model has capturing the underlying patterns of the time series.