

Analysis and forecasting of fishing in the United States

Group 3

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Goal

- Our goal is to predict the amount of fish in metric tons that needs to be captured to suffice the needs of population for United States.
- We plan to do a long forecast of 3 years to predict the same.
- We are using various forecasting techniques such as Naïve, Simple Moving Average, Holt-Winters, Regression, Arima, Exponential Smoothing and Random Walk Forest to achieve the goal.
- The best forecasting technique would be decided based on the accuracy measures. We are going to consider MAPE as a good accuracy measure since it is scale independent and can be used to compare different forecast scenarios.

Dataset

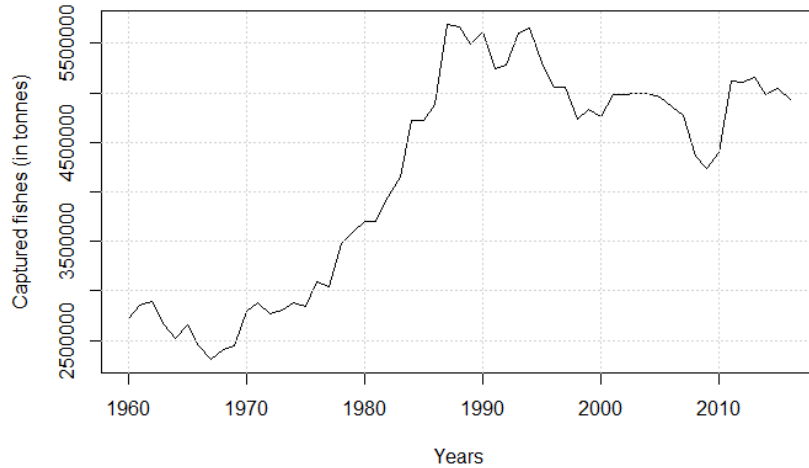
Entity <chr>	Code <chr>	Year <dbl>	Capture fisheries production (metric tons) <dbl>
United States	USA	1960	2714623
United States	USA	1961	2852004
United States	USA	1962	2897963
United States	USA	1963	2655052
United States	USA	1964	2519951
United States	USA	1965	2649980

Our data includes fish capture in metric tons for the United States from 1960 to 2016. This data was found on Kaggle after looking for fish captured in the world.

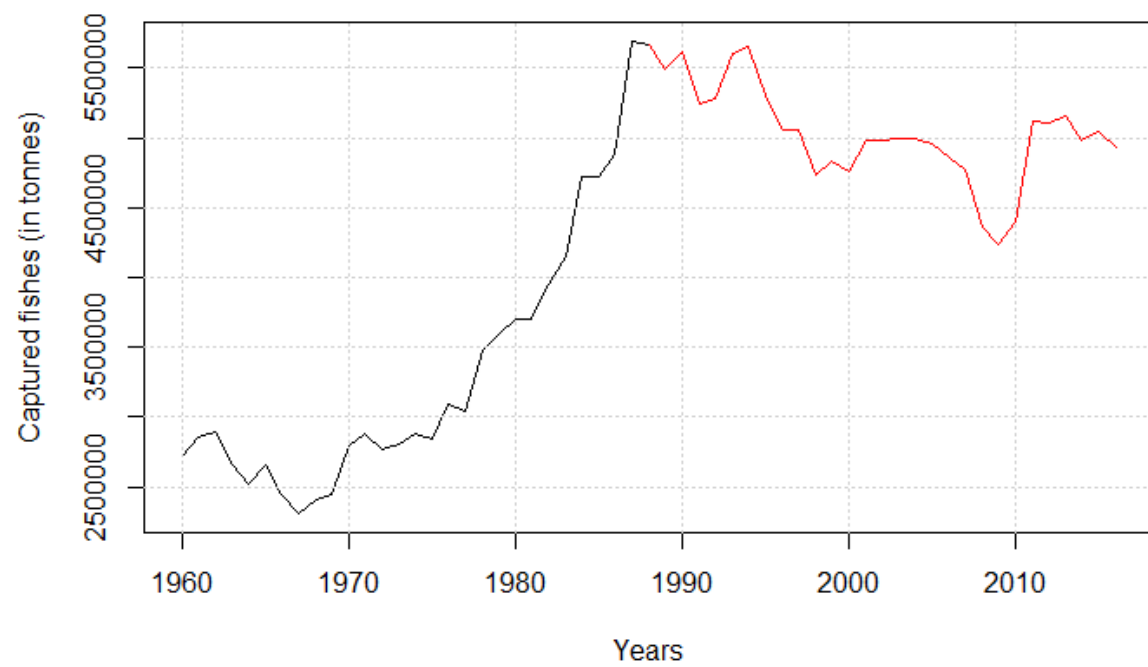
```

Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
2311726 2885967 4721775 4171508 5045443 5694242

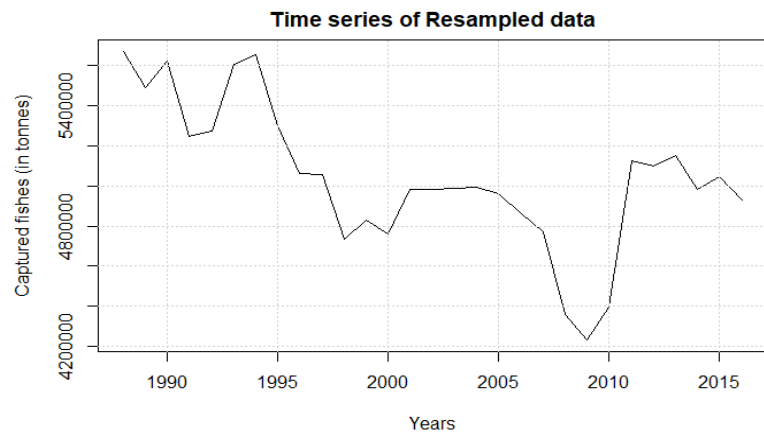
```



- Sudden rise before the data stabilizes
- Previous data not so relevant for forecasting as there was a rise due to certain factors which don't exist anymore.

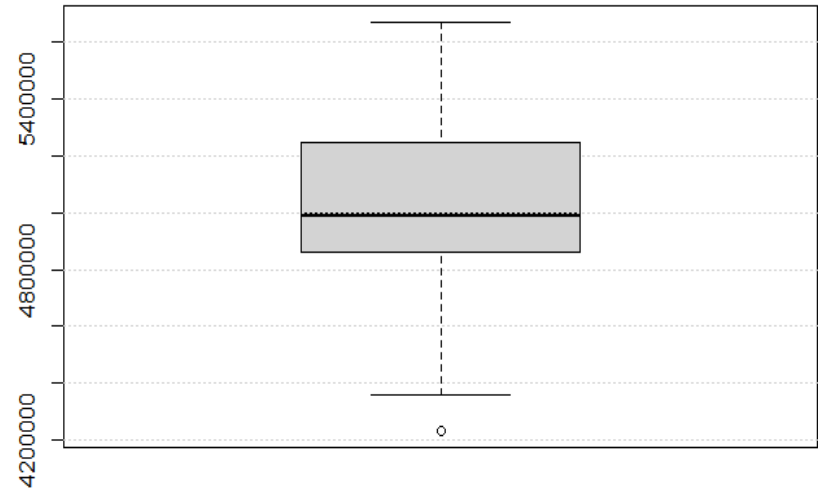


- New data from 1988 to 2016



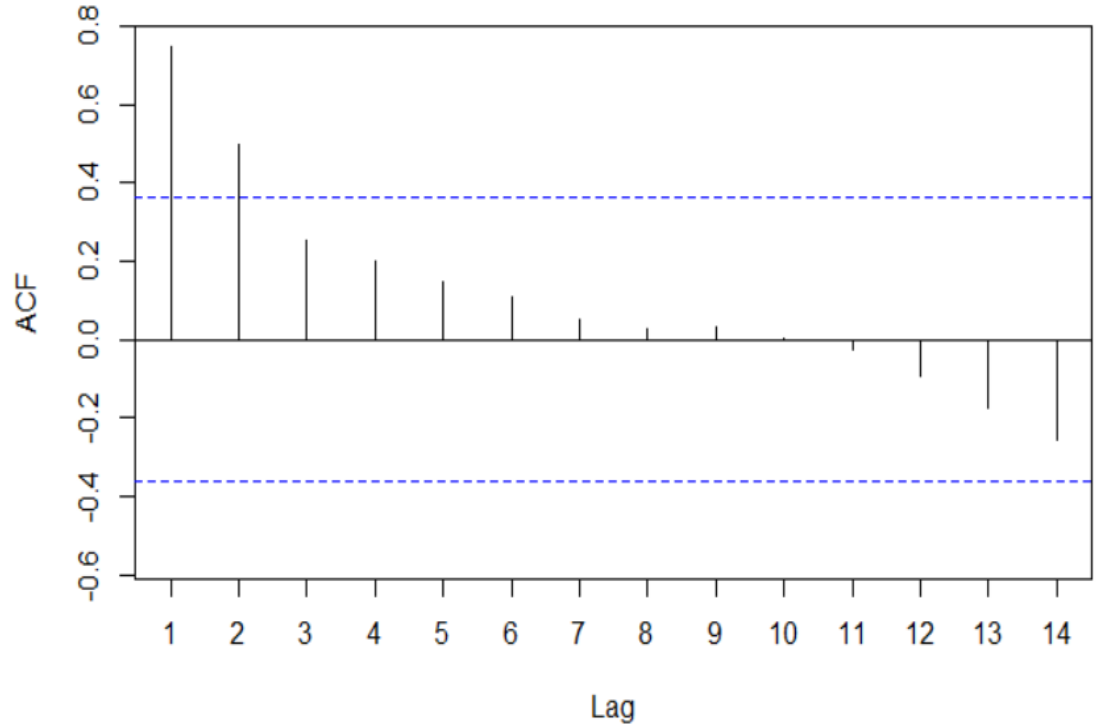
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
4233804	4858805	4995418	5040506	5244569	5670666

- The boxplot confirms the mean of the data from 1988 to 2016 is around 5000000 with an outlier.
- The 1st quartile is 4858805 whereas 3rd quartile is at 5244569. The median is at 4995418 and the mean is 5040506.



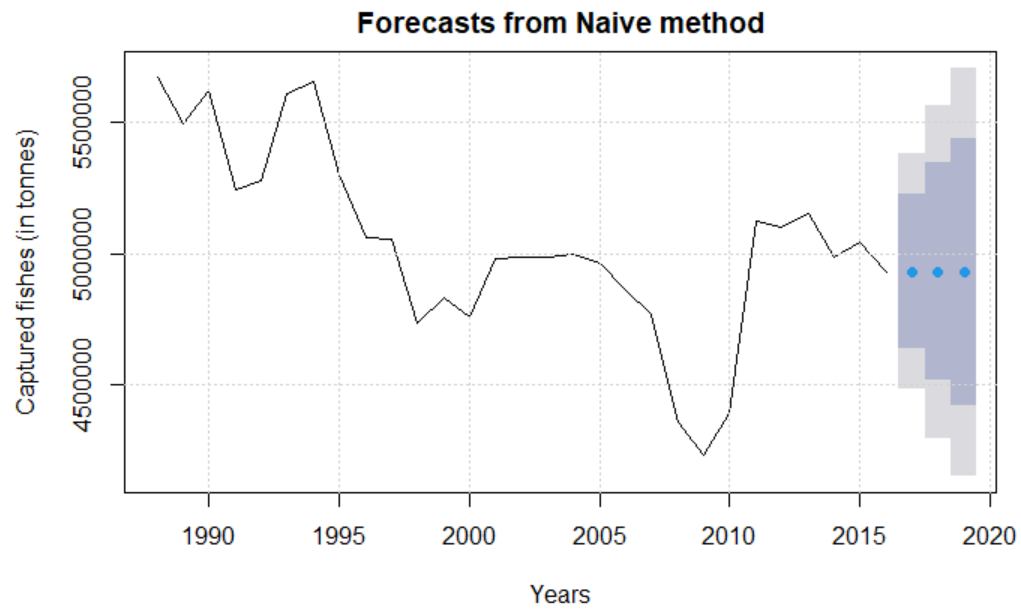
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
4233804	4858805	4995418	5040506	5244569	5670666

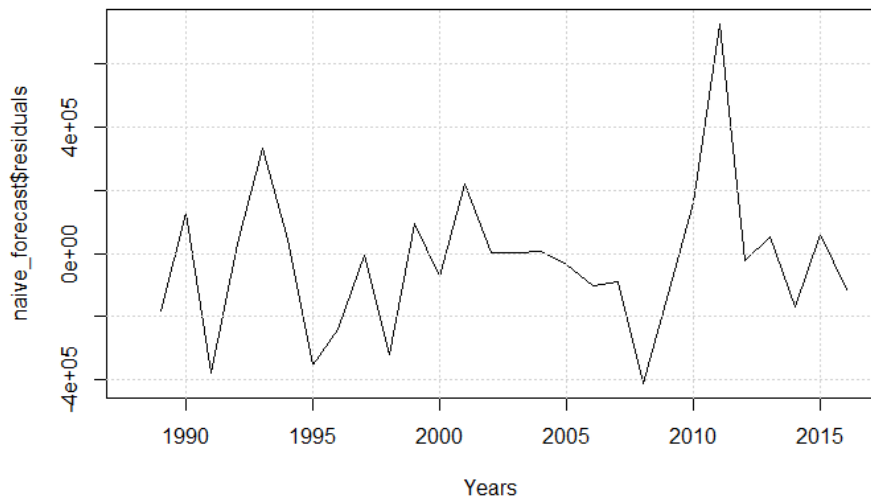
- Acf shows a high correlation with lag1.
- This states the current values are highly dependent on the previous values.



Naive Forecast

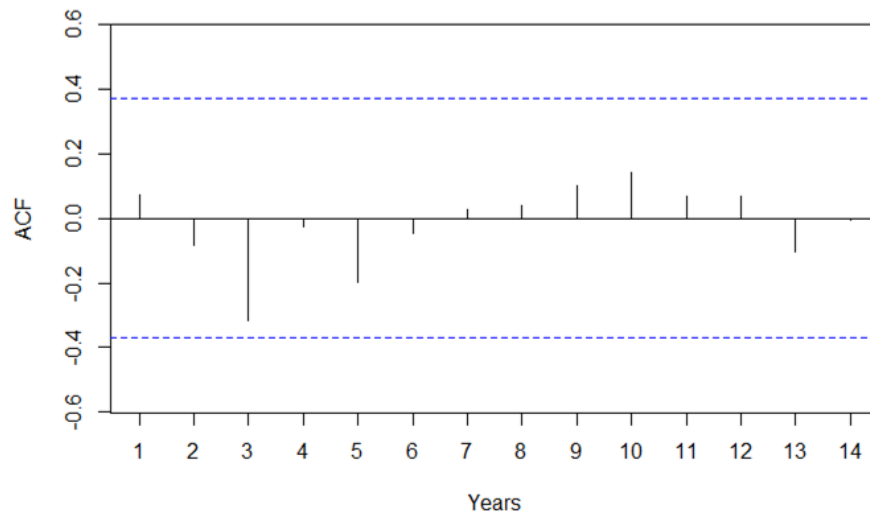
- Naïve forecast plot



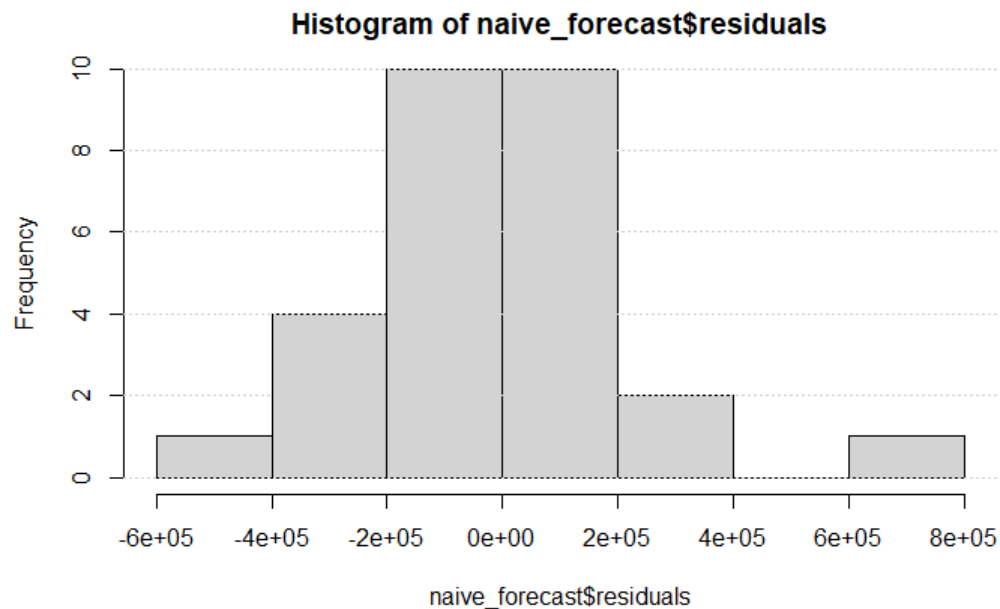


- ACF also shows no correlation between residuals.

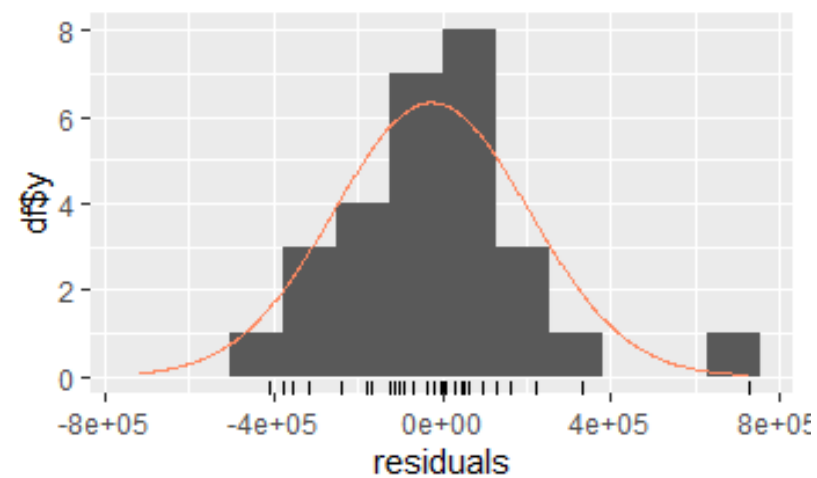
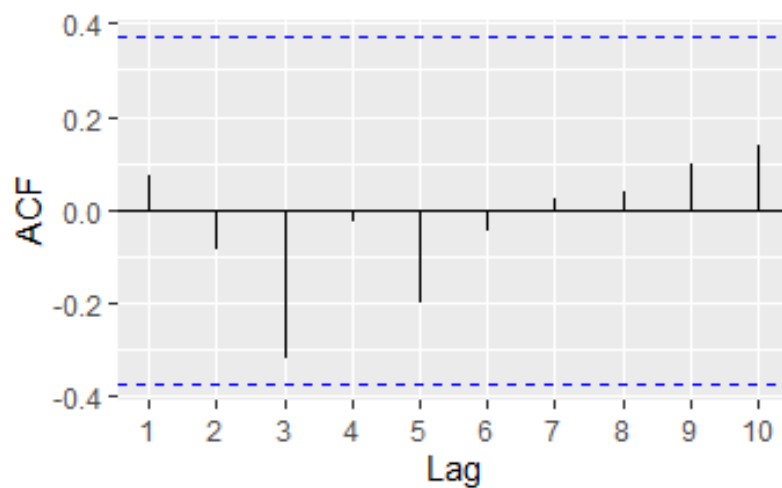
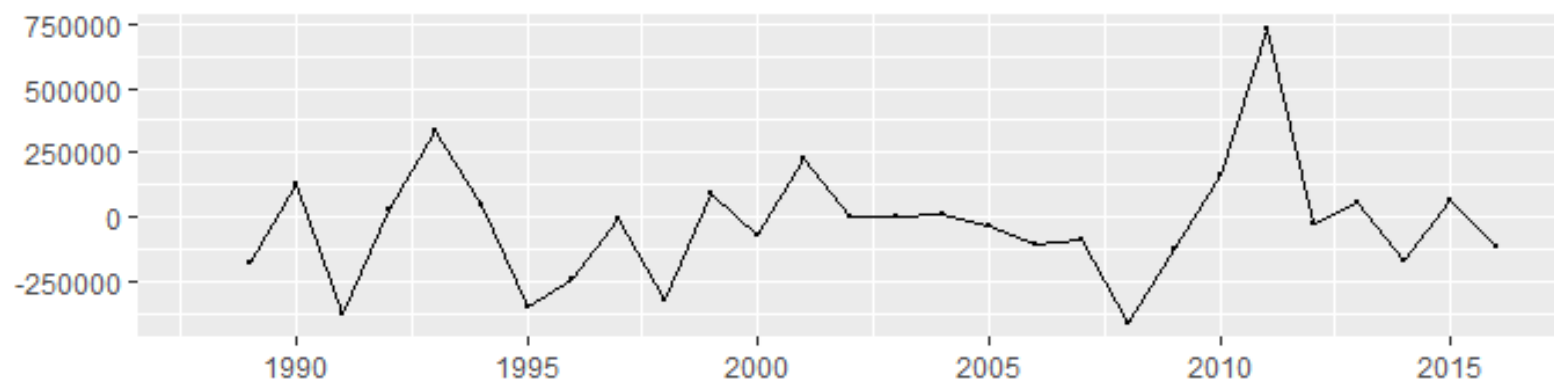
- The residual plot does not show any pattern.
- This means residuals are scattered randomly and they do not contribute much to data fluctuation.



- The histogram is somewhat normally distributed with a few outliers.



Residuals from Naive method



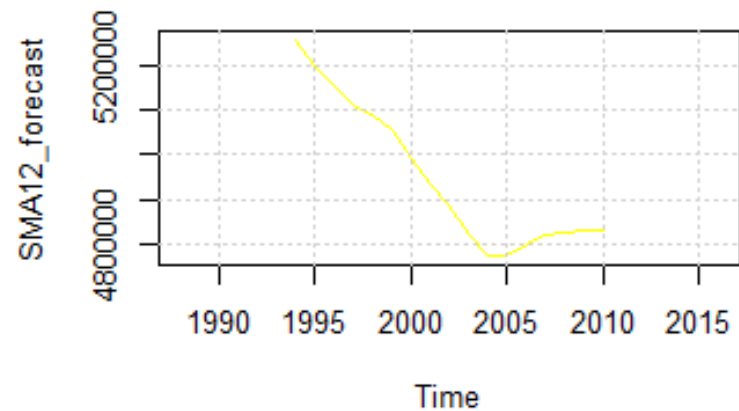
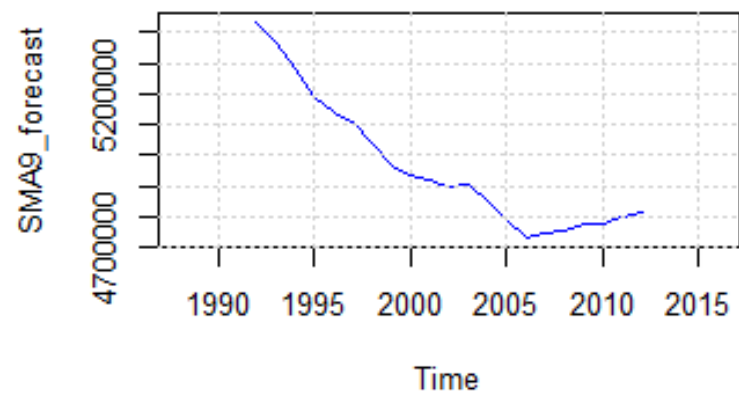
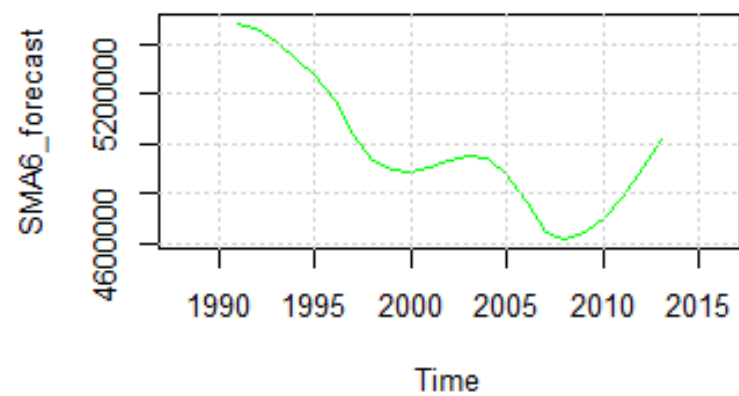
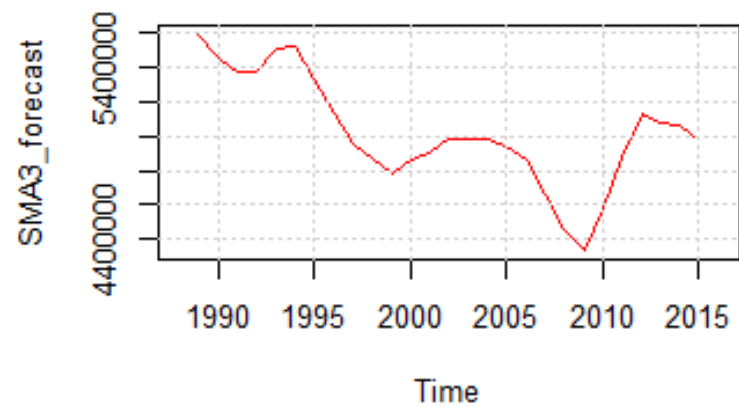
```
forecast(naive_forecast,h=3)
```

	Point Forecast <dbl>	Lo 80 <dbl>	Hi 80 <dbl>	Lo 95 <dbl>	Hi 95 <dbl>
2017	4931017	4638643	5223391	4483870	5378164
2018	4931017	4517538	5344496	4298656	5563378
2019	4931017	4424611	5437423	4156536	5705498

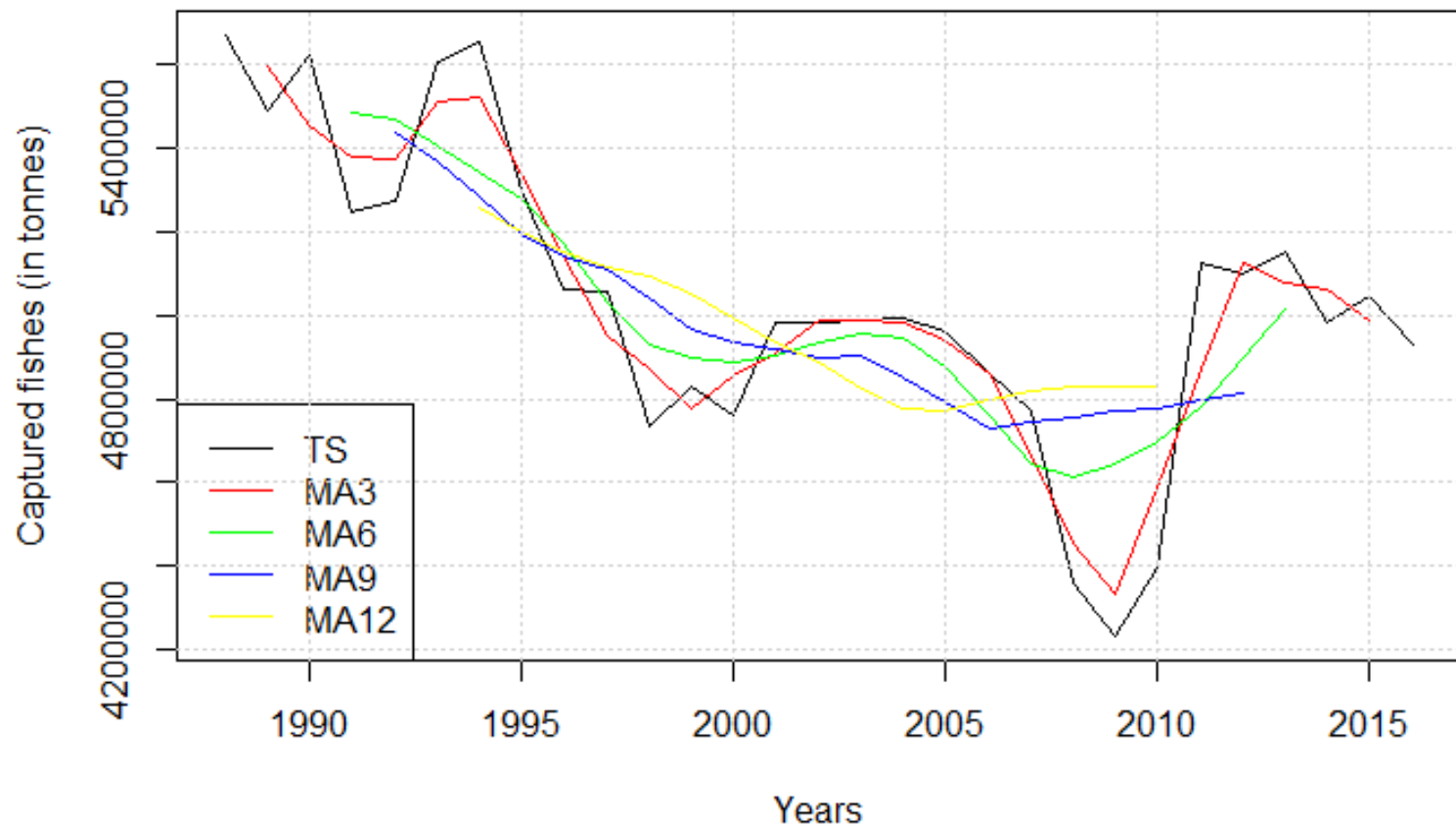
3 rows

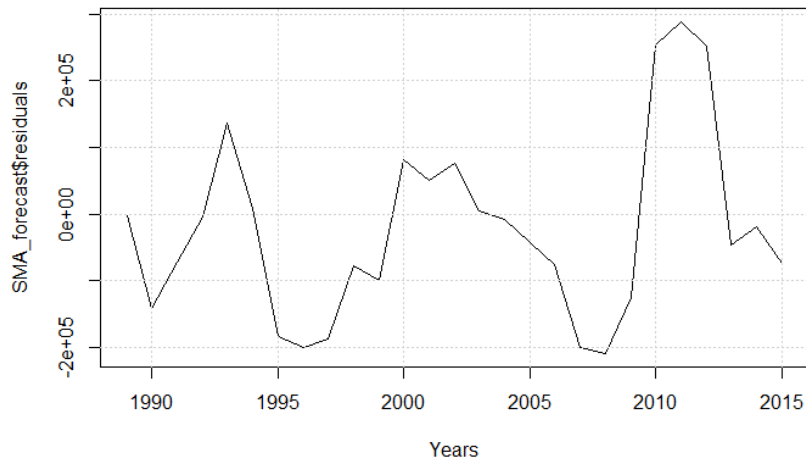
- The above table shows us the forecasted value.
- Naïve model predicted the point forecast to be 4931017 metric tons from 2017 to 2019.

Moving Averages



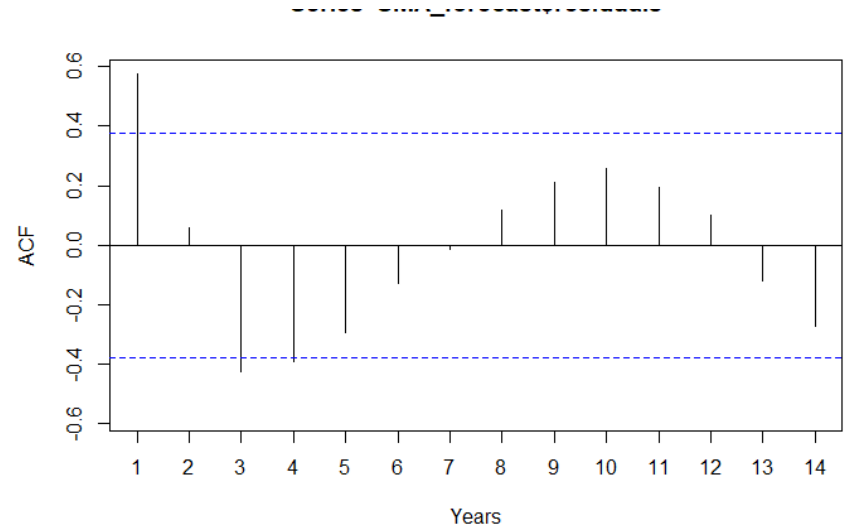
Forecast from Moving Averages method on Time Series



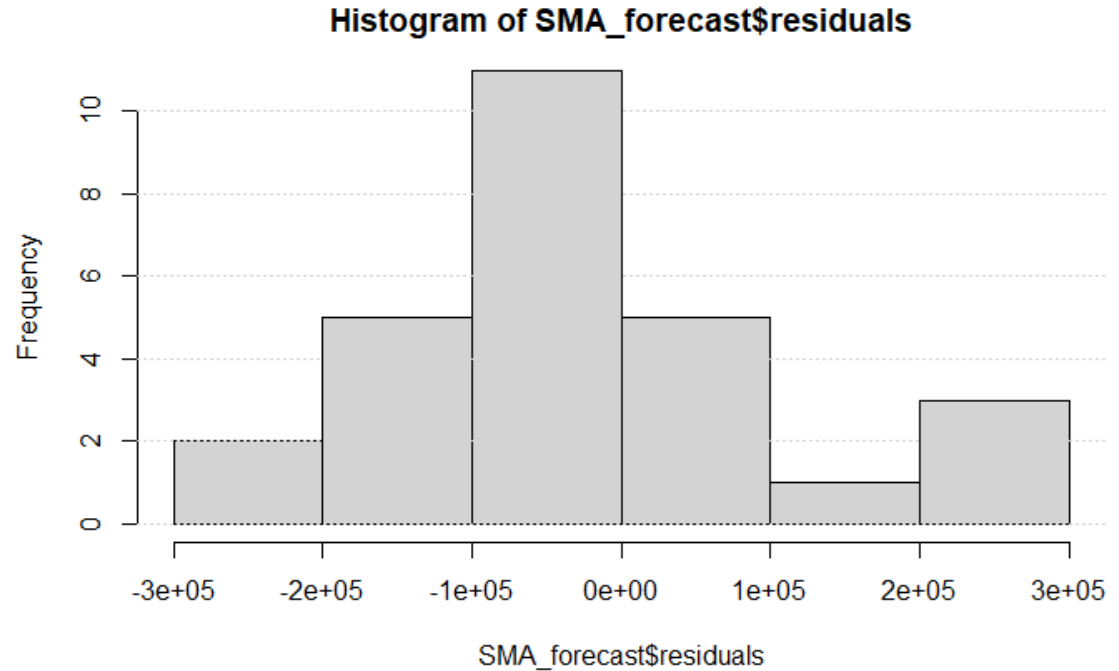


- ACF does shows some significant correlation between residuals. This is not ideal.

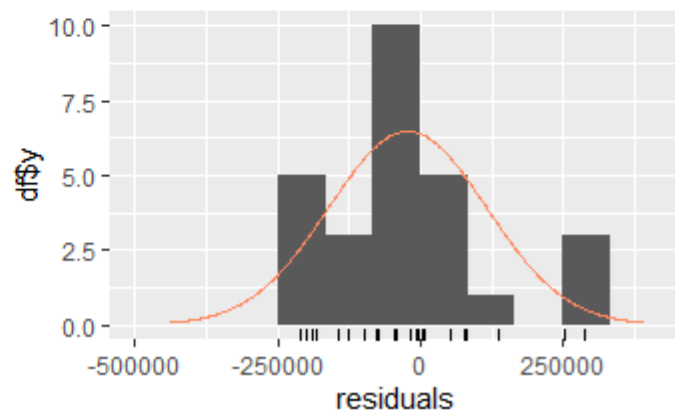
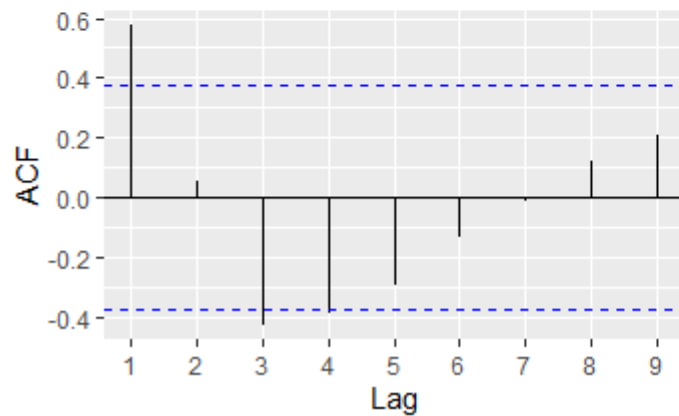
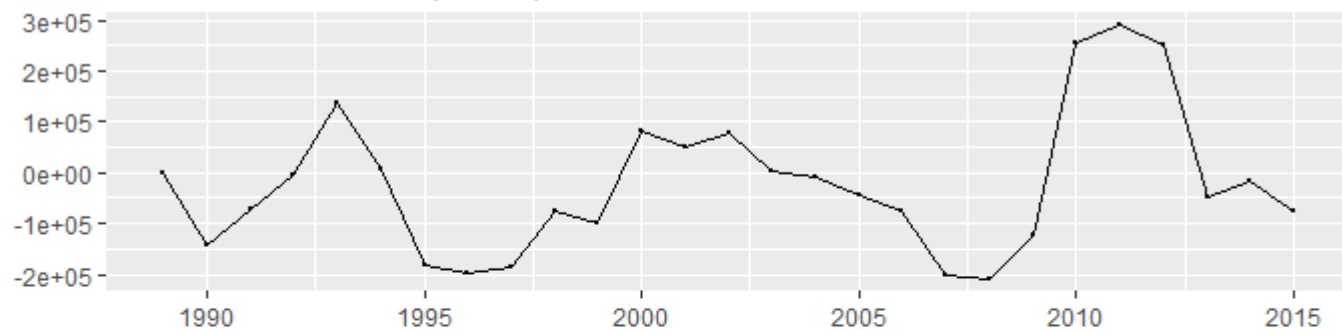
- The residual plot does not show any pattern.
- This means residuals are scattered randomly.

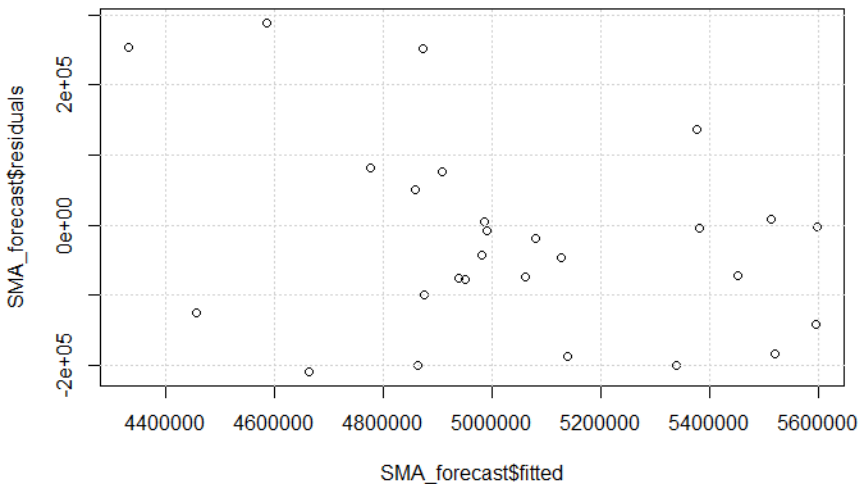


The residuals is not normally distributed. We can say it seems to right skewed very marginally.

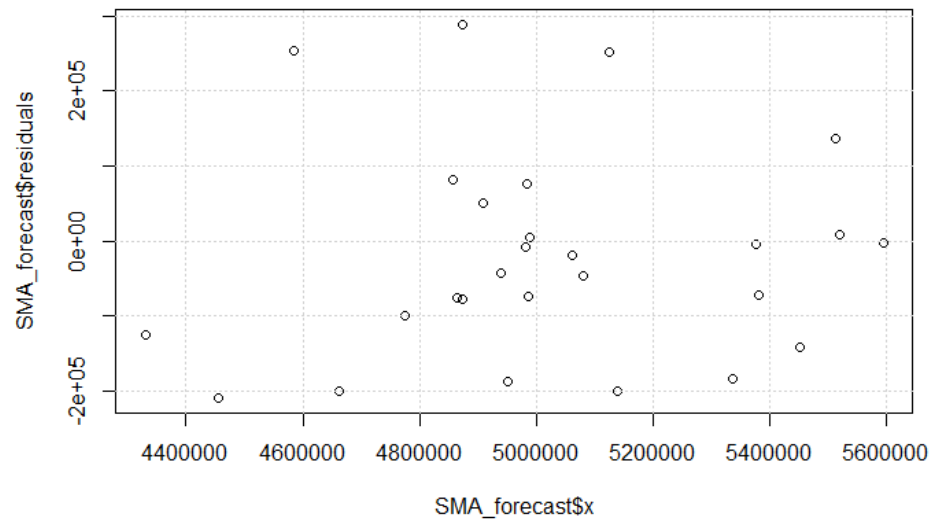


Residuals from ETS(A,N,N)





Here we don't see a pattern in the graph. This is a good sign. The residuals are scattered randomly.



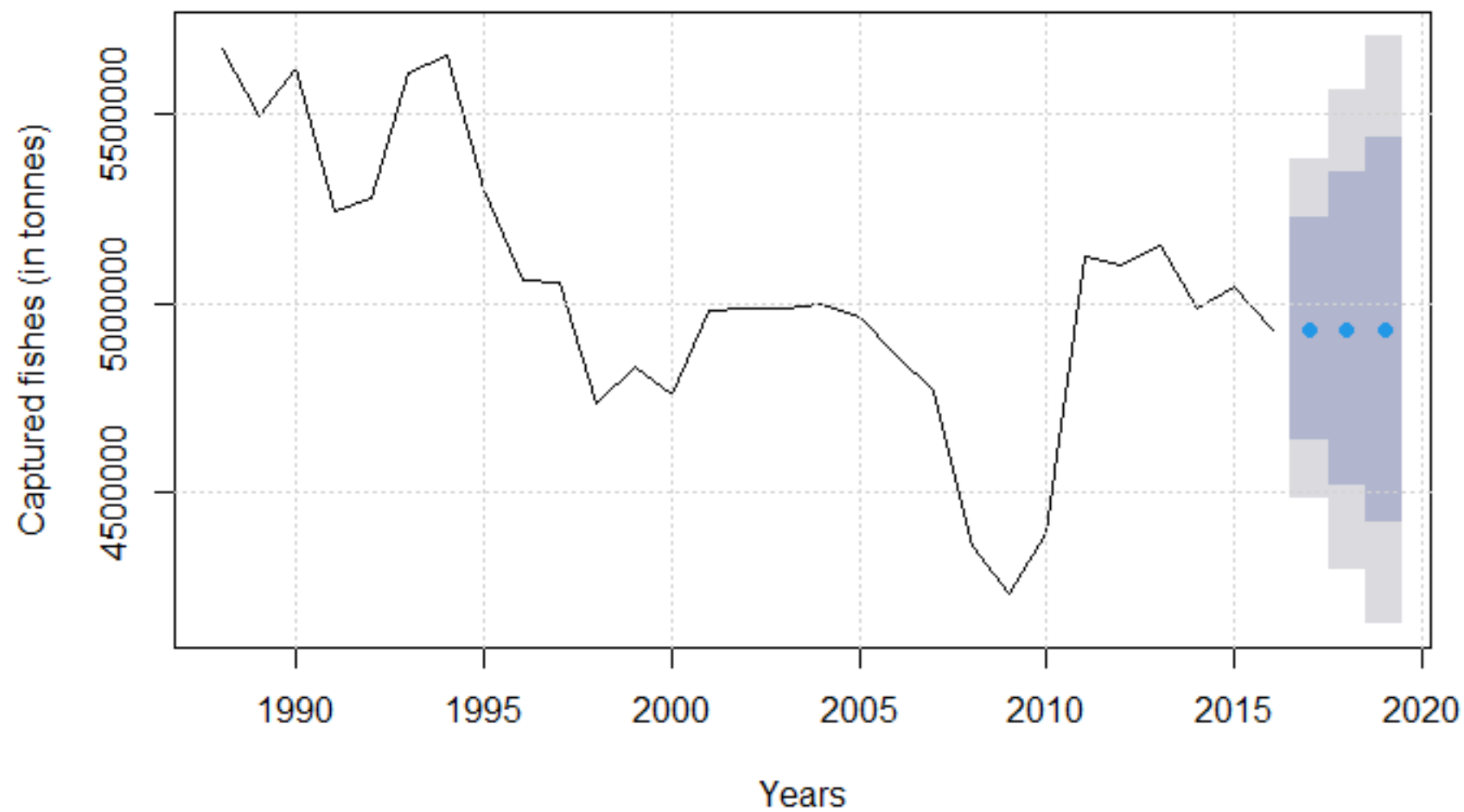
- Using Moving Avg with order 3 as recent data is better than all observations and smaller window provides more weight to recent data points

	Point Forecast <dbl>	Lo 80 <dbl>	Hi 80 <dbl>	Lo 95 <dbl>	Hi 95 <dbl>
2016	4986988	4804071	5169905	4707240	5266735
2017	4986988	4728317	5245659	4591385	5382591
2018	4986988	4670187	5303788	4502483	5471492
2019	4986988	4621181	5352794	4427535	5546441

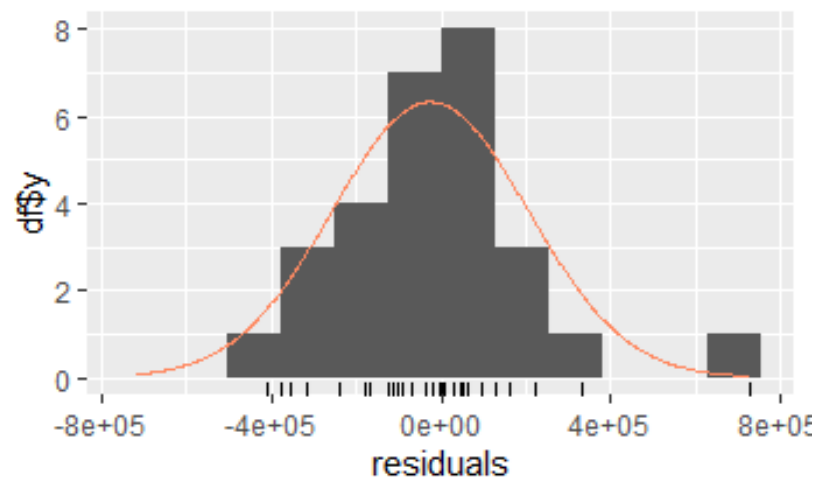
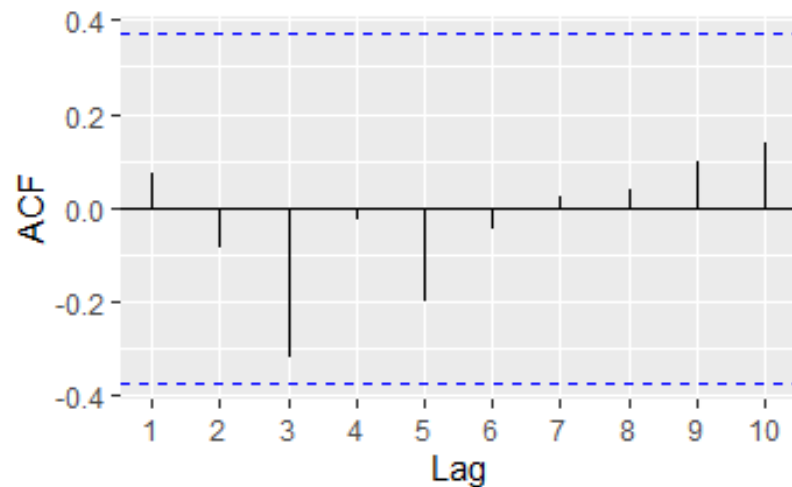
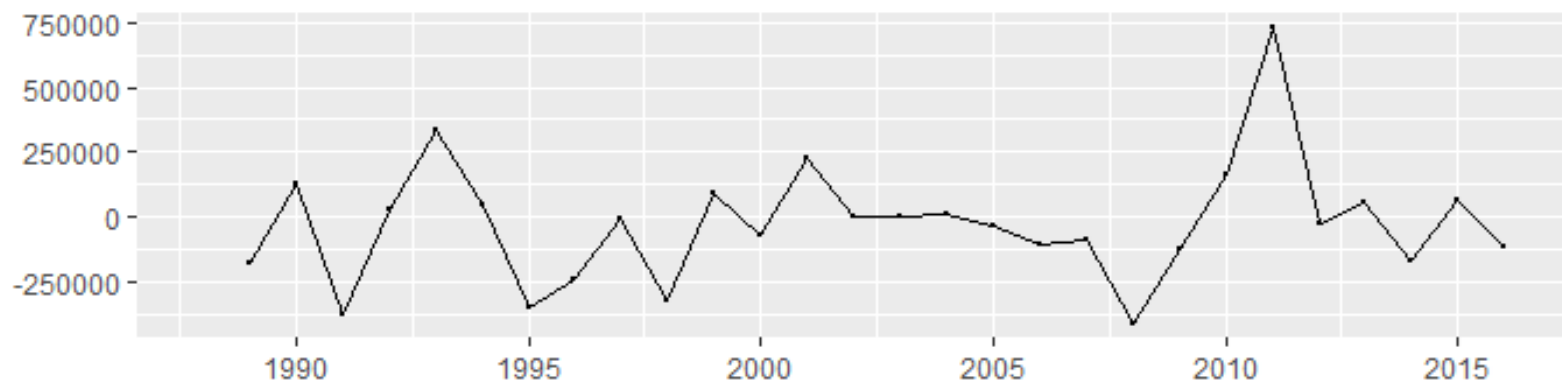
4 rows

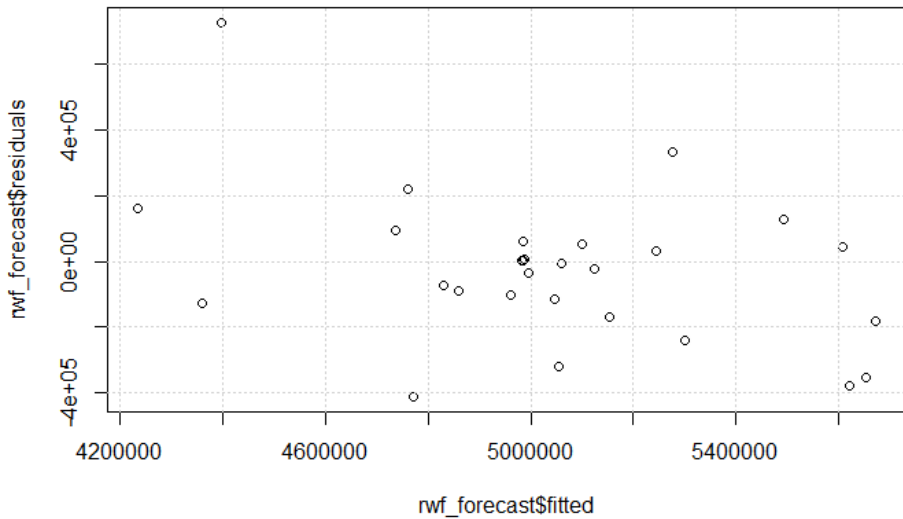
Random Walk Forecast

Forecasts from Random walk

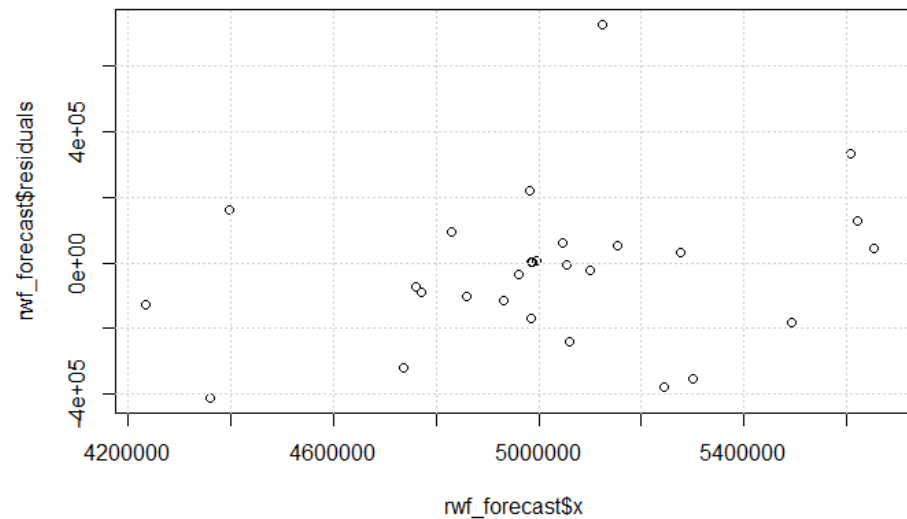


Residuals from Random walk





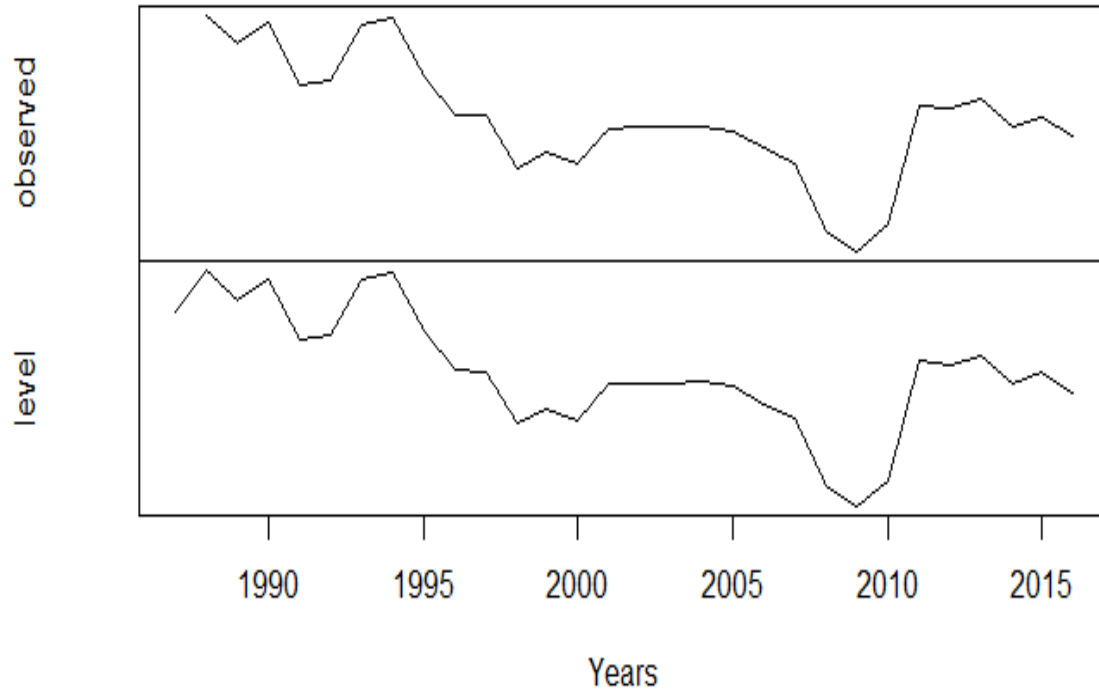
- The plots are scattered evenly.
- The residual is not significant



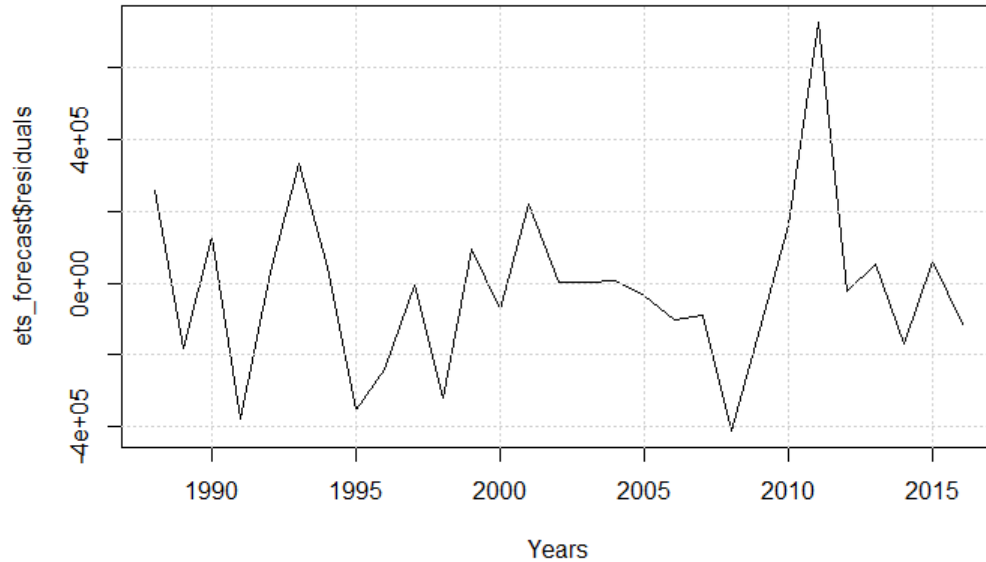
	Point Forecast <dbl>	Lo 80 <dbl>	Hi 80 <dbl>	Lo 95 <dbl>	Hi 95 <dbl>
2017	4931017	4638643	5223391	4483870	5378164
2018	4931017	4517538	5344496	4298656	5563378
2019	4931017	4424611	5437423	4156536	5705498
3 rows					

Exponential Smoothing

Decomposition by ETS(A,N,N) method

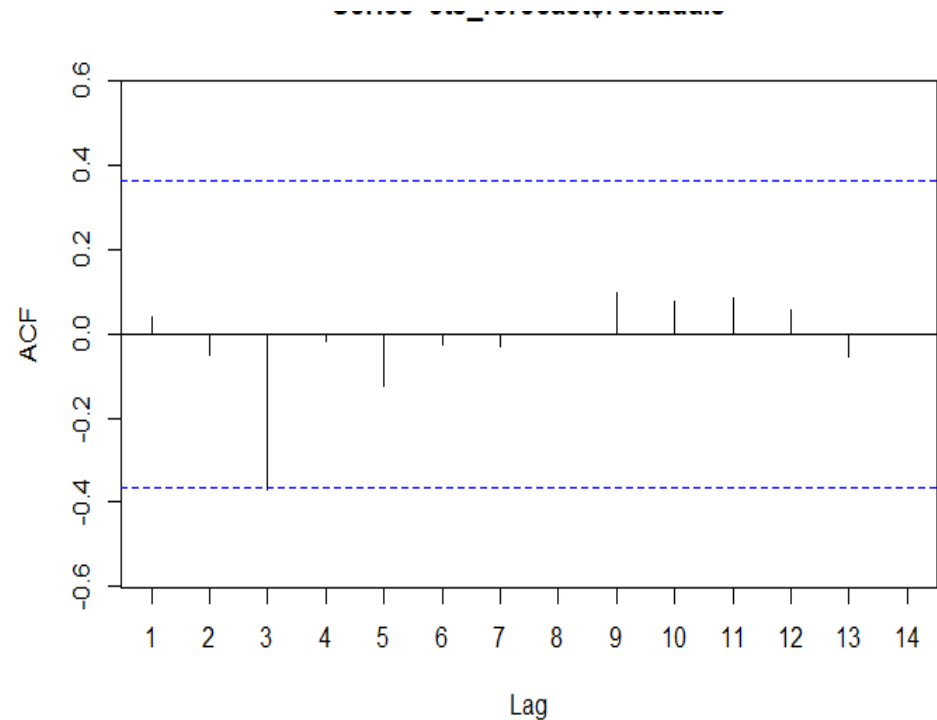


- The above graph is a comparison of the observed and the factors that affect the graph. Here we see the observed and level the same as there is no seasonality to change it.

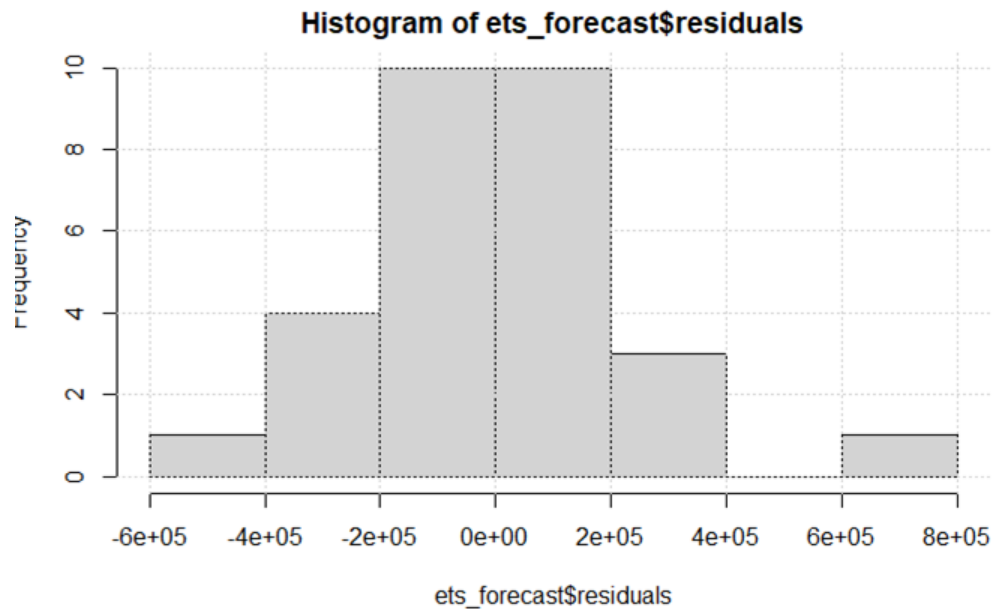


The plot is equally spread residuals around the horizontal line without a distinct pattern. This is a good indication that the residuals do not fluctuate the data.

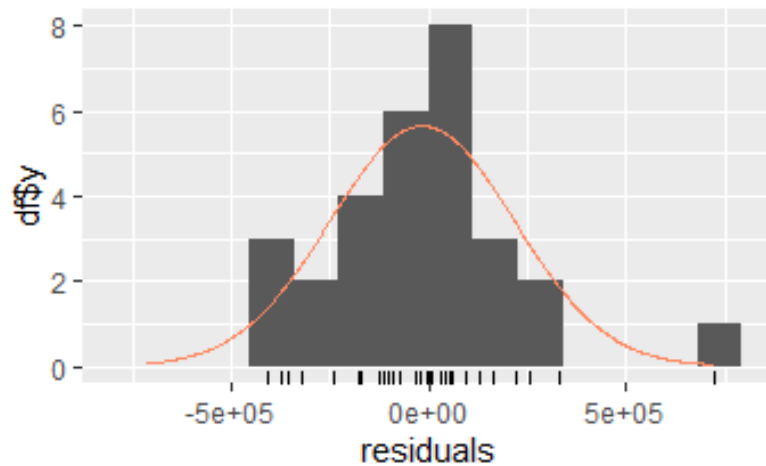
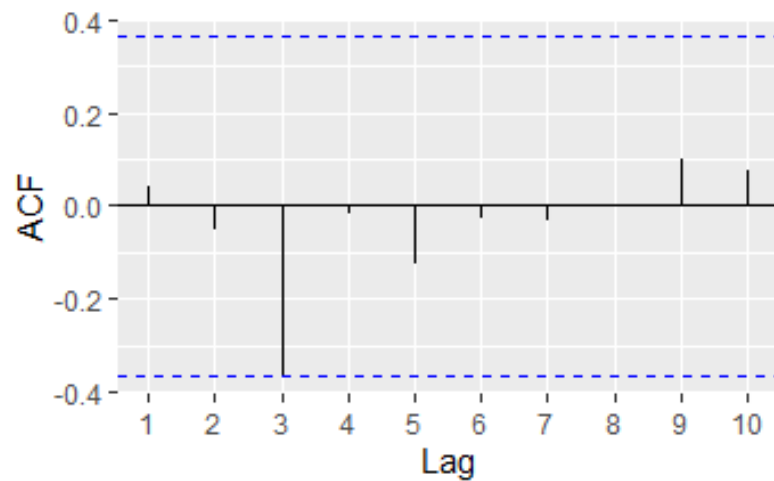
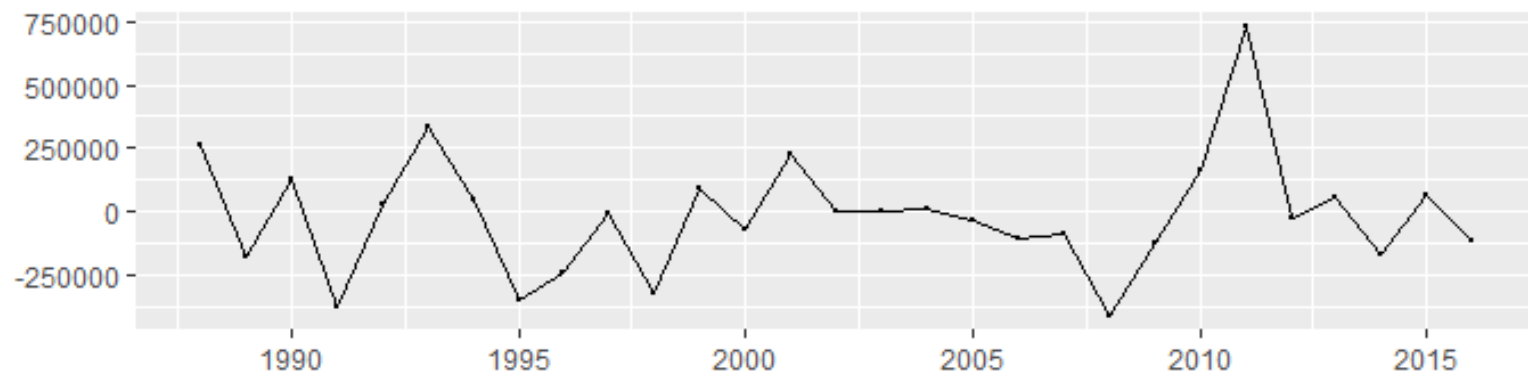
- Here, in the Acf, we don't see any significant lines which states that there is no correlation between the errors.

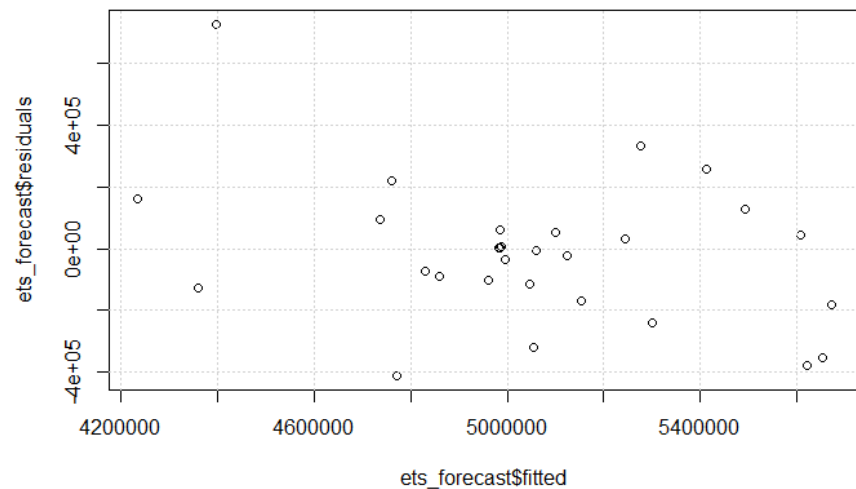


- The histogram is somewhat normally distributed with a few outliers.

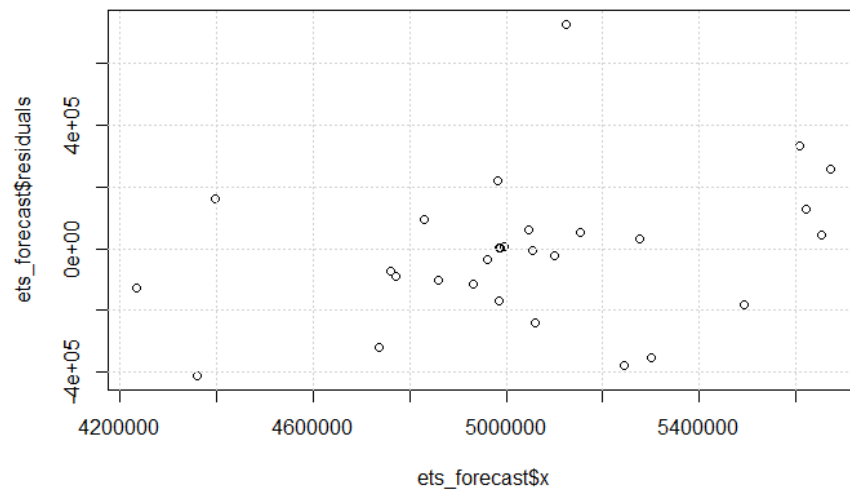


Residuals from ETS(A,N,N)





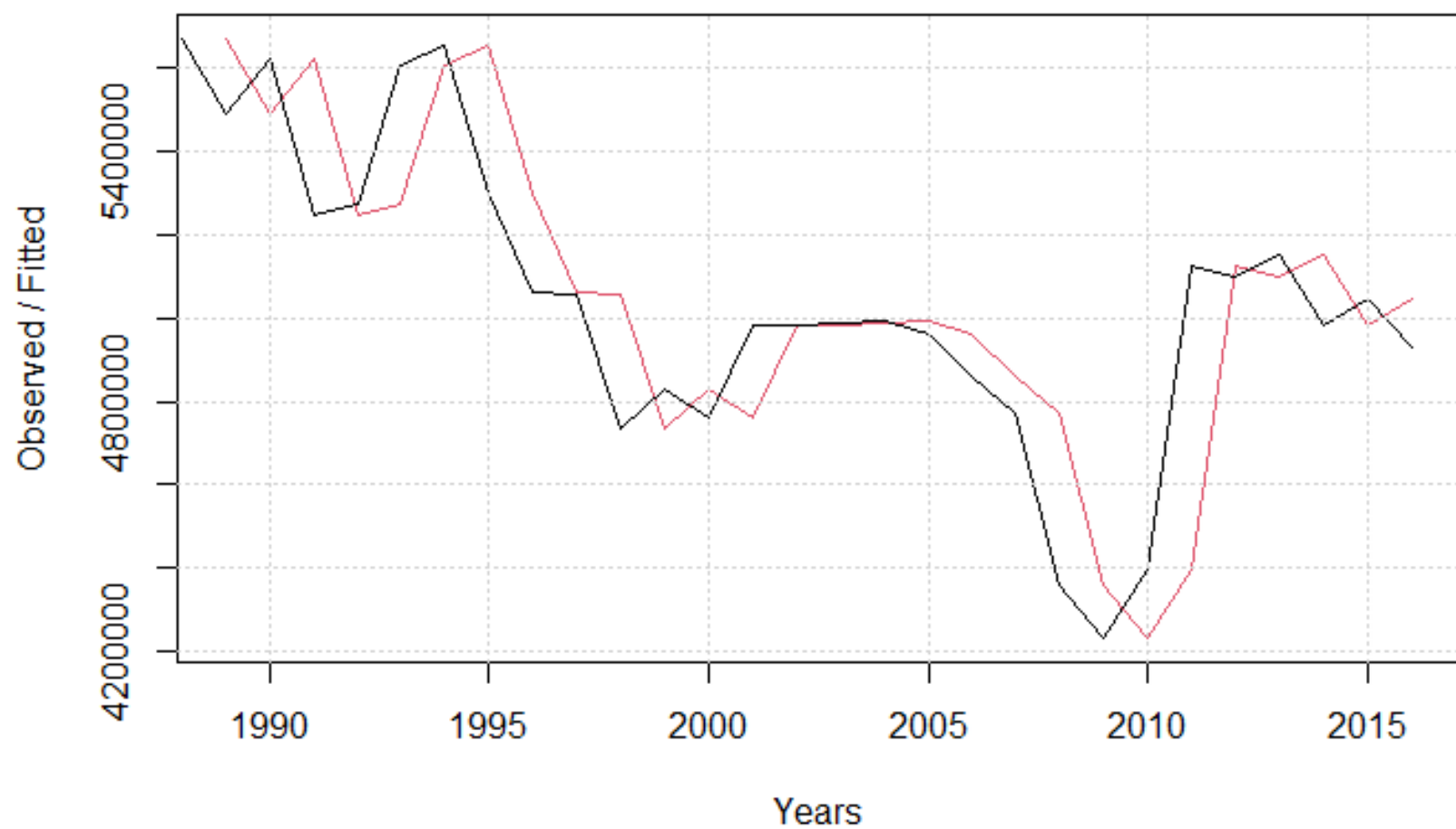
There is no patterns
between the fitted vs
residual and actual vs
residual plot



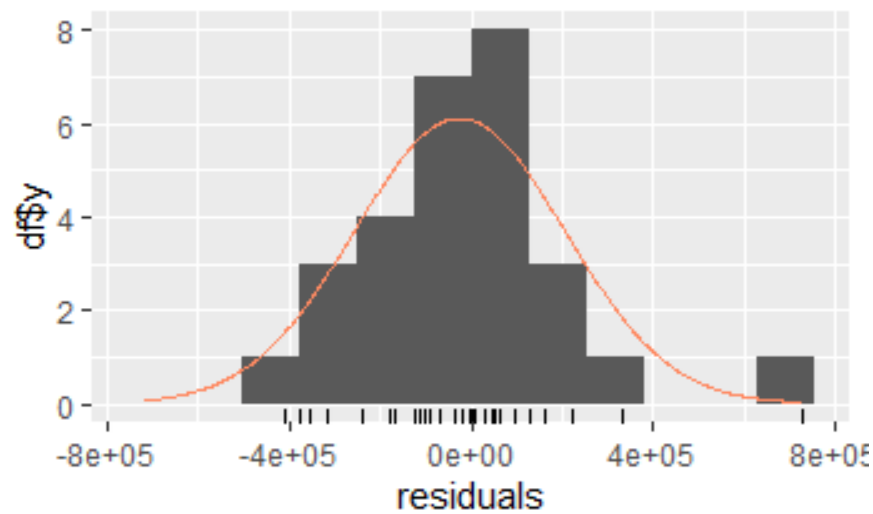
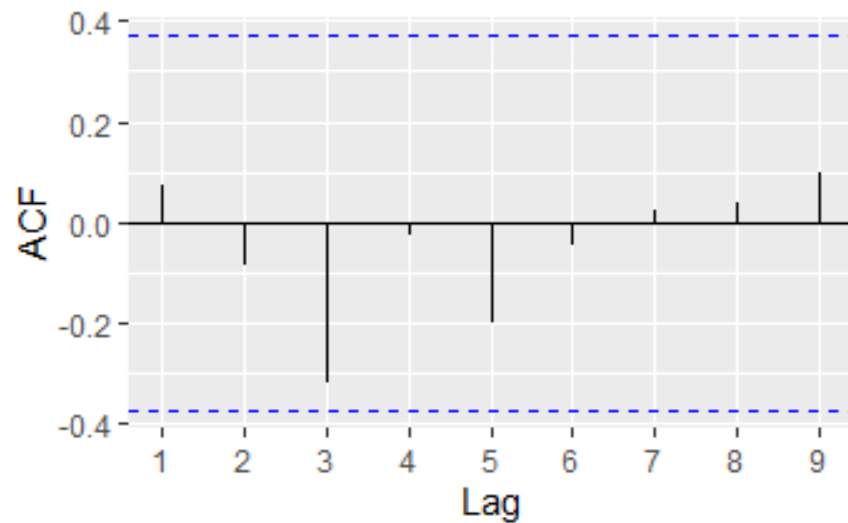
	Point Forecast <dbl>	Lo 80 <dbl>	Hi 80 <dbl>	Lo 95 <dbl>	Hi 95 <dbl>
2017	4931029	4626568	5235489	4465396	5396661
2018	4931029	4500478	5361579	4272558	5589499
2019	4931029	4403723	5458334	4124584	5737473
3 rows					

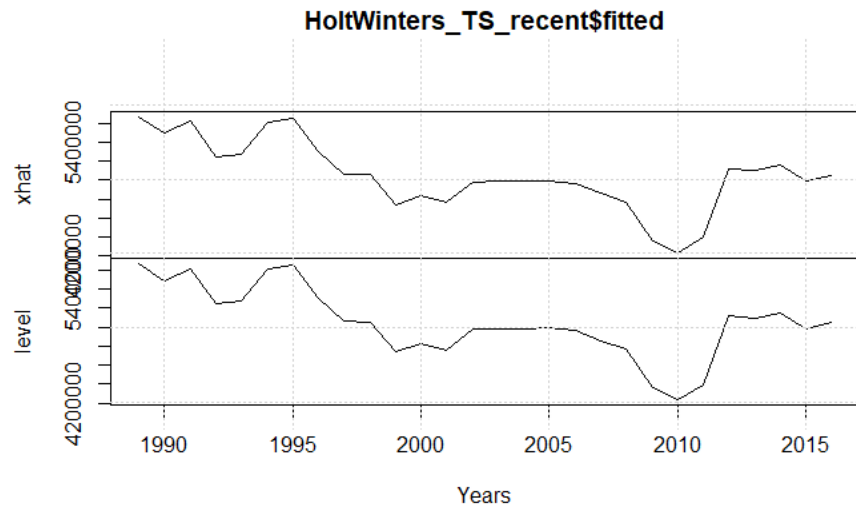
Holt-Winter Forecast

Holt-Winters filtering

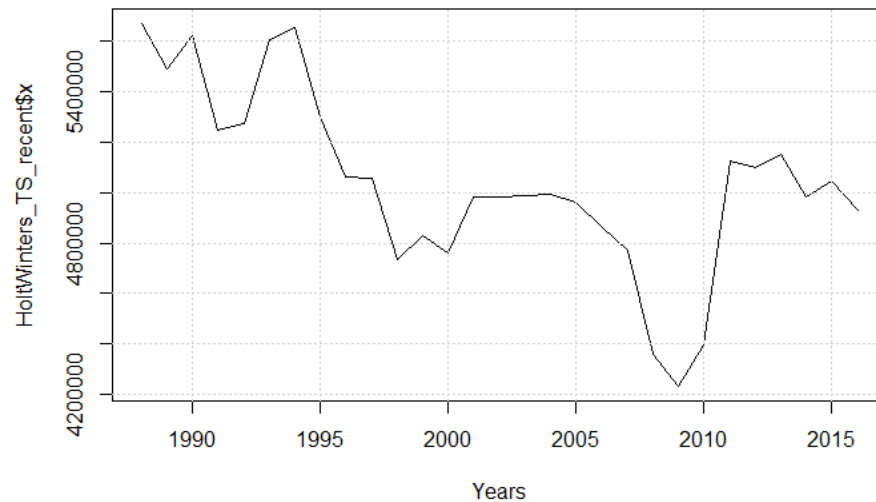


Residuals from HoltWinters

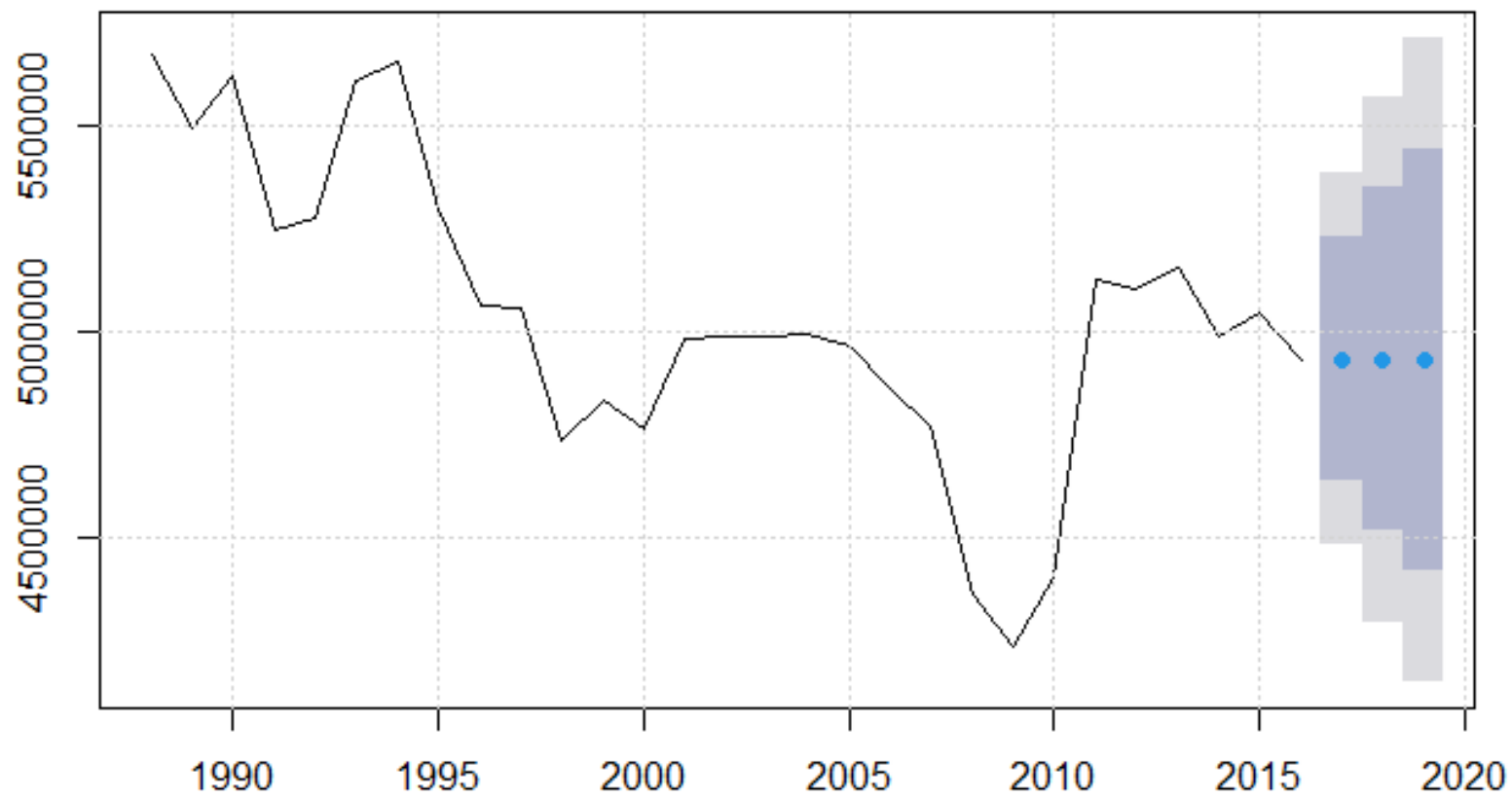




- Observed value compared to level
- Since there is no seasonality, both plots are similar



Forecasts from HoltWinters



	Point Forecast <dbl>	Lo 80 <dbl>	Hi 80 <dbl>	Lo 95 <dbl>	Hi 95 <dbl>
2017	4931025	4635287	5226762	4478733	5383316
2018	4931025	4512802	5349247	4291409	5570640
2019	4931025	4418815	5443234	4147667	5714382
3 rows					

Regression

essentially perfect fit: summary may be unreliable

Call:

```
lm(formula = FP_US$`Capture fisheries production (metric tons)` ~  
  lag(FP_US$`Capture fisheries production (metric tons)`, +1),  
  data = FP_US)
```

Residuals:

Min	1Q	Median	3Q	Max
-4.503e-09	-1.580e-11	5.160e-11	1.264e-10	7.671e-10

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-1.974e-09	3.268e-10	-6.039e+00	1.39e-07 ***
lag(FP_US\$`Capture fisheries production (metric tons)`, +1)	1.000e+00	7.575e-17	1.320e+16	< 2e-16 ***

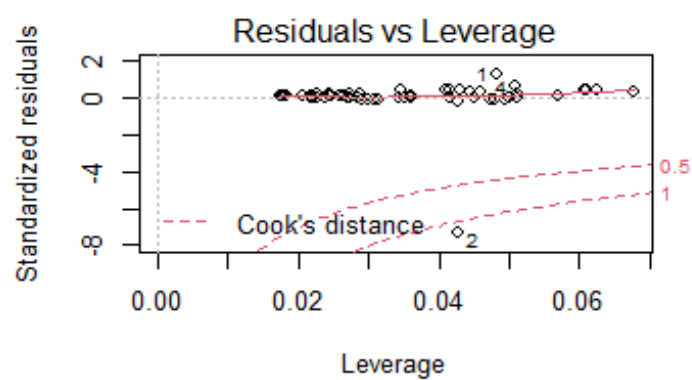
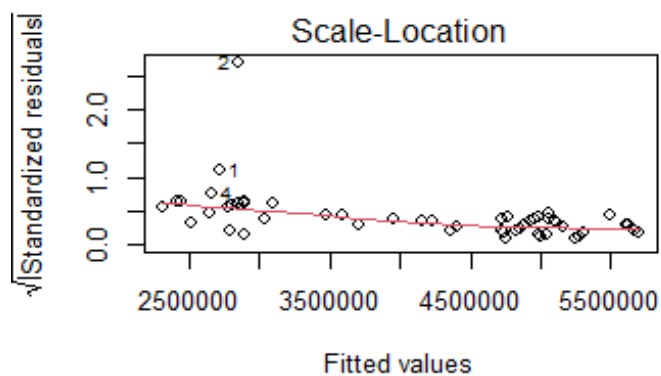
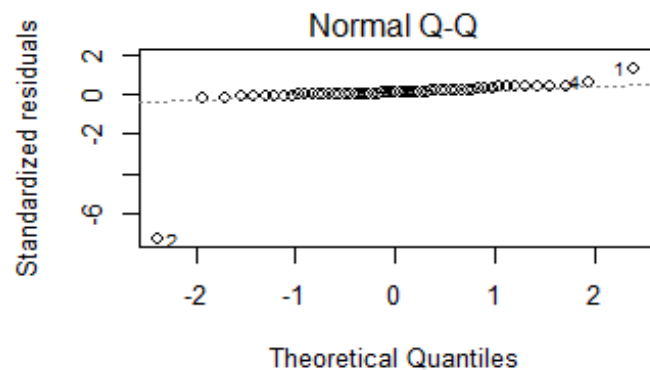
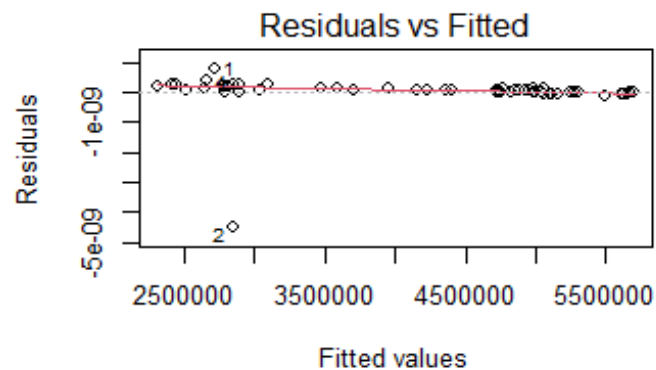
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 6.29e-10 on 55 degrees of freedom

Multiple R-squared: 1, Adjusted R-squared: 1

F-statistic: 1.743e+32 on 1 and 55 DF, p-value: < 2.2e-16

- Recent value is considered without any change, the current value will differ by -1.974e-09. For every increase of one metric ton in lag1, the current value will increase by 1.000e+00.
- The adjusted R-squared value is 1.



ARIMA

- This gives the d value in the Arima function. It tells you the number of differences that you should take to make the time series stationary.

```
ndiffs(FP_US_TS_recent)
```

```
[1] 1
```

- Best model is the one with lowest AIC

- (0,1,0)

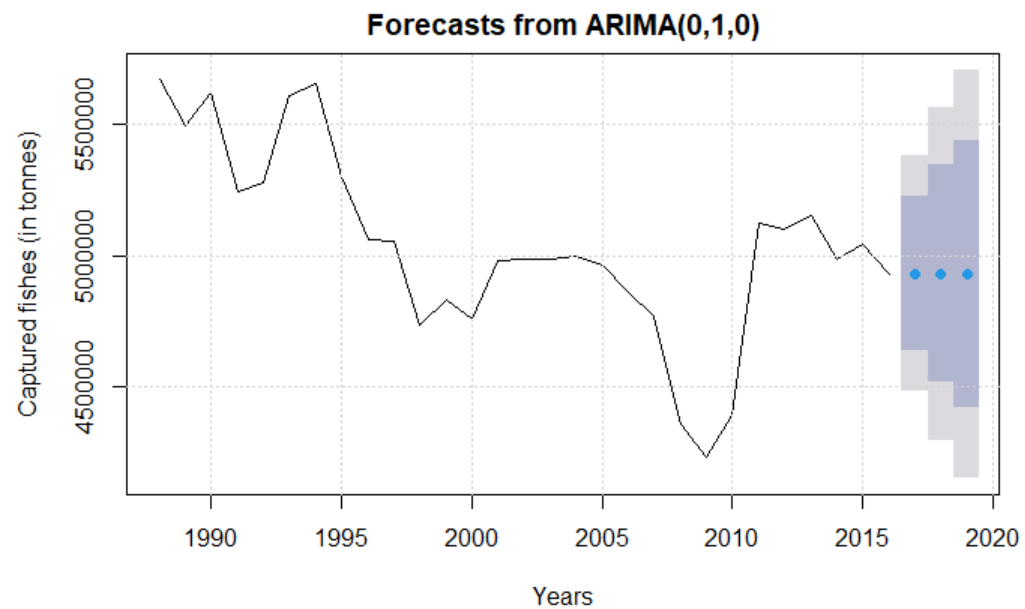
ARIMA(0,1,0)	: 772.5265
ARIMA(0,1,0) with drift	: 774.4747
ARIMA(0,1,1)	: 774.6563
ARIMA(0,1,1) with drift	: 776.8304
ARIMA(0,1,2)	: 777.1605
ARIMA(0,1,2) with drift	: 779.5101
ARIMA(0,1,3)	: 775.9411
ARIMA(0,1,3) with drift	: Inf
ARIMA(0,1,4)	: 778.0335
ARIMA(0,1,4) with drift	: 780.1718
ARIMA(0,1,5)	: Inf
ARIMA(0,1,5) with drift	: Inf

Best model: ARIMA(0,1,0)

Series: FP_US_TS_recent
ARIMA(0,1,0)

sigma^2 estimated as 5.205e+10: log likelihood=-385.19
AIC=772.37 AICc=772.53 BIC=773.7

- Arima forecast plot



- Naïve and Arima Forecast.

- Holts – Winter Forecast

- Exponential Smoothing Forecast

- Simple Moving Average Forecast

- If you notice, we are getting same point forecast value for all three years within the model. This is because our data is not seasonal and cyclic. So, it will simply take avg and print same result for all forecast.

	Point Forecast <dbl>	Lo 80 <dbl>	Hi 80 <dbl>	Lo 95 <dbl>	Hi 95 <dbl>
2017	4931017	4638643	5223391	4483870	5378164
2018	4931017	4517538	5344496	4298656	5563378
2019	4931017	4424611	5437423	4156536	5705498
3 rows					
	Point Forecast <dbl>	Lo 80 <dbl>	Hi 80 <dbl>	Lo 95 <dbl>	Hi 95 <dbl>
2017	4931025	4635287	5226762	4478733	5383316
2018	4931025	4512802	5349247	4291409	5570640
2019	4931025	4418815	5443234	4147667	5714382
3 rows					
	Point Forecast <dbl>	Lo 80 <dbl>	Hi 80 <dbl>	Lo 95 <dbl>	Hi 95 <dbl>
2017	4931029	4626568	5235489	4465396	5396661
2018	4931029	4500478	5361579	4272558	5589499
2019	4931029	4403723	5458334	4124584	5737473
3 rows					
SMA_forecast					
	Point Forecast <dbl>	Lo 80 <dbl>	Hi 80 <dbl>	Lo 95 <dbl>	Hi 95 <dbl>
2016	4986988	4804071	5169905	4707240	5266735
2017	4986988	4728317	5245659	4591385	5382591
2018	4986988	4670187	5303788	4502483	5471492
2019	4986988	4621181	5352794	4427535	5546441
4 rows					

Best Model

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Naïve	-26416.04	228140.4	160037.6	-0.6049683	3.205752	1	0.0720367 1
Moving Average	-22583.83	137342.9	108031.7	-0.467046	2.197547	0.9638667	0.5752261
Holt-Winters	-26417.51	228141.6	160036.7	-0.6050042	3.205737	0.9999942	0.0720964 6
Decomp	-16612.05	229233.4	163411.2	-0.4272953	3.252019	1.02108	0.0391081 4
ARIMA	-25309.6	224174.9	154714.6	-0.5806591	3.098657	0.9667391	0.0685086 6
Random Walk	-26416.04	228140.4	160037.6	-0.6049683	3.205752	1	0.0720367 1

- We are using MAPE as a measure of accuracy.
- Since the lowest MAPE value is of Moving average, we consider it as the best forecasting model.
- This was expected as Moving average works best when recent observations are better than all observations.
- Since, we saw correlation between the residuals in Acf for SMA, we choose some other model.
- The second best accuracy is for Arima.
- Final prediction :

```
MAPE <- 5
best_accuracy[1] <- naive_accuracy[MAPE]
best_accuracy[2] <- SMA_accuracy[MAPE]
best_accuracy[3] <- HoltWinters_accuracy[MAPE]
best_accuracy[4] <- ets_accuracy[MAPE]
best_accuracy[5] <- Arima_accuracy[MAPE]
best_accuracy[6] <- rwf_accuracy[MAPE]
```

```
best_accuracy
```

```
[1] 3.205752 2.197547 3.205737 3.252019 3.098657 3.205752
```

```
best_accuracy_MAPE = min(best_accuracy)
best_accuracy_MAPE
```

```
[1] 2.197547
```

	Point Forecast <dbl>	Lo 80 <dbl>	Hi 80 <dbl>	Lo 95 <dbl>	Hi 95 <dbl>
2017	4931017	4638643	5223391	4483870	5378164
2018	4931017	4517538	5344496	4298656	5563378
2019	4931017	4424611	5437423	4156536	5705498

3 rows