Processing data

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So far, we’ve imported and transformed our measures, combined them with our design information, and pre-processed and plotted our data. Now we’re going to do some processing of our raw data: smoothing and calculating derivatives.

If you haven’t already, load the necessary packages.

library(gcplyr)  
  
library(dplyr)  
library(ggplot2)

#This code was explained in sections 2, 3, and 4  
#Here we're re-running it so it's available for us to work with  
example\_tidydata <- trans\_wide\_to\_tidy(example\_widedata,  
 id\_cols = "Time")  
example\_design <- make\_design(  
 pattern\_split = ",", nrows = 8, ncols = 12,  
 "Bacteria\_strain" = make\_designpattern(  
 values = paste("Strain", 1:48),  
 rows = 1:8, cols = 1:6,  
 pattern = 1:48,  
 byrow = TRUE),  
 "Bacteria\_strain" = make\_designpattern(  
 values = paste("Strain", 1:48),  
 rows = 1:8, cols = 7:12,  
 pattern = 1:48,  
 byrow = TRUE),  
 "Phage" = make\_designpattern(  
 values = c("No Phage"),  
 rows = 1:8, cols = 1:6,  
 pattern = "1"),  
 "Phage" = make\_designpattern(  
 values = c("Phage Added"),  
 rows = 1:8, cols = 7:12,  
 pattern = "1"))  
ex\_dat\_mrg <- merge\_dfs(example\_tidydata, example\_design)  
#> Joining, by = "Well"  
ex\_dat\_mrg$Well <-   
 factor(ex\_dat\_mrg$Well,  
 levels = paste(rep(LETTERS[1:8], each = 12), 1:12, sep = ""))

# How to process and analyze your data

With your data and design information pre-processed, **your dataset is now organized in a way that’s easy to export and analyze**. It is also at this point that the next steps for what you can do diversify into many options.

Broadly speaking, there are two main approaches to analyzing growth curves data:

1. directly quantify attributes of the growth dynamics
2. fit the growth dynamics with a mathematical model, then extract parameters from the fitted model

The remaining functions of gcplyr can facilitate analyses following the first approach: directly quantifying attributes of the observed dynamics. If you’re interested in exploring model-fitting approaches, which can provide enormous analytical power, check out the **[Other growth curve analysis packages]** section. At this point, since the data is now well-organized, advanced users may also decide they want to write their own custom analyses (in lieu of, or alongside, gcplyr-based and/or fitting-based analyses).

So, how do we directly quantify attributes of growth curves? First, we may need to carry out smoothing of our data to reduce the effect of noise. Then, we typically need to calculate derivatives of our (smoothed) data. The (smoothed) density and (smoothed) derivatives will be what we analyze to identify features of our growth curves. gcplyr has a number of functions that facilitate these steps.

However, unlike the import, transformation, and merging steps we’ve done so far, different projects may require different analyses, and not all users will have the same analysis steps. The [**Smoothing**](#Smoothing), [**Calculating Derivatives**](#CalculatingDerivatives) and [**Analyzing**](#Analyzing) sections of this document, therefore, are written to highlight the functions available and provide examples of common analyses that you may want to run, rather than prescribing a set of analysis steps that everyone must do.

Before we dig into processing and analyzing our data, we first need to familiarize ourselves with the dplyr package and its functions group\_by and mutate. Why? Because the upcoming gcplyr processing functions are *best* used **within** dplyr::mutate. **If you’re already familiar with dplyr, feel free to skip this primer.** If you’re not familiar yet, don’t worry! This section provides a primer that will teach you all you need to know on using group\_by and mutate with gcplyr functions.

## A brief primer on dplyr

The R package dplyr provides a “grammar of data manipulation” that is useful for a broad array of data analysis tasks (in fact, dplyr is the direct inspiration for the name of this package!) For our purposes right now, we’re going to focus on two particular functions: group\_by and mutate.

The mutate function in dplyr allows users to easily create new columns in their data.frame’s. For us, we’re going to use mutate to create columns with our smoothed data and the derivatives we calculate. However, we want to make sure that smoothing and derivative-calculating are done on *each* unique well independently. In order to do that, we’re first going to use the group\_by function, which allows users to group the rows of their data.frame’s into groups that mutate will then treat independently.

For growth curves, this means we will:

1. group\_by our data so that every unique well is a group
2. mutate to create new columns with our smoothed data and calculated derivatives

Let’s walk through a simple example

For group\_by, we need to specify the data.frame to be grouped, and then we want to list all the columns needed to identify each unique well in our dataset. Typically, this includes all of our design columns along with the plate name and well name. Make sure you’re *not* grouping by Time, Absorbance, or anything else that varies *within* a well, since if you do dplyr will group timepoints within a well separately.

ex\_dat\_mrg <- group\_by(ex\_dat\_mrg, Well, Bacteria\_strain, Phage)  
  
head(ex\_dat\_mrg)  
#> # A tibble: 6 × 5  
#> # Groups: Well, Bacteria\_strain, Phage [6]  
#> Time Well Measurements Bacteria\_strain Phage   
#> <dbl> <fct> <dbl> <chr> <chr>   
#> 1 0 A1 0.003 Strain 1 No Phage  
#> 2 0 B1 0.001 Strain 7 No Phage  
#> 3 0 C1 0.002 Strain 13 No Phage  
#> 4 0 D1 0.002 Strain 19 No Phage  
#> 5 0 E1 0.002 Strain 25 No Phage  
#> 6 0 F1 0.001 Strain 31 No Phage

Notice that this hasn’t changed anything about our data.frame, but R now knows what the groups are. Now any calculations will be carried out on each unique well independently.

To use mutate, we simply have to specify:

1. the name of the variable we want results saved to
2. the function that calculates the new column

Note that the function has to return a vector that is as long as the number of data points in the group.

For a simple example, in the code below we’ve simply added one to the Measurements values and saved it in a column named Measurements\_plus1:

ex\_dat\_mrg <-  
 mutate(ex\_dat\_mrg,  
 Measurements\_plus1 = Measurements+1)  
  
head(ex\_dat\_mrg)  
#> # A tibble: 6 × 6  
#> # Groups: Well, Bacteria\_strain, Phage [6]  
#> Time Well Measurements Bacteria\_strain Phage Measurements\_plus1  
#> <dbl> <fct> <dbl> <chr> <chr> <dbl>  
#> 1 0 A1 0.003 Strain 1 No Phage 1.00  
#> 2 0 B1 0.001 Strain 7 No Phage 1.00  
#> 3 0 C1 0.002 Strain 13 No Phage 1.00  
#> 4 0 D1 0.002 Strain 19 No Phage 1.00  
#> 5 0 E1 0.002 Strain 25 No Phage 1.00  
#> 6 0 F1 0.001 Strain 31 No Phage 1.00

If you want additional columns, you simply add them to the mutate. For instance, if we also want a column with the Measurements plus two, we just add that as a second argument:

ex\_dat\_mrg <-  
 mutate(ex\_dat\_mrg,  
 Measurements\_plus1 = Measurements+1,  
 Measurements\_plus2 = Measurements+2)  
  
head(ex\_dat\_mrg)  
#> # A tibble: 6 × 7  
#> # Groups: Well, Bacteria\_strain, Phage [6]  
#> Time Well Measurements Bacteria\_strain Phage Measurements\_plus1 Measurements\_plus2  
#> <dbl> <fct> <dbl> <chr> <chr> <dbl> <dbl>  
#> 1 0 A1 0.003 Strain 1 No Phage 1.00 2.00  
#> 2 0 B1 0.001 Strain 7 No Phage 1.00 2.00  
#> 3 0 C1 0.002 Strain 13 No Phage 1.00 2.00  
#> 4 0 D1 0.002 Strain 19 No Phage 1.00 2.00  
#> 5 0 E1 0.002 Strain 25 No Phage 1.00 2.00  
#> 6 0 F1 0.001 Strain 31 No Phage 1.00 2.00

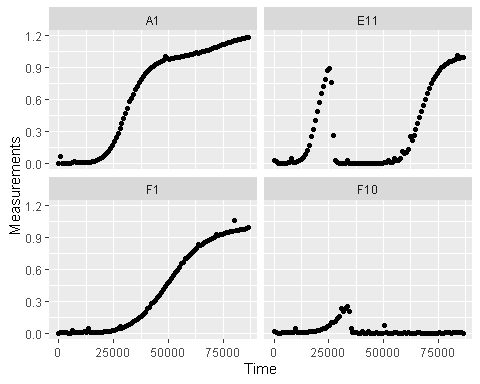
This is a rather simple example, but in the next sections I show how we can use mutate with smooth\_data and calc\_deriv to create new columns containing smoothed data and derivatives. If you want to learn more, dplyr has extensive documentation and examples of its own online. Feel free to explore them as desired, but this primer and the coming example should be sufficient to use the gcplyr processing functions, which (as a reminder) are best used *within* mutate.

# Processing data: smoothing

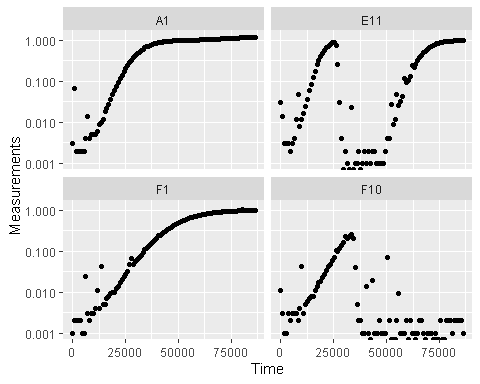
Oftentimes, growth curve data produced by a plate reader will have some noise it it. While sometimes this noise does not hinder analyses, sometimes it’s necessary to smooth the data in each well for analyses to succeed. gcplyr has a smooth\_data function that can carry out such smoothing. Generally you should carry out *as little* smoothing as is necessary for your analyses to work. That means that **right now you should skip this section** and go on to the [**Calculating Derivatives**](#CalculatingDerivatives) section, returning to this smoothing section if your derivatives are too noisy to analyze.

If you have returned in need of learning to use smooth\_data, let’s start by taking a look at a few wells from our example data, which have some noise.

#Here we've chosen four wells that, from our previous plot, seem   
# representative of the overall diversity of dynamics  
#In your own code, you should visualize all your data  
sample\_wells <- c("A1", "F1", "F10", "E11")  
  
#Plot with a linear y-axis  
ggplot(data = dplyr::filter(ex\_dat\_mrg, Well %in% sample\_wells),  
 aes(x = Time, y = Measurements)) +  
 geom\_point() +  
 facet\_wrap(~Well)



#Plot with a log y-axis  
ggplot(data = dplyr::filter(ex\_dat\_mrg, Well %in% sample\_wells),  
 aes(x = Time, y = Measurements)) +  
 geom\_point() +  
 facet\_wrap(~Well) +  
 scale\_y\_continuous(trans = "log10")  
#> Warning: Transformation introduced infinite values in continuous y-axis



Plotting our data with a log scale for the y-axis is particularly useful for growth curves because exponential growth is a straight line when plotted on a log scale.

From the log plot especially we can see that at low densities there’s a lot of noise relative to the density. In fact, this is a common occurrence: **at low densities, random noise tends to have a much larger effect** than at high densities. Unfortunately, calculating derivatives (especially the per-capita derivative) is very sensitive to such noise, so let’s smooth our data.

smooth\_data has four different smoothing algorithms to choose from: moving-average, moving-median, loess, and gam.

* moving-average is a simple smoothing algorithm that primarily acts to reduce the effects of outliers on the data
* moving-median is another simple smoothing algorithm that primarily acts to reduce the effects of outliers on the data
* loess is a spline-fitting approach that uses polynomial-like curves, which produces curves with smoothly changing derivatives, but can in some cases create curvature artifacts not present in the original data
* gam is also spline-fitting approach that uses polynomial-like curves, which produces curves with smoothly changing derivatives, but can in some cases create curvature artifacts not present in the original data

**Additionally, all four smoothing algorithms have a tuning parameter** that controls how “smoothed” the data are. For whichever smoothing method you’re using, **you should plot smoothing with multiple different tuning parameter values**, then choose the value that smooths the data as little as is necessary to reduce noise. Make sure to plot the smoothing for every well in your data, so that you’re choosing the best setting for all your data and not just one well.

Smoothing data is a step that alters the values you will analyze. Because of that, and because there are so many options for how to smooth your data, it is a step that can be rife with pitfalls. I recommend starting with the simplest and least “smoothed” smoothing, plotting your results, and only increasing your smoothing as much as is needed to enable downstream analyses. Additionally, when sharing your findings, it’s important to be transparent by sharing the raw data and smoothing methods, rather than treating the smoothed data as your source.

To use smooth\_data, pass your x and y values, your method of choice, and any additional arguments needed for the method. It will return a vector of your smoothed y values.

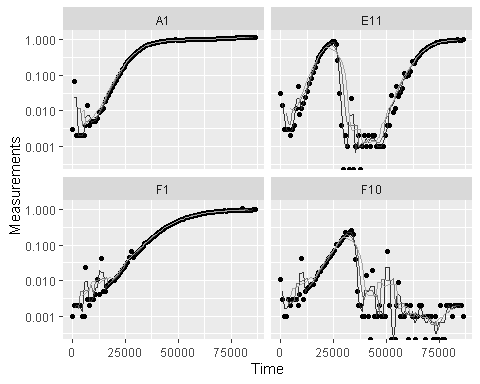
Since we only want to smooth within each unique well, we’ll first group\_by our data:

ex\_dat\_mrg <- group\_by(ex\_dat\_mrg, Well, Bacteria\_strain, Phage)

## Smoothing with moving-average

For moving-average, the tuning parameter is window\_width\_n, which specifies how many data points wide the moving window used to calculate the average is. Specifying the window\_width\_n is required, and larger values will be more “smoothed”. Here, we’ll show moving averages with windows that are 3, 7, and 11 data points wide (because the window is centered on each data point, it must be an odd number of data points wide). Note that moving-average returns NA for the window\_width\_n/2 points at the start and end of your data.

ex\_dat\_mrg <-  
 mutate(ex\_dat\_mrg,  
 smoothed3 = smooth\_data(x = Time, y = Measurements,  
 sm\_method = "moving-average", window\_width\_n = 3),  
 smoothed7 = smooth\_data(x = Time, y = Measurements,  
 sm\_method = "moving-average", window\_width\_n = 7),  
 smoothed11 = smooth\_data(x = Time, y = Measurements,  
 sm\_method = "moving-average", window\_width\_n = 11))  
  
#What does the smoothed data look like compared to the noisy original?  
#Lighter lines are wider window\_width\_n's and more "smoothed"  
ggplot(data = dplyr::filter(ex\_dat\_mrg, Well %in% sample\_wells),  
 aes(x = Time)) +  
 geom\_point(aes(y = Measurements)) +  
 geom\_line(aes(y = smoothed3), color = "gray20") +  
 geom\_line(aes(y = smoothed7), color = "gray45") +  
 geom\_line(aes(y = smoothed11), color = "gray65") +  
 facet\_wrap(~Well) +  
 scale\_y\_continuous(trans = "log10")  
#> Warning: Transformation introduced infinite values in continuous y-axis  
#> Transformation introduced infinite values in continuous y-axis  
#> Warning: Removed 2 row(s) containing missing values (geom\_path).  
#> Warning: Removed 6 row(s) containing missing values (geom\_path).  
#> Warning: Removed 10 row(s) containing missing values (geom\_path).

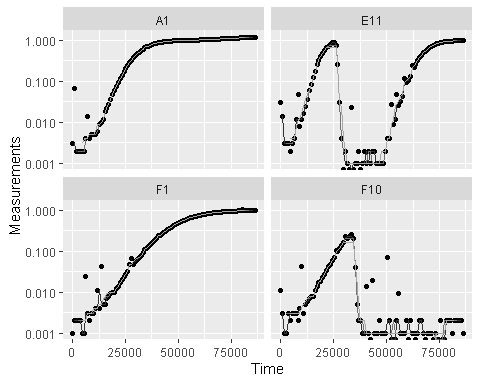


Here we can see that moving-average has helped reduce the effects of some of that early noise. However, with window\_width\_n = 11 (the lightest line), the smoothing has started biasing our medium-density data points to be higher than they actually are. Based on this, we’d probably want to use a window\_width\_n less than 11. Unfortunately, with smaller window\_width\_n our early data is still being affected by that early noise, so we should explore other smoothing methods, or try combining multiple smoothing methods.

## Smoothing with moving-median

For moving-median, the tuning parameter is also window\_width\_n, which specifies how many data points wide the moving window used to calculate the average is. Specifying the window\_width\_n is required, and larger values will be more “smoothed”. Here, we’ll show moving averages with windows that are 3, 7, and 11 data points wide (because the window is centered on each data point, it must be an odd number of data points wide). Note that moving-median returns NA for the window\_width\_n/2 points at the start and end of your data.

ex\_dat\_mrg <-  
 mutate(ex\_dat\_mrg,  
 smoothed3 =   
 smooth\_data(x = Time, y = Measurements,  
 sm\_method = "moving-median", window\_width\_n = 3),  
 smoothed7 =   
 smooth\_data(x = Time, y = Measurements,  
 sm\_method = "moving-median", window\_width\_n = 7),  
 smoothed11 =   
 smooth\_data(x = Time, y = Measurements,  
 sm\_method = "moving-median", window\_width\_n = 11))  
  
#What does the smoothed data look like compared to the noisy original?  
#Lighter lines are wider window\_width\_n's and more "smoothed"  
ggplot(data = dplyr::filter(ex\_dat\_mrg, Well %in% sample\_wells),  
 aes(x = Time)) +  
 geom\_point(aes(y = Measurements)) +  
 geom\_line(aes(y = smoothed3), color = "gray20") +  
 geom\_line(aes(y = smoothed7), color = "gray45") +  
 geom\_line(aes(y = smoothed11), color = "gray65") +  
 facet\_wrap(~Well) +  
 scale\_y\_continuous(trans = "log10")  
#> Warning: Transformation introduced infinite values in continuous y-axis  
#> Transformation introduced infinite values in continuous y-axis  
#> Transformation introduced infinite values in continuous y-axis  
#> Transformation introduced infinite values in continuous y-axis  
#> Warning: Removed 2 row(s) containing missing values (geom\_path).  
#> Warning: Removed 6 row(s) containing missing values (geom\_path).  
#> Warning: Removed 10 row(s) containing missing values (geom\_path).

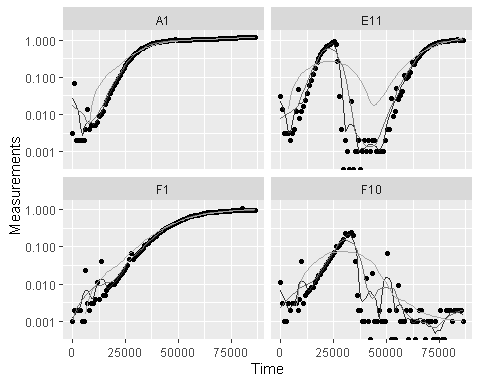


Here we can see that moving-median has really excluded that low-density noise, even with the smallest window\_width\_n = 3. Additionally, moving-median did not bias our larger data hardly at all, except with the widest window\_width\_n. However, it has produced a smoothed density that is fairly “jumpy”, something that wider window\_width\_n did not fix. **This is common with moving-median**, so often you may need to try other smoothing methods or combining moving-median with other methods.

## Smoothing with LOESS

For loess, the tuning parameter is the span argument. loess works by doing fits on subset windows of the data centered at each data point. These fits can be linear (degree = 1) or polynomial (typically degree = 2). span is the width of the window, as a fraction of all data points. For instance, with the default span of 0.75, 75% of the data points are included in each window. Thus, span values typically are between 0 and 1 (although see ?loess for use of span values greater than 1), and larger values are more “smoothed”. Here, we’ll show loess smoothing with spans of 0.1, 0.2, and 0.5 and degree = 1.

ex\_dat\_mrg <-  
 mutate(ex\_dat\_mrg,  
 smoothed1 = smooth\_data(x = Time, y = Measurements,  
 sm\_method = "loess", span = .1, degree = 1),  
 smoothed2 = smooth\_data(x = Time, y = Measurements,  
 sm\_method = "loess", span = .2, degree = 1),  
 smoothed5 = smooth\_data(x = Time, y = Measurements,  
 sm\_method = "loess", span = .5, degree = 1))  
  
#What does the smoothed data look like compared to the noisy original?  
#Lighter lines are larger span's and more "smoothed"  
ggplot(data = dplyr::filter(ex\_dat\_mrg, Well %in% sample\_wells),  
 aes(x = Time)) +  
 geom\_point(aes(y = Measurements)) +  
 geom\_line(aes(y = smoothed1), color = "gray20") +  
 geom\_line(aes(y = smoothed2), color = "gray45") +  
 geom\_line(aes(y = smoothed5), color = "gray65") +  
 facet\_wrap(~Well) +  
 scale\_y\_continuous(trans = "log10")  
#> Warning: Transformation introduced infinite values in continuous y-axis  
#> Warning in self$trans$transform(x): NaNs produced  
#> Warning: Transformation introduced infinite values in continuous y-axis  
#> Warning: Removed 9 row(s) containing missing values (geom\_path).

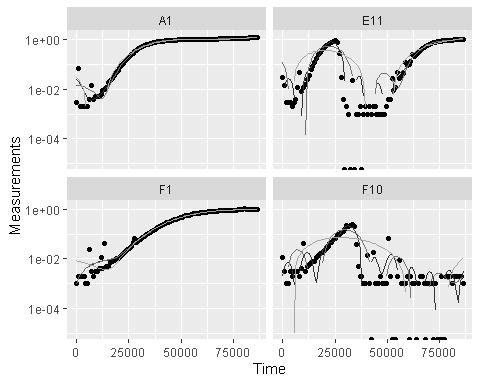


Here we can see that loess with smaller spans (darker lines) have smoothed the data somewhat but are still sensitive to outliers. However, loess with a larger span (lightest line) has introduced significant bias. To fix this, we might explore other smoothing methods, or combining loess with other smoothing methods.

## Smoothing with GAM

For gam, the primary tuning parameter is the k argument. gam works by doing fits on subsets of the data and linking these fits together. k determines how many link points (“knots”) it can use. If not specified, the default k value for smoothing a time series is 10, with **smaller values being more “smoothed”** (note this is opposite the trend with other smoothing methods). However, **unlike earlier methods, k values that are too large are also problematic**, as they will tend to ‘overfit’ the data. k cannot be larger than the number of data points, and should usually be substantially smaller than that. Also note that **gam can sometimes create artifacts**, especially oscillations in your density and derivatives. You should check that gam is not doing so before carrying on with your analyses. Here, we’ll show gam smoothing with k values of 5, 10, and 20.

ex\_dat\_mrg <-  
 mutate(ex\_dat\_mrg,  
 smoothed20 = smooth\_data(x = Time, y = Measurements,  
 sm\_method = "gam", k = 20),  
 smoothed10 = smooth\_data(x = Time, y = Measurements,  
 sm\_method = "gam", k = 10),  
 smoothed5 = smooth\_data(x = Time, y = Measurements,  
 sm\_method = "gam", k = 5))  
  
#What does the smoothed data look like compared to the noisy original?  
#Lighter lines are smaller k and more "smoothed"  
ggplot(data = dplyr::filter(ex\_dat\_mrg, Well %in% sample\_wells),  
 aes(x = Time)) +  
 geom\_point(aes(y = Measurements)) +  
 geom\_line(aes(y = smoothed20), color = "gray20") +  
 geom\_line(aes(y = smoothed10), color = "gray45") +  
 geom\_line(aes(y = smoothed5), color = "gray65") +  
 facet\_wrap(~Well) +  
 scale\_y\_continuous(trans = "log10")  
#> Warning: Transformation introduced infinite values in continuous y-axis  
#> Warning in self$trans$transform(x): NaNs produced  
#> Warning: Transformation introduced infinite values in continuous y-axis  
#> Warning in self$trans$transform(x): NaNs produced  
#> Warning: Transformation introduced infinite values in continuous y-axis  
#> Warning in self$trans$transform(x): NaNs produced  
#> Warning: Transformation introduced infinite values in continuous y-axis

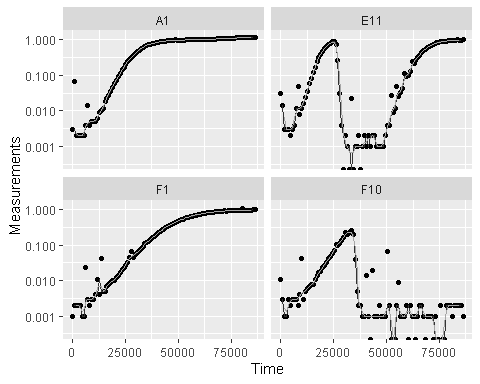


Here we can see that gam does alright when working with the no phage-added wells (A1 and F1): higher k values (darkest line) have smoothed the data but are still sensitive to those early outliers, while lower k values (lighter lines) have introduced significant bias. However, gam is struggling when phage have been added (E11 and F10). Across all the k values it has added many fluctuations and often dips into values of 0 or lower (plotted here as breaks in the line, since the log of numbers <= 0 are undefined). To fix this, we might explore other smoothing methods or combining gam with other smoothing methods.

## Combining multiple smoothing methods

Often, combining multiple smoothing methods can provide improved results. For instance, moving-median is particularly good at removing outliers, but not very good at producing continuously smooth data. In contrast, moving-average, loess, and gam work better at producing continuously smooth data, but aren’t as good at removing outliers. Here’s an example using the strengths of both moving-median and moving-average. (Note that earlier columns created in mutate are available during creation of later columns, so both can be done in one step):

ex\_dat\_mrg <-  
 mutate(ex\_dat\_mrg,  
 smoothed\_med3 =   
 smooth\_data(x = Time, y = Measurements,  
 sm\_method = "moving-median", window\_width\_n = 3),  
 #Note that for the second round, we're using the   
 #first smoothing as the input y  
 smoothed =   
 smooth\_data(x = Time, y = smoothed\_med3,  
 sm\_method = "moving-average", window\_width\_n = 3))  
  
#What does the smoothed data look like compared to the noisy original?  
#The first round of smoothing with moving-median is plotted in lighter colors  
#The second round of smoothing with moving-average is plotted in darker colors  
ggplot(data = dplyr::filter(ex\_dat\_mrg, Well %in% sample\_wells),  
 aes(x = Time)) +  
 geom\_point(aes(y = Measurements)) +  
 geom\_line(aes(y = smoothed\_med3), color = "gray20") +  
 geom\_line(aes(y = smoothed), color = "gray65") +  
 facet\_wrap(~Well) +  
 scale\_y\_continuous(trans = "log10")  
#> Warning: Transformation introduced infinite values in continuous y-axis  
#> Transformation introduced infinite values in continuous y-axis  
#> Transformation introduced infinite values in continuous y-axis  
#> Warning: Removed 2 row(s) containing missing values (geom\_path).  
#> Warning: Removed 4 row(s) containing missing values (geom\_path).



Here we can see that the combination of minimal moving-median and moving-average smoothing has produced a curve that has most of the noise removed with minimal introduction of bias. (Note that the first and last 2 data points are now NA because of the smoothing)

# Processing data: calculating derivatives

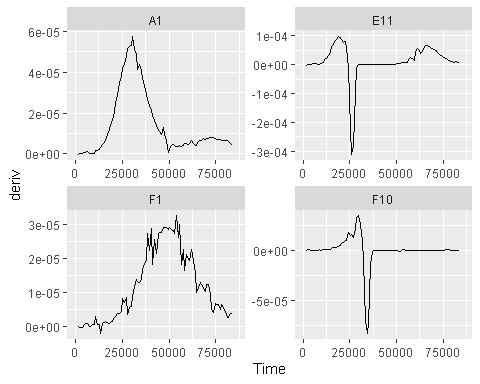
In many cases, identifying features of a growth curve requires looking not only at the absorbance data over time, but the slope of the absorbance data over time. gcplyr includes a calc\_deriv function that can be used to calculate the empirical derivative (slope) of absorbance data over time.

*If you’ve previously smoothed your absorbance data, remember to use those smoothed values rather than the original values!*

## A simple derivative

To calculate a simple derivative (the slope of our original data) using calc\_deriv, we simply have to provide the x and y values. Note that this is **not** the growth rate of the cells, but rather is a measure of how quickly the whole population was growing at each time point. This is useful for identifying events like population declines, or multiple rounds of growth.

ex\_dat\_mrg <- mutate(ex\_dat\_mrg,  
 deriv = calc\_deriv(x = Time, y = smoothed))  
  
#Now let's plot the derivative  
ggplot(data = dplyr::filter(ex\_dat\_mrg, Well %in% sample\_wells),  
 aes(x = Time, y = deriv)) +  
 geom\_line() +  
 facet\_wrap(~Well, scales = "free")  
#> Warning: Removed 5 row(s) containing missing values (geom\_path).

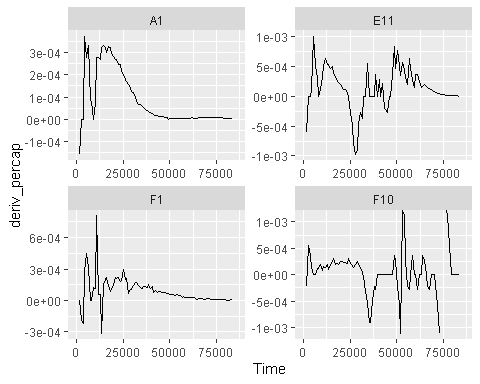


Here we can clearly see when the slope of the total population was increasing the fastest, and when it declines in the phage-added wells. But we can also see something surprising in Well A1 that may not have been immediately apparent visually: there is a second, slower, burst of growth later on. Such a pattern is common in bacterial growth curves and is called *diauxic growth*. Additionally, we can see in Well E11 when the bacteria start to grow again following near-extinction by phages, presumably after evolving resistance to the phage. (Note that the last value in the time series always becomes NA with calc\_deriv under default settings)

## Per-capita derivative

If we want to calculate the growth rate of the cells, we need to use calc\_deriv to return the **per-capita** derivative. Just as before, provide the x and y values, but now set percapita = TRUE. Note that in this case, you are required to specify a blank value, i.e. the value of your Measurements that corresponds to a population density of 0. If your data have already been normalized, simply add blank = 0.

ex\_dat\_mrg <- mutate(ex\_dat\_mrg,  
 deriv\_percap = calc\_deriv(x = Time, y = smoothed,  
 percapita = TRUE, blank = 0))  
  
#Now let's plot the per-capita derivative  
ggplot(data = dplyr::filter(ex\_dat\_mrg, Well %in% sample\_wells),  
 aes(x = Time, y = deriv\_percap)) +  
 geom\_line() +  
 facet\_wrap(~Well, scales = "free")  
#> Warning: Removed 5 row(s) containing missing values (geom\_path).



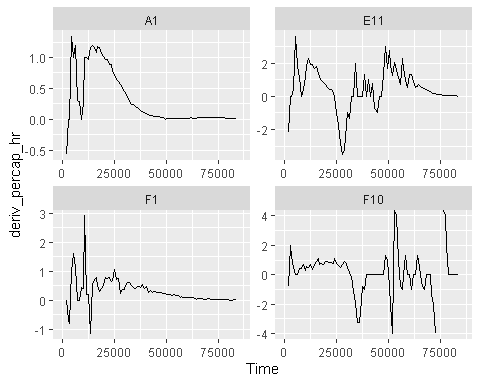
Here we can see that, in Well A1, the per-capita growth rate peaked much earlier in the time-series than might appear from the density dynamics or non per-capita derivative. We can also see that there was clearly a lag phase at the beginning before the bacteria started growing rapidly.

However, the other wells seem to have a lot of noise obscuring their per-capita growth rates. What happened? Why hasn’t our smoothing been sufficient? As I explore later, per-capita growth rates can be strongly affected by even small noise at very low densities, something that can be excluded simply by only analyzing per-capita growth when densities are above some minimum value.

## Changing the derivative units

To convert your x-axis (time) units in your derivative calculations to a different unit, use the x\_scale argument. Simply specify the ratio of your x units to the desired units. For instance, in our example data x is the number of *seconds* since the growth curve began. What if we wanted growth rate in *per-hour*? There are 3600 seconds in an hour, so we set x\_scale = 3600

ex\_dat\_mrg <-   
 mutate(ex\_dat\_mrg,  
 deriv\_percap\_hr = calc\_deriv(x = Time, y = smoothed,  
 percapita = TRUE, blank = 0,  
 x\_scale = 3600))  
  
#Now let's plot the derivative in units of Abs/hour  
ggplot(data = dplyr::filter(ex\_dat\_mrg, Well %in% sample\_wells),  
 aes(x = Time, y = deriv\_percap\_hr)) +  
 geom\_line() +  
 facet\_wrap(~Well, scales = "free")  
#> Warning: Removed 5 row(s) containing missing values (geom\_path).



Now we can see the bacterial growth rate in more-understandable units: peak growth rates are often around 1-2 times/hour (when ignoring the points that seem likely to be noise).

# What’s next?

Now that you’ve processed your data, you’re ready to analyze it!

1. Introduction: vignette("gcplyr")
2. Importing and transforming data: vignette("import\_transform")
3. Incorporating design information: vignette("incorporate\_designs")
4. Pre-processing and plotting your data: vignette("preprocess\_plot")
5. Processing your data: vignette("process") **6. Analyzing your data: vignette("analyze")**
6. Statistics, merging other data, and other resources: vignette("conclusion")