

시계열자료분석

Ch07 ARIMA

```
In [1]: ##### 경로 지정
#setwd("C:\\R-Project\\DAT\\Time Series Data")

options(repr.plot.width = 12, repr.plot.height = 6)
```

분산이 일정하지 않은 경우

```
In [2]: z <- AirPassengers
```

```
In [3]: z
```

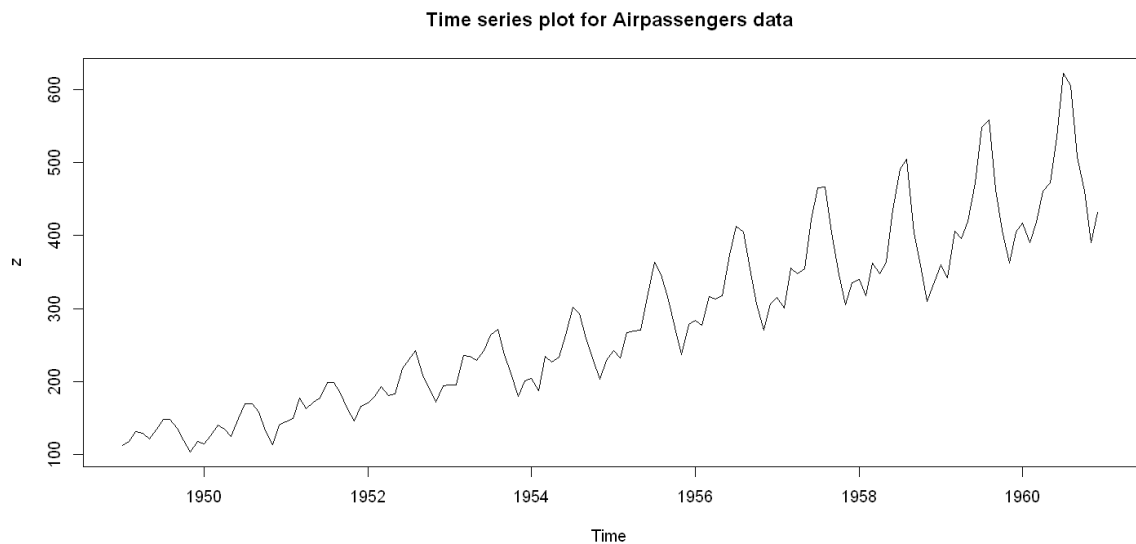
A Time Series: 12 × 12

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1949	112	118	132	129	121	135	148	148	136	119	104	118
1950	115	126	141	135	125	149	170	170	158	133	114	140
1951	145	150	178	163	172	178	199	199	184	162	146	166
1952	171	180	193	181	183	218	230	242	209	191	172	194
1953	196	196	236	235	229	243	264	272	237	211	180	201
1954	204	188	235	227	234	264	302	293	259	229	203	229
1955	242	233	267	269	270	315	364	347	312	274	237	278
1956	284	277	317	313	318	374	413	405	355	306	271	306
1957	315	301	356	348	355	422	465	467	404	347	305	336
1958	340	318	362	348	363	435	491	505	404	359	310	337
1959	360	342	406	396	420	472	548	559	463	407	362	405
1960	417	391	419	461	472	535	622	606	508	461	390	432

```
In [4]: class(z)
```

'ts'

```
In [5]: plot.ts(z, main = "Time series plot for Airpassengers data")
```



- Box-Cox transformation

$$f_{\lambda}(Z_t) = \begin{cases} \frac{Z_t^{\lambda} - 1}{\lambda}, & Z_t \geq 0, \lambda > 0 \\ \log(Z_t), & \lambda = 0 \end{cases}$$

```
In [6]: forecast::BoxCox.lambda(z, method='loglik')
```

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

0.2

```
In [7]: forecast::BoxCox.lambda(z, method = "guerrero")
```

-0.294715585559316

```
In [8]: forecast::BoxCox(z, lambda= forecast::BoxCox.lambda(z, method='loglik'))
```

A Time Series: 12 × 12

	Jan	Feb	Mar	Apr	May	Jun	Jul	
1949	7.847352	7.982144	8.276536	8.215632	8.047493	8.336343	8.583833	8.5
1950	7.915451	8.153584	8.452835	8.336343	8.132639	8.602141	8.965606	8.9
1951	8.528312	8.620350	9.094641	8.848653	8.998313	9.094641	9.412543	9.4
1952	8.981998	9.126173	9.324566	9.141833	9.172949	9.677811	9.835957	9.9
1953	9.368824	9.368824	9.912567	9.899908	9.823034	10.000000	10.250736	10.3
1954	9.484251	9.249564	9.899908	9.797051	9.887205	10.250736	10.666479	10.5
1955	9.987634	9.874459	10.285240	10.308071	10.319435	10.799092	11.262611	11.1
1956	10.475107	10.398058	10.819103	10.778978	10.829071	11.351000	11.678616	11.6
1957	10.799092	10.656090	11.190490	11.117061	11.181384	11.750682	12.078927	12.0
1958	11.042269	10.829071	11.244701	11.117061	11.253666	11.852637	12.265784	12.3
1959	11.226711	11.061098	11.621691	11.538992	11.734774	12.130041	12.649244	12.7
1960	11.710799	11.497014	11.726798	12.049443	12.130041	12.564701	13.102063	13.0

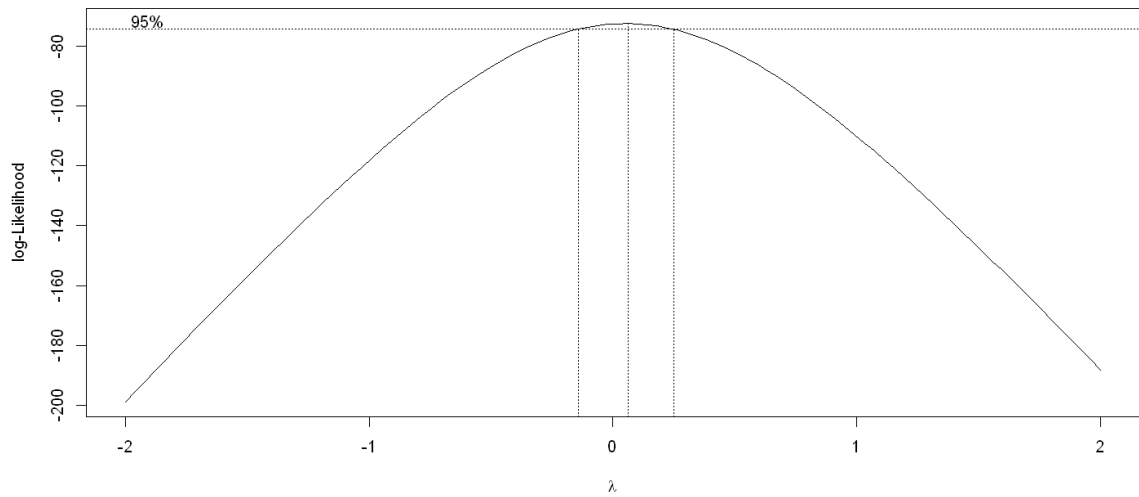
In [9]: `forecast::BoxCox(z,lambda= 'auto')`

A Time Series: 12 × 12

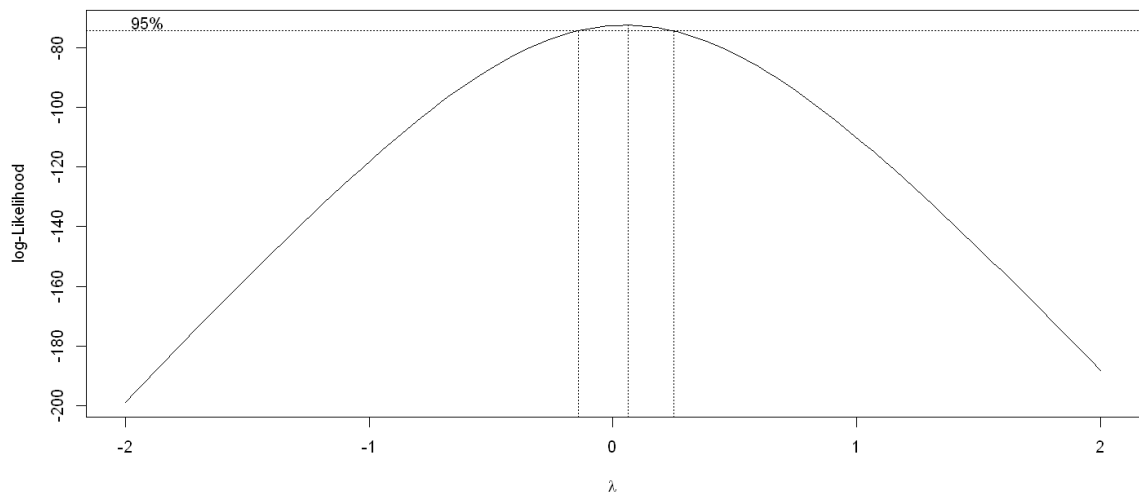
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	
1949	2.548535	2.561426	2.588461	2.582990	2.567558	2.593773	2.615143	2.615143	2.
1950	2.555089	2.577352	2.603953	2.593773	2.575434	2.616686	2.646282	2.646282	2.
1951	2.610433	2.618215	2.656336	2.636968	2.648852	2.656336	2.680161	2.680161	2.
1952	2.647572	2.658759	2.673698	2.659957	2.662328	2.699069	2.709945	2.720109	2.
1953	2.676962	2.676962	2.715111	2.714262	2.709067	2.720927	2.737151	2.742897	2.
1954	2.685357	2.668111	2.714262	2.707296	2.713408	2.737151	2.762643	2.756996	2.
1955	2.720109	2.712549	2.739332	2.740768	2.741481	2.770427	2.796406	2.787934	2.
1956	2.751119	2.746379	2.771588	2.769257	2.772164	2.801154	2.818211	2.814887	2.
1957	2.770427	2.762027	2.792485	2.788447	2.791987	2.821853	2.837961	2.838662	2.
1958	2.784288	2.772164	2.795437	2.788447	2.795922	2.826939	2.846793	2.851301	2.
1959	2.794460	2.785340	2.815307	2.811044	2.821052	2.840400	2.864196	2.867286	2.
1960	2.819842	2.808860	2.820650	2.836545	2.840400	2.860440	2.883580	2.879651	2.

In [10]: `t <- 1:length(z)`

In [11]: `MASS::boxcox(z~t)`



```
In [12]: bc <- MASS::boxcox(z~t)
```



```
In [13]: #bc
```

```
In [14]: which.max(bc$y)
```

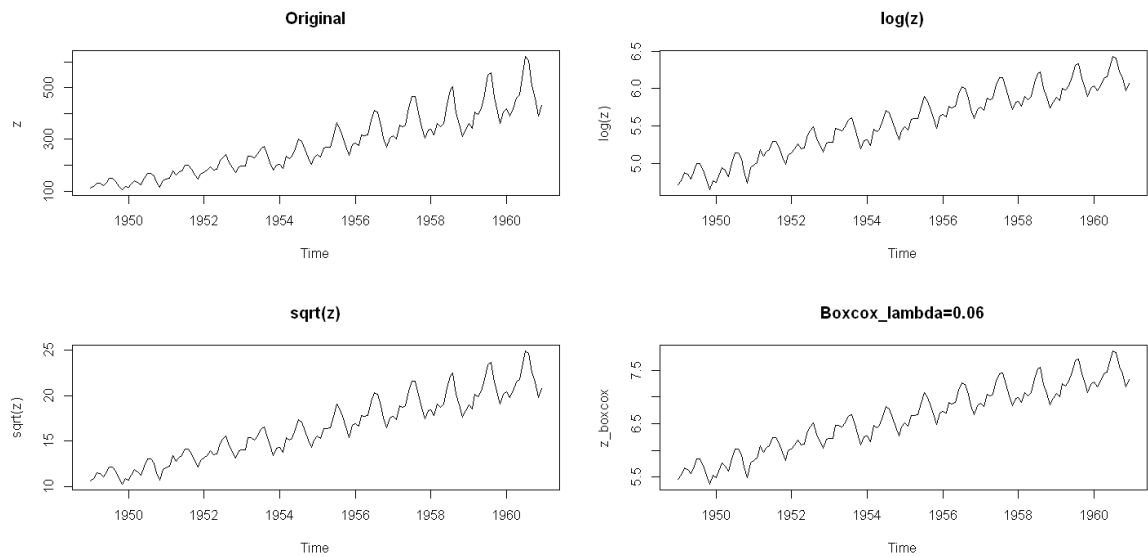
```
52
```

```
In [15]: bc$x[which.max(bc$y)]
```

```
0.060606060606061
```

```
In [16]: z_boxcox <- forecast::BoxCox(z, lambda=bc$x[which.max(bc$y)])
```

```
In [17]: par(mfrow=c(2,2))
plot.ts(z, main = "Original")
plot.ts(log(z), main = "log(z)")
plot.ts(sqrt(z), main = "sqrt(z)")
plot.ts(z_boxcox, main = "Boxcox_lambda=0.06")
graphics.off()
```



로그변환을 수행한다.

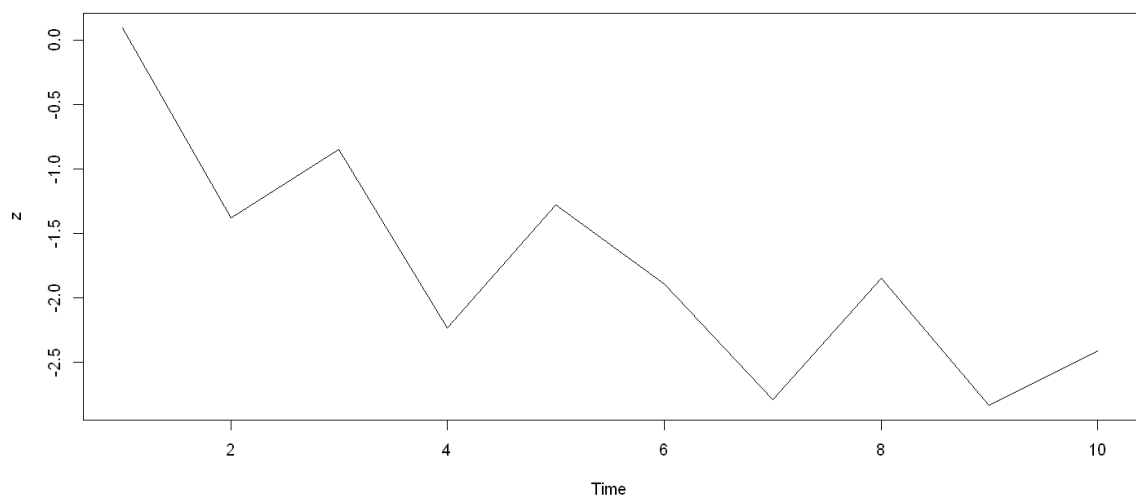
확률적 추세 제거

- 확률보행과정의 정상화

$$Z_t = Z_{t-1} + \epsilon_t, \quad \epsilon_t \sim WN(0, \sigma^2) - \text{AR}(1) \text{ with } \phi = 1$$

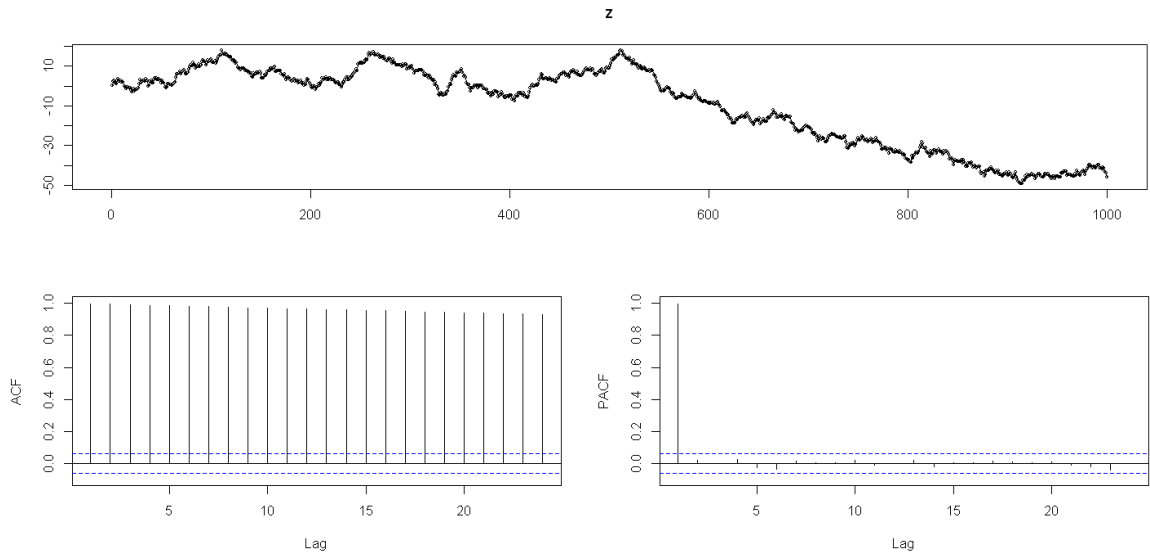
```
In [18]: e <- round(rnorm(10),2)
z <- cumsum(e)

plot.ts(z)
```



```
In [19]: e <- round(rnorm(1000),2)
z <- cumsum(e)

forecast::tsdisplay(z, lag.max=24)
```



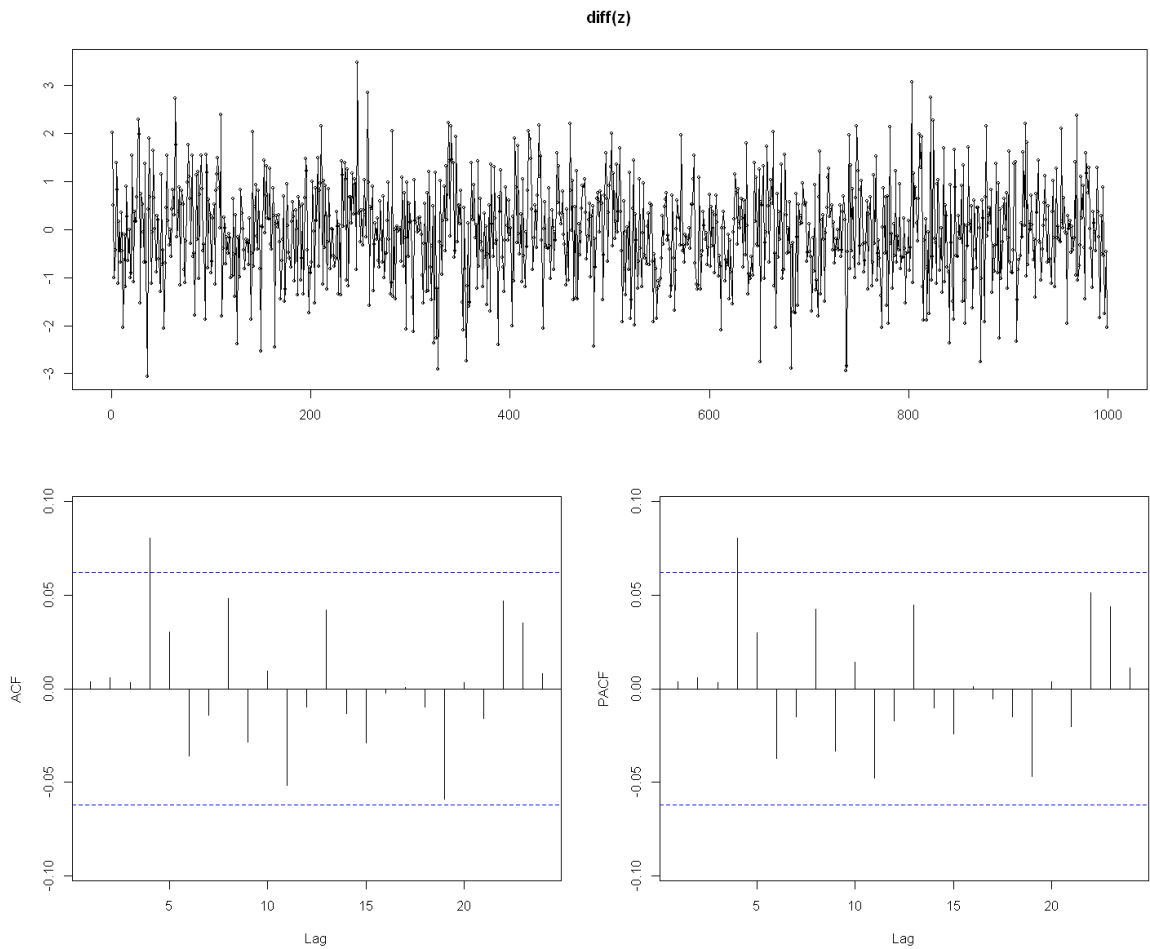
ACF가 아주 천천히 감소하므로 확률적 추세가 있다고 할 수 있다.

1차 차분을 수행한다.

$$\Delta Z_t = Z_t - Z_{t-1} = \epsilon_t$$

차분한 확률보행과정의 시도표 및 ACF/PACF 그림

```
In [20]: options(repr.plot.width = 12, repr.plot.height = 10)
forecast::tsdisplay(diff(z), lag.max=24)
```



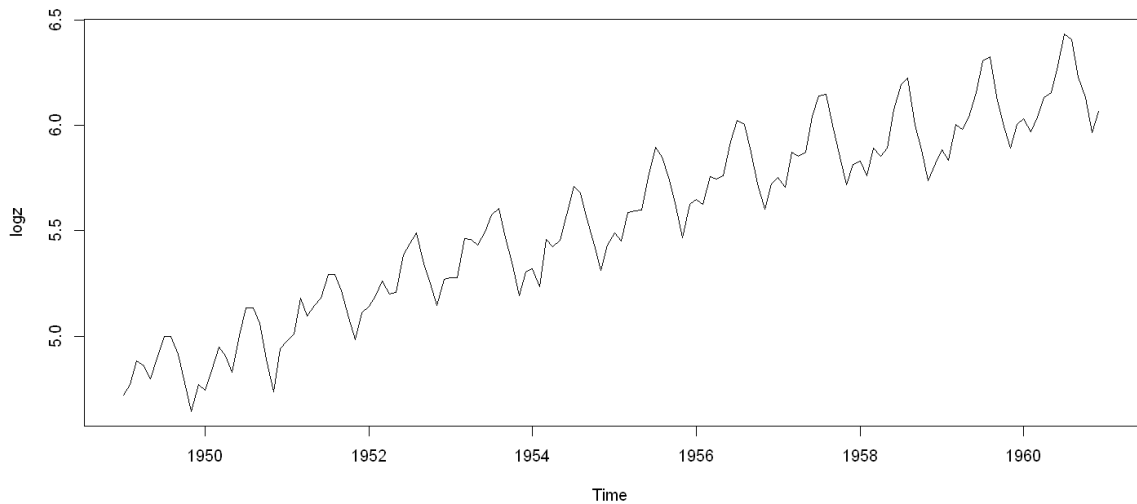
차분을 했더니 정상 시계열이 됨.

$$\Delta Z_t \sim WN = ARMA(0,0) \Rightarrow Z_t \sim ARIMA(0,1,0)$$

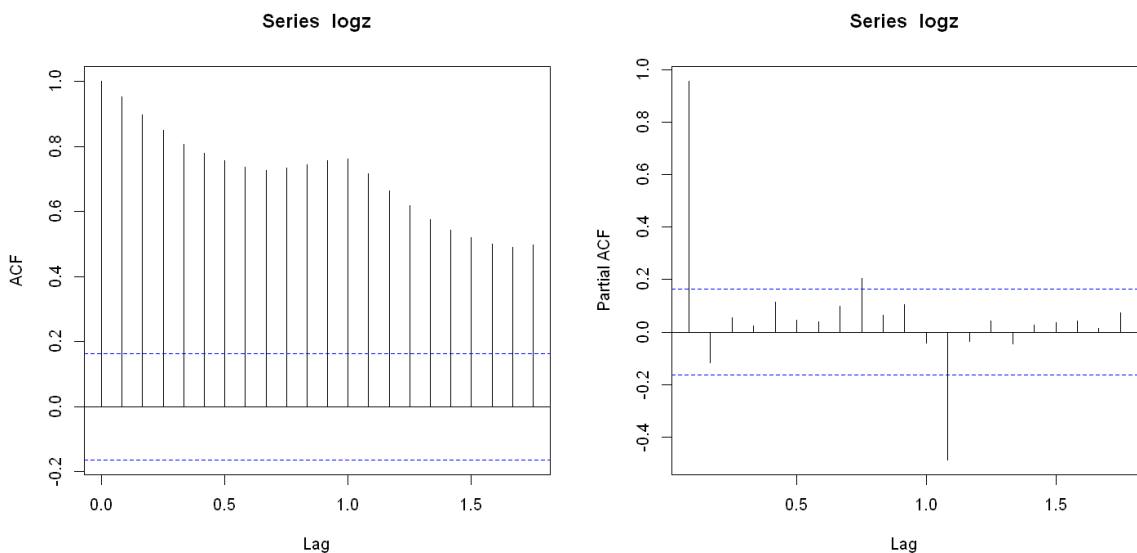
- 로그변환한 Airpassengers data 에 대한 확률적 추세 확인

```
In [21]: logz <- log(AirPassengers)

options(repr.plot.width = 12, repr.plot.height = 6)
plot.ts(logz)
```

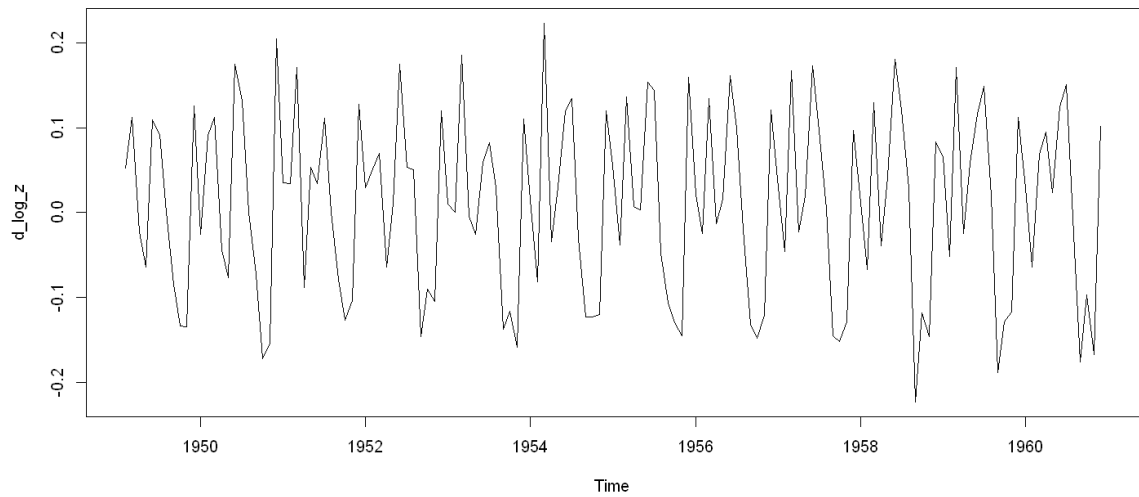


```
In [22]: par(mfrow=c(1,2))
acf(logz)
pacf(logz)
```

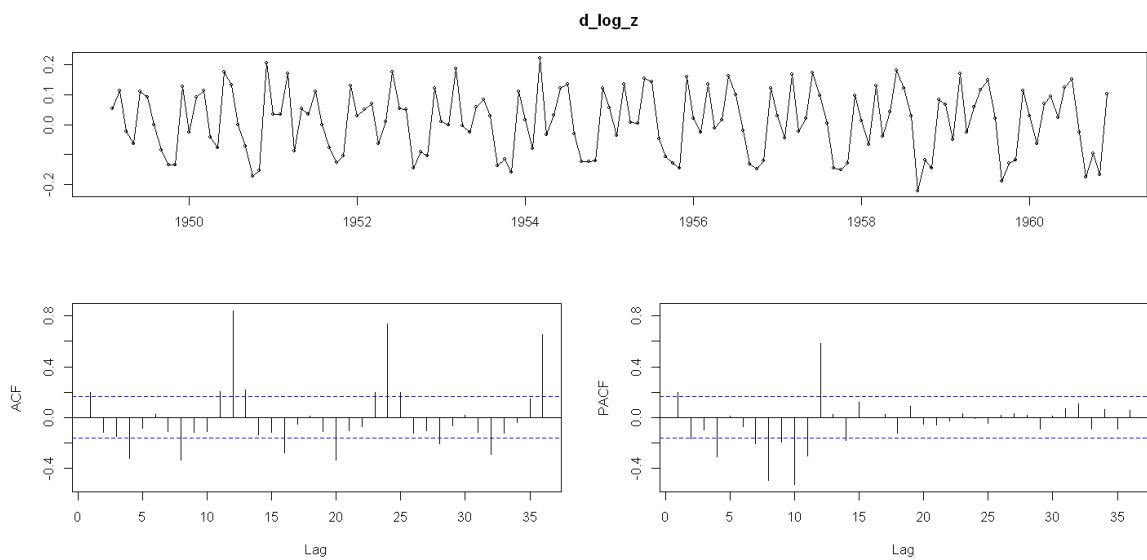


차분을 진행한다. $\Delta Z_t = (1 - B)Z_t = Z_t - Z_{t-1}$

```
In [23]: d_log_z = diff(logz)
plot.ts(d_log_z)
```



```
In [24]: forecast::tsdisplay(d_log_z, lag.max=36)
```

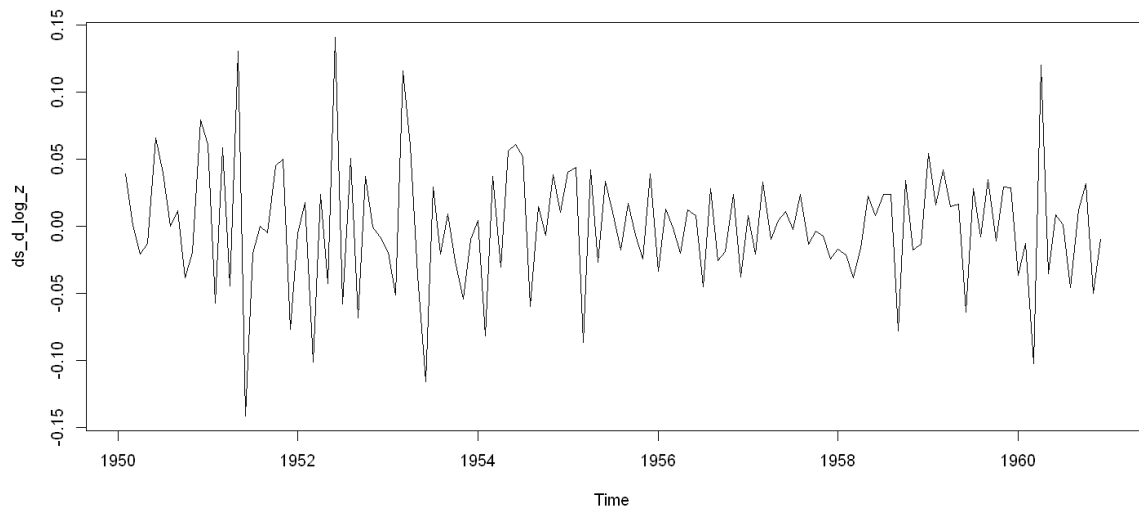


여전히 계절성분이 남아있으므로, 계절차분 진행

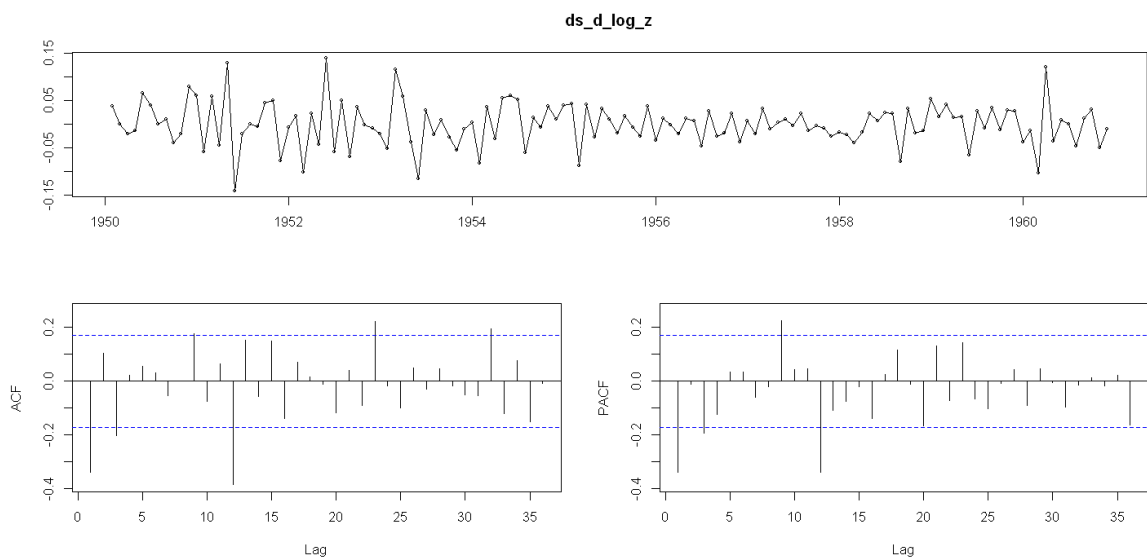
$$\Delta_{12}\Delta Z_t = (1 - B^{12})(1 - B)Z_t = (1 - B^{12})(Z_t - Z_{t-1}) = Z_t - Z_{t-1} - Z_{t-12} - Z_{t-1}$$



```
In [25]: ds_d_log_z <- diff(d_log_z, 12)
plot.ts(ds_d_log_z)
```

```
In [26]: forecast::tsdisplay(ds_d_log_z, lag.max=36)
```

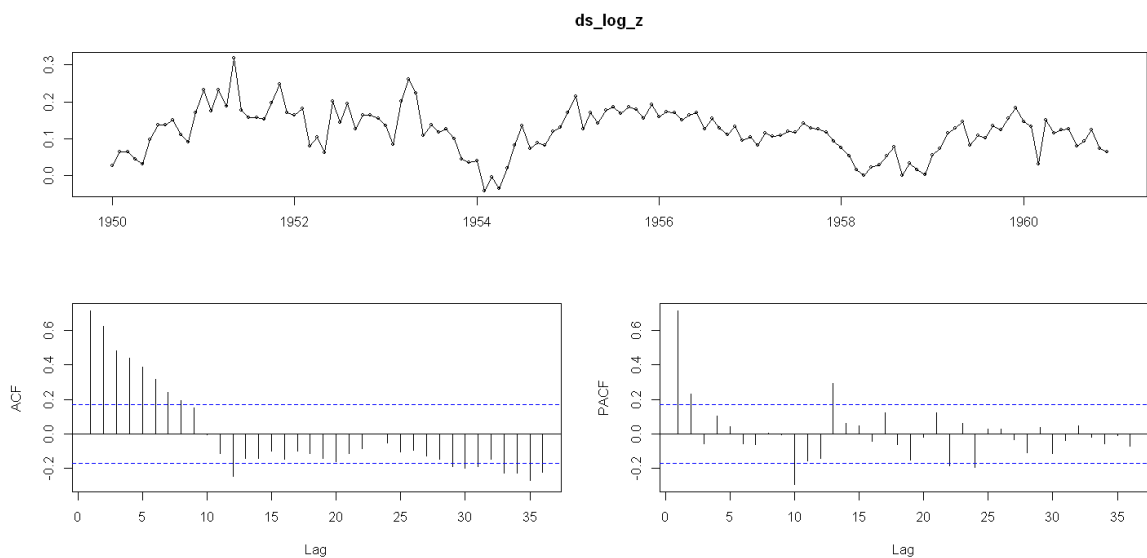


하지만, 일반적으로 계절성분과 추세가 동시에 있는 경우 계절차분을 먼저 진행한다.

```
In [27]: ds_log_z <- diff(logz, 12)
          ts.plot(ds_log_z)
```



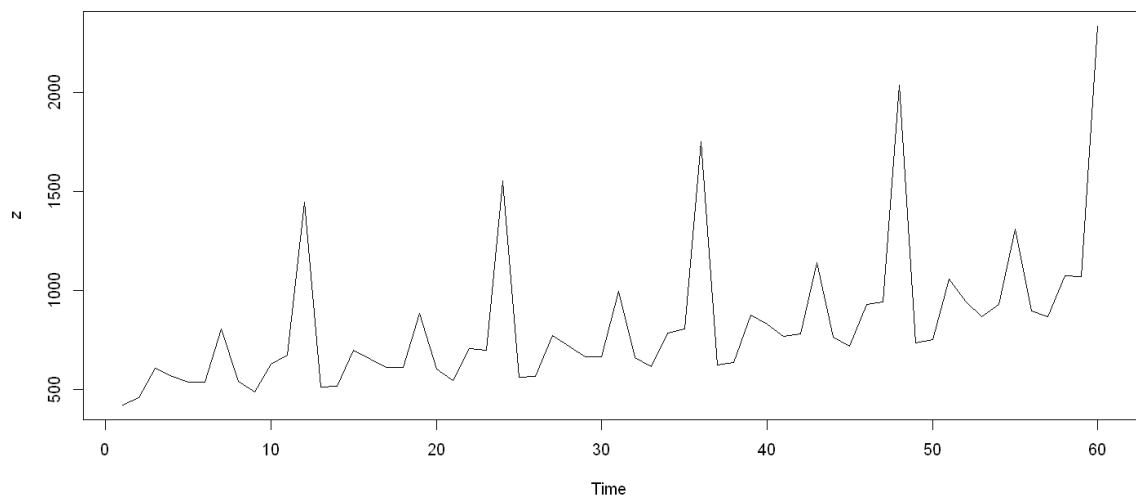
```
In [28]: forecast::tsdisplay(ds_log_z, lag.max=36)
```



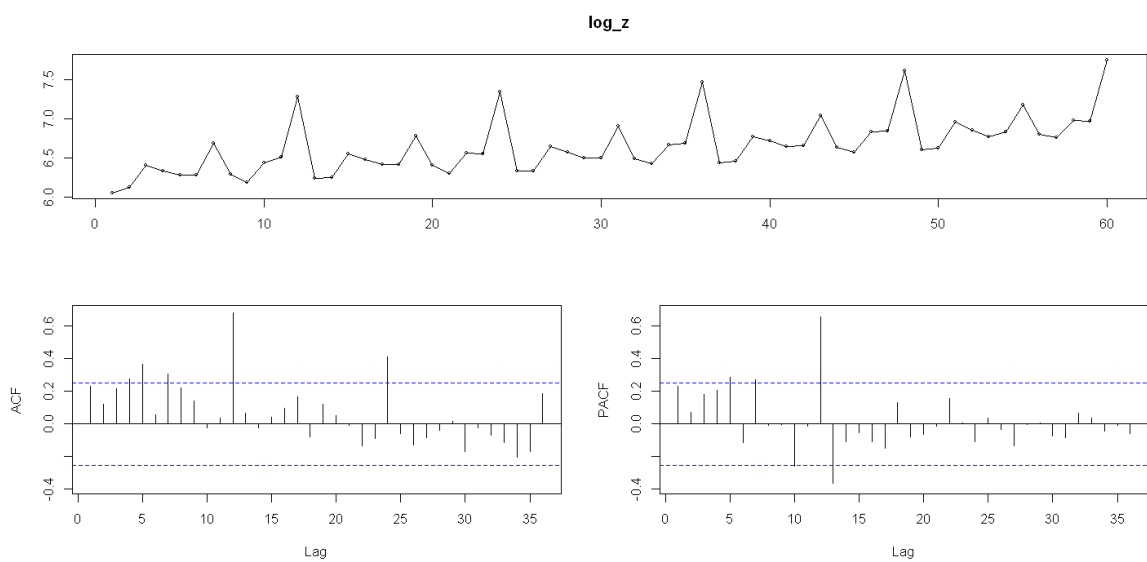
확률적추세가 있어 보이지만, AR 모형에서 ACF가 감소하는 형태라고 할 수도 있다. 이 경우에는 추세를 제거하기 위한 차분을 더 진행하는 것을 결정하는 것이 어렵다.

depart data

```
In [29]: z <- scan("depart.txt")
plot.ts(z)
```

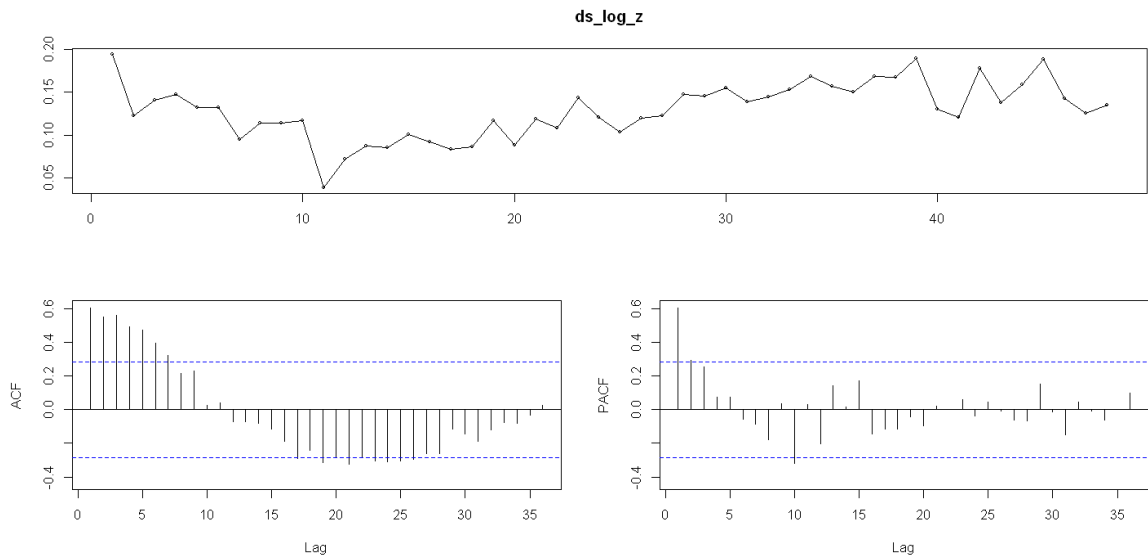


```
In [30]: log_z <- log(z)
forecast::tsdisplay(log_z, lag.max=36)
```



계절차분을 먼저 진행

```
In [31]: ds_log_z <- diff(log_z, 12)
forecast::tsdisplay(ds_log_z, lag.max=36)
```



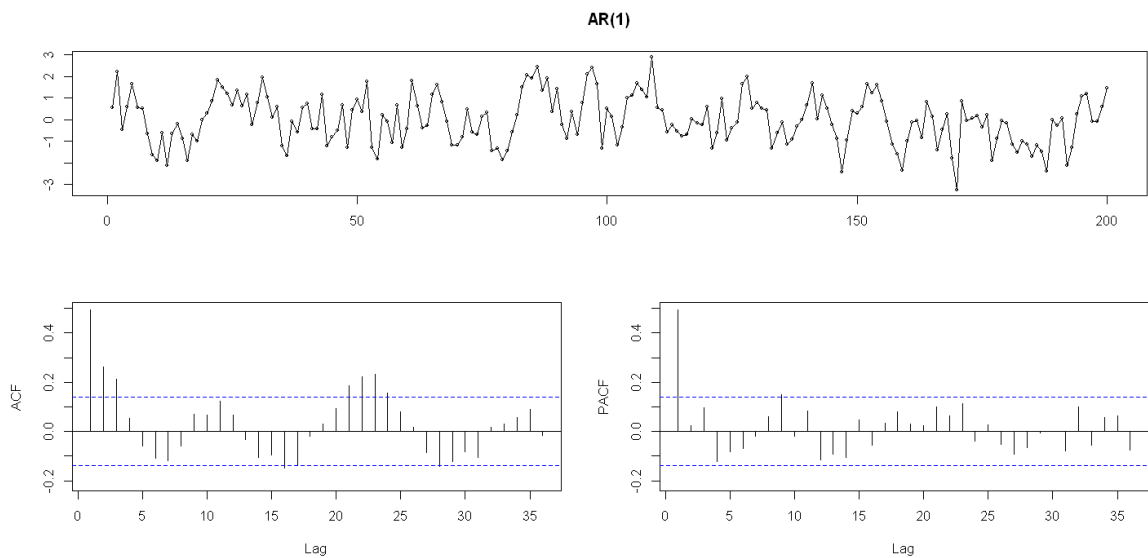
이 데이터 시도표 상으로는 확률적인 추세가 있어보이지만, 역시 ACF만 보고 차분이 필요한가에 대한 결정을 하는 것이 쉽지 않다.

여러가지 Simulation

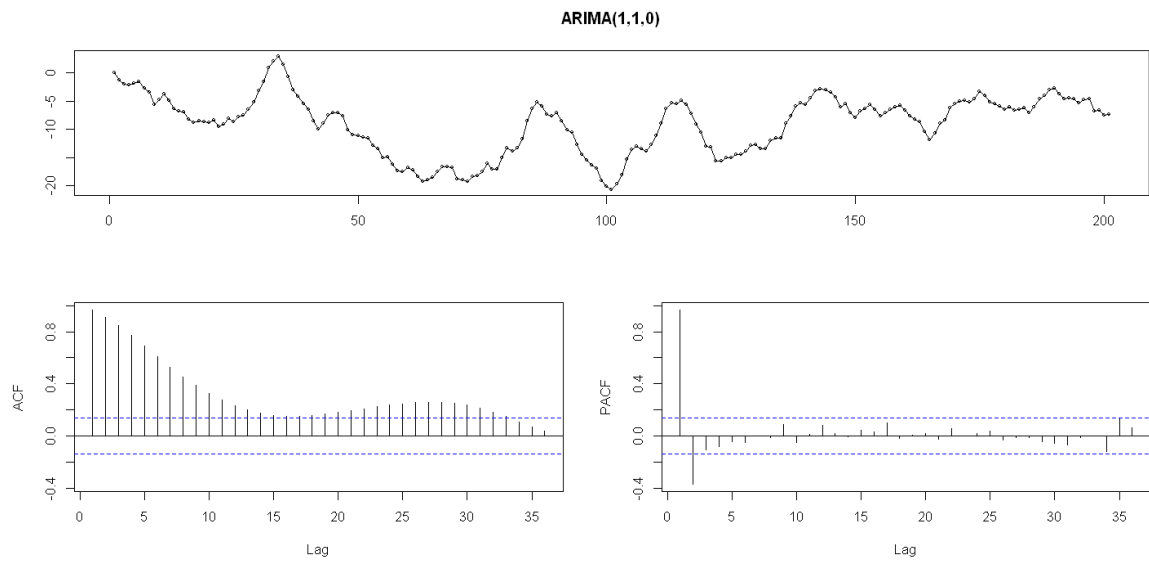
```
In [32]: n <- 200

x = arima.sim(n=n, list(order=c(1,0,0), ar=0.5)) #AR(1)
z = arima.sim(n=n, list(order=c(1,1,0), ar=0.5)) #ARIMA(1,1,0)
```

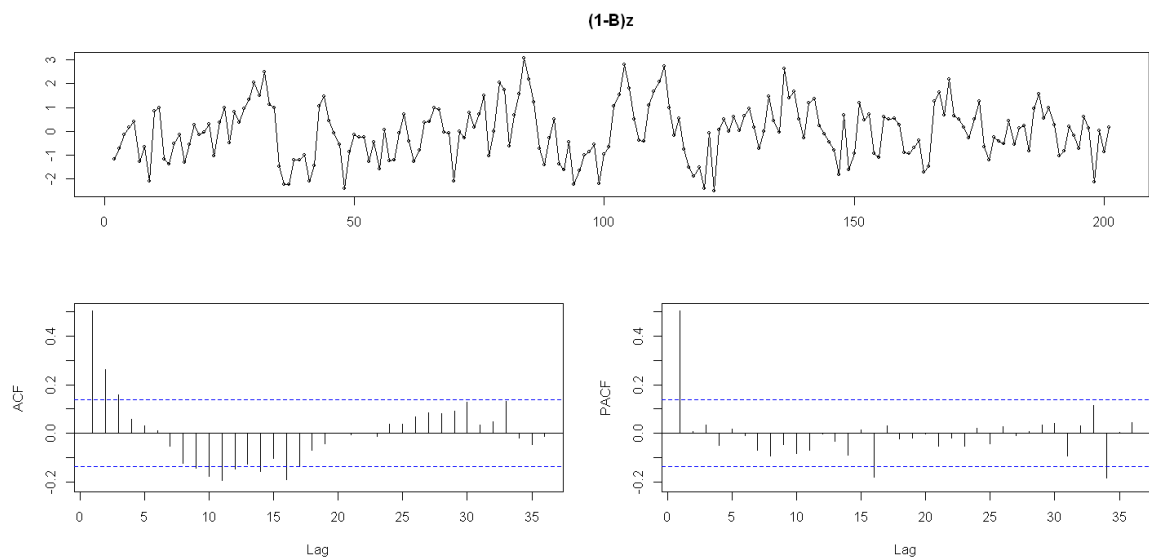
```
In [33]: forecast::tsdisplay(x, lag.max=36, main = "AR(1)")
```



```
In [34]: forecast::tsdisplay(z, lag.max=36, main = "ARIMA(1,1,0)")
```



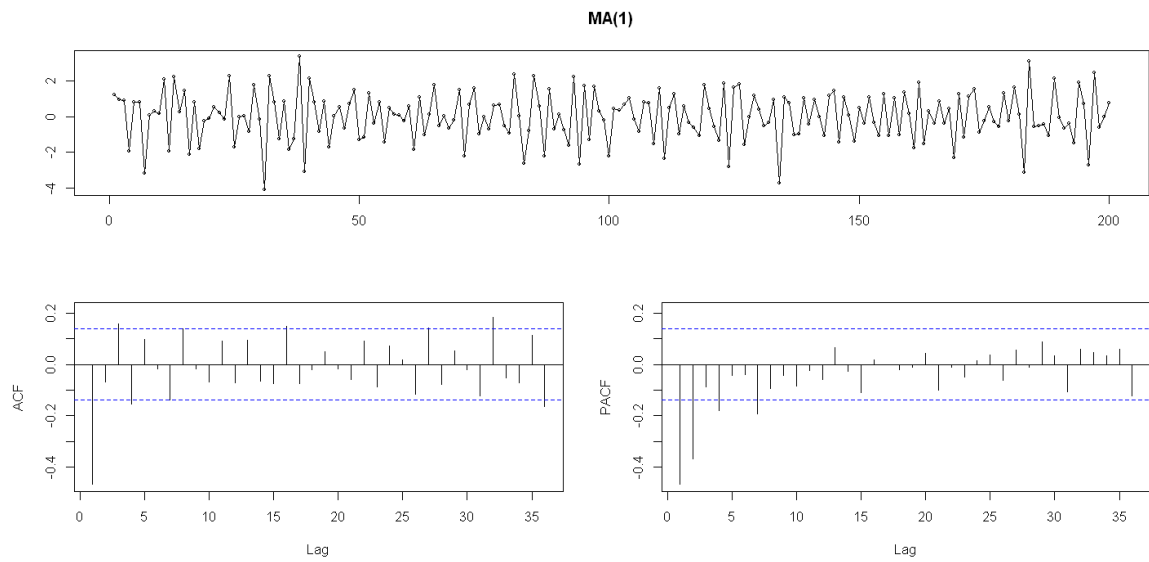
```
In [35]: forecast::tsdisplay(diff(z), lag.max=36, main = "(1-B)z")
```



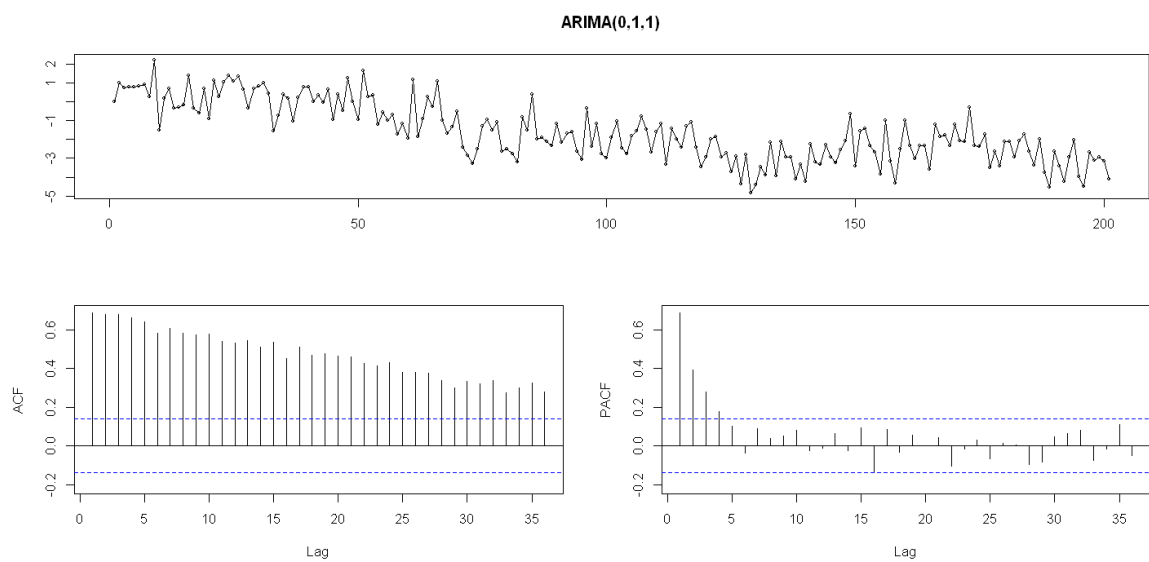
```
In [36]: n <- 200

x = arima.sim(n=n, list(order=c(0,0,1), ma=-0.8)) #MA(1)
z = arima.sim(n=n, list(order=c(0,1,1), ma=-0.8)) #ARIMA(1,1,0)
```

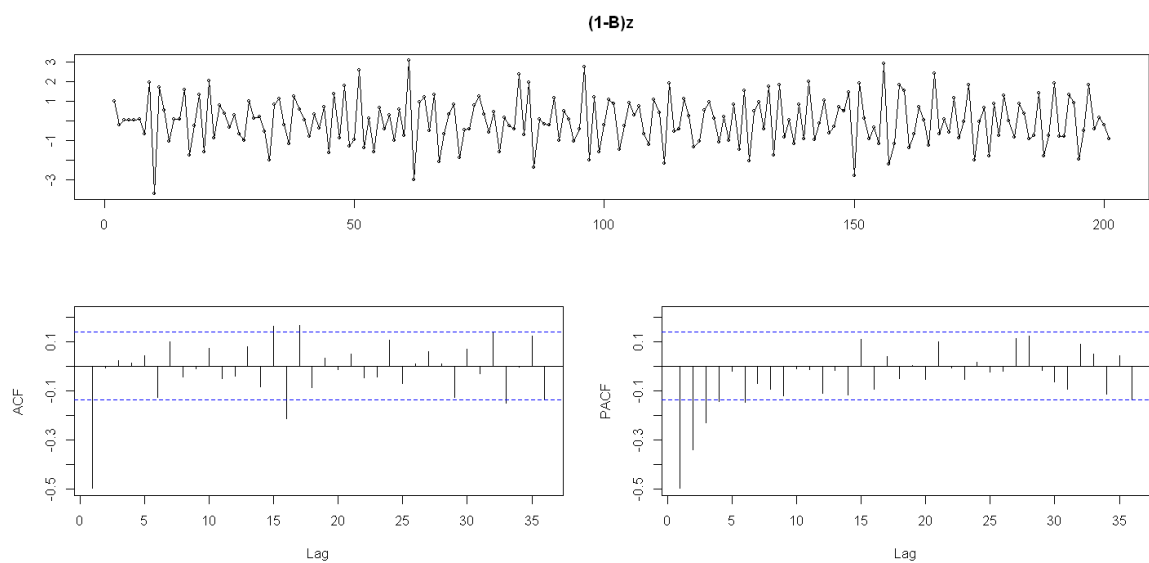
```
In [37]: forecast::tsdisplay(x, lag.max=36, main = "MA(1)")
```



```
In [38]: forecast::tsdisplay(z, lag.max=36, main = "ARIMA(0,1,1)")
```



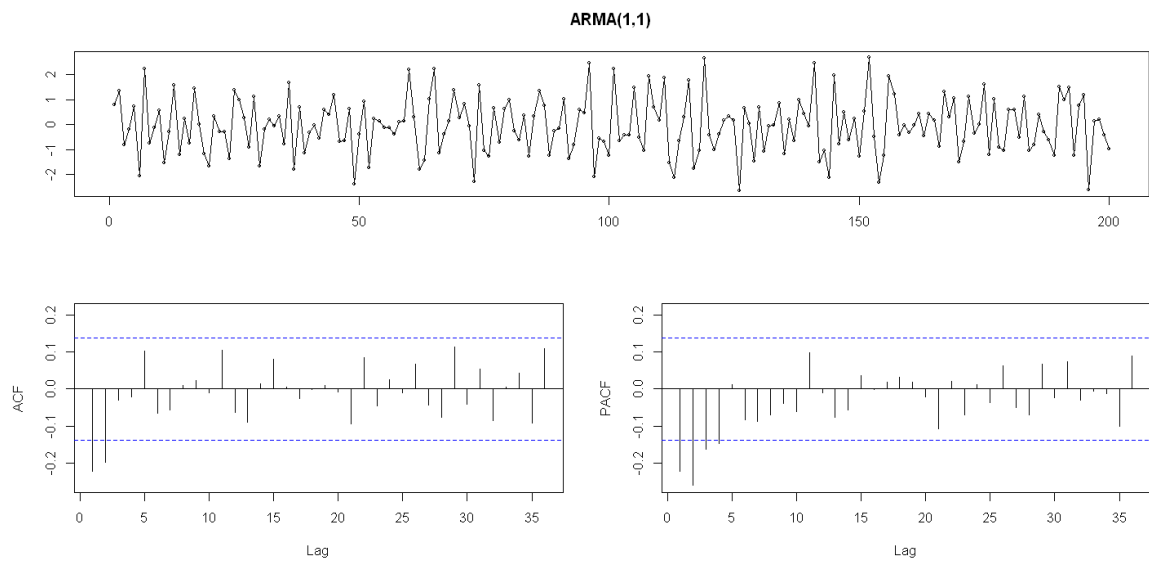
```
In [39]: forecast::tsdisplay(diff(z), lag.max=36, main = "(1-B)z")
```



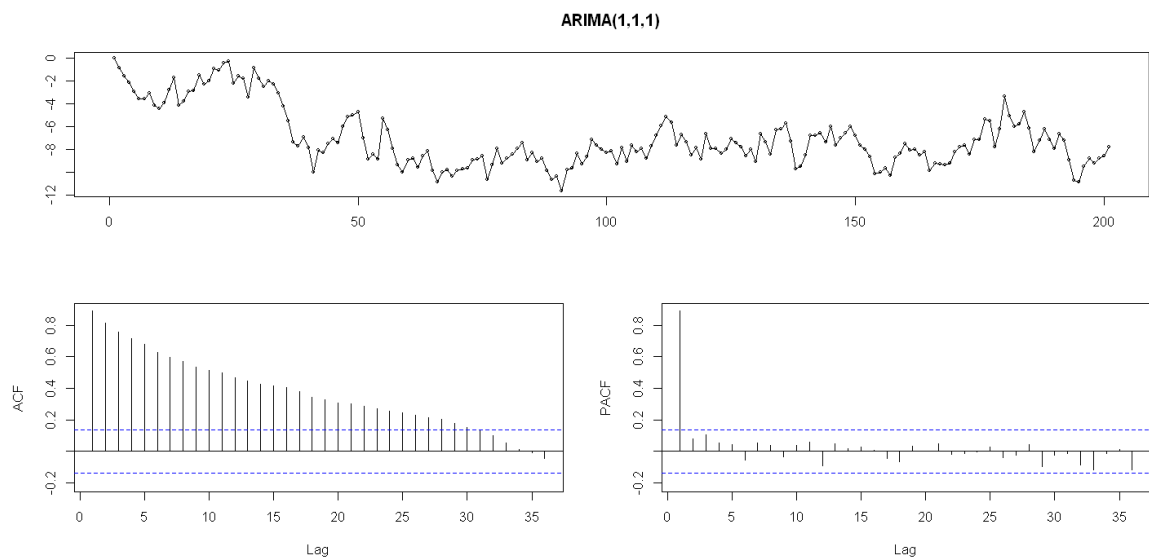
In [40]: `n <- 200`

```
x = arima.sim(n=n, list(order=c(1,0,1), ar=0.5, ma=-0.8)) #ARMA(1,1)
z = arima.sim(n=n, list(order=c(1,1,1), ar=0.5, ma=-0.8)) #ARIMA(1,1,1)
```

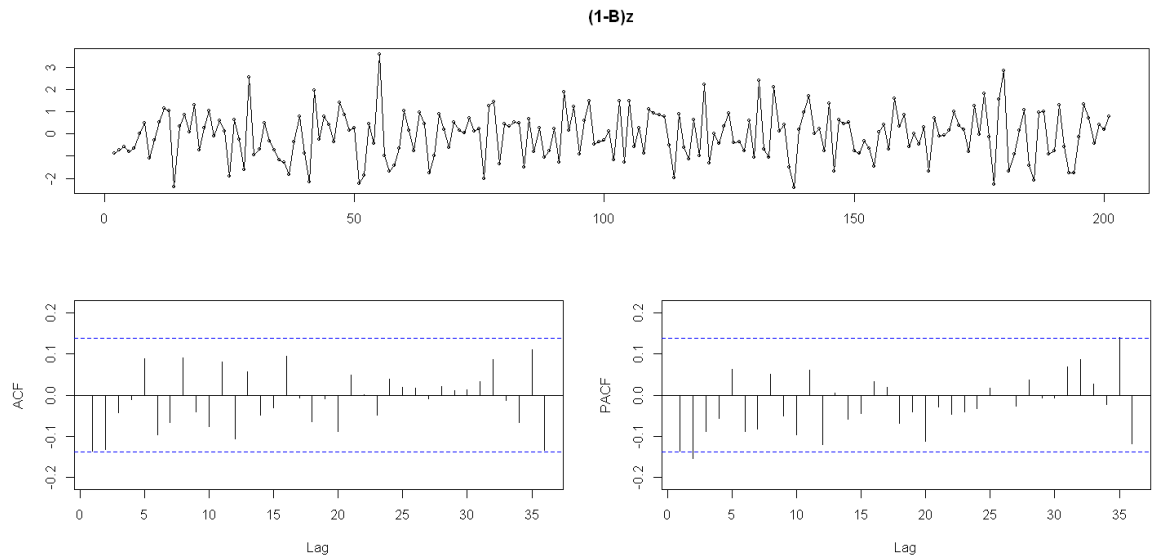
In [41]: `forecast::tsdisplay(x, lag.max=36, main = "ARMA(1,1)")`



In [42]: `forecast::tsdisplay(z, lag.max=36, main = "ARIMA(1,1,1)")`



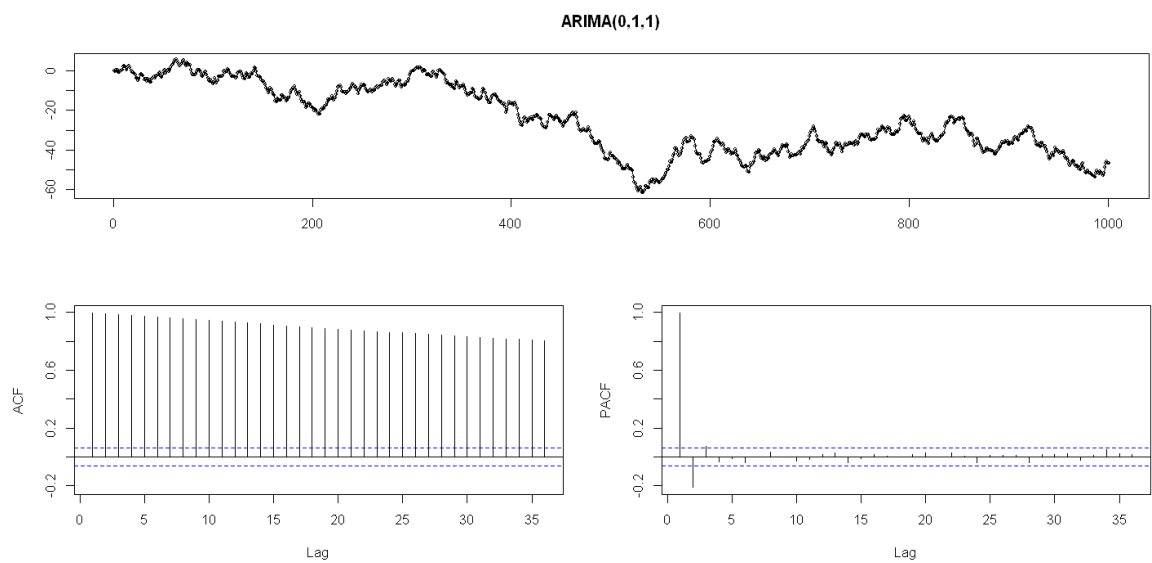
In [43]: `forecast::tsdisplay(diff(z), lag.max=36, main = "(1-B)z")`



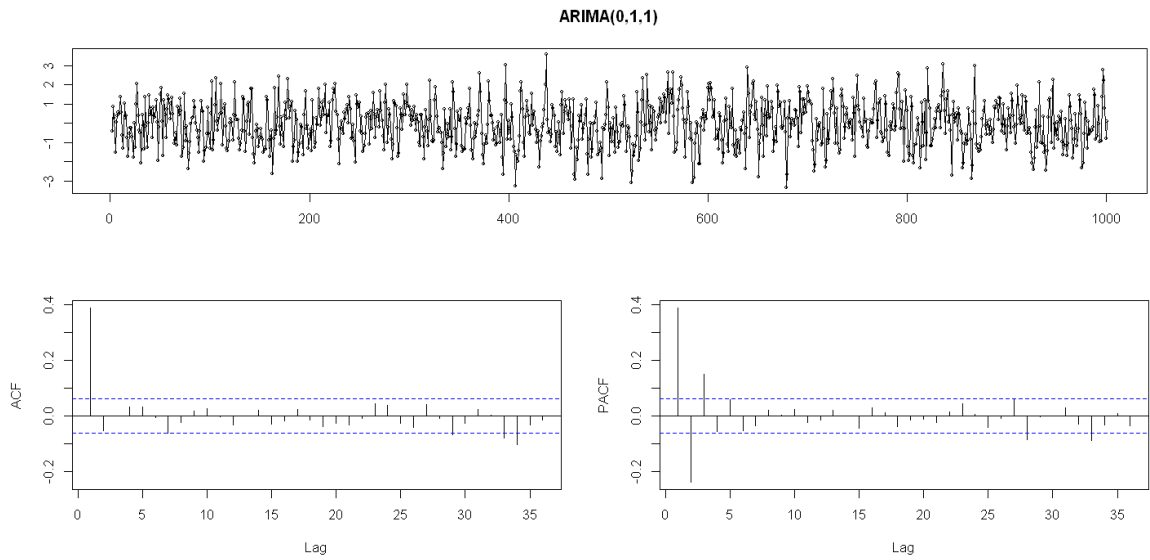
과대차분

```
In [44]: ## ARIMA(0,1,1)
z = arima.sim(n=1000, list(order=c(0,1,1), ma=0.5))
```

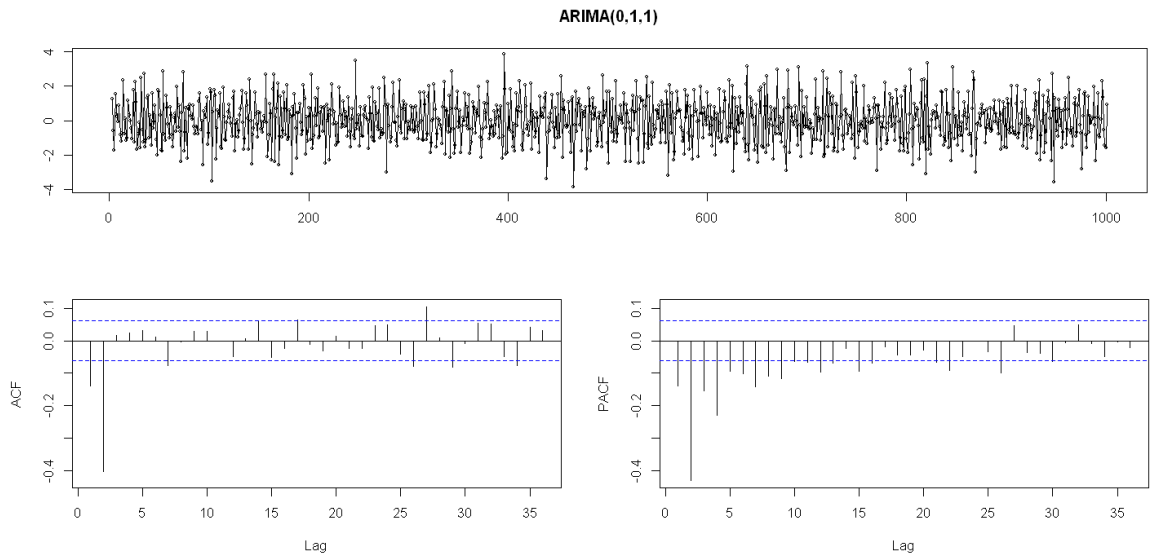
```
In [45]: forecast::tsdisplay(z, lag.max=36, main = "ARIMA(0,1,1)")
```



```
In [46]: #한 번 차분
d_z <- diff(z)
forecast::tsdisplay(d_z, lag.max=36, main = "ARIMA(0,1,1)")
```

```
In [47]: # 한 번 더 차분
d2_z <- diff(d_z)
forecast::tsdisplay(d2_z, lag.max=36, main = "ARIMA(0,1,1)")
```



한 번 차분을 하면 정상시계열이 된다. 그리고 한 번 더 차분해도 마찬가지로 정상시계열이다.

```
In [48]: sd(z)
sd(diff(z))
sd(diff(diff(z)))
```

```
17.3192131234587
1.14928524536831
1.27185972921689
```

차분을 두 번 하고 나면 분산이 커진다. 이를 과대차분이라고 한다.

```
In [ ]:
```