MATH550/SCC461: Statistics in Practice
Lab 4
Time manipulation using R

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Contents

Before you start

- Compare your submission for last weeks coursework with the solution that is on moodle. Look for differences. Make sure to intergrate any improvements in style into this weeks code.
- Revise the Summary sections on Data Manipulation and Basic Plots from Lab 2.
- As usual, to save the code you write for this lab, create a new R script in your R progamming folder, on your H drive,
- Write a few introductory comments at the top stating that this script covers the basics handling dates and times in R, along with how to aggregate and summarise data.
- Add your favourite packages to the start of your script:

```
library(ggplot2)
library(dplyr)
library(tidyverse)
```

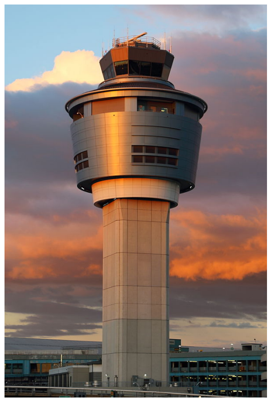
Dates and timestamps in R

Date-time data is typically generated by an automated process or system. See Figure 1 for examples. Data collected in this fashion can be thought of as an event log, with one column containing the date and time of the event, and the remaining columns capturing whatever measures thought necessary.

You may not know this yet, but when working with event-log data, the date-time component can be very frustrating to work with. To begin with, a timestamp may take on a variety of forms:

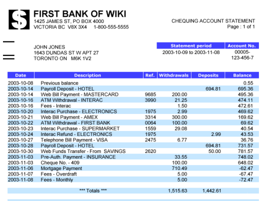
```
2014/08/12 19:47
2014/12/08 19:47:01
12/08/2014 19:47:01
19:47:01 12/08/2014
7.47PM 12-AUG-14
```

Figure 1: Examples of services or systems that generate date-time-based data.



Air traffic control direct aircraft on the ground and through controlled air space. They prevent collisions and organise the flow of air traffic.

The GPS tracker a runner users when they go out training continuously logs their location over time.



FIRST BANK OF WIKI
1425 JAMES ST, PO BOX 4000
VICTORIA BC V8X 3X4 1-800-555-5555

CHEQUING ACCOUNT STATEMENT
Page : 1 of 1

JOHN JONES
1643 DUNDAS ST W APT 27
TORONTO ON M6K 1V2

Statement period	Account No.
2003-10-09 to 2003-11-08	00005-123-456-7

Date	Description	Ref.	Withdrawals	Deposits	Balance
2003-10-08	Previous balance				0.55
2003-10-14	Payroll Deposit - HOTEL			694.81	695.36
2003-10-14	Web Bill Payment - MASTERCARD	9685	200.00		495.36
2003-10-16	ATM Withdrawal - INTERAC	3990	21.25		474.11
2003-10-16	Fees - Interac		1.50		472.61
2003-10-20	Interac Purchase - ELECTRONICS	1975	2.99		469.62
2003-10-21	Web Bill Payment - AMEX	3314	300.00		169.62
2003-10-22	ATM Withdrawal - FIRST BANK	0064	100.00		69.62
2003-10-23	Interac Purchase - SUPERMARKET	1559	29.08		40.54
2003-10-24	Interac Refund - ELECTRONICS	1975		2.99	43.53
2003-10-27	Telephone Bill Payment - VISA	2475	6.77		36.76
2003-10-28	Payroll Deposit - HOTEL			694.81	731.57
2003-10-30	Web Funds Transfer - From SAVINGS	2620		50.00	781.57
2003-11-03	Pre-Auth. Payment - INSURANCE		33.55		748.02
2003-11-03	Cheque No. - 409		100.00		648.02
2003-11-06	Mortgage Payment		710.49		-62.47
2003-11-07	Fees - Overdraft		5.00		-67.47
2003-11-08	Fees - Monthly		5.00		-72.47
	*** Totals ***		1,515.63	1,442.61	

A bank statement is an event-log of transactions.

As you can see timestamps can come in many different formats, which makes recognising and parsing them a challenge. Will R recognise the format that we have? If it does, we still face problems specific to timestamps. How can we easily extract components of the timestamp, such as the year, month, or number of seconds? How can we switch between time zones, or compare times from places that use daylight savings time (DST) with times from places that do not? Handling timestamps becomes even more complicated when we try to do arithmetic with them. Conventions such as leap years and DST make it unclear what we mean by "one day from now" or "exactly two years away." Even leap seconds can disrupt a seemingly simple calculation. This complexity affects other tasks too, such as constructing sensible tick marks for plotting date-time data.

While base R handles some of these problems, the syntax it uses can be confusing and difficult to remember. Moreover, the correct R code often changes depending on the *type* of date-time object being used. This is exactly why the `lubridate` package was created; in order to address these problems and makes it easier to work with date-time data in R. It also provides tools for manipulating timestamps in novel but useful ways. Specifically, `lubridate` helps us to:

- Identify and parse date-time data;
- Extract and modify components of a date-time, such as years, months, days, hours, minutes, and seconds;
- Perform accurate calculations with date-times and time-spans;
- Handle time zones and daylight savings time.

Before we continue install the `lubridate` package:

```
>   install.packages("lubridate")
```

Now add the `lubridate` package to the top of your script next to `dplyr` and `ggplot2`.

Parsing timestamps

We can parse dates and timestamps in R using the `ymd()` series of functions provided by `lubridate`, these are shown in Table 1. These functions parse character strings into date-time objects. The letters `y`, `m`, and `d` in the function names correspond to the year, month, and day elements of a timestamp. To parse a timestamp, choose the function name that matches the order of elements in the timestamp. For example, in the following date the month element comes first, followed by the day and then the year. So we would use the `mdy()` function:

```
> mdy("12/01/2010")
# [1] "2010-12-01 UTC"
```

The same function can also be used to parse `"Dec 1st, 2010"`:

```
> mdy("Dec 1st, 2010")
# [1] "2010-12-01 UTC"
```

The `ymd()` series of functions can also parse vectors of dates:

```
> dmy(c("31.12.2010", "01.01.2011"))
# [1] "2010-12-31 UTC" "2011-01-01 UTC"
```

These functions automatically recognise the separators commonly used to record dates. These include: "-", "/", ".", and 'no separator'. When a `ymd()` function is applied to a vector, it assumes that all of the elements within the vector have the same order and the same separators.

Order of elements in the timestamp	Parse function
year, month, day	`ymd()`
year, day, month	`ydm()`
month, day, year	`mdy()`
day, month, year	`dmy()`
hour, minute	`hm()`
hour, minute, second	`hms()`
year, month, day, hour, minute, second	`ymd_hms()`
hour, minute, second, day, month, year	`hms_dmy()`

Table 1: Parse-function names are based on the order that the year, month, and day appear within the dates to be parsed. Other variations exist, just use your imagination.

Manipulating timestamps

Most timestamps include a year value, a month value, a day value and so on. Together these elements specify the exact moment that an event occurred or when an observation was made. We can easily extract each element of a timestamp with the accessor functions listed in Table 2. For example, if we save the current system time:[1]

[1] Note that this was the system time when this example was written. `now()` will return a different timestamp each time it is used.

```
> stamp <- now()
```

We can then extract each of its elements:

```
> year(stamp)
# [1] 2015
> minute(stamp)
# [1] 1
```

For the month and weekday elements (`mday` and `wday`), we can also specify whether we want to extract the numerical value of the element, an abbreviation of the name of the month or weekday, or the full name. For example:

```
> month(stamp)
# [1] 10

> month(stamp, label=TRUE)
# [1] Oct

> month(stamp, label=TRUE, abbr=FALSE)
# [1] October

> wday(stamp, label=TRUE, abbr=FALSE)
# [1] Sunday
```

Table 2: Each date-time element can be extracted with its own accessor function.

Component	Accessor
Year	`year()`
Month	`month()`
Week	`week()`
Day of year	`yday()`
Day of month	`mday()`
Day of week	`wday()`
Hour	`hour()`
Minute	`minute()`
Second	`second()`
Time zone	`tz()`

Arithmetic with timestamps

Arithmetic with timestamps is more complicated than arithmetic with numbers, but it can be done accurately and easily with `lubridate`. What complicates arithmetic with timestamps? Clock times are periodically re-calibrated to reflect astronomical conditions, such as the hour of daylight or the Earth's tilt on its axis relative to the sun. We know these re-calibrations as daylight savings time, leap years, and leap seconds. Consider how one of these conventions might complicate a simple addition task. If today were January 1st, 2010 and we wished to know what day it would be one year from now, we could simply add 1 to the years element of our date:

```
> mdy("January 1st, 2010") + years(1)
# [1] "2011-01-01 UTC"
```

Alternatively, we could add 365 to the days element of our date because a year is equivalent to 365 days:

```
> mdy("January 1st, 2010") + days(365)
# [1] "2011-01-01 UTC"
```

However, troubles arise if we try the same for January 1st, 2012. 2012 is a leap year, which means it has an extra day. Our two approaches above now give us different answers because the length of a year has changed:

```
> mdy("January 1st, 2012") + years(1)
# [1] "2013-01-01 UTC"
> mdy("January 1st, 2012") + days(365)
# [1] "2012-12-31 UTC"
```

At different moments in time, the lengths of months, weeks, days, hours, and even minutes will also vary. We can consider these to be *relative* units of time; their length is relative to when they occur. In contrast, seconds always have a consistent length. Hence, seconds are *exact* units of time. Researchers may be interested in exact lengths, relative lengths, or both. For example, the speed of a physical object is most precisely measured in exact lengths. The opening bell of the stock market is more easily modelled with relative lengths.

In general, we can change timestamps by adding or subtracting units of time from them. To do this use the helper functions; `years()`, `months()`, `weeks()`, `days()`, `hours()`, `minutes()`, and `seconds()`. Where the first and only argument is the amount of that unit of time:

```
>   stamp - hours(48) - minutes(30)
# [1] "2015-09-22 12:31:55 BST"
```

Intervals and durations

Often we do not want to necessarily *change* a timestamp, but actually calculate the difference between two timestamps. For example, between the start and end of an event to calculate the duration, or to count down to a particular event. We first define an interval using between our two time-points:

```
halloween <- ymd("2014-10-31")
christmas <- ymd("2014-12-25")
interval  <- interval(halloween, christmas)
interval
# [1] 2014-10-31 UTC--2014-12-25 UTC
```

After which we can choose to express this interval as a duration in terms of a specific time-unit (e.g. weeks, days, or seconds):

```
interval / dweeks(1)
interval / ddays(1)
interval / dseconds(1)
```

In order to express an interval as a duration we divide by similar functions to those used in the arithmetic section but they are all prefixed with ‘`d`’.

Unix time

To overcome the issues with relative time, some systems store timestamps simply as the number of seconds since “00:00:00, Thursday, 1st January 1970 (UTC)". When time is stored like this it is referred to as Unix-time or time-since-Epoch.[2] To convert a date-time object to Unix time, simply change the object type to numeric:

```
> event <- ymd_hms("2001-09-09 01:46:40", tz="UTC")
> as.numeric(event)
# [1] 1e+09
```

To convert from Unix-time back to a timestamp, take the Unix-time value (which is just a number of seconds) and add it to the origin:

```
> origin <- ymd_hms("1970-01-01 00:00:00", tz="UTC")
> origin + seconds(10^9) # 1 billion seconds
# [1] "2001-09-09 01:46:40 UTC"
```

Rounding time

Like all measurements, timestamps have a precision; they are often measured to the nearest day, minute, or second. This means that timestamps can be rounded. To perform this rounding we use: `round_date()`, `floor_date()`, and `ceiling_date()`. The first argument of each function is a timestamp or vector of timestamps to be rounded. The second argument is the unit to round to. For example, we could round 11:33, 20th April 2010 to the nearest day:

```
april20 <- ymd_hms("2010-04-20 11:33:29")
round_date(april20, "day")
# [1] "2010-04-20 UTC"
```

Note that rounding a timestamp to a particular day sets the hours, minutes and seconds components of the timestamp to 00. If the timestamp is in the afternoon then it will be rounded up to the next day:

```
april20 <- ymd_hms("2010-04-20 14:15:02")
round_date(april20, "day")
# [1] "2010-04-21 UTC"
```

Similarly, rounding to the nearest month, sets the day to 01 regardless of which month it is rounded to:

```
round_date(april20, "month")
# [1] "2010-05-01 UTC"
```

We can use `ceiling_date()` to find the last day of a month. Do this by ceiling a timestamp to the next month and then subtract one day:

[2] 

Unix time passed 1,000,000,000 seconds on 2001-09-09 01:46:40 UTC. It was celebrated in Copenhagen, Denmark at a party held by a group of computer geeks (03:46 local time).

```
ceiling_date(april20, "month") - days(1)
# [1] "2010-04-30 UTC"
```

A Real Example: Sea Ice Extent

We are now going to put some of this `lubridate` knowledge into practice by exploring the data collected as part of the routine monitoring of the amount of sea ice at the Artic.[3]

[3] This is collected by the National Snow and Ice Data Center (NSIDC) and is available at:
http://nsidc.org/data/G02135.

Certain satelites that pass over the Arctic have equipment that allows them to measure the presence of sea ice and its density. What we are interested in is the *extent* of the sea ice i.e. the surface area when viewed from above. Figure 2 shows the extent of the sea ice in October, 2013.

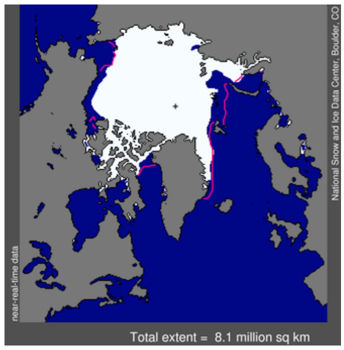
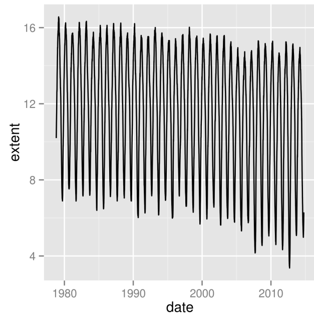


Figure 2: Extent of the Arctic sea ice in October, 2013. Outline shows the median ice edge.



1. Download the 'NH_sea_ice_extent_2014-10-10.csv' data set from the SSC.461 moodle page into your working directory. Within R, read this into an object called 'sea_ice' (or similar).

2. Use `head()` to look at the first few rows of `sea_ice` and parse the `date` column accordingly. The `extent` column is a measure of the top-down surface area of the sea ice in million square-kilometres.

3. If you use the `class()` function on `sea_ice$date` you'll see that it's a numeric type (i.e. a number). We need to change this so that R recognises that it's a data. Run the blow command and check the class again

```
sea_ice$date <- ymd(sea_ice$date)
```

4. Plot the extent of the sea ice over time.

```
ggplot(sea_ice) +
  geom_line(aes(x=date, y=extent))
```

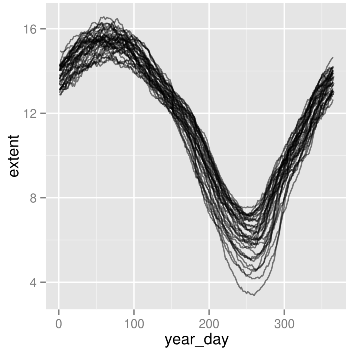
What can be seen here is that while there is clear seasonal variation, there also appears to be a downward trend over time.

5. To focus on the seasonal variation, we need to create a graphic that shows `extent` from January to December on the x-axis, with each year then having its own line. To do this we first need to create two extra variables based on 'date'; one which contains the year component, and the other containing the day of the year (1-365):

```
sea_ice$year <- year(sea_ice$date)
sea_ice$year_day <- yday(sea_ice$date)

head(sea_ice)
#         date   extent year year_day
# 1 1978-10-26 10.19591 1978      299
# 2 1978-10-28 10.34363 1978      301
# 3 1978-10-30 10.46621 1978      303
# 4 1978-11-01 10.65538 1978      305
# 5 1978-11-03 10.76997 1978      307
# 6 1978-11-05 10.96294 1978      309
```

Using these two new variables we can now create a seasonal plot. Note that in order to tell `ggplot()` to produce a separate line for each year we specify '`group=year`' as part of `aes()`.

```
ggplot(sea_ice) +
  geom_line(aes(x=year_day, y=extent, group=year),
            alpha=0.5)
```



To highlight which lines belong to which year modify the plot so we colour each line according to year:

```
ggplot(sea_ice) +
  geom_line(aes(x=year_day, y=extent, group=year, colour=year),
            alpha=0.5) +
  theme(legend.position="top")
```

To change the colours used for the gradient, and the labels shown on the colour bar for year, add `scale_colour_gradient()` to your `ggplot()` command:

```
ggplot(sea_ice) +
  geom_line(aes(x=year_day, y=extent, group=year, colour=year),
            alpha=0.5) +
  scale_colour_gradient(low="red", high="blue") +
  theme(legend.position="top")
```

Try other colours to see if you can find something that looks pretty. An alternative to picking colours yourself is to use the colour brewer:

```
library(RColorBrewer)
palette <- brewer.pal(3, name="BrBG")

ggplot(sea_ice) +
  geom_line(aes(x=year_day, y=extent, group=year, colour=year),
            alpha=0.5) +
  scale_colour_gradient(low=palette[1], high=palette[3]) +
  theme(legend.position="top")
```

Try setting `name` in `brewer.pal()` to any of the following: `BrBG`, `PiYG`, `PRGn`, `PuOr`, `RdBu`, `RdGy`, `RdYlBu`, `RdYlGn`, `Spectral`.

Summarising data over time

When wanting to look at year-on-year trends, we often want to look past any variation due to seasonality. There are three ways of doing this:

- Only look at the same time point at each year e.g. numbers for October every year.
- Create an average for a fixed time unit e.g. average per year.
- Calculate an average of a moving window e.g. average of the last 30 days of observations and move this window across the whole time range.

We will consider each of these approaches using the R packages we have covered so far in the course. The first of these is the simplest to implement, we begin by keeping only October observations:

```
sea_ice$month <- month(sea_ice$date)
sea_ice_oct <- filter(sea_ice,  month == 10)
head(sea_ice_oct)
```

However, we have more than one observation per month, and they are not always at the same day within the month. One solution to this is to use only the first observation for each October, but to do this we need to work out which one that is. To do this we use `group_by()` and `summarise()` from `dplyr`.

Group by and summarise

In order to break-up our data frame into small subgroups so that we can perform the same calculation on each subgroup, we use `group_by()` from `dplyr`, whose first argument is the data frame of interest and all subsequent arguments are the variables to be grouped on. The following will create groups for each unique value in `year`:

```
  sea_ice_oct_grp <- group_by(sea_ice_oct, year)
```

Inside `sea_ice_oct_grp` is a grouped data frame. To summarise each group we send `sea_ice_oct_grp` to the `summarise()` function which will produce a new data frame containing the grouping variable (just `year` in this case) and any summary variables we decide to calculate:

```
  oct_summary <- summarise(sea_ice_oct_grp,
    date     = first(date),
    extent   = first(extent),
    year_day = first(year_day)
  )
```

The code above summarises each group simply by taking the first row in each subgroup and stores the results in a data frame called `oct_summary`. This is, of course, a very crude summary. But it does give us one observation per October of every year.

```
>   head(oct_summary)
# Source: local data frame [6 x 4]
#
#    year       date   extent year_day
#   (dbl)     (time)    (dbl)    (dbl)
# 1  1978 1978-10-26 10.19591      299
# 2  1979 1979-10-01  7.36108      274
# 3  1980 1980-10-01  8.16997      275
# 4  1981 1981-10-02  7.94249      275
# 5  1982 1982-10-01  7.71411      274
# 6  1983 1983-10-02  8.09429      275
```

We see that the extent of the sea ice for the first observation in October, 1978 as 10.3 million sq-km. Also, we can see that by asking for the first date, it has now been converted to Unix time. To convert it back to a timestamp see the section on Unix time.

Using `ggplot()` and `oct_summary`, you should now try to produce a graph showing the extent of the sea ice in October for each year (shown here in Figure 3).

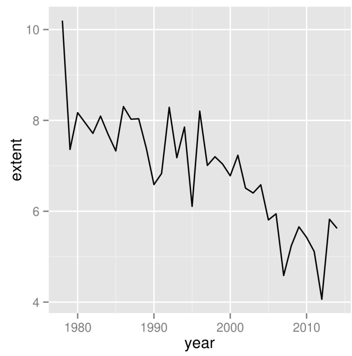


Figure 3: Ice extent (million sq-km) in October each year. Only first observation in October each year was used.

Yearly averages

To calculate the average of a variable in a data frame, we pass the variable to the `mean()` function:

```
mean(sea_ice$extent)
# [1] 11.44243
```

This calculated the mean across all observations of `extent`. Repeat the process of grouping and summarising, but on year instead of month. And instead of capturing the first observation, calculate the mean of the extent observations within each group. Thus you will be able to visualise change in yearly-average of ice extent over time. The graph you produce should look like Figure 4.

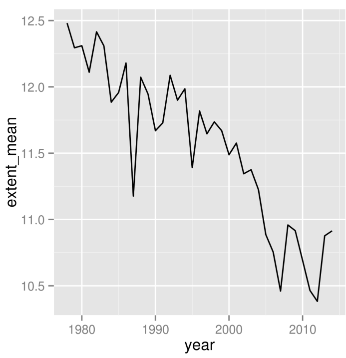


Figure 4: Average ice extent (million sq-km) for each year. Note the difference in scale on the y-axis between the October graph and this yearly graph. Look back at seasonal variation to understand the cause for the difference.

Moving average

So far, to get past the seasonal variation, we have averaged over distinct subsets of data. An alternative to this is to average over a moving window of the data, this type of average is called a moving or rolling average. At each observation, we use it and the previous, say, 12 months of observations to calculate an average. We then move on to the next observation and then calculate its average based on its previous 12 months. This process runs until we reach the last row in our data, but only starts once we have at least 12 months of data:

```
  min(sea_ice$date) + months(12)
# [1] "1979-10-26 UTC"
```

This would be the first time point at which our average is calculated. To calculate the moving average, we iterate over the rows in `sea_ice` using a `for` loop:

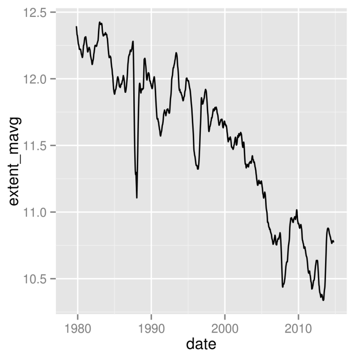
```
  for (i in 1:nrow(sea_ice)) {
      # << moving average code >>
  }
```

There are several steps we need to take in order to calculate the moving average. For each row we need to:

- Identify if we can start calculating the average yet.
- Identify the 12-month subset.
- Calculate and store the average for this subset.

Note that once you execute the code below, it will take a while to finish, as looping is a slow process in R, and we have a lot of rows to loop over:

```
# create our new variable, fill it with missing values
sea_ice$extent_mavg <- NA

# set our window size (in days)
window_size <- 365

# when do we start our averaging?
start_at <- min(sea_ice$date) + days(window_size)

for (i in 1:nrow(sea_ice)) {
    current_date <- sea_ice$date[i]

    # are we at or beyond the start date yet?
    if (current_date >= start_at) {
      # identify the previous 12-month subset
      from <- current_date - days(window_size)
      sub_set <- filter(sea_ice, (date > from) & (date <= current_date))

      # calc and store average
      sea_ice$extent_mavg[i] <- mean(sub_set$extent)
    }
}
```



In a similar fashion to the previous group-averaging, now visualise the moving average results over time.

What happens to the graph when you modify your window size to be 6 months (183 days)? What about a window size of 18 months (548 days)?

A timestamp split over several columns

The original sea ice extent data did not actually contain a timestamp. The timestamp you parsed earlier was created by combining several columns in the original data. The original data is in '`orig_NH_seaice_extent.csv`' in the data sets folder on Moodle. Download this to your working directory and load it into R:

```
sea_ice_orig <- read.csv("orig_NH_seaice_extent.csv")
names(sea_ice_orig)
# remove junk columns
sea_ice_orig <- select(sea_ice_orig, -Missing, -Source.Data)
head(sea_ice_orig)
```

We have three columns used to capture the time of the observation (`Year`, `Monday`, and `Day`). To turn this into a timestamp we need to join each row of year, month and day together. To do this we use the `str_c()` function from the `stringr` package. Install this package and the load it using `library()`, check the help page for `str_c()` and test how it works:

```
> str_c(2014, 09, 15)
# [1] "2014915"
```

```
> str_c(2014, 09, 15, sep="/")
# [1] "2014/9/15"
```

We can also use vectors:

```
animal <- c("monkey", "human", "cat", "dog", "zebra")
food <- c("banana", "pizza", "fish", "anything", "grass")
str_c(animal, " would like ", food)
```

The `collapse` arugment combines all strings together:

```
str_c(animal, " would like ", food, collapse=", and ")
```

Use `str_c()` along with `mutate()` to create a date variable within the `sea_ice_orig` data frame. Depending on how you use the sep argument, `sea_ice_orig` should look something like this:

```
head(sea_ice_orig)
#   Year Month Day   Extent     date
# 1 2014     1   1 12.97145 2014/1/1
# 2 2014     1   2 13.06702 2014/1/2
# 3 2014     1   3 13.13399 2014/1/3
# 4 2014     1   4 13.22008 2014/1/4
# 5 2014     1   5 13.12213 2014/1/5
# 6 2014     1   6 13.11912 2014/1/6
```

There are several other useful functions in the `stringr` package which we will cover next week. Along with more general ways to summarise a data frame.

Time zones

Time zones give multiple names to the same *instance* of time. For example,

```
# Australian Christmas lunch
aus_christmas <- ymd_hms("2010-12-25 13:00:00",
                         tz="Australia/Melbourne")

# in UK time
with_tz(aus_christmas, tz="GMT")
# [1] "2010-12-25 02:00:00 GMT"
```

Both of these describe the same instant. The first shows how the instant is labelled in Melbourne time (AEDT). While the second shows the same instant but labelled in Greenwich Mean Time (GMT). Time zones complicate date-time data but are useful for mapping clock time to local daylight conditions. When working with instants, it is standard to give the clock time as it appears in the Coordinated Universal time zone (UTC). This saves calculations but can be annoying if your computer insists on translating times to your current time zone. It may also be inconvenient to discuss clock times that occur in a place unrelated to the data. `lubridate` tries to ease the frustration caused by different time zones in data by two ways. First, we can change the time zone in which an instant is displayed by using the function `with_tz()`. This changes how the clock time is displayed, but not the specific instant of time that is referred to. For example:

```
uk_christmas <- ymd_hms("2010-12-25 13:00:00", tz="GMT")
with_tz(uk_christmas, "UTC")
# [1] "2010-12-25 13:00:00 UTC"
with_tz(aus_christmas, "UTC")
# [1] "2010-12-25 02:00:00 UTC"
```

`force_tz()` does the opposite of `with_tz()`; it changes the actual instant of time saved in the object, while keeping the displayed clock time the same. The new time zone value is the indicator of this change. For example, the code below moves us to a new instant that occurs 11 hours later.

```
force_tz(aus_christmas, "UTC")
# [1] "2010-12-25 13:00:00 UTC"
```

`with_tz()` and `force_tz()` only work with time zones recognised by R. To see a long list of these:

```
OlsonNames()
```

Finally, note that the `ymd_hms` family of functions will, by default, parse all timestamps as being in the UTC timezone. Regardless of whether the timestamp contains a reference to the actual timezone.

Here is an example of a timestamp in USA Eastern Standard Time (EST) being overwritten as UTC:

```
ymd_hms("2010-12-25 13:00:00 EST")
# [1] "2010-12-25 13:00:00 UTC"
```

To ensure your timestamp is parsed as being in the correct timezone you need to pass the timezone to the `tz` argument of the `ymd_hms`() function:

```
ymd_hms("2010-12-25 13:00:00 EST", tz="EST")
# [1] "2010-12-25 13:00:00 EST"
```

Note that if you the `tz` argument has to be a valid timezone otherwise `with_tz()` will not perform the proper conversion when converting it to a different timezone:

```
tz_pickle <- ymd_hms("2010-12-25 13:00:00", tz="PICKLE")

with_tz(tz_pickle, "UTC")
# [1] "2010-12-25 13:00:00 UTC"
```

The timezone PICKLE is silently replaced to UTC, even though PICKLE is not an actual timezone. A more real example; while 'EST' is a valid timezone in R, USA Central Standard Time (CST) is not, although it *is* an actual timezone.

```
any(OlsonNames() == "EST")
# [1] TRUE
any(OlsonNames() == "CST")
# [1] FALSE
any(OlsonNames() == "CST6CDT")
# [1] TRUE
```

Instead of 'CST' we have to use 'CST6CDT' which represents both the CST and CDT timezones (both are GMT - 6 hours).

Because of all these issues, a generally good strategy is:

- Check your timezones are valid by comparing against `OlsonNames()`, correcting any that are not.
- Parse using the appropriate function.
- Convert all timestamps to UTC.