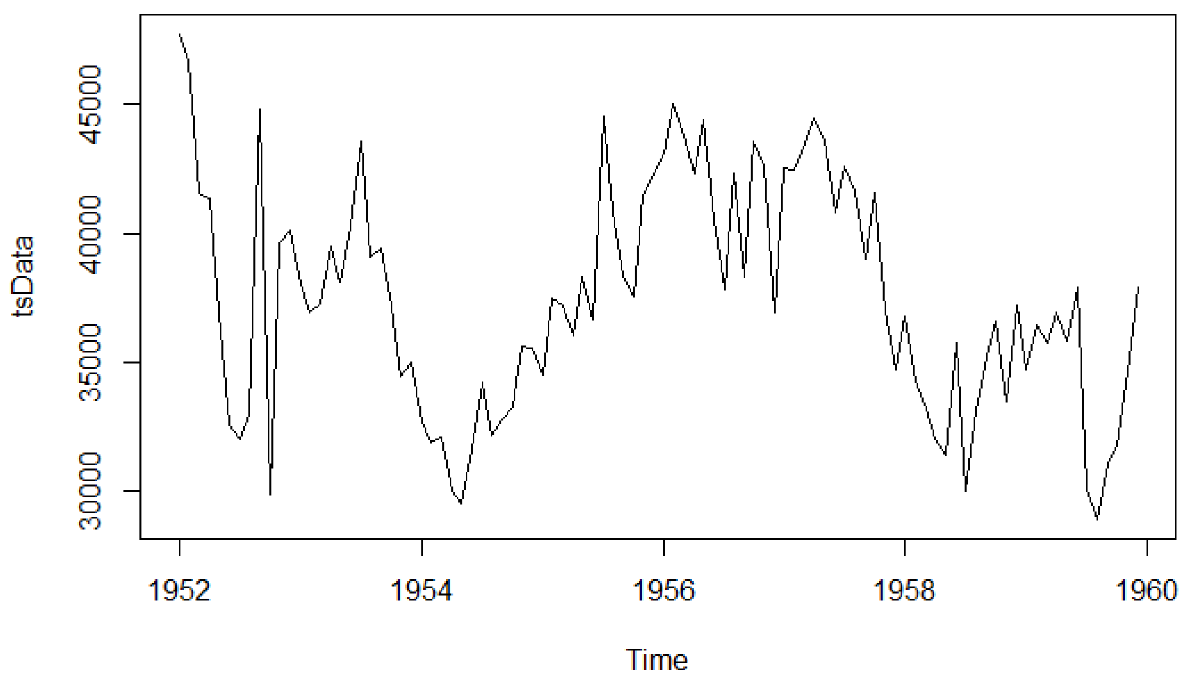
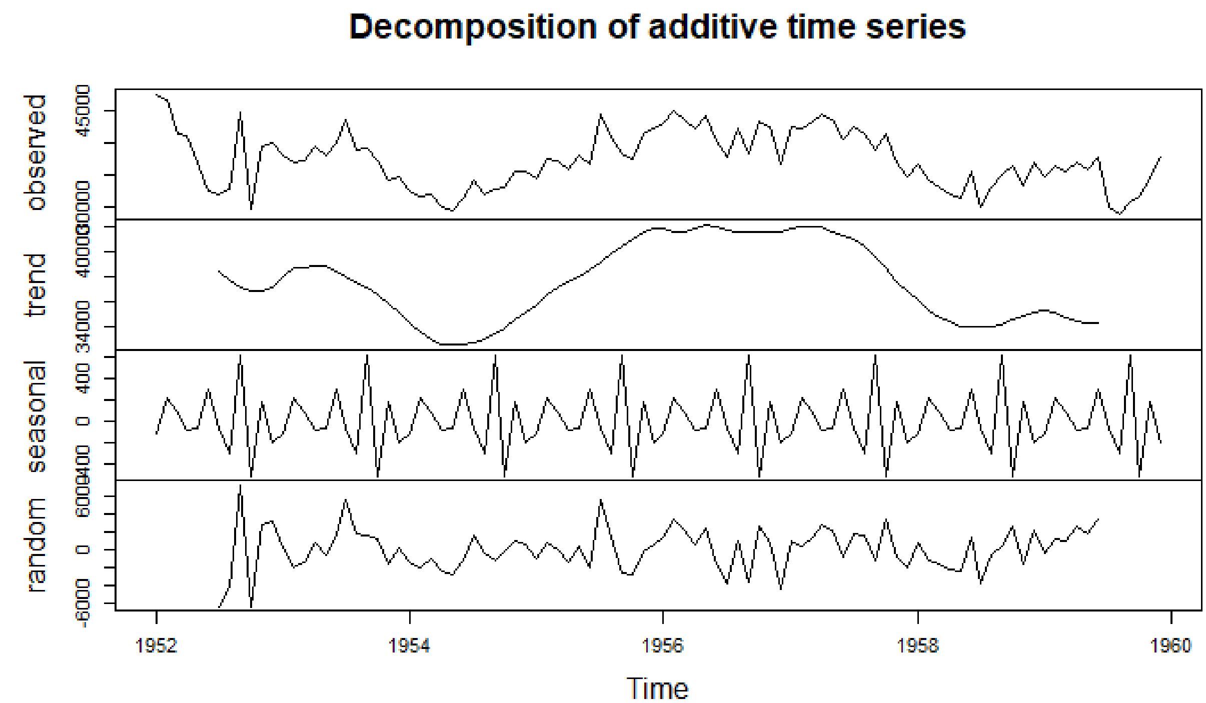
Visualizing Data:

```
coaldata <- c (47730,46704,41535,41319,36962,32558,31995,32993,44834,29883,39611,
40099,38051,36927,37272,39457,38097,40226,43589,39088,39409,37226,
34421,34975,32710,31885,32106,30029,29501,31620,34205,32153,32764,
33230,35636,35550,34529,37498,37229,36021,38281,36676,44541,40850,
38404,37575,41476,42267,43062,45036,43769,42298,44412,40498,37830,
42294,38330,43554,42579,36911,42541,42430,43465,44468,43597,40774,
42573,41635,39030,41572,37027,34732,36817,34295,33218,32034,31417,
35719,30001,33096,35196,36550,33463,37195,34748,36461,35754,36943,
35854,37912,30095,28931,31020,31746,34613,37901)

coaldata
tsData = ts(coaldata,start = c(1952,1), frequency = 12)
plot(tsData)
```




```
components.ts = decompose(tsData)
plot(components.ts)
```

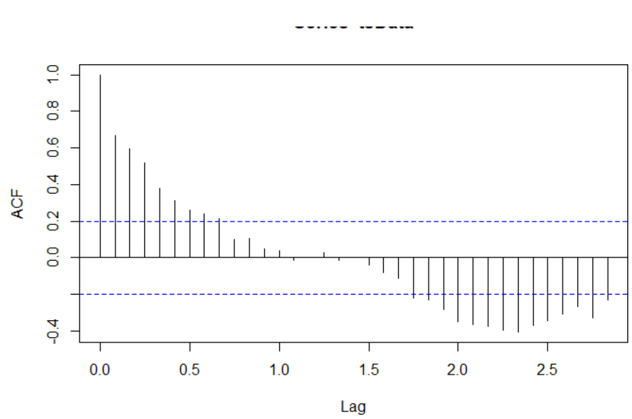


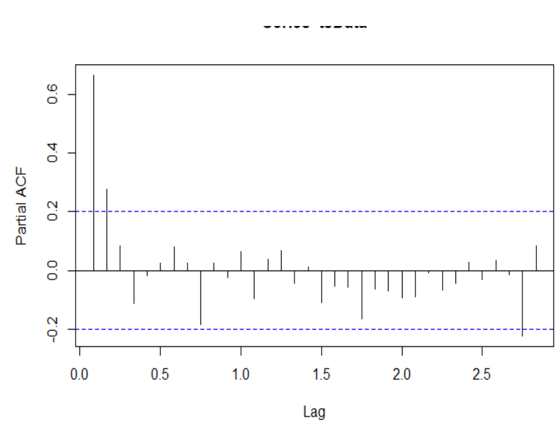
Here we get 4 components:

- Observed – the actual data plot
- Trend – the overall upward or downward movement of the data points
- Seasonal – any monthly/yearly pattern of the data points
- Random – unexplainable part of the data

Checking the ACF and PACF plots of the data to determine the order of the model to be used.

acf(tsData,lag.max=34)
pacf(tsData, lag.max=34)





Fitting a model:

We see here that the ACF is exponentially decreasing with lag, and the PACF is significant till 2 values of lag. In such a case we use the AR(2) model.

Although comparing AR1 and AR2 AIC and BIC values to confirm:

fitARIMA <- arima(tsData, order=c(2,0,0),method="ML")
fitARIMAR2 <- arima(tsData, order=c(1,0,0),method="ML")
AIC(fitARIMAR1)
[1] 1822.801
BIC(fitARIMAR1)
[1] 1833.059
AIC(fitARIMAR2)
[1] 1830.813
BIC(fitARIMAR2)
[1] 1838.506

Here again we can confirm that the AR(2) model is a better fit.

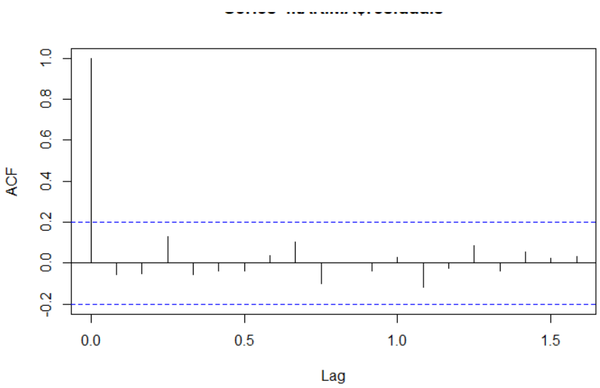
install.packages('FitAR')
library(lmtest)
coeftest(fitARIMA)

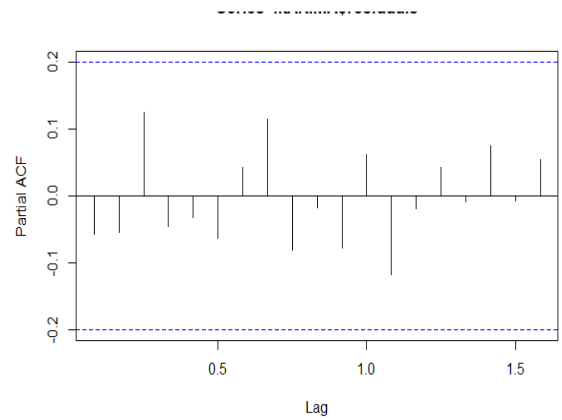
```
z test of coefficients:

           Estimate Std. Error z value  Pr(>|z|)
ar1       4.8390e-01 9.6492e-02  5.0149 5.306e-07 ***
ar2       3.2228e-01 9.8802e-02  3.2619  0.001107 **
intercept 3.7980e+04 1.5418e+03 24.6337 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Residual Diagnostics:

We need to check if the residual corresponds to the white noise.

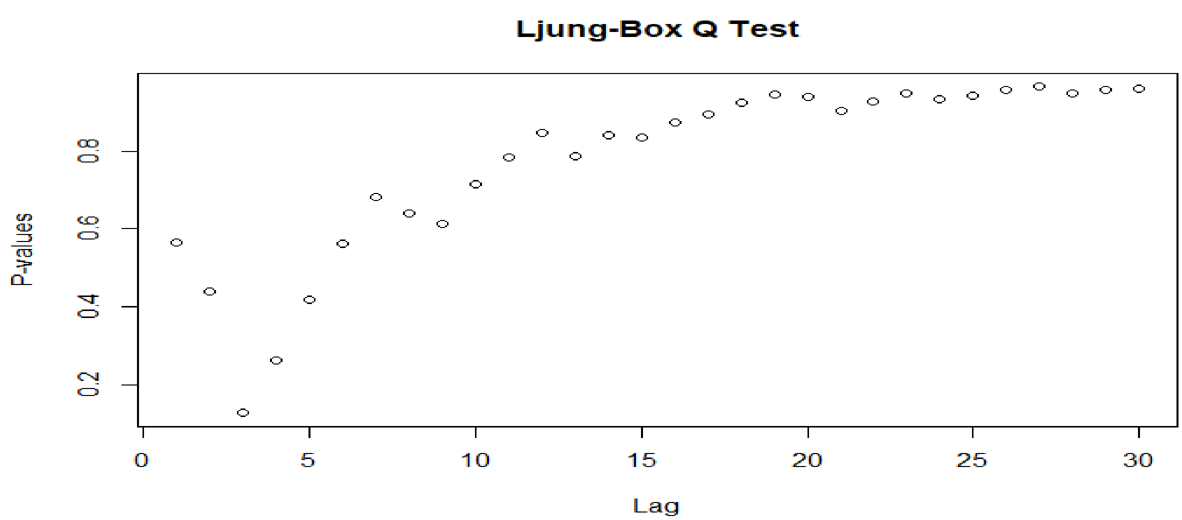
acf(fitARIMA$residuals)
pacf(fitARIMA$residuals)





The ACF of the residuals shows no significant autocorrelations.

boxresult<-LjungBoxTest (fitARIMA$residuals,k=2,StartLag=1)
plot(boxresult[,3],main= "Ljung-Box Q Test", ylab= "P-values", xlab= "Lag")



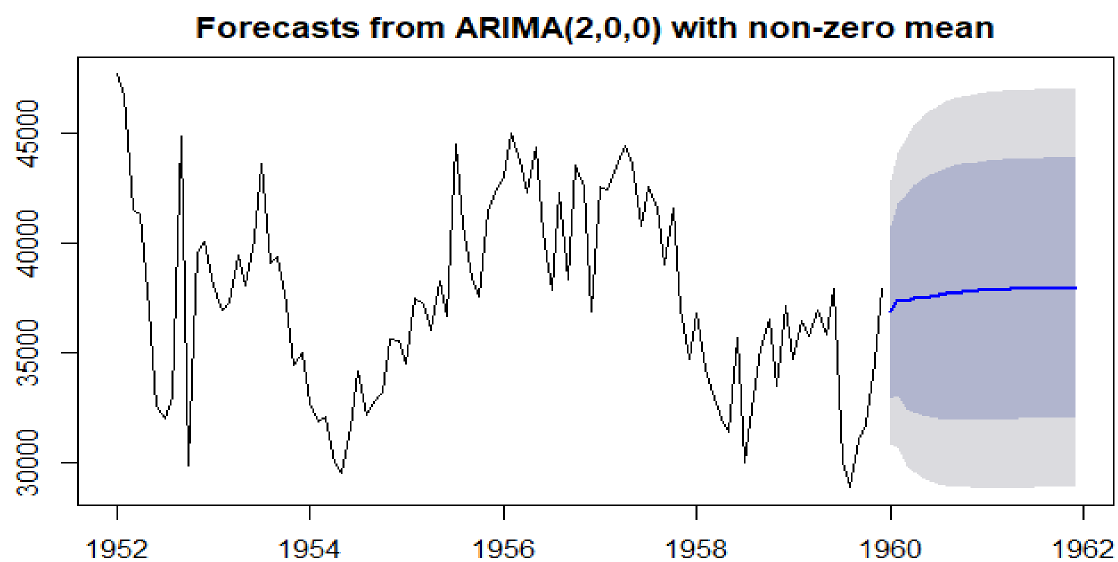
The p-values for the Ljung-Box Q test all are well above 0.05, indicating “non-significance.”
As all the graphs are in support of the assumption that there is no pattern in the residuals, we can go ahead and calculate the forecast.

Predicting Future values:

predict(fitARIMA,n.ahead = 24)

```
$pred
          Jan      Feb      Mar      Apr      May      Jun      Jul      Aug      Sep      Oct      Nov      Dec
1960 36856.68 37411.00 37342.66 37488.24 37536.66 37607.01 37656.66 37703.36 37741.95 37775.68 37804.43 37829.22
1961 37850.48 37868.76 37884.45 37897.94 37909.52 37919.47 37928.02 37935.37 37941.67 37947.09 37951.75 37955.75

$se
          Jan      Feb      Mar      Apr      May      Jun      Jul      Aug      Sep      Oct      Nov      Dec
1960 3066.510 3406.662 3810.096 4027.030 4196.592 4312.159 4397.160 4458.319 4503.088 4535.790 4559.789 4577.414
1961 4590.379 4599.922 4606.953 4612.134 4615.954 4618.771 4620.849 4622.381 4623.512 4624.346 4624.962 4625.416
```

plot(forecast(fitARIMA,h = 24))



The forecasts are shown as a blue line, with the 80% prediction intervals as a dark shaded area, and the 95% prediction intervals as a light shaded area.