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title: "Code TS4"  

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Sala  

date: "2025-04-15"  

output: html_document  

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``` r  

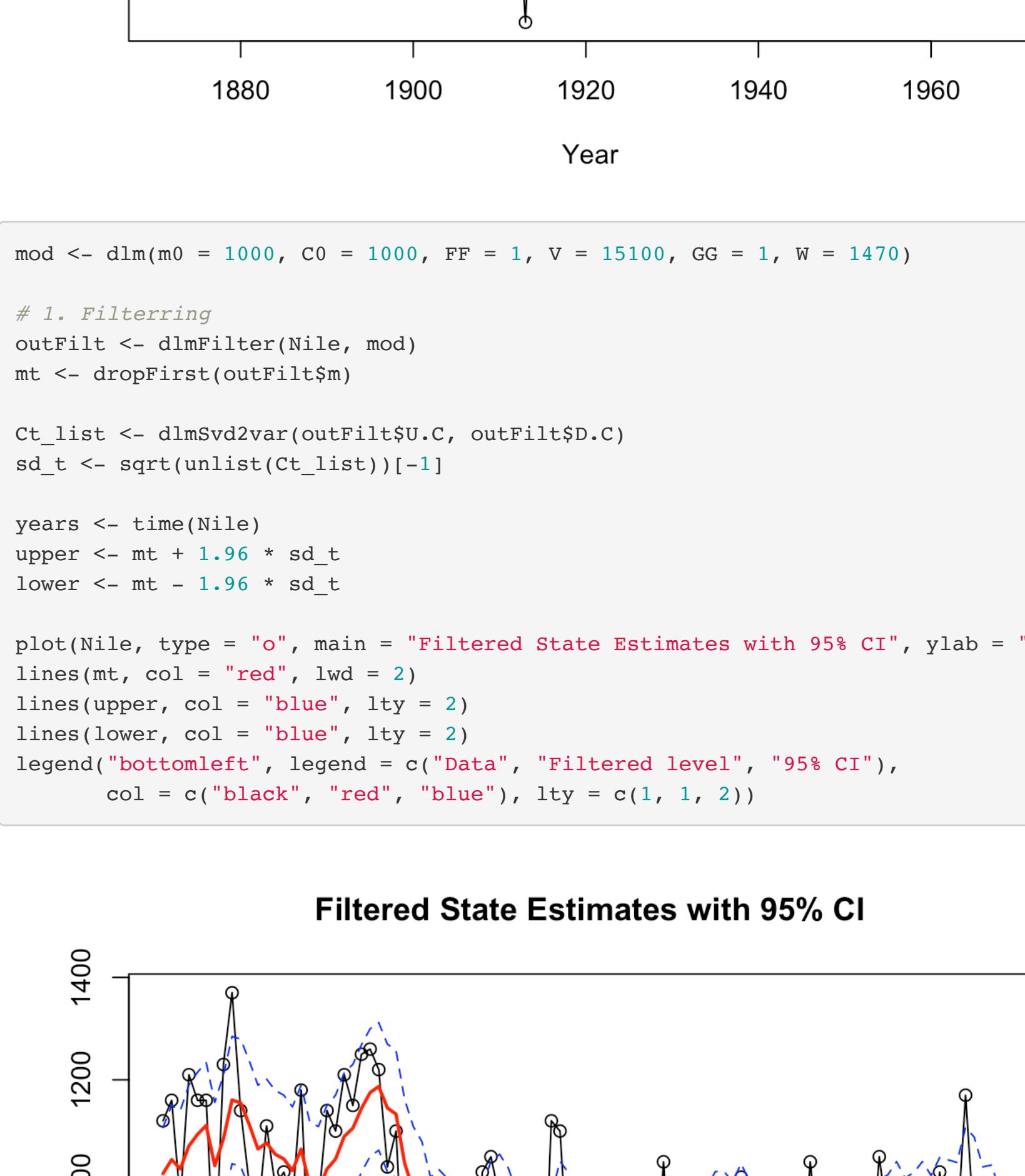
library(dlm)

data(Nile)

plot(Nile, type = "o", main = "Nile River Annual Flow", ylab = "Flow", xlab = "Year")

```

**Nile River Annual Flow**



```

mod <- dlm(m0 = 1000, C0 = 1000, FF = 1, V = 15100, GG = 1, W = 1470)

1. Filtering

outFilt <- dlmFilter(Nile, mod)

mt <- dropFirst(outFilt$m)

Ct_list <- dlmSvd2var(outFilt$U.C, outFilt$D.C)

sd_t <- sqrt(unlist(Ct_list))[-1]

years <- time(Nile)

upper <- mt + 1.96 * sd_t

lower <- mt - 1.96 * sd_t

plot(Nile, type = "o", main = "Filtered State Estimates with 95% CI", ylab = "Level")

lines(mt, col = "red", lwd = 2)

lines(upper, col = "blue", lty = 2)

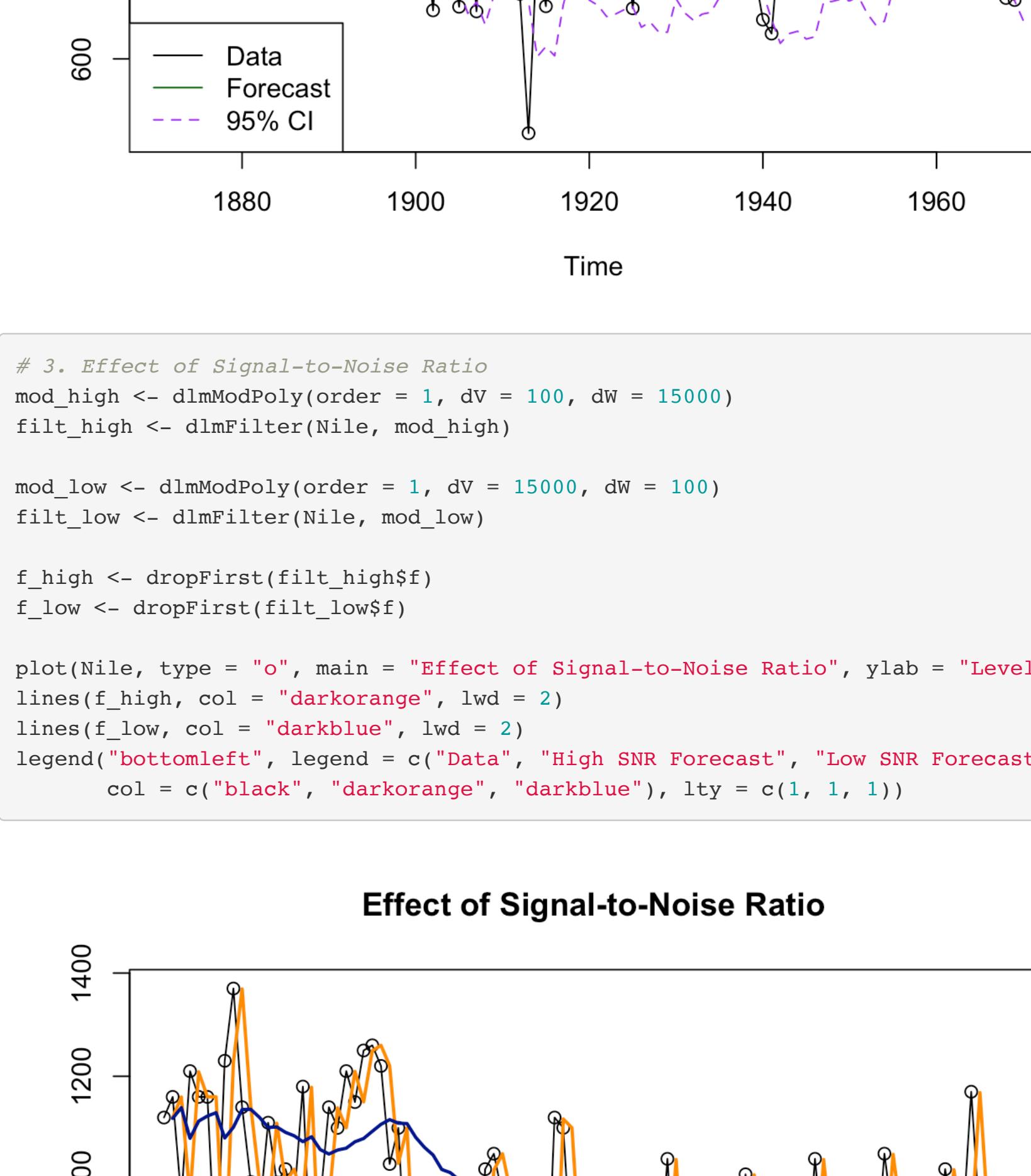
lines(lower, col = "blue", lty = 2)

legend("bottomleft", legend = c("Data", "Filtered level", "95% CI"),

 col = c("black", "red", "blue"), lty = c(1, 1, 2))

```

**Filtered State Estimates with 95% CI**



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2. Online Forecasting

ft <- dropFirst(outFilt$f)

Q_list <- dlmSvd2var(outFilt$U.R, outFilt$D.R)

sqrtQ <- sqrt(unlist(Q_list))[-1]

upper_f <- ft + 1.96 * sqrtQ

lower_f <- ft - 1.96 * sqrtQ

plot(Nile, type = "o", main = "One-step-ahead Forecasts with 95% CI", ylab = "Level")

lines(ft, col = "darkgreen", lwd = 2)

lines(upper_f, col = "purple", lty = 2)

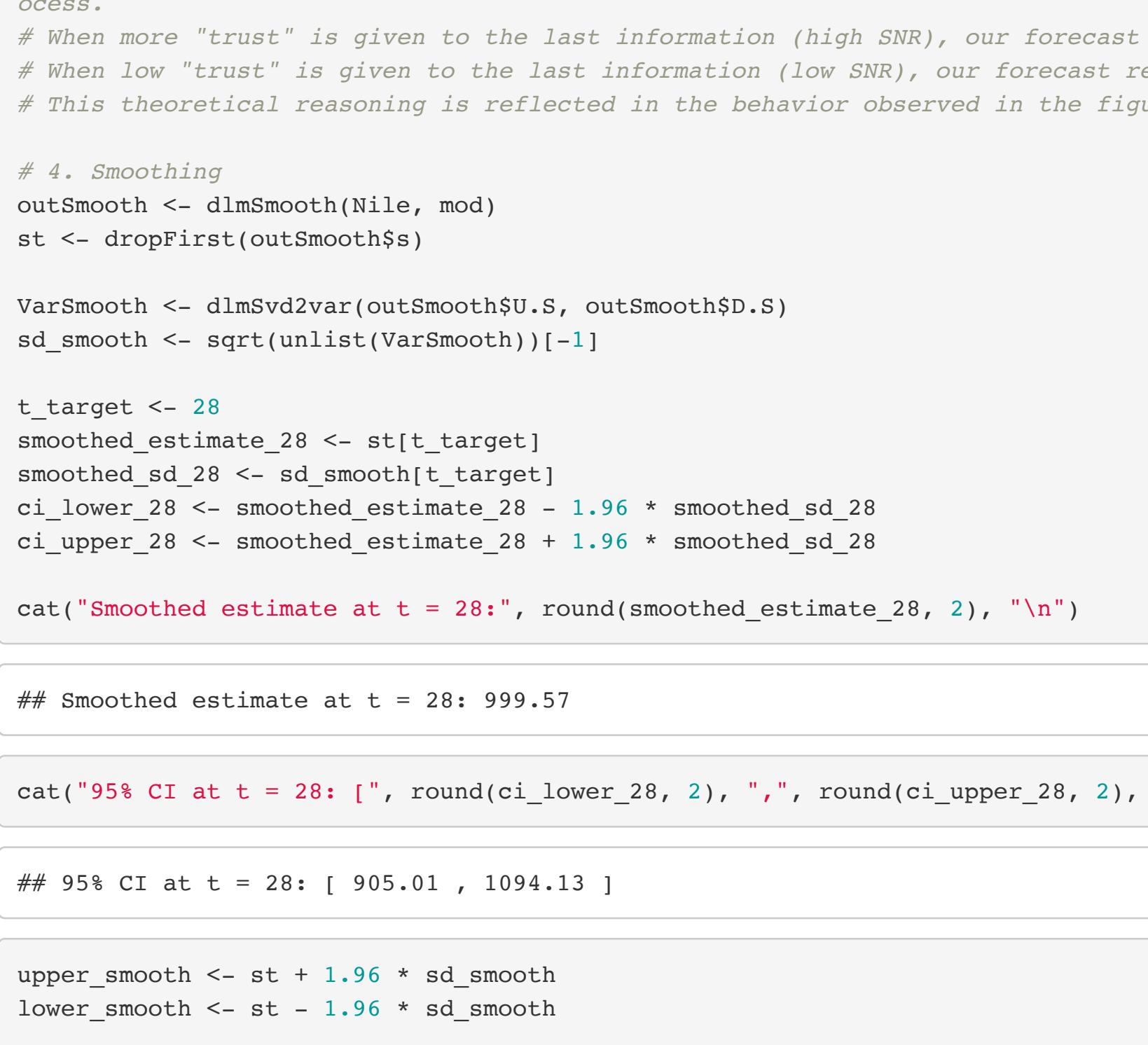
lines(lower_f, col = "purple", lty = 2)

legend("bottomleft", legend = c("Data", "Forecast", "95% CI"),

 col = c("black", "darkgreen", "purple"), lty = c(1, 1, 2))

```

**One-step-ahead Forecasts with 95% CI**



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3. Effect of Signal-to-Noise Ratio

mod_high <- dlmModPoly(order = 1, dv = 100, dw = 15000)

filt_high <- dlmFilter(Nile, mod_high)

mod_low <- dlmModPoly(order = 1, dv = 15000, dw = 100)

filt_low <- dlmFilter(Nile, mod_low)

f_high <- dropFirst(filt_high$f)

f_low <- dropFirst(filt_low$f)

plot(Nile, type = "o", main = "Effect of Signal-to-Noise Ratio", ylab = "Level")

lines(f_high, col = "darkorange", lwd = 2)

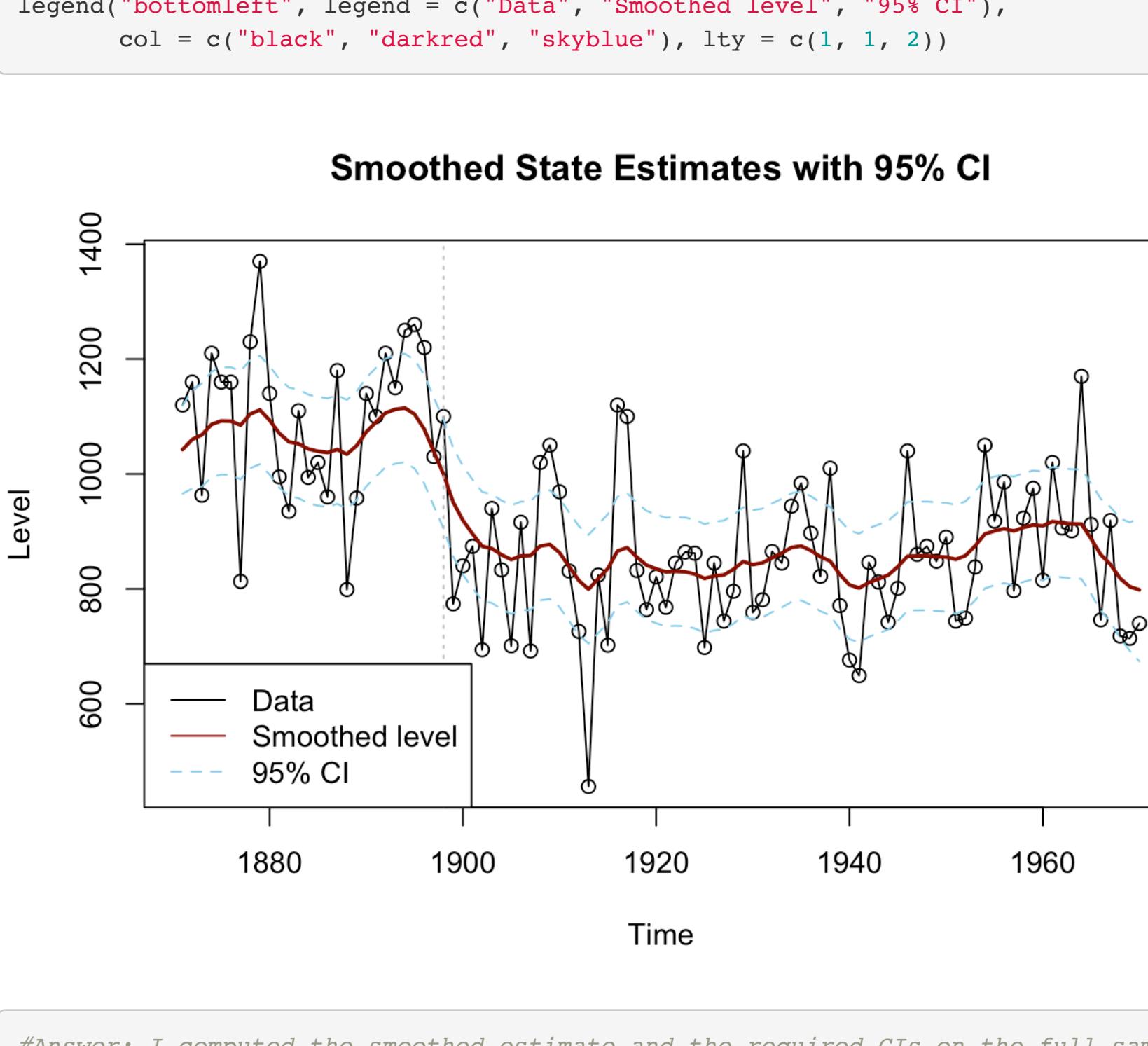
lines(f_low, col = "darkblue", lwd = 2)

legend("bottomleft", legend = c("Data", "High SNR Forecast", "Low SNR Forecast"),

 col = c("black", "darkorange", "darkblue"), lty = c(1, 1, 1))

```

**Effect of Signal-to-Noise Ratio**



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#Answer: the signal to noise ratio vastly affects our one step ahead forecast. Indeed, consider the following two scenarios:

In one case sigma-w is large and sigma-e is small and in the other it is the exact opposite.

In the first scenario we have that the variation observed in the time series is mainly determined by the variation of the latent state process.

In the second scenario instead, the observed variation is mainly determined by measurement error.

So, we say that in the first case we have a high signal-to-noise ratio while in the second case we have a lower one.

All of this has crucial implications: in the second scenario, the new information (yt) is not crucially used to determine our forecast,

as we deem that the variability is caused by noisy and unreliable measurements (high sigma-e).

In the first scenario instead, we trust the new information (yt) to help estimate the movement in the latent process.

When more "trust" is given to the last information (high SNR), our forecast closely follows the observed data.

When low "trust" is given to the last information (low SNR), our forecast reacts less to new observations.

This theoretical reasoning is reflected in the behavior observed in the figure above.

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4. Smoothing

outSmooth <- dlmSmooth(Nile, mod)

st <- dropFirst(outSmooth$s)

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VarSmooth <- dlmSvd2var(outSmooth$U.S, outSmooth$D.S)
sd_smooth <- sqrt(unlist(VarSmooth))[-1]

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t_target <- 28
smoothed_estimate_28 <- st[t_target]
smoothed_sd_28 <- sd_smooth[t_target]
ci_lower_28 <- smoothed_estimate_28 - 1.96 * smoothed_sd_28
ci_upper_28 <- smoothed_estimate_28 + 1.96 * smoothed_sd_28

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cat("Smoothed estimate at t = 28:", round(smoothed_estimate_28, 2), "\n")

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Smoothed estimate at t = 28: 999.57

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cat("95% CI at t = 28: [", round(ci_lower_28, 2), ", ", round(ci_upper_28, 2), "]\n")

```

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95% CI at t = 28: [905.01 , 1094.13]

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```

upper_smooth <- st + 1.96 * sd_smooth
lower_smooth <- st - 1.96 * sd_smooth

```

```

plot(Nile, type = "o", main = "Smoothed State Estimates with 95% CI", ylab = "Level")
lines(st, col = "darkred", lwd = 2)
lines(upper_smooth, col = "skyblue", lty = 2)
lines(lower_smooth, col = "skyblue", lty = 2)
abline(v = time(Nile)[t_target], col = "gray", lty = 3)
legend("bottomleft", legend = c("Data", "Smoothed level", "95% CI"),
 col = c("black", "darkred", "skyblue"), lty = c(1, 1, 2))

```

**Smoothed State Estimates with 95% CI**



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#Answer: I computed the smoothed estimate and the required CIs on the full sample.
Subsequently, I retrieved the posterior mean, the posterior variance and the CI of the observation at t = 28.

```