#### TSA Tutorial

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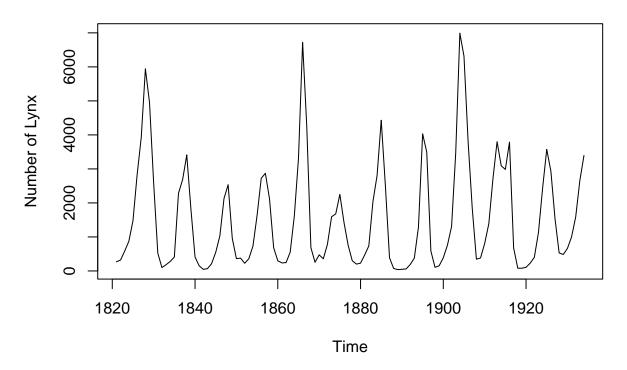
2025-09-19

### 1. Analysis of lynx Dataset

The lynx dataset contains annual lynx trappings from 1821 to 1934, known for its distinct cyclical pattern.

```
# Load libraries once for the entire document
library(forecast)
Registered S3 method overwritten by 'quantmod':
  method
  as.zoo.data.frame zoo
library(tseries)
library(imputeTS)
Attaching package: 'imputeTS'
The following object is masked from 'package:tseries':
    na.remove
# Exploratory Data Analysis
# Check if the dataset is a time series object
data("lynx")
str(lynx)
Time-Series [1:114] from 1821 to 1934: 269 321 585 871 1475 \dots
print("Dataset: lynx - Annual lynx trappings (1821-1934), time series confirmed.")
[1] "Dataset: lynx - Annual lynx trappings (1821-1934), time series confirmed."
# Plot the time series
plot(lynx, main = "Lynx Trapping Time Series", ylab = "Number of Lynx")
```

# **Lynx Trapping Time Series**

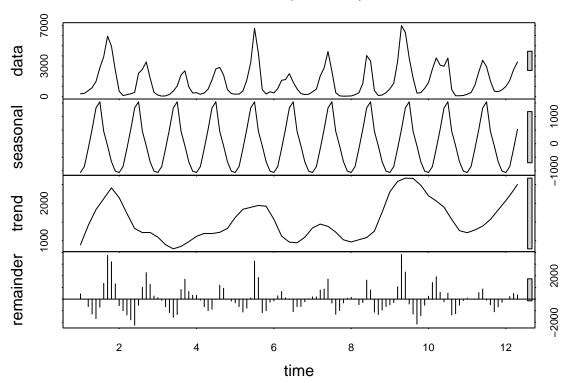


#### summary(lynx)

```
Min. 1st Qu. Median Mean 3rd Qu. Max. 39.0 348.2 771.0 1538.0 2566.8 6991.0
```

```
# Decomposition using STL for cyclical patterns
lynx_ts <- ts(lynx, frequency = 10) # 10 year cycle
decomp_lynx <- stl(lynx_ts, s.window = "periodic")
plot(decomp_lynx, main = "STL Decomposition: Lynx")</pre>
```

#### **STL Decomposition: Lynx**

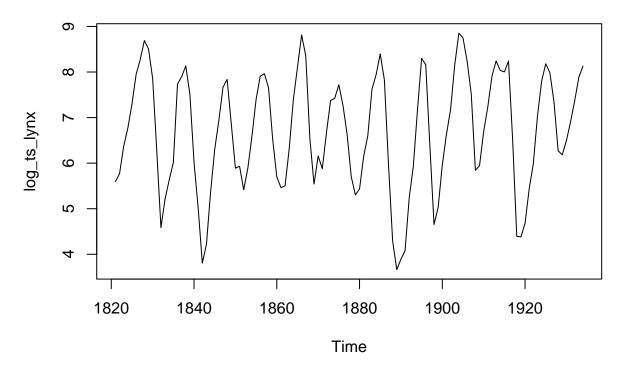


```
# Data Preprocessing
# Check for missing values (none)
sum(is.na(lynx))
```

#### [1] 0

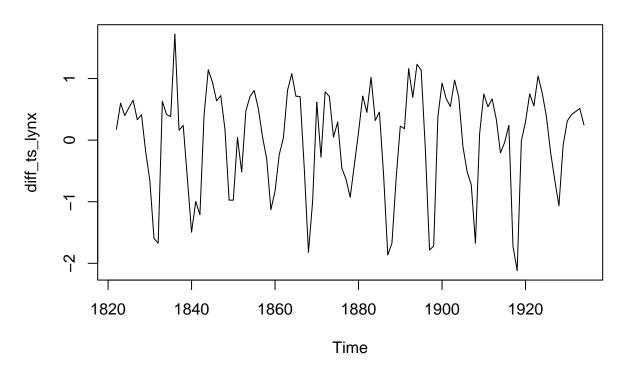
```
# Apply log transformation to stabilize variance
log_ts_lynx <- log(lynx)
plot(log_ts_lynx, main = "Log-Transformed Lynx Series")</pre>
```

# **Log-Transformed Lynx Series**



```
# Apply first differencing to achieve stationarity
diff_ts_lynx <- diff(log_ts_lynx, differences = 1)
plot(diff_ts_lynx, main = "First Difference of Log-Transformed Lynx")</pre>
```

## First Difference of Log-Transformed Lynx



```
# Stationarity Testing
# ADF Test for the original series
adf_original_lynx <- adf.test(lynx)</pre>
```

Warning in adf.test(lynx): p-value smaller than printed p-value

```
print(adf_original_lynx)
```

Augmented Dickey-Fuller Test

```
data: lynx
Dickey-Fuller = -6.3068, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary
```

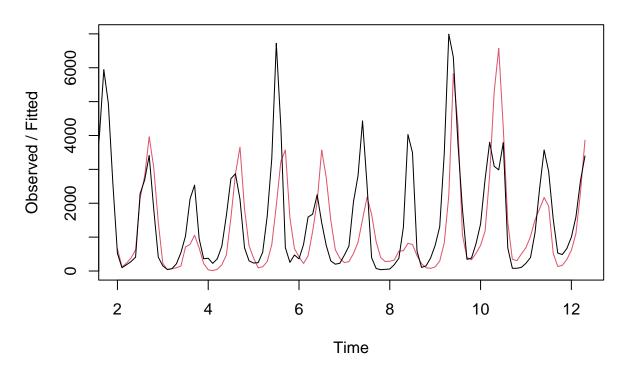
```
# KPSS Test for the original series
kpss_original_lynx <- kpss.test(lynx)</pre>
```

```
Warning in kpss.test(lynx): p-value greater than printed p-value
```

```
print(kpss_original_lynx)
```

```
KPSS Test for Level Stationarity
data: lynx
KPSS Level = 0.070147, Truncation lag parameter = 4, p-value = 0.1
# ADF Test for the differenced series
adf_diff_lynx <- adf.test(diff_ts_lynx)</pre>
Warning in adf.test(diff_ts_lynx): p-value smaller than printed p-value
print(adf_diff_lynx)
    Augmented Dickey-Fuller Test
data: diff_ts_lynx
Dickey-Fuller = -8.8658, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary
# KPSS Test for the differenced series
kpss_diff_lynx <- kpss.test(diff_ts_lynx)</pre>
Warning in kpss.test(diff_ts_lynx): p-value greater than printed p-value
print(kpss_diff_lynx)
    KPSS Test for Level Stationarity
data: diff_ts_lynx
KPSS Level = 0.017293, Truncation lag parameter = 4, p-value = 0.1
# Modelling and Forecasting
# Fit Holt-Winters model on the original series
# Use a multiplicative model due to varying amplitude of the cycles
hw_model_lynx <- HoltWinters(lynx_ts, seasonal = "multiplicative")</pre>
plot(hw_model_lynx, main = "Holt-Winters Fit: Lynx")
```

## **Holt-Winters Fit: Lynx**



#### summary(hw\_model\_lynx)

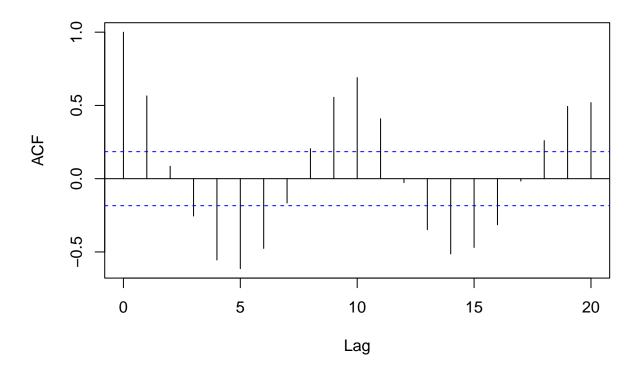
```
Length Class Mode
fitted
             416
                    mts
                           numeric
             114
                           numeric
                    ts
alpha
               1
                    -none- numeric
beta
               1
                    -none- numeric
gamma
               1
                    -none- numeric
coefficients 12
                    -none- numeric
seasonal
               1
                    -none- character
SSE
               1
                    -none- numeric
call
                    -none- call
```

```
# Fit AR(1) and MA(1) models on the differenced series
ar_model_lynx <- arima(diff_ts_lynx, order = c(1, 0, 0))
summary(ar_model_lynx)</pre>
```

```
s.e. 0.0770
             0.1441
sigma^2 estimated as 0.4635: log likelihood = -117.08, aic = 240.16
Training set error measures:
                                RMSE
                                           MAE
                                                     MPE
                                                            MAPE
                                                                       MASE
Training set -0.0009755728 0.6807822 0.5353477 -5.899207 211.5224 0.9166508
Training set 0.1969268
ma_model_lynx <- arima(diff_ts_lynx, order = c(0, 0, 1))</pre>
summary(ma_model_lynx)
Call:
arima(x = diff_ts_lynx, order = c(0, 0, 1))
Coefficients:
         ma1 intercept
      0.6632
                0.0217
s.e. 0.0689
                0.1027
sigma^2 estimated as 0.4341: log likelihood = -113.48, aic = 232.95
Training set error measures:
                                         MAE
                                                                     MASE
                               RMSE
                                                  MPE
                                                          MAPE
Training set 0.0002041239 0.6588284 0.5236113 35.71677 149.7891 0.8965551
Training set 0.09711448
# ACF/PACF plots to check for remaining patterns
```

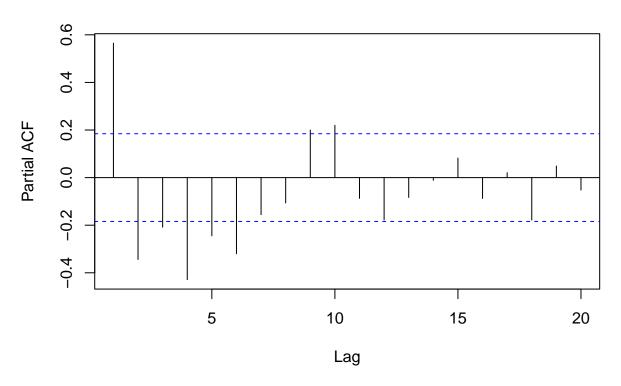
```
acf(diff_ts_lynx, main = "ACF: Differenced Lynx")
```

**ACF: Differenced Lynx** 



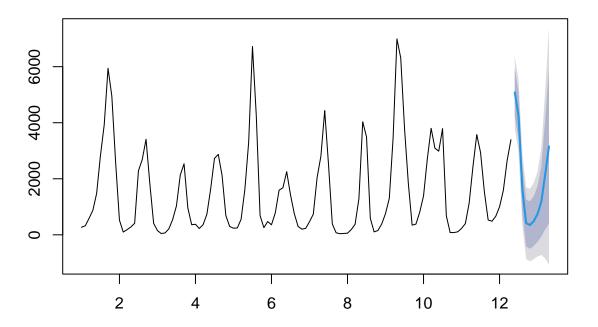
pacf(diff\_ts\_lynx, main = "PACF: Differenced Lynx")

**PACF: Differenced Lynx** 



```
# Final Forecast
# Forecast using Holt-Winters
hw_forecast_lynx <- forecast(hw_model_lynx, h = 10)
plot(hw_forecast_lynx, main = "Holt-Winters Forecast: Lynx")</pre>
```

#### **Holt-Winters Forecast: Lynx**



#### print(hw\_forecast\_lynx)

```
Point Forecast
                          Lo 80
                                   Hi 80
                                               Lo 95
                                                        Hi 95
12.40
           5081.6927 4246.97305 5916.412
                                           3805.0991 6358.286
12.50
           4243.9745 3398.72236 5089.227
                                           2951.2729 5536.676
12.60
           1613.0584
                      774.49396 2451.623
                                            330.5847 2895.532
12.70
            415.8762 -420.13052 1251.883
                                           -862.6858 1694.438
12.80
            348.9585 -497.37314 1195.290
                                           -945.3941 1643.311
12.90
            492.2393 -396.24164 1380.720
                                           -866.5750 1851.054
13.00
            745.0700 -247.37853 1737.518
                                           -772.7490 2262.889
                      -58.08881 2438.123
                                           -718.7961 3098.830
13.10
           1190.0170
13.20
           2148.4816 194.79919 4102.164
                                           -839.4178 5136.381
13.30
           3155.1187
                      396.76913 5913.468 -1063.4129 7373.650
```

### 2. Analysis of sunspots Dataset

The sunspots dataset contains monthly sunspot counts from 1749 to 1983, a classic example of cyclical data with a period of approximately 11 years.

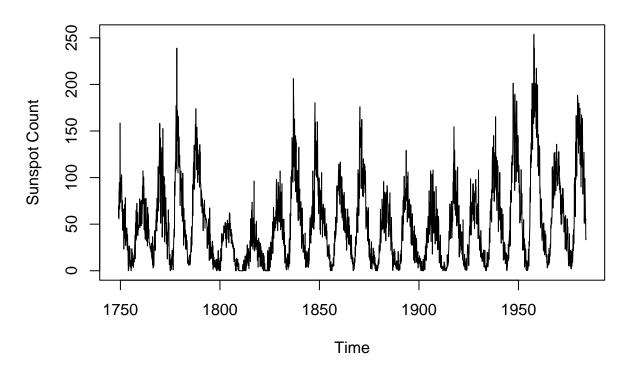
```
# Exploratory Data Analysis
data("sunspots")
str(sunspots)
```

Time-Series [1:2820] from 1749 to 1984: 58 62.6 70 55.7 85 83.5 94.8 66.3 75.9 75.5 ...

```
print("Dataset: sunspots - Monthly sunspots (1749-1983), time series confirmed.")
[1] "Dataset: sunspots - Monthly sunspots (1749-1983), time series confirmed."

plot(sunspots, main = "Monthly Sunspots Time Series", ylab = "Sunspot Count")
```

## **Monthly Sunspots Time Series**

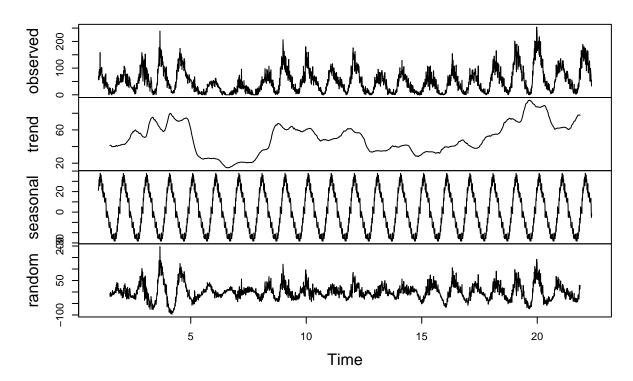


#### summary(sunspots)

```
Min. 1st Qu. Median Mean 3rd Qu. Max. 0.00 15.70 42.00 51.27 74.92 253.80
```

```
# Decomposition (Solar cycle is ~11 years, which is 132 months)
sunspots_ts_adj <- ts(sunspots, frequency = 132)
decomp_sunspots <- decompose(sunspots_ts_adj, type = "additive")
plot(decomp_sunspots)</pre>
```

## **Decomposition of additive time series**

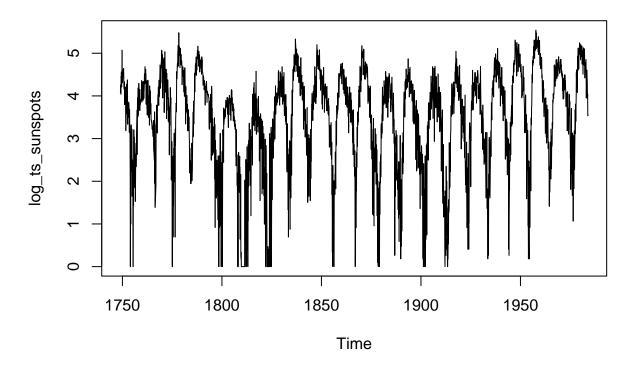


```
# Data Preprocessing
# Check for missing values (none)
sum(is.na(sunspots))
```

[1] 0

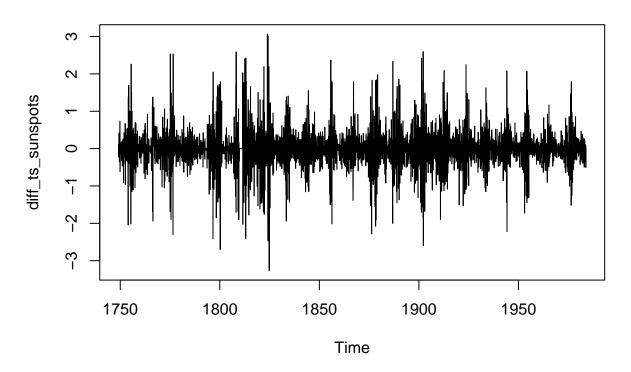
```
# Log transformation to handle zeroes and stabilize variance
log_ts_sunspots <- log(sunspots + 1) # Add 1 to avoid log(0)
plot(log_ts_sunspots, main = "Log-Transformed Sunspots")</pre>
```

# **Log-Transformed Sunspots**



```
# Apply first differencing
diff_ts_sunspots <- diff(log_ts_sunspots, differences = 1)
plot(diff_ts_sunspots, main = "First Difference of Log-Transformed Sunspots")</pre>
```

### First Difference of Log-Transformed Sunspots



```
# Stationarity Testing
# Original series tests
adf_original_sunspots <- adf.test(sunspots)</pre>
Warning in adf.test(sunspots): p-value smaller than printed p-value
```

print(adf\_original\_sunspots)

Augmented Dickey-Fuller Test

data: sunspots
Dickey-Fuller = -6.494, Lag order = 14, p-value = 0.01
alternative hypothesis: stationary

kpss\_original\_sunspots <- kpss.test(sunspots)</pre>

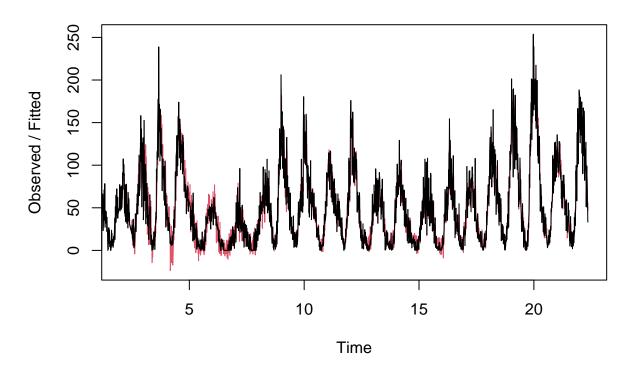
Warning in kpss.test(sunspots): p-value smaller than printed p-value

print(kpss\_original\_sunspots)

KPSS Test for Level Stationarity

```
data: sunspots
KPSS Level = 1.1672, Truncation lag parameter = 9, p-value = 0.01
# Differenced series tests
adf_diff_sunspots <- adf.test(diff_ts_sunspots)</pre>
Warning in adf.test(diff_ts_sunspots): p-value smaller than printed p-value
print(adf_diff_sunspots)
    Augmented Dickey-Fuller Test
data: diff_ts_sunspots
Dickey-Fuller = -12.875, Lag order = 14, p-value = 0.01
alternative hypothesis: stationary
kpss_diff_sunspots <- kpss.test(diff_ts_sunspots)</pre>
Warning in kpss.test(diff_ts_sunspots): p-value greater than printed p-value
print(kpss_diff_sunspots)
    KPSS Test for Level Stationarity
data: diff_ts_sunspots
KPSS Level = 0.0074249, Truncation lag parameter = 9, p-value = 0.1
# Modelling and Forecasting
\# Fit Holt-Winters model
hw_model_sunspots <- HoltWinters(sunspots_ts_adj, seasonal = "additive")</pre>
plot(hw_model_sunspots, main = "Holt-Winters Fit: Sunspots")
```

### **Holt-Winters Fit: Sunspots**



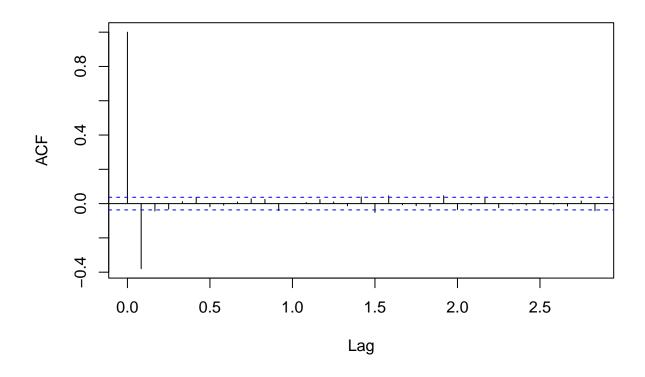
#### summary(hw\_model\_sunspots)

```
Length Class Mode
fitted
             10752 mts
                            numeric
              2820 ts
                            numeric
alpha
                     -none- numeric
beta
                    -none- numeric
                 1
gamma
                  1
                    -none- numeric
{\tt coefficients}
               134
                    -none- numeric
seasonal
                     -none- character
SSE
                  1
                    -none- numeric
call
                    -none- call
```

```
# Fit AR(1) and MA(1) models on the differenced series
ar_model_sunspots <- arima(diff_ts_sunspots, order = c(1, 0, 0))
summary(ar_model_sunspots)</pre>
```

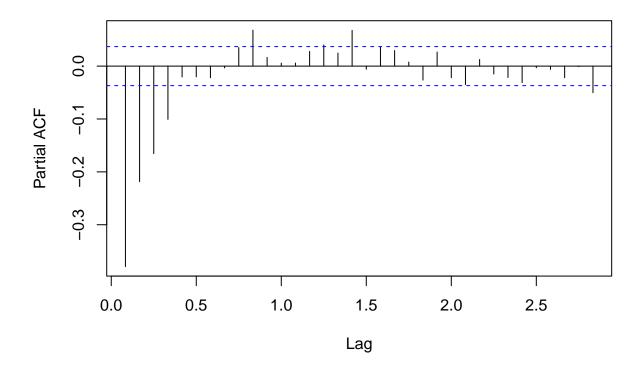
```
s.e. 0.0174
                 0.0071
sigma^2 estimated as 0.2696: log likelihood = -2152.32, aic = 4310.64
Training set error measures:
                      ME
                              RMSE
                                         MAE MPE MAPE
                                                           MASE
                                                                       ACF1
Training set 3.372672e-06 0.5192026 0.3500949 NaN Inf 0.5705126 -0.08291571
ma_model_sunspots <- arima(diff_ts_sunspots, order = c(0, 0, 1))</pre>
summary(ma_model_sunspots)
Call:
arima(x = diff_ts_sunspots, order = c(0, 0, 1))
Coefficients:
         ma1 intercept
              -0.0002
      -0.5517
                 0.0042
    0.0163
s.e.
sigma^2 estimated as 0.2487: log likelihood = -2038.65, aic = 4083.3
Training set error measures:
                      ME
                              RMSE
                                         MAE MPE MAPE
                                                           MASE
                                                                      ACF1
Training set 3.797023e-05 0.4986648 0.3422004 NaN Inf 0.5576478 0.03456532
# ACF/PACF plots
acf(diff_ts_sunspots, main = "ACF: Differenced Sunspots")
```

**ACF: Differenced Sunspots** 



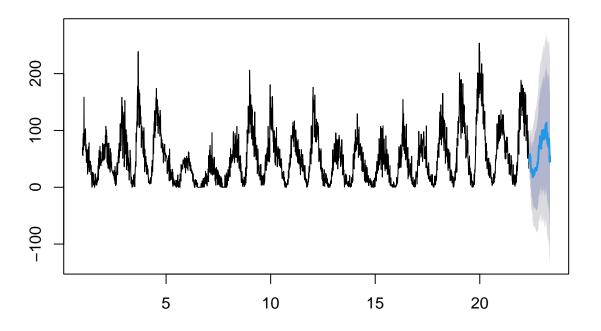
pacf(diff\_ts\_sunspots, main = "PACF: Differenced Sunspots")

# **PACF: Differenced Sunspots**



```
# Final Forecast
# Forecast using Holt-Winters
hw_forecast_sunspots <- forecast(hw_model_sunspots, h = 132) # 11 years
plot(hw_forecast_sunspots, main = "Holt-Winters Forecast: Sunspots")</pre>
```

# **Holt-Winters Forecast: Sunspots**



#### print(hw\_forecast\_sunspots)

		_				
	Point	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
22.36364		46.40565	24.0709667	68.74033	12.247701	80.56359
22.37121		54.70815	30.1593657	79.25693	17.164027	92.25226
22.37879		54.30686	27.7277796	80.88593	13.657667	94.95604
22.38636		58.16247	29.6975438	86.62739	14.629123	101.69581
22.39394		55.64495	25.4115794	85.87832	9.407001	101.88290
22.40152		56.78671	24.8827674	88.69064	7.993843	105.57957
22.40909		46.82933	13.3380482	80.32061	-4.391165	98.04983
22.41667		50.16853	15.1618031	85.17525	-3.369636	103.70669
22.42424		53.71939	17.2601627	90.17862	-2.040187	109.47897
22.43182		38.49650	0.6404557	76.35254	-19.399323	96.39232
22.43939		37.81370	-1.3894171	77.01682	-22.142295	97.76970
22.44697		37.55118	-2.9542416	78.05660	-24.396517	99.49888
22.45455		29.33043	-12.4367057	71.09757	-34.546894	93.20776
22.46212		27.06775	-15.9240901	70.05960	-38.682598	92.81811
22.46970		25.85804	-18.3245769	70.04065	-41.713440	93.42951
22.47727		31.17518	-14.1669449	76.51730	-38.169614	100.51997
22.48485		29.94000	-16.5327046	76.41271	-41.133871	101.01388
22.49242		31.91456	-15.6618746	79.49100	-40.847319	104.67644
22.50000		29.10853	-19.5466038	77.76366	-45.303076	103.52014
22.50758		30.54653	-19.1639016	80.25696	-45.479013	106.57207
22.51515		28.89909	-21.8446940	79.64287	-48.706829	106.50500
22.52273		23.19495	-28.5615524	74.95146	-55.959792	102.34970

```
22.53030
               17.79374 -34.9560548 70.54353 -62.880109 98.46759
                                                -63.315477 101.01426
22.53788
               18.84939 -34.8753290
                                     72.57411
22.54545
               22.18253 -32.4997387
                                      76.86479
                                                -61.446781 105.81183
22.55303
               25.19787 -30.4254563
                                     80.82120
                                                -59.870668 110.26641
22.56061
               29.88564 -26.6630914
                                     86.43438
                                                -56.598183 116.36947
               23.55247 -33.9067725
                                     81.01170
22.56818
                                                -64.323856 111.42879
22.57576
               21.44128 -36.9142587
                                      79.79682
                                                -67.805814 110.68837
22.58333
               20.87892 -38.3593565
                                     80.11720
                                                -69.718206 111.47605
22.59091
               22.47765 -37.6304005
                                      82.58571
                                                -69.449682 114.40499
22.59848
               26.63052 -34.3349075
                                     87.59594
                                                -66.608053 119.86908
22.60606
               22.68551 -39.1253924
                                     84.49641
                                                -71.846107 117.21712
               25.28008 -37.3648856
                                     87.92505
22.61364
                                                -70.527129 121.08729
22,62121
               29.14548 -34.3225971
                                     92.61356
                                                -67.920567 126.21153
                                                -69.607312 127.01022
22.62879
               28.70145 -35.5791934
                                     92.98210
               28.48923 -36.5938361
                                      93.57231
                                                -71.046733 128.02520
22.63636
22.64394
               29.40567 -36.4700498
                                     95.28139
                                                -71.342551 130.15390
22.65152
               33.84516 -32.8137917 100.50411
                                                -68.100908 135.79122
22.65909
               30.03165 -37.4014251
                                     97.46473
                                                -73.098341 133.16165
               31.58734 -36.6110824
                                                -72.713146 135.88783
22.66667
                                     99.78576
22.67424
               31.19863 -37.7566459 100.15390
                                                -74.259362 136.65661
22.68182
               29.74557 -39.9583336 99.44947
                                                -76.857351 136.34849
               31.24089 -39.2036848 101.68547
                                                -76.494793 138.97658
22.68939
               30.36640 -40.8111461 101.54395
                                                -78.490265 139.22307
22.69697
               33.82264 -38.0804059 105.72569
22.70455
                                                -76.143580 143.78886
22.71212
               29.37514 -43.2461547 101.99644
                                                -81.689547 140.43983
22.71970
               32.90401 -40.4285077 106.23652
                                                -79.248395 145.05641
               33.69710 -40.3397924 107.73400
                                                -79.532558 146.92677
22.72727
22.73485
               37.11113 -37.6235135 111.84577
                                                -77.185644 151.40790
               35.27712 -40.1488179 110.70305
                                                -80.076896 150.63113
22.74242
22.75000
               38.13103 -37.9799200 114.24197
                                                -78.270621 154.53267
22.75758
               41.04253 -35.7473216 117.83238
                                                -76.397412 158.48247
22.76515
               44.24404 -33.2187623 121.70684
                                                -74.225092 162.71317
22.77273
               40.91069 -37.2192660 119.04065
                                                -78.578767 160.40015
22.78030
               45.62613 -33.1653316 124.41760
                                                -74.875013 166.12728
22.78788
               48.70142 -30.7460482 128.14888
                                                -72.802995 170.20583
               52.24121 -27.8568805 132.33930
22.79545
                                                -70.258249 174.74067
22.80303
               53.99754 -26.7459341 134.74102
                                                -69.488948 177.48403
22.81061
               61.77406 -19.6096810 143.15780
                                                -62.691632 186.23976
               65.44815 -16.5708568 147.46717
                                                -59.989099 190.88541
22.81818
               72.88565 -9.7637516 155.53504
                                                -53.515700 199.28699
22.82576
22.83333
               69.26475 -14.0102612 152.53976
                                                -58.093390 196.62289
               69.35904 -14.5369251 153.25500
                                                -58.948764 197.66684
22.84091
22.84848
               73.42049 -11.0918577 157.93284
                                                -55.829992 202.67097
22.85606
               70.37733 -14.7469430 155.50160
                                                -59.809010 200.56367
22.86364
               72.67318 -13.0586449 158.40501
                                                -58.442333 203.78870
               75.75749 -10.5776142 162.09260
                                                -56.280660 207.79565
22.87121
22.87879
               89.75322
                          2.8190132 176.68742
                                                -43.201174 222.70761
22.88636
               86.42616
                        -1.1030406 173.95535
                                                -47.438198 220.29051
22.89394
               82.82810 -5.2920749 170.94827
                                                -51.940077 217.59627
22.90152
               85.80860
                         -2.8986122 174.51581
                                                -49.857374 221.47458
                                                -49.545208 223.57054
               87.01266 -2.2777287 176.30306
22.90909
22.91667
               76.14976 -13.7200247 166.01955
                                               -61.294217 213.59375
22.92424
               75.28586 -15.1596115 165.73134
                                               -63.038553 213.61028
22.93182
               67.98651 -23.0310101 159.00402 -71.212773 207.18579
```

```
22.93939
               85.31535 -6.2706356 176.90134 -54.753328 225.38403
                                               -52.443401 229.42203
22.94697
               88.48932
                         -3.6616348 180.64027
22.95455
               85.42423 -7.2882451 178.13670
                                               -56.367263 227.21572
22.96212
               78.70624 -14.5643729 171.97685
                                               -63.938852 221.35133
22.96970
               99.57523
                          5.7497932 193.40066
                                               -43.918390 243.06884
               98.04207
                                               -46.295078 242.37922
22.97727
                          3.6650828 192.41906
22.98485
               87.12092 -7.8044225 182.04627
                                               -58.054864 232.29671
22.99242
               91.42867
                        -4.0418801 186.89922
                                               -54.580936 237.43827
23.00000
               83.38603 -12.6266323 179.39868
                                               -63.452663 230.22471
23.00758
               85.68757 -10.8641555 182.23929
                                               -61.975550 233.35068
23.01515
               89.16018 -7.9276114 186.24798
                                               -59.322785 237.64315
               97.27965 -0.3412719 194.90057
                                               -52.018666 246.57797
23.02273
23,03030
              100.87891
                          2.7277527 199.03006
                                               -49.230330 250.98814
23.03788
               90.60323 -8.0753052 189.28177
                                               -60.312567 241.51903
                                               -64.041290 239.39486
               87.67679 -11.5263317 186.87990
23.04545
23.05303
               97.35265
                         -2.3722892 197.07759
                                               -55.163482 249.86878
23.06061
               93.73604 -6.5080005 193.98008
                                               -59.573990 247.04607
23.06818
               94.91579 -5.8446799 195.67626
                                               -59.184051 249.01563
                                               -70.226843 239.54441
23.07576
               84.65878 -16.6154843 185.93305
23.08333
               98.17277 -3.6127011 199.95824
                                               -57.494674 253.84021
23.09091
               87.90648 -14.3876411 190.20059
                                               -68.538876 244.35183
               86.63050 -16.1697486 189.43075
                                               -70.588913 243.84991
23.09848
               86.27304 -17.0308636 189.57694
                                               -71.716645 244.26272
23.10606
              101.42770 -2.3774090 205.23281
                                               -57.328514 260.18391
23.11364
23.12121
               99.76289 -4.5410173 204.06680
                                               -59.756171 259.28195
23.12879
               92.98284 -11.8174891 197.78318
                                               -67.295434 253.26112
              102.65831 -2.6361124 207.95272
                                               -58.375610 263.69222
23.13636
23.14394
              110.14802
                          4.3618278 215.93422
                                               -51.638001 271.93405
               96.71939 -9.5563114 202.99508
                                               -65.815267 259.25404
23.15152
23.15909
               95.04843 -11.7145267 201.81138
                                               -68.231421 258.32828
23.16667
               90.14487 -17.1031305 197.39287
                                               -73.876791 254.16653
23.17424
              101.08222 -6.6486389 208.81308
                                               -63.677910 265.84235
23.18182
               98.24167 -9.9698924 206.45323
                                               -67.253634 263.73698
23.18939
                                               -52.425969 280.02849
              113.80126
                         5.1111175 222.49140
23.19697
               97.15456 -12.0120656 206.32118
                                               -69.801386 264.11050
               96.21424 -13.4267988 205.85527
                                               -71.467257 263.89573
23.20455
23.21212
               82.78394 -27.3294621 192.89734
                                               -85.619976 251.18785
23.21970
               87.03687 -23.5468814 197.62062
                                               -82.086383 256.16012
23.22727
               96.03704 -15.0150684 207.08915
                                               -73.802503 265.87658
               84.82337 -26.6951239 196.34187
                                               -85.729450 255.37620
23.23485
               84.71784 -27.2651029 196.70079
23.24242
                                               -86.545293 255.98098
23.25000
               76.35935 -36.0861240 188.80482
                                               -95.611162 248.32986
23.25758
               86.87895 -26.0271604 199.78506
                                               -85.796044 259.55394
23.26515
               84.72719 -28.6376772 198.09206 -88.649415 258.10380
23.27273
               71.87527 -41.9465119 185.69706 -102.200125 245.95067
               72.17790 -42.0989735 186.45477 -102.593495 246.94929
23.28030
23.28788
               80.27297 -34.4571853 195.00312
                                               -95.191659 255.73759
23.29545
               83.45643 -31.7252207 198.63808 -92.698703 259.61156
23.30303
               85.90203 -29.7293566 201.53341 -90.940914 262.74497
23.31061
               80.89949 -35.1798833 196.97887
                                               -96.628594 258.42758
               75.78031 -40.7453357 192.30596 -102.430288 253.99091
23.31818
23.32576
               69.35153 -47.6186822 186.32175 -109.538974 248.24204
23.33333
               61.01667 -56.3964307 178.42977 -118.551171 240.58451
               51.42838 -66.4259410 169.28270 -128.814249 231.67101
23.34091
```

```
23.34848 44.72717 -73.5667227 163.02106 -136.187727 225.64207 23.35606 54.57811 -64.1537329 173.30995 -127.006573 236.16279
```

#### 3. Analysis of USAccDeaths Dataset

The USAccDeaths dataset contains monthly totals of accidental deaths in the USA from 1973 to 1978. It exhibits a clear seasonal pattern.

```
# Exploratory Data Analysisdata("USAccDeaths")
str(USAccDeaths)

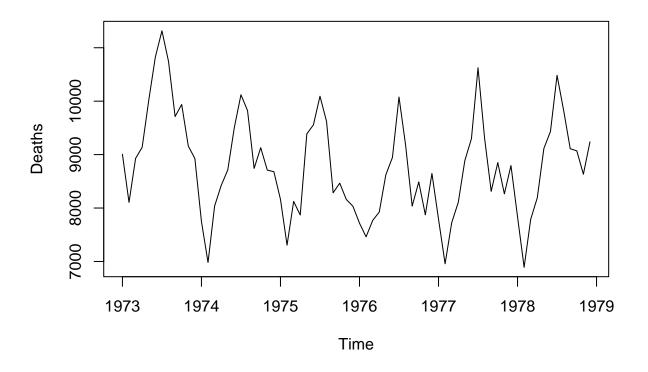
Time-Series [1:72] from 1973 to 1979: 9007 8106 8928 9137 10017 ...

print("Dataset: USAccDeaths - Monthly accidental deaths (1973-1978), time series confirmed.")

[1] "Dataset: USAccDeaths - Monthly accidental deaths (1973-1978), time series confirmed."

plot(USAccDeaths, main = "US Accidental Deaths Time Series", ylab = "Deaths")
```

#### **US Accidental Deaths Time Series**

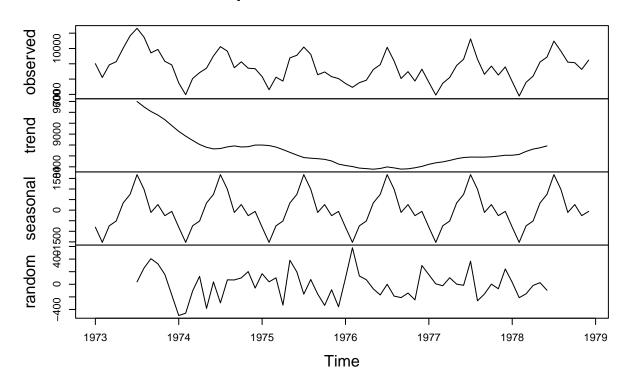


```
summary(USAccDeaths)
```

Min. 1st Qu. Median Mean 3rd Qu. Max. 6892 8089 8728 8789 9323 11317

```
# Decomposition (monthly data has a frequency of 12)
decomp_usac <- decompose(USAccDeaths, type = "additive")
plot(decomp_usac)</pre>
```

## **Decomposition of additive time series**

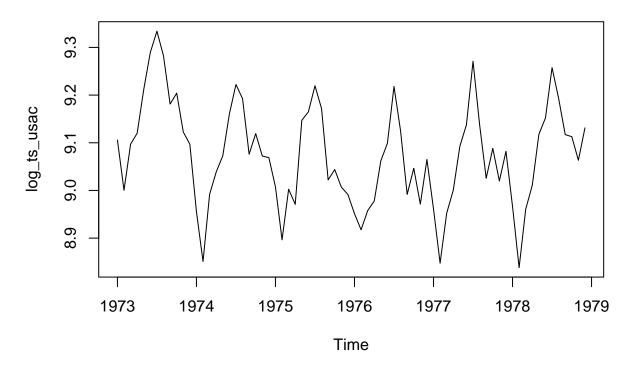


```
# Data Preprocessing
# Check for missing values (none)
sum(is.na(USAccDeaths))
```

[1] 0

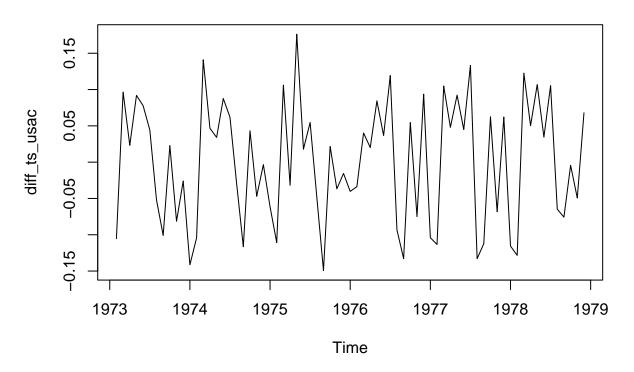
```
# Apply log transformation
log_ts_usac <- log(USAccDeaths)
plot(log_ts_usac, main = "Log-Transformed USAccDeaths")</pre>
```

# Log-Transformed USAccDeaths



```
# Apply first differencing
diff_ts_usac <- diff(log_ts_usac, differences = 1)
plot(diff_ts_usac, main = "First Difference of Log-Transformed USAccDeaths")</pre>
```

### First Difference of Log-Transformed USAccDeaths



```
# Stationarity Testing
# Original series tests
adf_original_usac <- adf.test(USAccDeaths)
print(adf_original_usac)</pre>
```

Augmented Dickey-Fuller Test

data: USAccDeaths

Dickey-Fuller = -3.8221, Lag order = 4, p-value = 0.02268

alternative hypothesis: stationary

```
kpss_original_usac <- kpss.test(USAccDeaths)</pre>
```

Warning in kpss.test(USAccDeaths): p-value greater than printed p-value

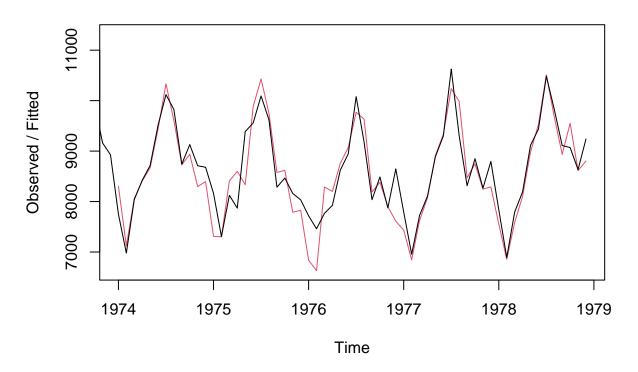
```
print(kpss_original_usac)
```

KPSS Test for Level Stationarity

data: USAccDeaths
KPSS Level = 0.19799, Truncation lag parameter = 3, p-value = 0.1

```
# Differenced series tests
adf_diff_usac <- adf.test(diff_ts_usac)</pre>
Warning in adf.test(diff_ts_usac): p-value smaller than printed p-value
print(adf_diff_usac)
    Augmented Dickey-Fuller Test
data: diff_ts_usac
Dickey-Fuller = -4.4292, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary
kpss_diff_usac <- kpss.test(diff_ts_usac)</pre>
Warning in kpss.test(diff_ts_usac): p-value greater than printed p-value
print(kpss_diff_usac)
    KPSS Test for Level Stationarity
data: diff_ts_usac
KPSS Level = 0.028077, Truncation lag parameter = 3, p-value = 0.1
# Modelling and Forecasting
# Fit Holt-Winters model
hw_model_usac <- HoltWinters(USAccDeaths, seasonal = "additive")</pre>
plot(hw_model_usac, main = "Holt-Winters Fit: USAccDeaths")
```

#### Holt-Winters Fit: USAccDeaths



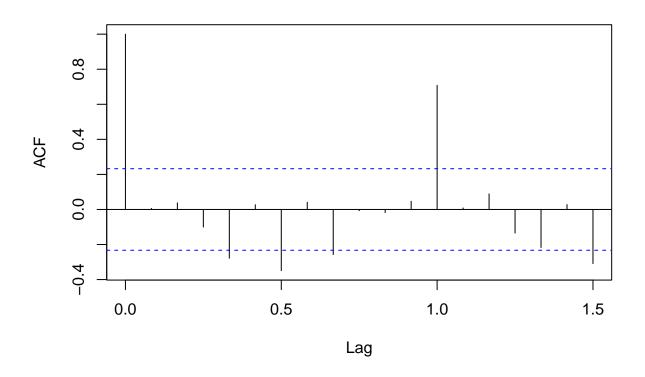
#### summary(hw\_model\_usac)

```
Length Class Mode
fitted
             240
                    mts
                            numeric
              72
                           numeric
                    ts
alpha
               1
                    -none- numeric
beta
               1
                    -none- numeric
gamma
               1
                    -none- numeric
coefficients
              14
                    -none- numeric
seasonal
               1
                    -none- character
SSE
               1
                    -none- numeric
call
                    -none- call
```

```
# Fit AR(1) and MA(1) models on the differenced series
ar_model_usac <- arima(diff_ts_usac, order = c(1, 0, 0))
summary(ar_model_usac)</pre>
```

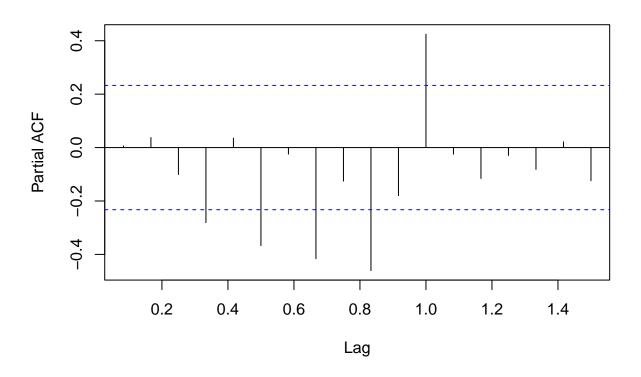
```
s.e. 0.1197 1e-02
sigma^2 estimated as 0.007029: log likelihood = 75.25, aic = -144.5
Training set error measures:
                               RMSE
                                           MAE
                                                    MPE
                                                            MAPE
                                                                      MASE
                      ME
Training set 9.236496e-06 0.08384114 0.07374253 99.78922 99.78922 0.7626056
Training set -0.0002881081
ma_model_usac <- arima(diff_ts_usac, order = c(0, 0, 1))</pre>
summary(ma_model_usac)
Call:
arima(x = diff_ts_usac, order = c(0, 0, 1))
Coefficients:
        ma1 intercept
      0.0058
                 4e-04
s.e. 0.1153
                 1e-02
sigma^2 estimated as 0.007029: log likelihood = 75.25, aic = -144.5
Training set error measures:
                               RMSE
                                           MAE
                                                    MPE
                                                                     MASE
                                                            MAPE
Training set 8.807277e-06 0.08384126 0.07374478 99.81644 99.81644 0.762629
Training set 0.0001709799
# ACF/PACF plots
acf(diff_ts_usac, main = "ACF: Differenced USAccDeaths")
```

**ACF: Differenced USAccDeaths** 



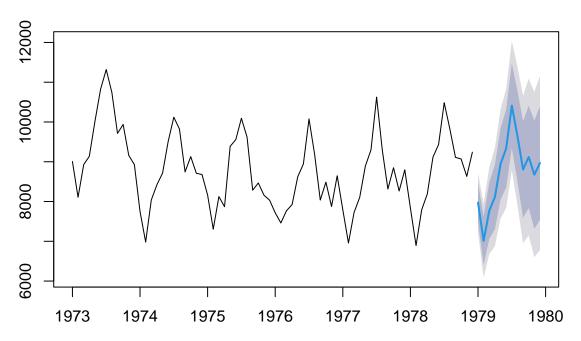
pacf(diff\_ts\_usac, main = "PACF: Differenced USAccDeaths")

### **PACF: Differenced USAccDeaths**



```
# Final Forecast
# Forecast using Holt-Winters
hw_forecast_usac <- forecast(hw_model_usac, h = 12) # 1 year
plot(hw_forecast_usac, main = "Holt-Winters Forecast: USAccDeaths")</pre>
```

# **Holt-Winters Forecast: USAccDeaths**



#### print(hw\_forecast\_usac)

		Point	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jan	1979		7973.432	7489.493	8457.371	7233.311	8713.553
Feb	1979		7013.363	6407.222	7619.504	6086.350	7940.376
Mar	1979		7770.193	7058.507	8481.878	6681.763	8858.622
Apr	1979		8113.432	7306.220	8920.645	6878.907	9347.958
May	1979		8944.468	8048.465	9840.472	7574.149	10314.788
Jun	1979		9336.042	8356.086	10315.997	7837.329	10834.755
Jul	1979	:	10410.583	9350.304	11470.862	8789.027	12032.140
Aug	1979		9648.107	8510.309	10785.905	7907.995	11388.219
Sep	1979		8805.344	7592.241	10018.447	6950.063	10660.625
Oct	1979		9120.328	7833.696	10406.959	7152.594	11088.061
Nov	1979		8676.792	7318.072	10035.512	6598.809	10754.774
Dec	1979		8967.858	7538.228	10397.488	6781.428	11154.288