

Trend And Decompositions

Jan 12 2016

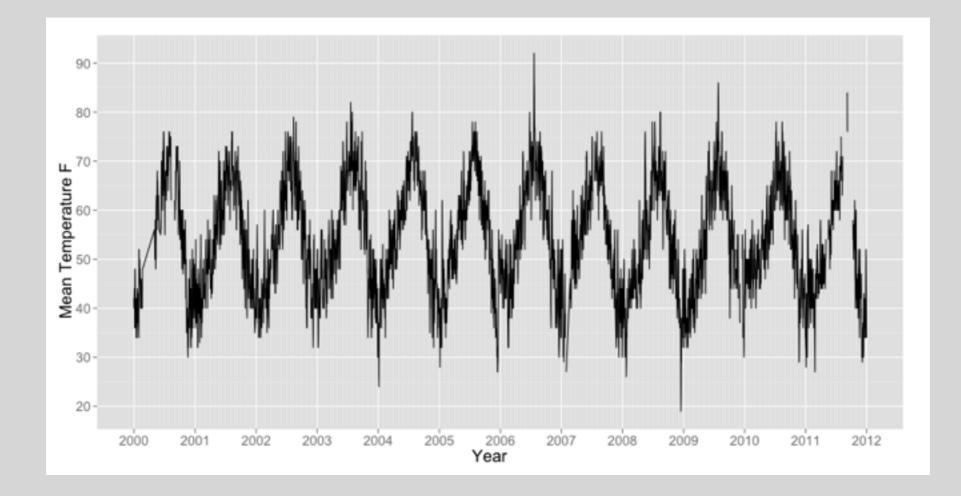
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Announcements

Tomorrow only: Office hour 2-3pm not 1-2pm

Your turn



Brainstorm: How could we get a feel for the long term trend in this series?

Exploring the trend

It's often hard to see a trend in the presence of noise or seasonality, some options:

Aggregate

use annual data instead

Smooth

moving average or add a line or curve

Subtract

remove noise/seasonality



To examine the long term trend we could average out the seasonality by averaging over the length of the seasonal cycle.

E.g. with temperature, average over a year.

We saw how to do this with dplyr, last week.

We could also achieve this same goal using a model.

areaate

We could fit a regression model with a fixed effect for each year, and examine those fixed effects,

 $temp_t = \mu_{year(t)} + noise$

different mean for each year

> I want to treat year like a category not a number

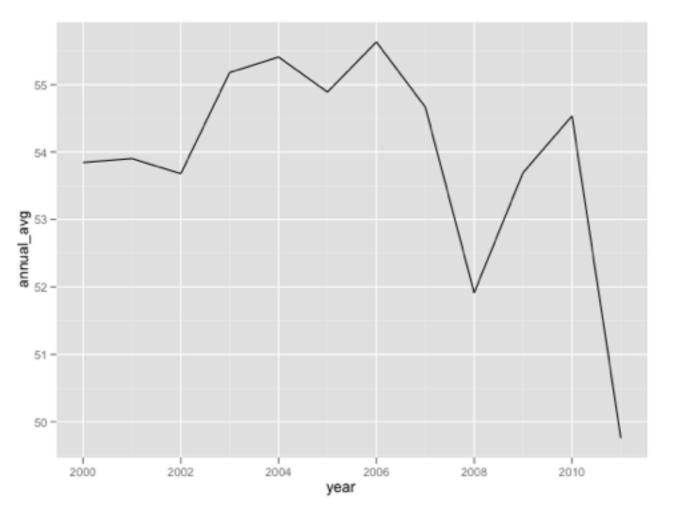
Missing values are given NA in fitted and residuals

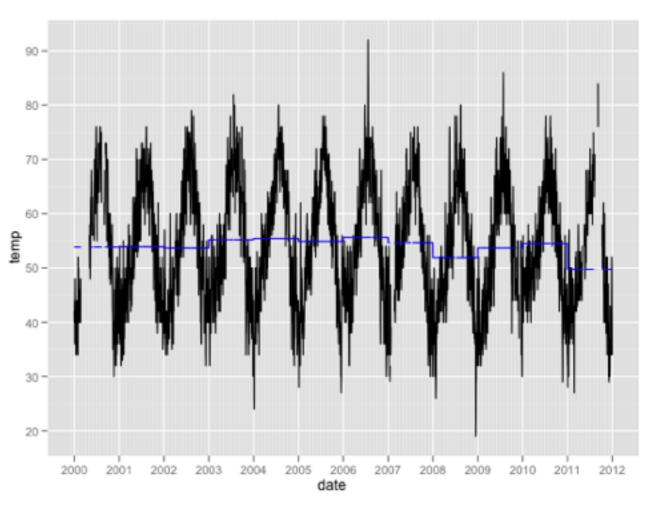
ate

corv\$annual_avg <- fitted(year_fit)</pre>

qplot(year, annual_avg, data = corv, geom = "line")

qplot(date, temp, data = corv, geom = "line") + geom_line(aes(y = annual_avg), colour = "blue")





Your turn

Discuss with your neighbor:

What are the dangers of aggregating over a fine time resolution?

Outliers - average sensitive to single or a few observations (median, maybe keep other summaries)

Lumped all variation into "noise", ignoring variation below the level of aggregation.

Overlook short term changes

If the true "seasonality" isn't at the same frequency as the aggregation level, weird artifacts.

Missing values?

How many observations went into summary?

Smooth

Moving average filter Linear regression 1m Local regression loess many more ... (gam)

A moving average takes the average of n consecutive values.

If it is centered, take the average of 2q+1 consecutive values giving a half weight to numbers on each end.

For daily data, I might do a moving average over 7 days with equal weights (this is not a centered moving average).

Or, q = 15, approximately a monthly moving average

q =?, approximately a yearly moving average

filter works on ts objects, so let's get our temperatures in to ts properly.

There were dates missing from our series:

all_days <- data.frame(date = seq(ymd("2000/01/01"), ymd("2013/12/31"), by = "day"))

merge them together

```
corv <- inner_join(corv, all_days)</pre>
```

force it to be in time order

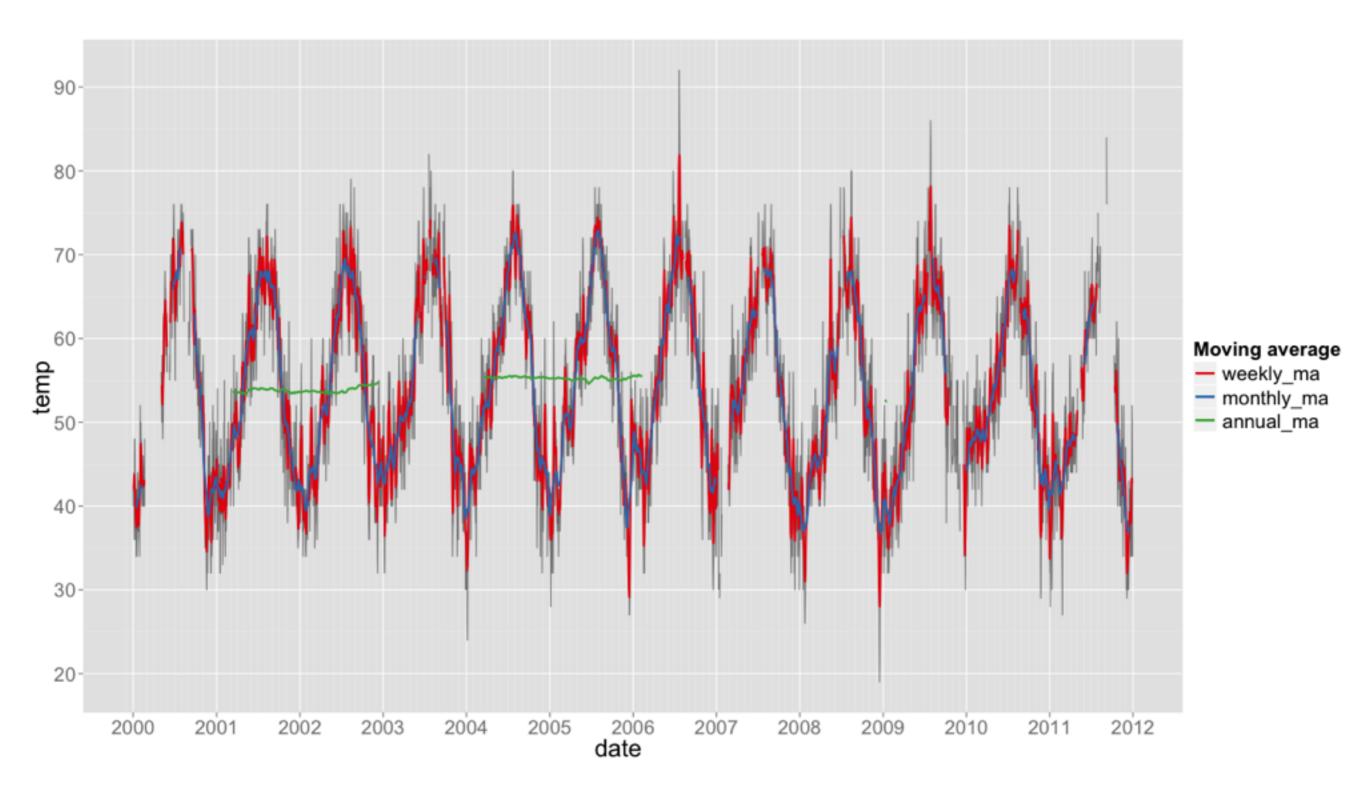
```
corv <- corv[order(corv$date), ]</pre>
```

make a ts object

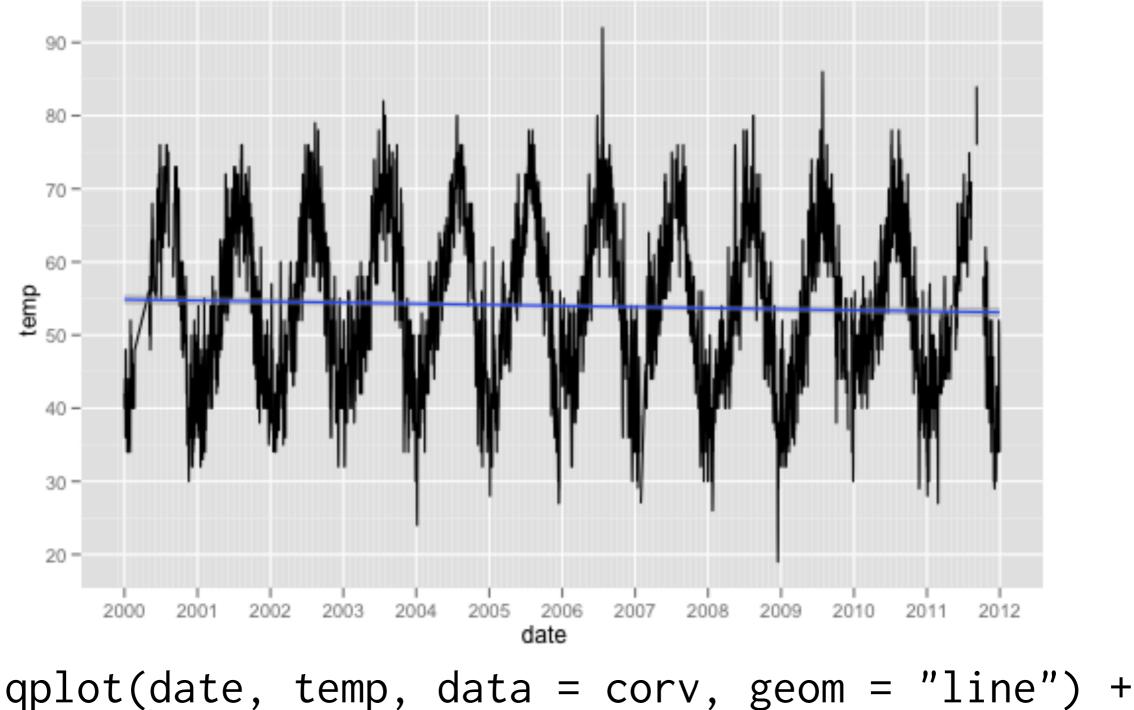
corv_ts <- ts(corv\$temp, start = 2000, freq = 365.25)</pre>

n <- 7 # we have daily data so this is a week corv\$weekly_ma <- filter(corv_ts, filter = rep(1, n)/n) n <- 30 # approximately a month corv\$monthly_ma <- filter(corv_ts, filter = c(1/2, rep(1, n-1), 1/2)/n) n <- 365 # approximately a year corv\$annual_ma <- filter(corv_ts, filter = rep(1, n)/n)</pre>

```
qplot(date, temp, data = corv, geom = "line", alpha = I(0.5)) +
geom_line(aes(y = weekly_ma, colour = "weekly_ma"), size = 1) +
geom_line(aes(y = monthly_ma, colour = "monthly_ma"), size = 1) +
geom_line(aes(y = annual_ma, colour = "annual_ma"), size = 1) +
scale_colour_brewer("Moving average", pal = "Set1") +
big_font
```

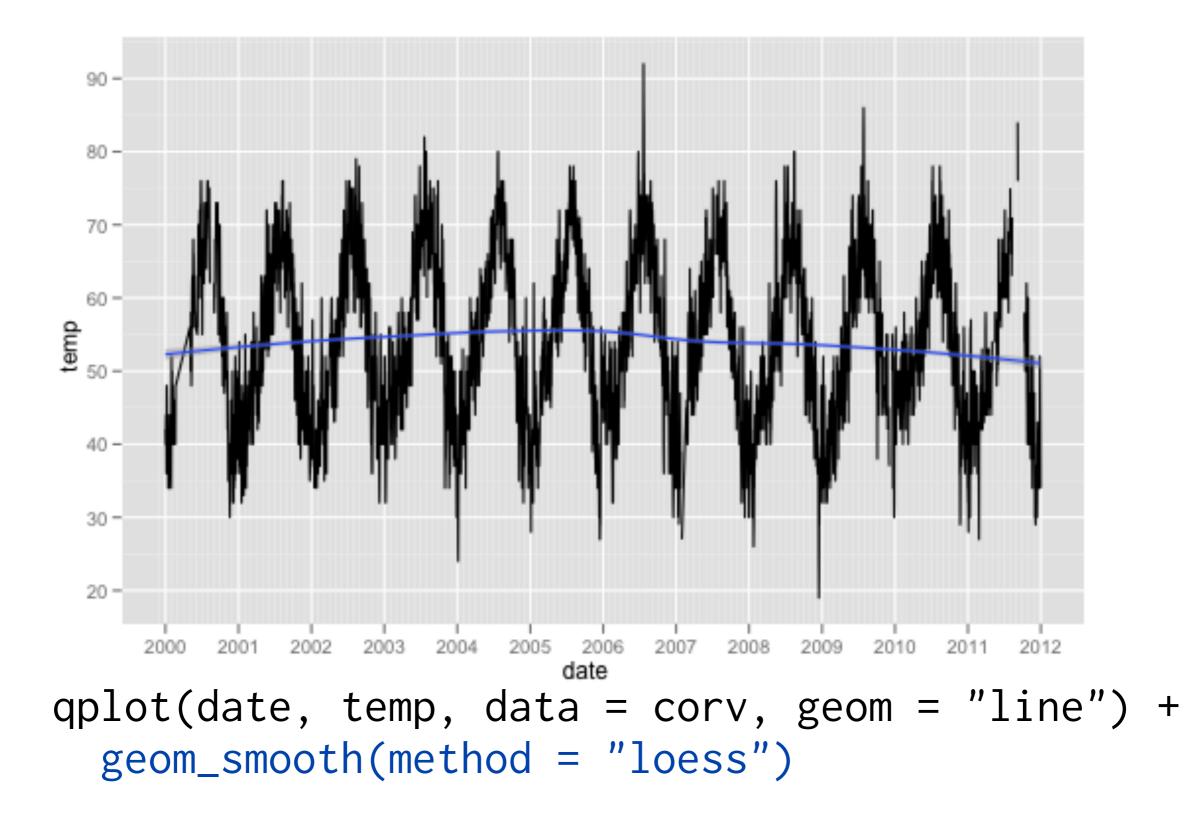


Smooth: Linear regression 1m

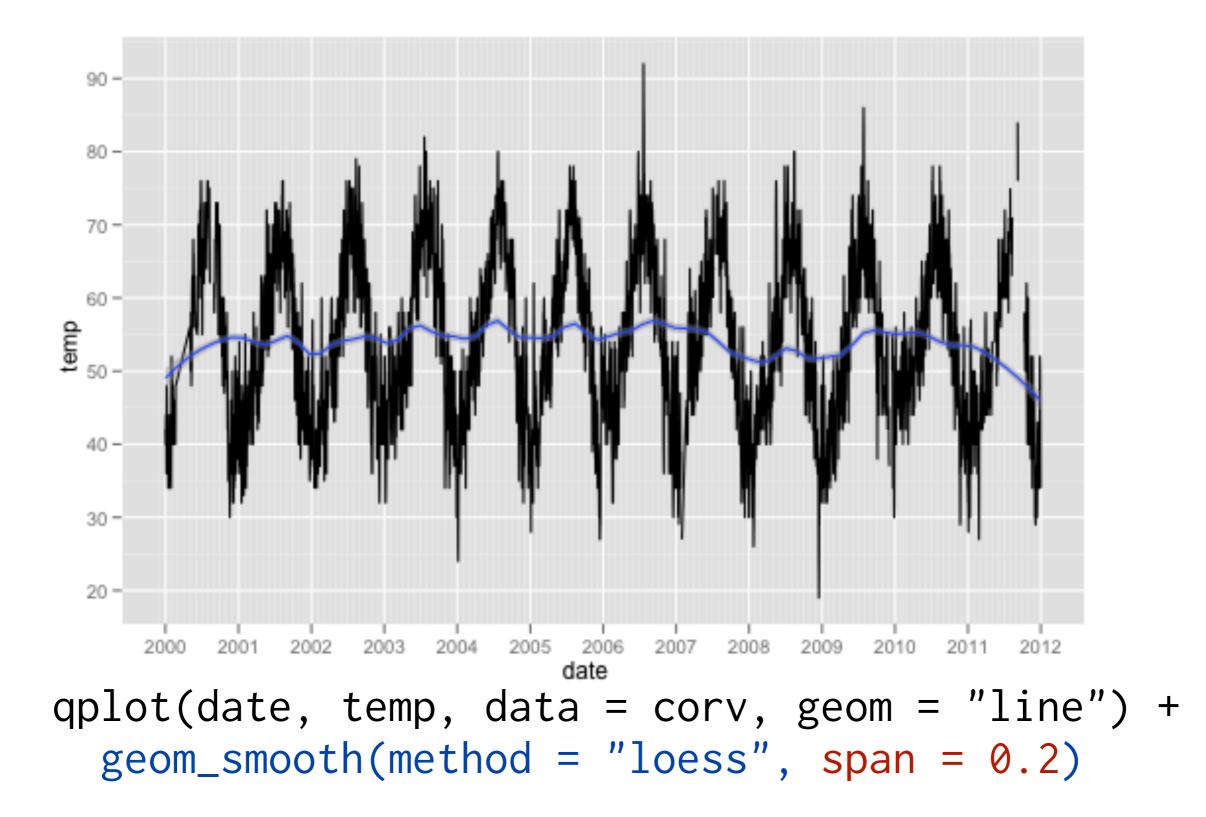


geom_smooth(method = "lm", se = FALSE)

Smooth: Local regression loess



Smooth: Local regression loess



Your turn

Discuss with your neighbor:

How do you choose a smooth (between methods, or smoothing amount)?

It depends!

Depends on the data, on your goal, on your interest, your purpose for the smooth.

Goal: prediction/forecasting, might choose method based on forecast horizon.

Does ease of interpretation matter?

Rely on defaults, (dangerous), guess and check, trial and error.

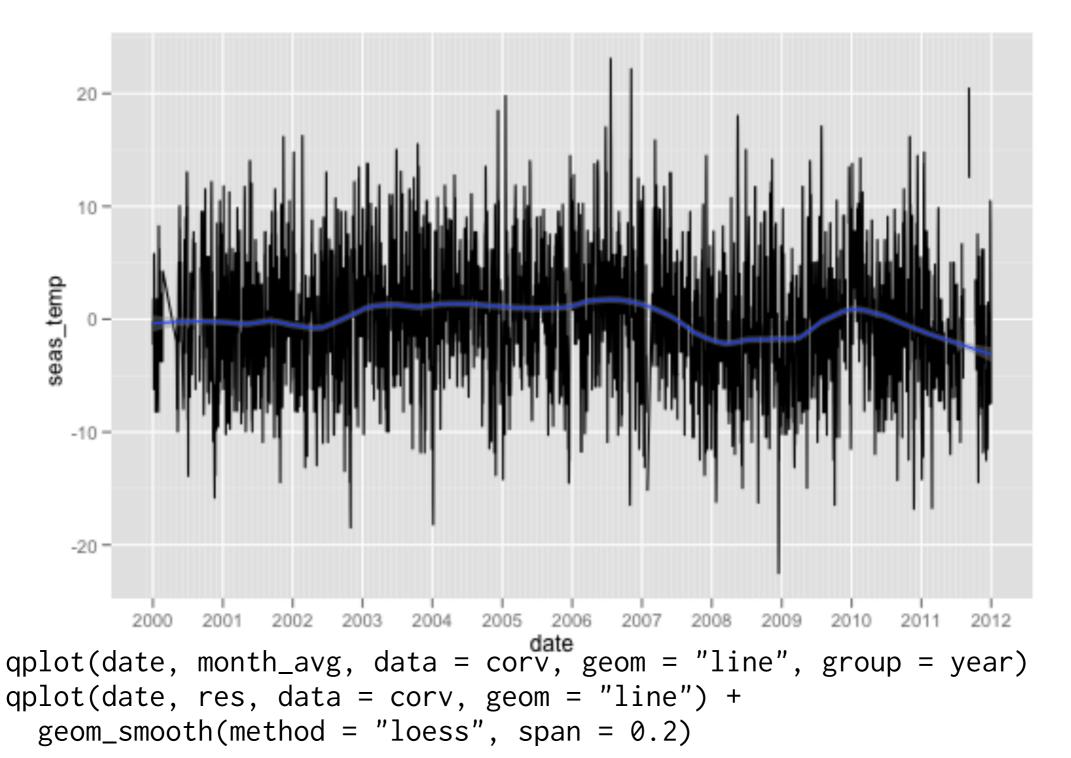
Be wary of "optimal" defaults

Try until it "looks good"

Subject matter knowledge

Subtract

month_fit <- lm(temp ~ factor(month), data = corv, na.action = na.exclude)
corv\$month_avg <- predict(month_fit)
corv\$res <- residuals(month_fit)</pre>



A common decomposition

$X_t = M_t + S_t + Z_t$

Variable measured at time t Trend Seasonality Noise

 $\begin{aligned} x_t &= m_t s_t z_t \\ x_t &= m_t s_t + z_t \end{aligned}$

some multiplicative analogs

Suggests a general approach

- Describe and model the most obvious part
- Subtract it from the series and repeat
- When there is just "noise" left, examine it's variance and correlation

Hints for subtracting

Find a model for the part you want to subtract using: 1m, loess, ...

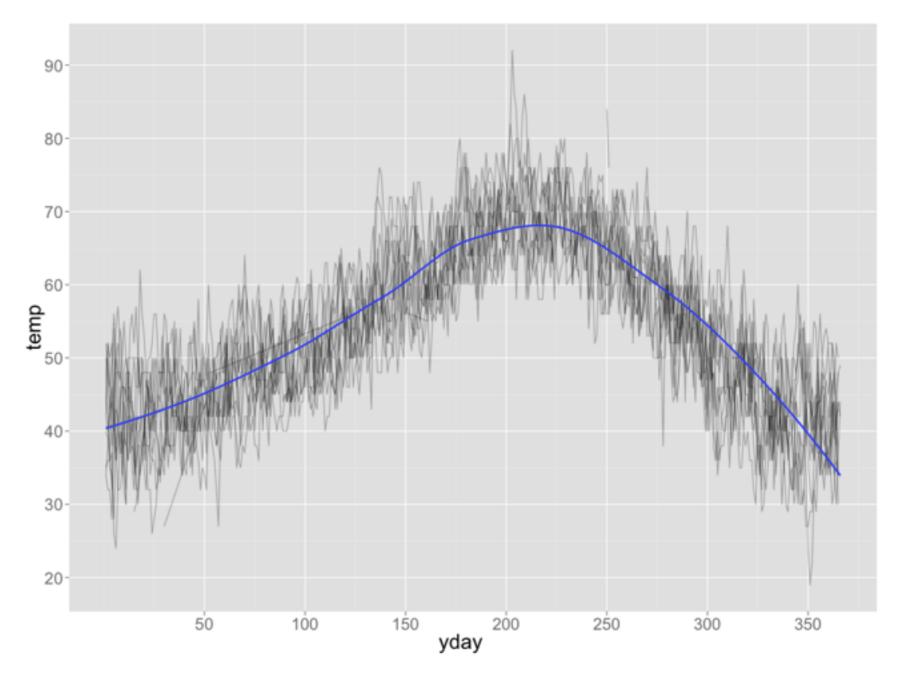
- Fit the model (with na.action = na.exclude)
- Use predict to get the model prediction
- and residuals to do the subtraction

If you want to use a moving average, the output from filter is the prediction, do the subtraction "by hand"

An example

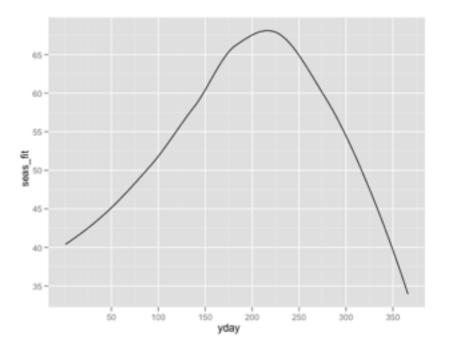
Corvallis data, the largest variation is from the seasonal pattern.

Might be nice to use a smooth.

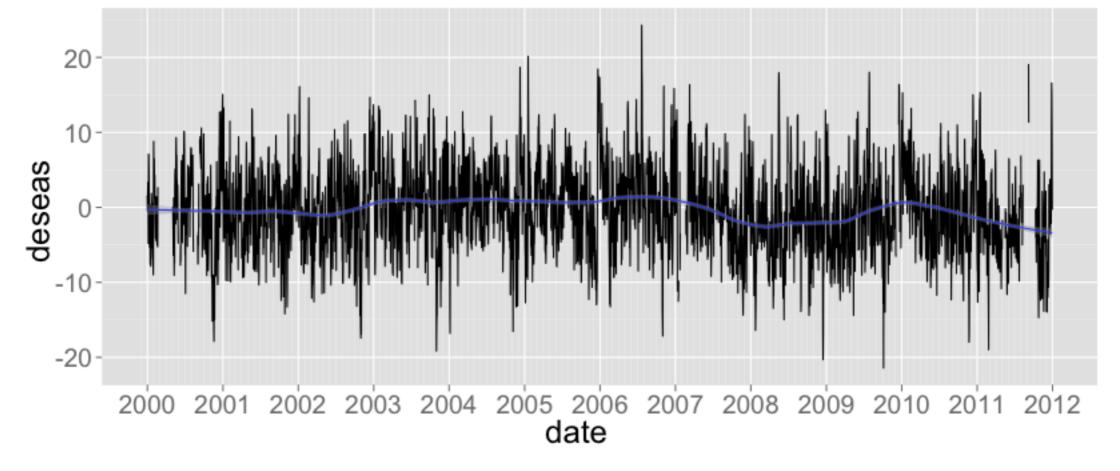


qplot(yday, temp, data = corv, geom = "line", group = year, alpha = I(.3)) +
geom_smooth(method = "loess", aes(group = 1), size = 1)

qplot(yday, seas_fit, data = corv, geom = "line")



qplot(date, deseas, data = corv, geom = "line") +
geom_smooth(method = "loess", span = 0.2)



Your turn

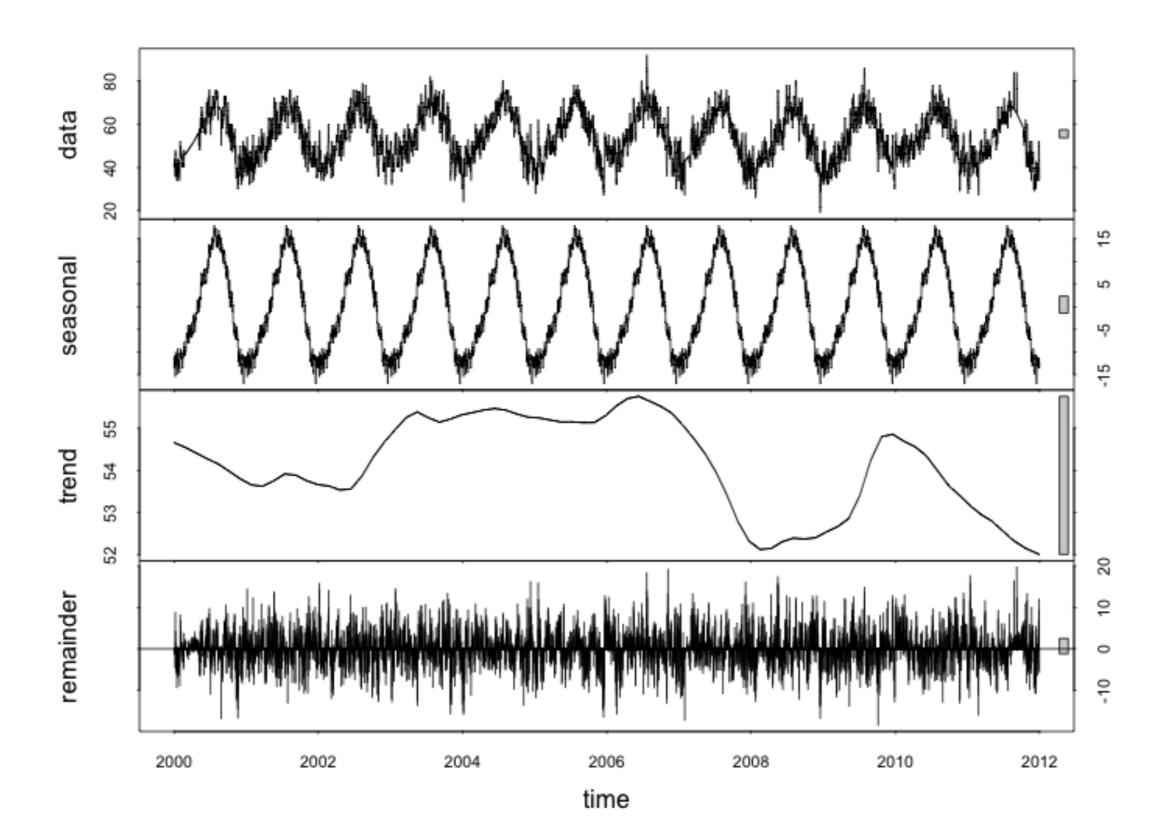


Where would you start with this series?

Two automatic approaches

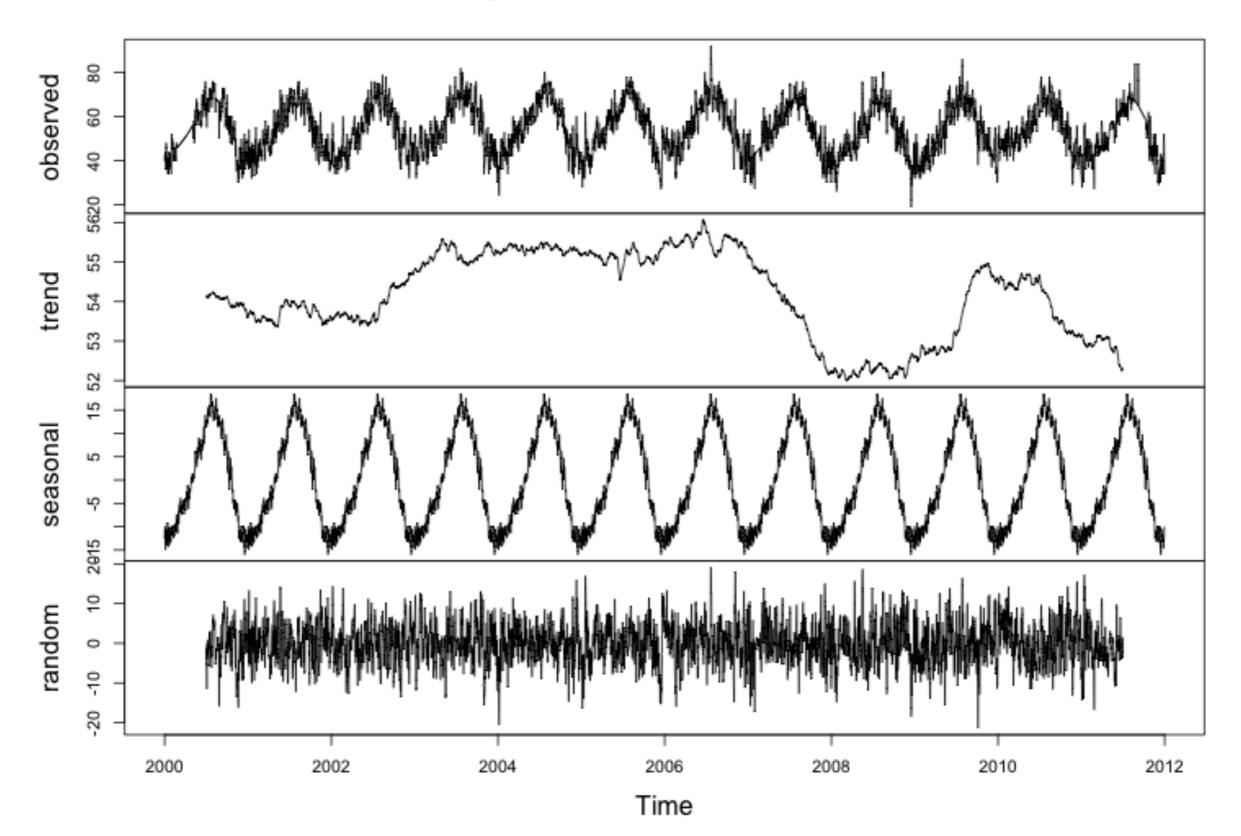
stl iteration of local regression smooths

decompose iteration of moving averages neither like missing values plot(stl(corv_ts2, 365.25))



plot(decompose(corv_ts2))

Decomposition of additive time series





Examining variance and correlation