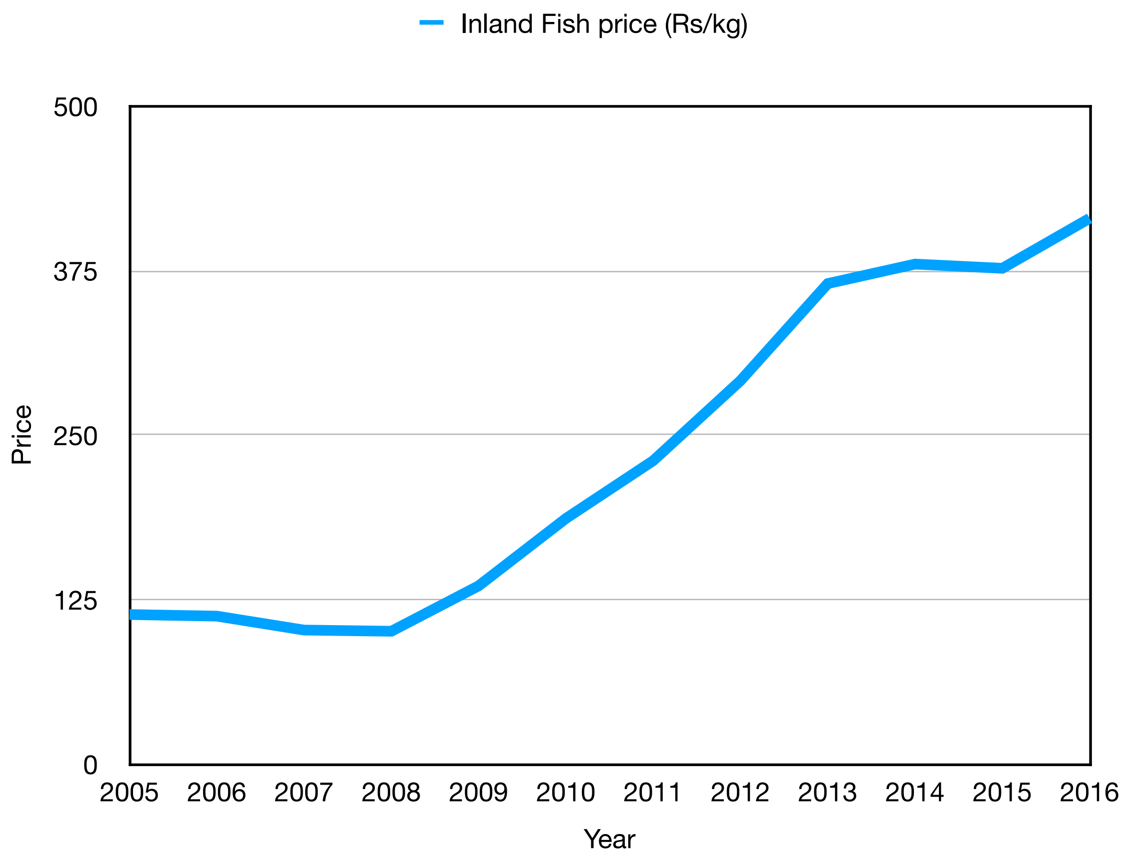
Time Series Analysis of Fish Prices in India

Inland Fish Prices

Dataset Information-

Dataset gives information about prices of inland fish (Rs/kg) from year 2005 till 2016.

Time Series plot of Inland Fish Prices



Check for Time Series Stationarity

We will use augmented dickey fuller test to check for stationarity of the given time series.

```
> adf.test(time_series_inland_prices)

	Augmented Dickey-Fuller Test

data:  time_series_inland_prices
Dickey-Fuller = -2.1147, Lag order = 2, p-value = 0.5287
alternative hypothesis: stationary
```

```
> inland_prices_d1<-diff(time_series_inland_prices,differences = 1)
> adf.test(inland_prices_d1)

	Augmented Dickey-Fuller Test

data:  inland_prices_d1
Dickey-Fuller = 0.14557, Lag order = 2, p-value = 0.99
alternative hypothesis: stationary
```

```
> inland_prices_d2<-diff(prices$Inland.Fish.price..Rs.kg.,differences = 2)
> adf.test(inland_prices_d2)

	Augmented Dickey-Fuller Test

data:  inland_prices_d2
Dickey-Fuller = -5.2718, Lag order = 2, p-value = 0.01
alternative hypothesis: stationary
```

We can observe that p-value becomes less than 0.05 only after 2nd order differencing so after 2nd order differencing the trend is removed and time series becomes stationary.

Time Series Models

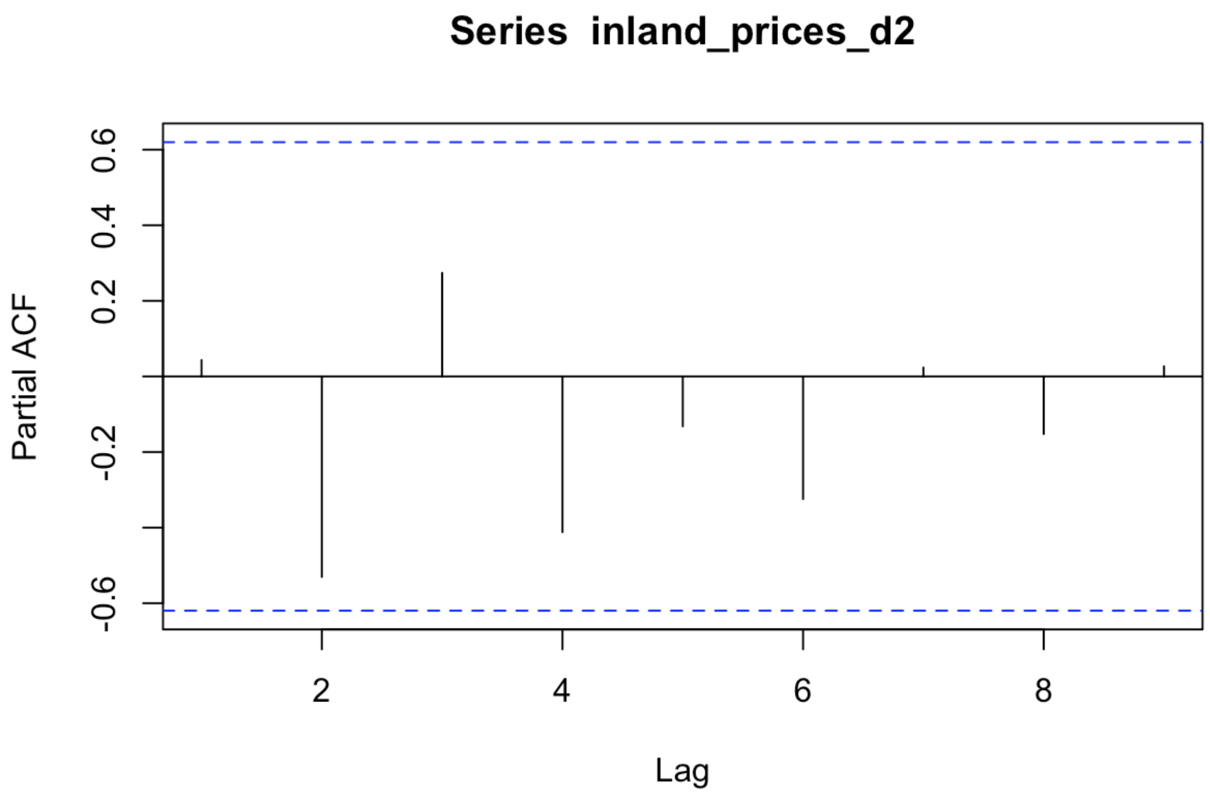
- **Naive Model**

```
> inland_prices_model1<-naive(time_series_inland_prices)
> inland_prices_f1<-forecast(inland_prices_model1)
> summary(inland_prices_f1)

Forecast method: Naive method

Model Information:
Call: naive(y = time_series_inland_prices)

Residual sd: 38.926

Error measures:
                ME     RMSE      MAE      MPE     MAPE MASE      ACF1
Training set 27.37 38.92603 30.26091 10.25772 12.65943    1 0.4867295

Forecasts:
     Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
2017         414.77 364.8843 464.6557 338.4764 491.0636
2018         414.77 344.2210 485.3190 306.8745 522.6655
2019         414.77 328.3654 501.1746 282.6256 546.9144
2020         414.77 314.9986 514.5414 262.1828 567.3572
2021         414.77 303.2222 526.3178 244.1723 585.3677
2022         414.77 292.5755 536.9645 227.8896 601.6504
2023         414.77 282.7848 546.7552 212.9161 616.6239
2024         414.77 273.6719 555.8681 198.9791 630.5609
2025         414.77 265.1129 564.4271 185.8892 643.6508
2026         414.77 257.0175 572.5225 173.5084 656.0316
```

- **AR Model**

Pacf plot for finding p value.

```
plot(pacf(inland_prices_d2))
```

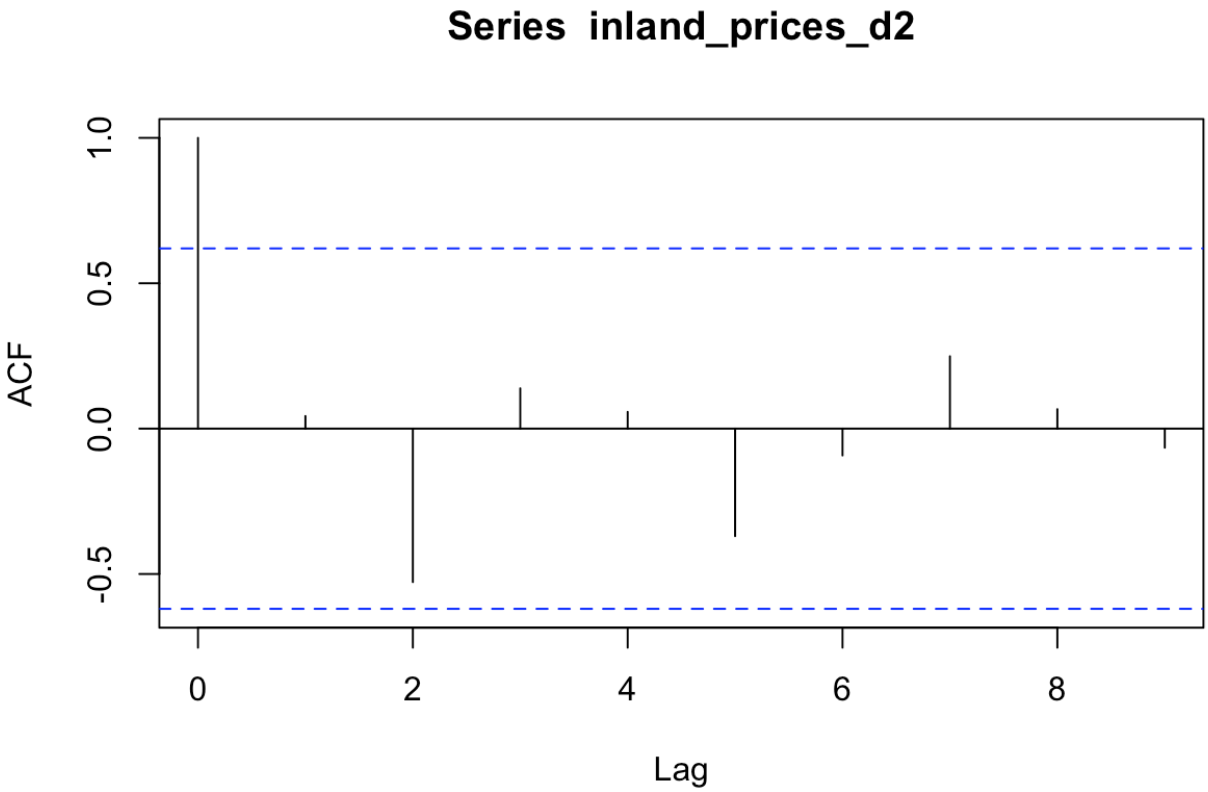


All values line within the boundaries hence p value is 0 and AR model is suited for use for the given time series.

- **MA Model**

Acf plot for finding q value.

```
plot(acf(inland_prices_d2))
```



Value of q is also 0 hence MA model is also for suited for performing time series analysis on prices of inland fish products.

- **ARIMA Model**

Values of p, d, q are 0, 2, 0 respectively.

```
> inland_prices_model2<-arima(time_series_inland_prices,order=c(0,2,0))
> inland_prices_f2<-forecast(inland_prices_model2)
> summary(inland_prices_f2)

Forecast method: ARIMA(0,2,0)

Model Information:

Call:
arima(x = time_series_inland_prices, order = c(0, 2, 0))


sigma^2 estimated as 772.2:  log likelihood = -47.44,  aic = 96.87

Error measures:
                   ME     RMSE      MAE      MPE     MAPE      MASE       ACF1
Training set 3.255468 25.36795 18.89801 2.597707 8.069666 0.6245023 0.04866344

Forecasts:
     Point Forecast      Lo 80     Hi 80       Lo 95     Hi 95
2017         452.74 417.12677  488.3532  398.27427  507.2057
2018         490.71 411.07640  570.3436  368.92092  612.4991
2019         528.68 395.42750  661.9325  324.88788  732.4721
2020         566.65 371.58831  761.7117  268.32889  864.9711
2021         604.62 340.50522  868.7348  200.69130 1008.5487
2022         642.59 302.86144  982.3186  123.02001 1162.1600
2023         680.56 259.17859 1101.9414   36.11274 1325.0073
2024         718.53 209.87134 1227.1887  -59.39629 1496.4563
2025         756.50 155.27949 1357.7205 -162.98742 1675.9874
2026         794.47  95.68798 1493.2520 -274.22488 1863.1649
```

- **ARIMA Model using Auto Arima Function**

auto.arima() function in R returns the best model according to AIC, AICc or BIC value.

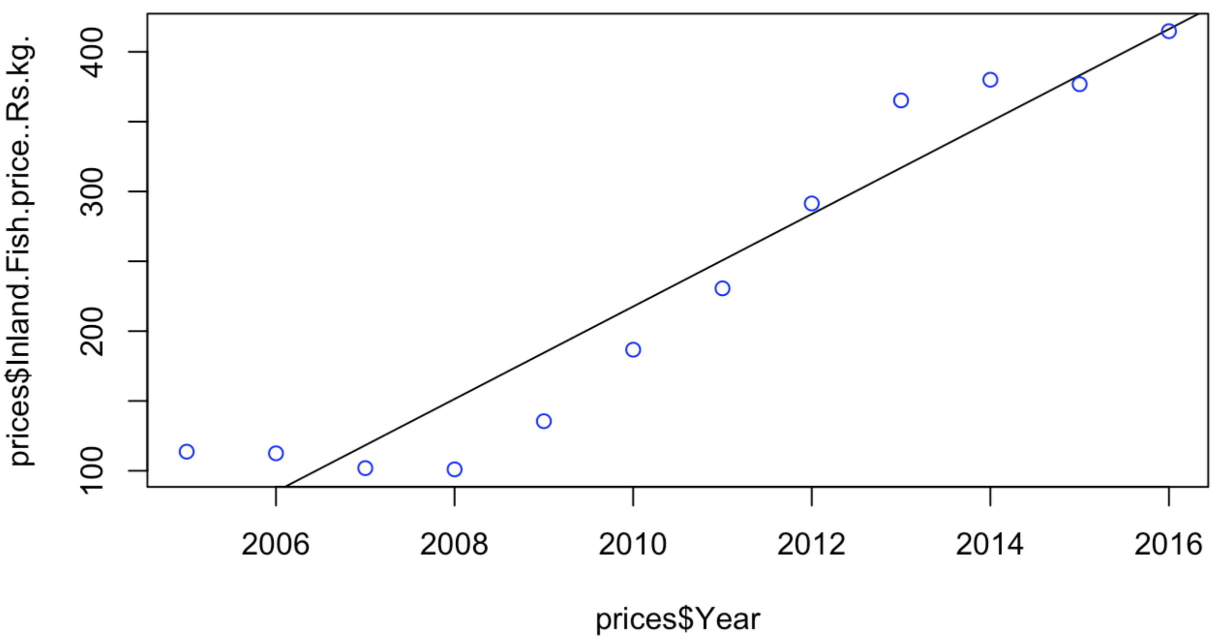
```
> m100<-auto.arima(time_series_inland_prices,seasonal = FALSE)
> f100<-forecast(m100)
> summary(f100)

Forecast method: ARIMA(0,1,0) with drift

Model Information:
Series: time_series_inland_prices
ARIMA(0,1,0) with drift

Coefficients:
        drift
      27.3700
s.e.   8.3455

sigma^2 estimated as 842.7:  log likelihood=-52.14
AIC=108.27   AICc=109.77   BIC=109.07

Error measures:
                      ME     RMSE      MAE       MPE  MAPE      MASE      ACF1
Training set 0.007194163 26.50049 22.99886 -4.171437 12.84 0.7600188 0.4864455

Forecasts:
     Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
2017         442.14 404.9368 479.3432 385.2426 499.0374
2018         469.51 416.8967 522.1233 389.0449 549.9751
2019         496.88 432.4421 561.3179 398.3308 595.4292
2020         524.25 449.8435 598.6565 410.4551 638.0449
2021         551.62 468.4311 634.8089 424.3935 678.8465
2022         578.99 487.8611 670.1189 439.6203 718.3597
2023         606.36 507.9295 704.7905 455.8236 756.8964
2024         633.73 528.5034 738.9566 472.7998 794.6602
2025         661.10 549.4903 772.7097 490.4077 831.7923
2026         688.47 570.8231 806.1169 508.5445 868.3955
```

Auto.arima() functions returns ARIMA(0,1,0) model with drift but RMSE value of this model is slightly worse compared to the previous model.

- **Linear Regression Model**

```
> inland_prices_model4<-lm(prices$Inland.Fish.price..Rs.kg.~prices$Year)
> summary(inland_prices_model4)

Call:
lm(formula = prices$Inland.Fish.price..Rs.kg. ~ prices$Year)

Residuals:
    Min      1Q  Median      3Q     Max 
-50.395 -22.825  -3.943  27.980  61.638 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -66335.662   6389.069  -10.38 1.13e-06 ***
prices$Year     33.111      3.178   10.42 1.09e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 38 on 10 degrees of freedom
Multiple R-squared:  0.9157,	Adjusted R-squared:  0.9072 
F-statistic: 108.6 on 1 and 10 DF,  p-value: 1.089e-06
```

```
> plot(prices$Year,prices$Inland.Fish.price..Rs.kg.,col="blue",abline(lm(prices$Inland.Fish.price..Rs.
kg.~prices$Year)))
```



- **Non Linear Regression Model**

```
> y_var<-prices$Inland.Fish.price..Rs.kg.
> x_var<-prices$Year
> inland_prices_model7<-lm(y_var ~ poly(x_var,3,raw=TRUE))
> summary(inland_prices_model7)

Call:
lm(formula = y_var ~ poly(x_var, 3, raw = TRUE))

Residuals:
    Min      1Q  Median      3Q     Max 
-40.673 -23.607  -5.507  25.450  57.972 

Coefficients: (1 not defined because of singularities)
                             Estimate Std. Error t value Pr(>|t|)  
(Intercept)                 6.868e+06  3.781e+06   1.816   0.1027  
poly(x_var, 3, raw = TRUE)1 -6.865e+03  3.762e+03  -1.825   0.1013  
poly(x_var, 3, raw = TRUE)2  1.716e+00  9.355e-01   1.834   0.0999 .
poly(x_var, 3, raw = TRUE)3         NA         NA      NA       NA  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 34.18 on 9 degrees of freedom
Multiple R-squared:  0.9386,    Adjusted R-squared:  0.925 
F-statistic: 68.79 on 2 and 9 DF,  p-value: 3.522e-06
```

Performance of Non linear regression model is better than linear regression model but not as good as ARIMA model.

- **Exponential Smoothing Model**

```
> inland_prices_model5<-ets(time_series_inland_prices)
> inland_prices_f5<-forecast(inland_prices_model5)
> summary(inland_prices_f5)

Forecast method: ETS(M,N,N)

Model Information:
ETS(M,N,N)

Call:
 ets(y = time_series_inland_prices)

  Smoothing parameters:
    alpha = 0.9999

  Initial states:
    l = 109.5469

  sigma:  0.217

     AIC     AICc      BIC
121.7974 124.7974 123.2521

Error measures:
                   ME     RMSE      MAE      MPE     MAPE      MASE      ACF1
Training set 25.43749 37.29081 28.08737 9.708023 11.90965 0.9281733 0.5314533

Forecasts:
     Point Forecast      Lo 80    Hi 80       Lo 95     Hi 95
2017       414.7662 299.426502 530.1059  238.369353  591.1631
2018       414.7662 249.750795 579.7816  162.396914  667.1355
2019       414.7662 210.285075 619.2473  102.039305  727.4931
2020       414.7662 175.848959 653.6834   49.373811  780.1586
2021       414.7662 144.453137 685.0793    1.358043  828.1744
2022       414.7662 115.083901 714.4485  -43.558327  873.0907
2023       414.7662  87.141624 742.3908  -86.292351  915.8248
2024       414.7662  60.236376 769.2960 -127.440378  956.9728
2025       414.7662  34.097150 795.4353 -167.416874  996.9493
2026       414.7662   8.525972 821.0064 -206.524617 1036.0570
```

- **Holt Winters Model**

```
> inland_prices_model6<-HoltWinters(time_series_inland_prices,beta=FALSE,gamma=FALSE)
> inland_prices_f6<-forecast(inland_prices_model6)
> summary(inland_prices_f6)

Forecast method: HoltWinters

Model Information:
Holt-Winters exponential smoothing without trend and without seasonal component.

Call:
HoltWinters(x = time_series_inland_prices, beta = FALSE, gamma = FALSE)

Smoothing parameters:
 alpha: 0.9999327
 beta : FALSE
 gamma: FALSE

Coefficients:
      [,1]
a 414.7674

Error measures:
                   ME     RMSE      MAE      MPE     MAPE     MASE      ACF1
Training set 27.37161 38.92793 30.26248 10.25823 12.66003 1.000052 0.4867633

Forecasts:
     Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
2017       414.7674 377.5628 451.9721 357.8678 471.6671
2018       414.7674 362.1539 467.3810 334.3019 495.2330
2019       414.7674 350.3300 479.2049 316.2188 513.3161
2020       414.7674 340.3619 489.1730 300.9739 528.5609
2021       414.7674 331.5798 497.9551 287.5429 541.9920
2022       414.7674 323.6401 505.8948 275.4002 554.1347
2023       414.7674 316.3388 513.1961 264.2339 565.3010
2024       414.7674 309.5430 519.9919 253.8405 575.6944
2025       414.7674 303.1601 526.3748 244.0788 585.4561
2026       414.7674 297.1231 532.4118 234.8459 594.6889
```

- **Holt Winters Model with Trend Smoothing**

```
> inland_prices_model7<-HoltWinters(time_series_inland_prices,gamma=FALSE)
> inland_prices_f7<-forecast(inland_prices_model7)
> summary(inland_prices_f7)

Forecast method: HoltWinters

Model Information:
Holt-Winters exponential smoothing with trend and without seasonal component.

Call:
HoltWinters(x = time_series_inland_prices, gamma = FALSE)

Smoothing parameters:
 alpha: 1
 beta : 1
 gamma: FALSE

Coefficients:
    [,1]
a 414.77
b  37.97

Error measures:
                ME     RMSE    MAE      MPE     MAPE      MASE       ACF1
Training set 3.917 27.78915 22.657 3.126575 9.665329 0.7487217 0.04325722

Forecasts:
     Point Forecast     Lo 80     Hi 80       Lo 95     Hi 95
2017         452.74 415.57515  489.9048  395.901270  509.5787
2018         490.71 407.60687  573.8131  363.614735  617.8053
2019         528.68 389.62187  667.7381  316.008945  741.3511
2020         566.65 363.08974  770.2103  255.331453  877.9685
2021         604.62 328.99811  880.2419  183.092694 1026.1473
2022         642.59 288.05994  997.1201  100.383070 1184.7969
2023         680.56 240.81959 1120.3004    8.035073 1353.0849
2024         718.53 187.70979 1249.3502  -93.289449 1530.3494
2025         756.50 129.08515 1383.9148 -203.048206 1716.0482
2026         794.47  65.24302 1523.6970 -320.786422 1909.7264
```

Conclusion

The 2 models which stand out in terms of performance are ARIMA(0,2,0) model and Holt Winters Model with trend smoothing.

Forecast using The 2 Top Models

- **Holt Winters Model With trend Smoothing**

Forecasts:

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2017	452.74	415.57515	489.9048	395.901270	509.5787
2018	490.71	407.60687	573.8131	363.614735	617.8053
2019	528.68	389.62187	667.7381	316.008945	741.3511
2020	566.65	363.08974	770.2103	255.331453	877.9685
2021	604.62	328.99811	880.2419	183.092694	1026.1473
2022	642.59	288.05994	997.1201	100.383070	1184.7969
2023	680.56	240.81959	1120.3004	8.035073	1353.0849
2024	718.53	187.70979	1249.3502	-93.289449	1530.3494
2025	756.50	129.08515	1383.9148	-203.048206	1716.0482
2026	794.47	65.24302	1523.6970	-320.786422	1909.7264

- **ARIMA Model**

Forecasts:

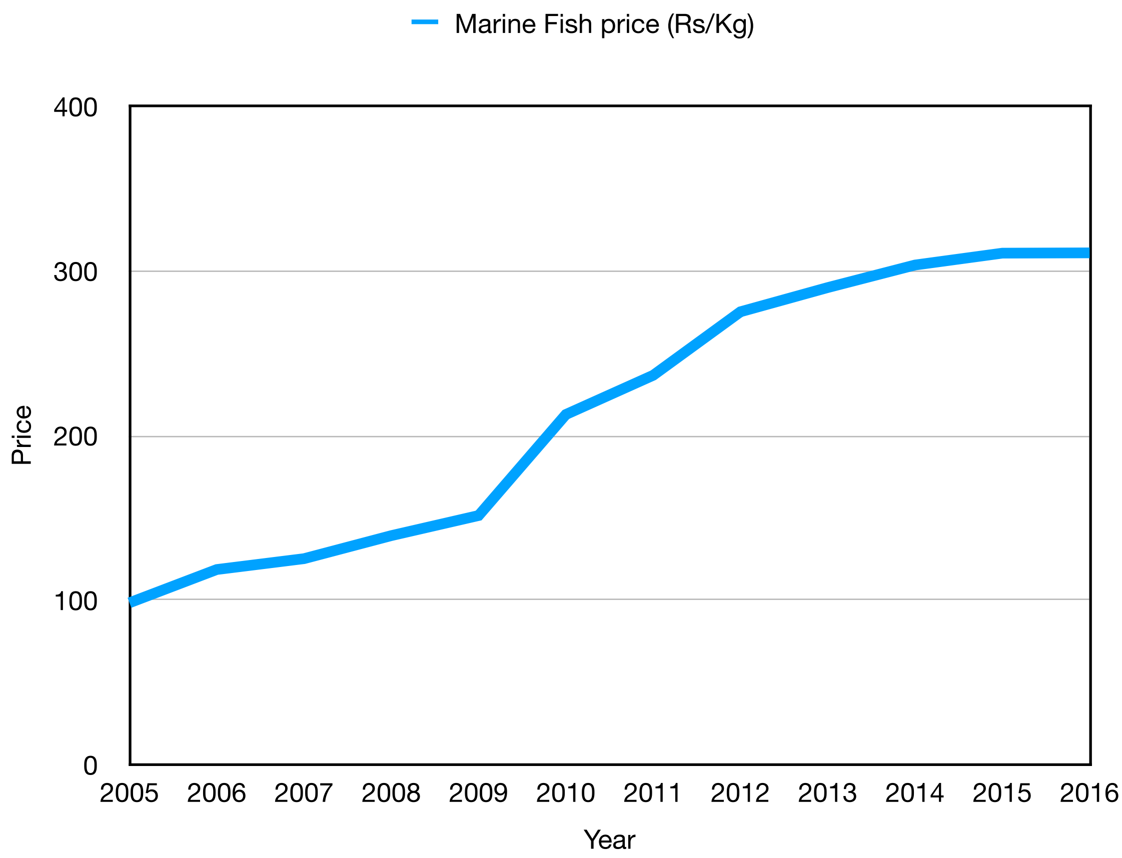
	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2017	452.74	417.12677	488.3532	398.27427	507.2057
2018	490.71	411.07640	570.3436	368.92092	612.4991
2019	528.68	395.42750	661.9325	324.88788	732.4721
2020	566.65	371.58831	761.7117	268.32889	864.9711
2021	604.62	340.50522	868.7348	200.69130	1008.5487
2022	642.59	302.86144	982.3186	123.02001	1162.1600
2023	680.56	259.17859	1101.9414	36.11274	1325.0073
2024	718.53	209.87134	1227.1887	-59.39629	1496.4563
2025	756.50	155.27949	1357.7205	-162.98742	1675.9874
2026	794.47	95.68798	1493.2520	-274.22488	1863.1649

Marine Fish Prices

Dataset Information-

Dataset gives information about prices of marine fish (Rs/Kg) from year 2005 till 2016.

Time Series Plot of Marine Fish Prices



Check for Time Series Stationarity

```
> time_series_marine_prices <- ts(prices$Marine.Fish.price..Rs.Kg.,start=2005,end=2016)
> adf.test(time_series_marine_prices)

	Augmented Dickey-Fuller Test

data:  time_series_marine_prices
Dickey-Fuller = -2.0551, Lag order = 2, p-value = 0.5514
alternative hypothesis: stationary

> marine_prices_d1<-diff(time_series_marine_prices,differences = 1)
> adf.test(marine_prices_d1)

	Augmented Dickey-Fuller Test

data:  marine_prices_d1
Dickey-Fuller = -1.3282, Lag order = 2, p-value = 0.8283
alternative hypothesis: stationary

> marine_prices_d2<-diff(time_series_marine_prices,differences = 2)
> adf.test(marine_prices_d2)

	Augmented Dickey-Fuller Test

data:  marine_prices_d2
Dickey-Fuller = -2.7746, Lag order = 2, p-value = 0.2773
alternative hypothesis: stationary

> marine_prices_d3<-diff(time_series_marine_prices,differences = 3)
> adf.test(marine_prices_d3)

	Augmented Dickey-Fuller Test

data:  marine_prices_d3
Dickey-Fuller = -5.5071, Lag order = 2, p-value = 0.01
alternative hypothesis: stationary
```

Only after performing 3rd order differencing p-value becomes less than 0.05 and time series becomes stationary.

Time Series Models

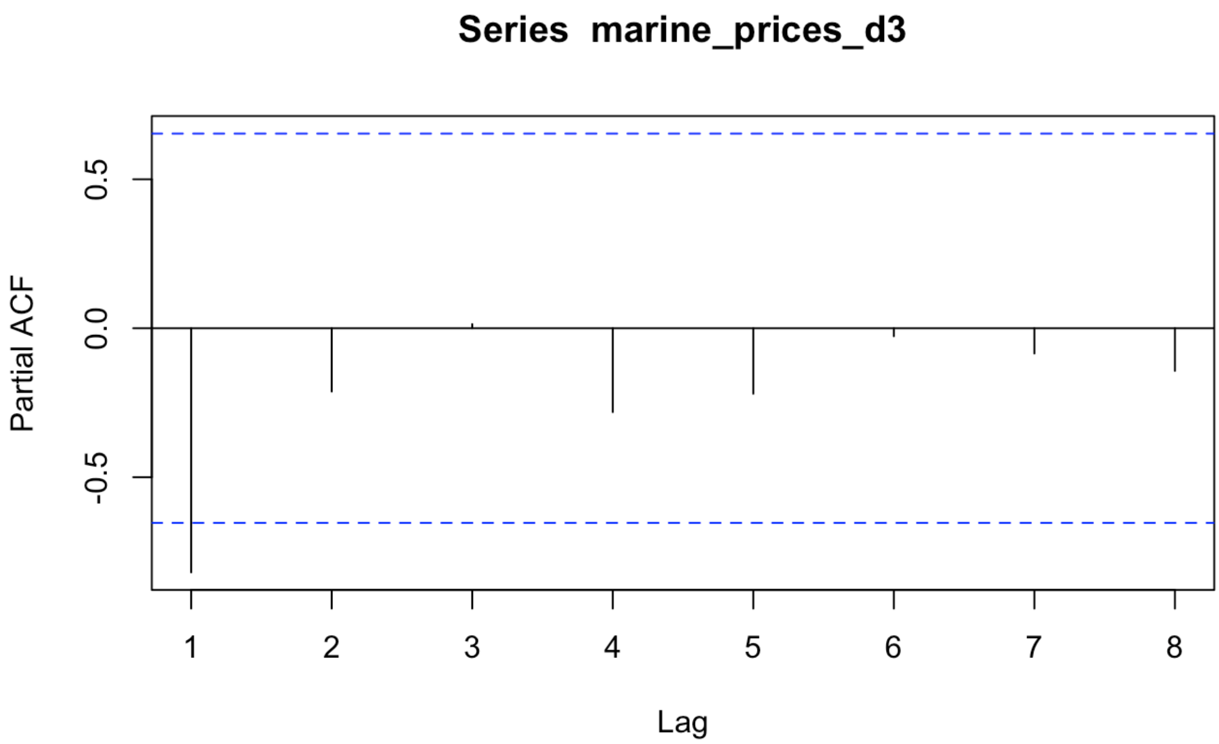
- **Naive Model**

```
> marine_prices_model1<-naive(time_series_marine_prices)
> marine_prices_f1<-forecast(marine_prices_model1)
> summary(marine_prices_f1)

Forecast method: Naive method

Model Information:
Call: naive(y = time_series_marine_prices)

Residual sd: 25.3672

Error measures:
                   ME     RMSE      MAE      MPE     MAPE MASE      ACF1
Training set 19.32545 25.36722 19.32545 9.574149 9.574149    1 0.1031969

Forecasts:
     Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
2017         310.98 278.4706 343.4894 261.2612 360.6988
2018         310.98 265.0048 356.9552 240.6670 381.2930
2019         310.98 254.6721 367.2879 224.8645 397.0955
2020         310.98 245.9612 375.9988 211.5423 410.4177
2021         310.98 238.2868 383.6732 199.8053 422.1547
2022         310.98 231.3486 390.6114 189.1942 432.7658
2023         310.98 224.9682 396.9918 179.4363 442.5237
2024         310.98 219.0295 402.9305 170.3539 451.6061
2025         310.98 213.4518 408.5082 161.8235 460.1365
2026         310.98 208.1763 413.7837 153.7553 468.2047
```

- **AR Model**

Pacf plot for finding p value.

```
plot(pacf(marine_prices_d3))
```



P value is 1.

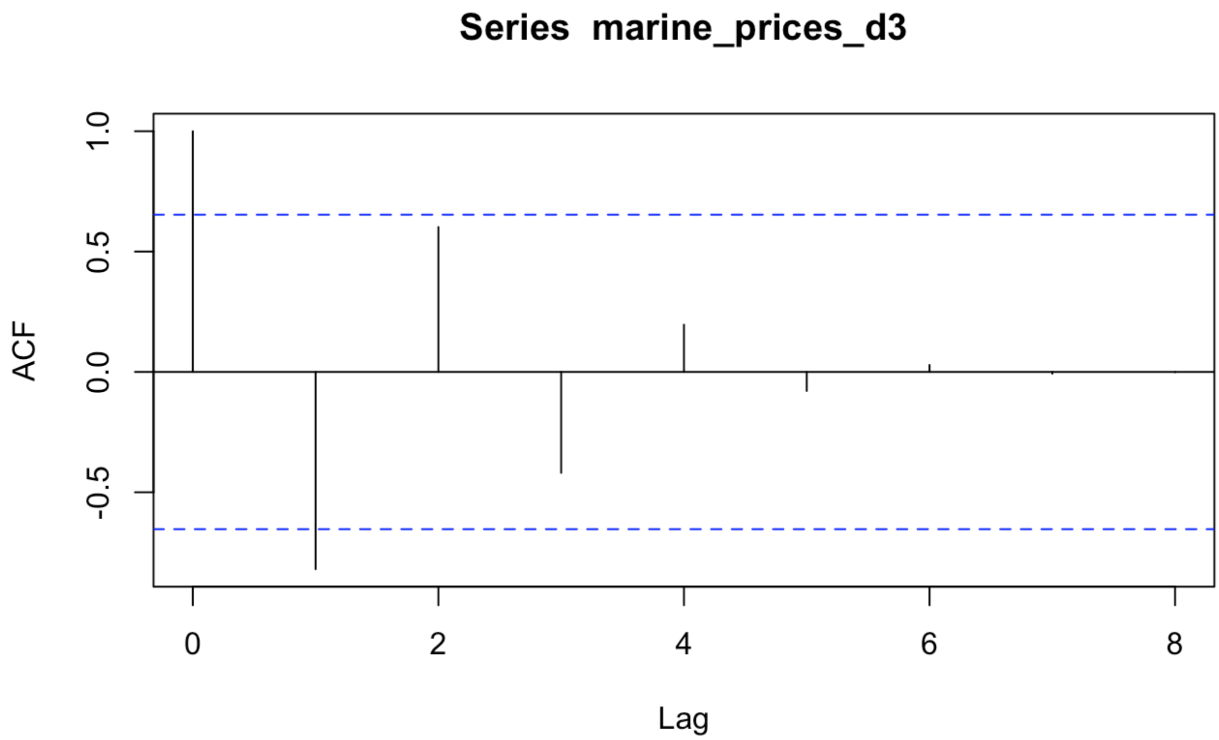
```
> marine_prices_model2<-ar(time_series_marine_prices)
> marine_prices_f2<-forecast(marine_prices_model2)
> summary(marine_prices_f2)

Forecast method: AR(1)

Model Information:

Call:
ar(x = time_series_marine_prices)

Coefficients:
     1
0.8053

Order selected 1  sigma^2 estimated as  2695

Error measures:
                   ME     RMSE      MAE      MPE     MAPE     MASE     ACF1
Training set 17.61575 26.02569 21.29592 5.950932 8.799148 1.101962 0.432155

Forecasts:
     Point Forecast    Lo 80    Hi 80     Lo 95    Hi 95
2017       292.1733 225.6379 358.7087 190.41618 393.9304
2018       277.0283 191.6010 362.4556 146.37853 407.6781
2019       264.8322 169.1265 360.5379 118.46302 411.2014
2020       255.0108 153.1927 356.8288  99.29350 410.7280
2021       247.1016 141.5087 352.6946  85.61115 408.5921
2022       240.7325 132.7620 348.7029  75.60591 405.8590
2023       235.6034 126.1188 345.0880  68.16108 403.0457
2024       231.4730 121.0175 341.9285  62.54589 400.4001
2025       228.1468 117.0663 339.2274  58.26375 398.0299
2026       225.4683 113.9842 336.9523  54.96814 395.9684
```

AR model is clearly not suited for the given time series.

- **MA Model**

Acf plot for finding q value.

```
plot(acf(marine_prices_d3))
```



Q value from above graph is 1.

```
> marine_prices_model3<-ma(time_series_marine_prices,order = 1)
> marine_prices_f3<-forecast(marine_prices_model3)
> summary(marine_prices_f3)

Forecast method: ETS(A,N,N)

Model Information:
ETS(A,N,N)

Call:
 ets(y = object, lambda = lambda, biasadj = biasadj, allow.multiplicative.trend = allow.multiplicativ
e.trend)

  Smoothing parameters:
    alpha = 0.9999

  Initial states:
    l = 98.432

  sigma:  26.607

     AIC     AICc      BIC
112.3792 115.3792 113.8339

Error measures:
                  ME     RMSE      MAE      MPE     MAPE      MASE       ACF1
Training set 17.7141 24.28877 17.71944 8.774384 8.779812 0.9168965 0.09604099

Forecasts:
     Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
2017         310.98 276.8817 345.0782 258.8312 363.1288
2018         310.98 262.7602 359.1998 237.2341 384.7258
2019         310.98 251.9240 370.0360 220.6616 401.2983
2020         310.98 242.7886 379.1714 206.6902 415.2697
2021         310.98 234.7401 387.2199 194.3811 427.5789
2022         310.98 227.4636 394.4964 183.2527 438.7073
2023         310.98 220.7722 401.1878 173.0191 448.9409
2024         310.98 214.5440 407.4160 163.4938 458.4661
2025         310.98 208.6943 413.2657 154.5475 467.4124
2026         310.98 203.1615 418.7984 146.0859 475.8741
```

Performance of MA model is slightly better compared to first 2 models.

- **ARIMA Model**

p=1, d=3 and q=1

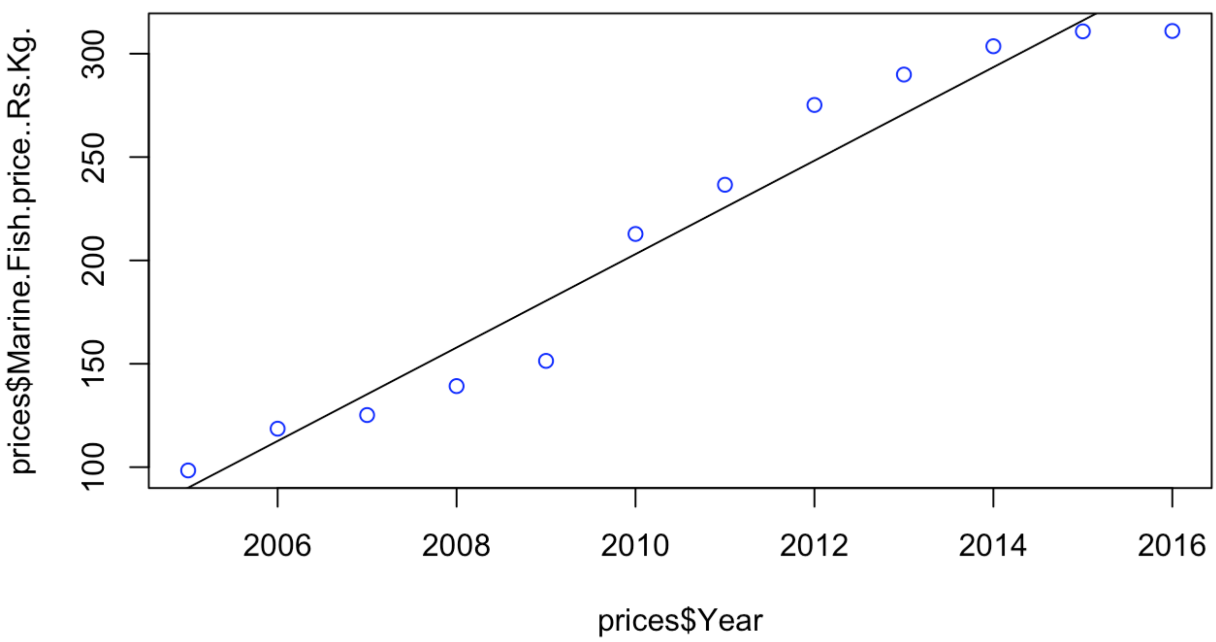
```
> marine_prices_model4<-arima(time_series_marine_prices,order=c(1,3,1))
> marine_prices_f4<-forecast(marine_prices_model4)
> summary(marine_prices_f4)

Forecast method: ARIMA(1,3,1)

Model Information:

Call:
arima(x = time_series_marine_prices, order = c(1, 3, 1))

Coefficients:
          ar1      ma1
      -0.5734  -0.7285
s.e.   0.2859   0.4504

sigma^2 estimated as 414.4:  log likelihood = -40.82,  aic = 87.63

Error measures:
                    ME     RMSE      MAE      MPE     MAPE      MASE       ACF1
Training set -1.318664 17.62862 11.91384 0.376983 5.261358 0.6164842 0.03090037

Forecasts:
     Point Forecast       Lo 80    Hi 80      Lo 95     Hi 95
2017       308.0868   281.98259 334.1910  268.16385  348.0098
2018       299.8574   248.39638 351.3183  221.15459  378.5601
2019       287.5893   197.28806 377.8905  149.48548  425.6930
2020       270.5385   132.43169 408.6453   59.32237  481.7546
2021       249.1316    51.31278 446.9505  -53.40619  551.6695
2022       223.1241   -45.63380 491.8820 -187.90564  634.1539
2023       192.6562  -159.46440 544.7768 -345.86578  731.1781
2024       157.6474  -290.45588 605.7507 -527.66743  842.9622
2025       118.1439  -439.27242 675.5602 -734.35078  970.6385
2026        74.1192  -606.35037 754.5888 -966.56920 1114.8076
```

Performance of the model is better compared to all other models seen so far.

- **Linear Regression Model**

```
> marine_prices_model5<-lm(prices$Marine.Fish.price..Rs.Kg. ~ prices$Year)
> summary(marine_prices_model5)

Call:
lm(formula = prices$Marine.Fish.price..Rs.Kg. ~ prices$Year)

Residuals:
    Min      1Q  Median      3Q     Max 
-29.079 -12.216   7.146  10.290  26.899 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -45237.532   3189.187  -14.19 5.97e-08 ***
prices$Year     22.607      1.586   14.25 5.71e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 18.97 on 10 degrees of freedom
Multiple R-squared:  0.9531,	Adjusted R-squared:  0.9484 
F-statistic: 203.1 on 1 and 10 DF,  p-value: 5.711e-08
```

```
> plot(prices$Year,prices$Marine.Fish.price..Rs.Kg.,col="blue",abline(lm(prices$Marine.Fish.price..Rs.
Kg. ~ prices$Year)))
```



- **Non Linear Regression Model**

```
> y_v<-prices$Marine.Fish.price..Rs.Kg.
> x_v<-prices$Year
> marine_prices_model6<-lm(y_v ~ poly(x_v,2,raw=TRUE))
> summary(marine_prices_model6)

Call:
lm(formula = y_v ~ poly(x_v, 2, raw = TRUE))

Residuals:
    Min      1Q  Median      3Q     Max 
-33.220 -12.415   5.312  11.722  22.758 

Coefficients:
                            Estimate Std. Error t value Pr(>|t|)
(Intercept)               -1.777e+06  2.136e+06  -0.832    0.427
poly(x_v, 2, raw = TRUE)1  1.745e+03  2.125e+03   0.822    0.433
poly(x_v, 2, raw = TRUE)2 -4.284e-01  5.284e-01  -0.811    0.438

Residual standard error: 19.3 on 9 degrees of freedom
Multiple R-squared:  0.9563,	Adjusted R-squared:  0.9466 
F-statistic: 98.41 on 2 and 9 DF,  p-value: 7.646e-07
```

- **Exponential Smoothing Model**

```
> marine_prices_model7<-ets(time_series_marine_prices)
> marine_prices_f7<-forecast(marine_prices_model7)
> summary(marine_prices_f7)

Forecast method: ETS(A,N,N)

Model Information:
ETS(A,N,N)

Call:
 ets(y = time_series_marine_prices)

  Smoothing parameters:
    alpha = 0.9999

  Initial states:
    l = 98.432

  sigma:  26.607

     AIC     AICc      BIC
112.3792 115.3792 113.8339

Error measures:
                 ME     RMSE      MAE      MPE     MAPE      MASE       ACF1
Training set 17.7141 24.28877 17.71944 8.774384 8.779812 0.9168965 0.09604099

Forecasts:
     Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
2017         310.98 276.8817 345.0782 258.8312 363.1288
2018         310.98 262.7602 359.1998 237.2341 384.7258
2019         310.98 251.9240 370.0360 220.6616 401.2983
2020         310.98 242.7886 379.1714 206.6902 415.2697
2021         310.98 234.7401 387.2199 194.3811 427.5789
2022         310.98 227.4636 394.4964 183.2527 438.7073
2023         310.98 220.7722 401.1878 173.0191 448.9409
2024         310.98 214.5440 407.4160 163.4938 458.4661
2025         310.98 208.6943 413.2657 154.5475 467.4124
2026         310.98 203.1615 418.7984 146.0859 475.8741
```

- **Holt Winters Model**

```
> marine_prices_model8<-HoltWinters(time_series_marine_prices,beta=FALSE,gamma=FALSE)
> marine_prices_f8<-forecast(marine_prices_model8)
> summary(marine_prices_f8)

Forecast method: HoltWinters

Model Information:
Holt-Winters exponential smoothing without trend and without seasonal component.

Call:
HoltWinters(x = time_series_marine_prices, beta = FALSE, gamma = FALSE)

Smoothing parameters:
 alpha: 0.9999215
 beta : FALSE
 gamma: FALSE

Coefficients:
    [,1]
a 310.98

Error measures:
                   ME     RMSE      MAE      MPE     MAPE     MASE      ACF1
Training set 19.32697 25.36845 19.32697 9.574829 9.574829 1.000078 0.1032885

Forecasts:
     Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
2017         310.98 288.8930 333.0669 277.2009 344.7591
2018         310.98 279.7455 342.2144 263.2110 358.7489
2019         310.98 272.7263 349.2337 252.4760 369.4840
2020         310.98 266.8087 355.1513 243.4258 378.5342
2021         310.98 261.5952 360.3648 235.4524 386.5075
2022         310.98 256.8818 365.0782 228.2439 393.7161
2023         310.98 252.5473 369.4126 221.6150 400.3450
2024         310.98 248.5130 373.4470 215.4449 406.5151
2025         310.98 244.7238 377.2362 209.6498 412.3101
2026         310.98 241.1399 380.8201 204.1687 417.7912
```

- **Holt Winter Model with Trend Smoothing**

```
> marine_prices_model9<-HoltWinters(time_series_marine_prices,gamma=FALSE)
> marine_prices_f9<-forecast(marine_prices_model9)
> summary(marine_prices_f9)

Forecast method: HoltWinters

Model Information:
Holt-Winters exponential smoothing with trend and without seasonal component.

Call:
HoltWinters(x = time_series_marine_prices, gamma = FALSE)

Smoothing parameters:
 alpha: 1
 beta : 0
 gamma: FALSE

Coefficients:
    [,1]
a 310.98
b  20.20

Error measures:
                 ME    RMSE    MAE        MPE     MAPE      MASE      ACF1
Training set -0.962 17.2588 13.602 -0.7690803 6.282781 0.7038386 0.1078844

Forecasts:
     Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
2017         331.18 307.9018 354.4582 295.5790 366.7810
2018         351.38 318.4596 384.3004 301.0326 401.7274
2019         371.58 331.2610 411.8990 309.9173 433.2427
2020         391.78 345.2236 438.3364 320.5781 462.9819
2021         411.98 359.9283 464.0317 332.3738 491.5862
2022         432.18 375.1603 489.1997 344.9758 519.3842
2023         452.38 390.7916 513.9684 358.1887 546.5713
2024         472.58 406.7393 538.4207 371.8853 573.2747
2025         492.78 422.9454 562.6146 385.9771 599.5829
2026         512.98 439.3678 586.5922 400.3999 625.5601
```

Conclusion

The top 2 models turn out to be ARIMA model and Holt Winter model with trend smoothing. Their RMSE values are very similar to each other.

Forecast using Top 2 Models

- **ARIMA Model**

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2017	308.0868	281.98259	334.1910	268.16385	348.0098
2018	299.8574	248.39638	351.3183	221.15459	378.5601
2019	287.5893	197.28806	377.8905	149.48548	425.6930
2020	270.5385	132.43169	408.6453	59.32237	481.7546
2021	249.1316	51.31278	446.9505	-53.40619	551.6695
2022	223.1241	-45.63380	491.8820	-187.90564	634.1539
2023	192.6562	-159.46440	544.7768	-345.86578	731.1781
2024	157.6474	-290.45588	605.7507	-527.66743	842.9622
2025	118.1439	-439.27242	675.5602	-734.35078	970.6385
2026	74.1192	-606.35037	754.5888	-966.56920	1114.8076

- **Holt Winter Model with Trend Smoothing**

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2017	331.18	307.9018	354.4582	295.5790	366.7810
2018	351.38	318.4596	384.3004	301.0326	401.7274
2019	371.58	331.2610	411.8990	309.9173	433.2427
2020	391.78	345.2236	438.3364	320.5781	462.9819
2021	411.98	359.9283	464.0317	332.3738	491.5862
2022	432.18	375.1603	489.1997	344.9758	519.3842
2023	452.38	390.7916	513.9684	358.1887	546.5713
2024	472.58	406.7393	538.4207	371.8853	573.2747
2025	492.78	422.9454	562.6146	385.9771	599.5829
2026	512.98	439.3678	586.5922	400.3999	625.5601