Using Spatial Data with R

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Contents

Prerequisites and Preparations

To get the most out of this workshop you should have:

- a **basic knowledge** of R and/or be familiar with the topics covered in the Introduction to R.
- have a recent version of R and RStudio installed.

Recommended:

- Create a new RStudio project `R-spatial` in a new folder `R-spatial`.
- Create a new folder under `R-spatial` and call it `data`.
- If you have your working directory set to `R-spatial` which contains a folder called `data` you can copy, paste, and run the following lines in R:

```
download.file("http://bit.ly/R-spatial-data", "R-spatial-data.zip")
unzip("R-spatial-data.zip", exdir = "data")
```

You can also download the data manually here R-spatial-data.zip and extract them.

- Open up a new R Script file `R-spatial.R` for the code you'll create during the workshop.
- Install and load the following libraries:
  - `sf`
  - `sp`
  - `rgdal`
  - `raster`
  - `rgeos`
  - `dplyr`
- For the mapping section install and load these additional libraries:
  - `classInt`
  - `RColorBrewer`
  - `ggplot2`
  - `ggmap`
  - `tmap`
  - `leaflet`(On Mac installing binary version is ok)

References

Bivand, RS., Pebesma, E., Gómez-Rubio, V. (2013): Applied Spatial Data Analysis with R

Brunsdon, C. and Comber, L. (2015): An Introduction to R for Spatial Analysis and Mapping

Lovelace, R., Nowosad, J., Muenchow. J. (2019): Geocomputation with R

Spatial Data Analysis and Modeling with R

CRAN Task View: Analysis of Spatial Data

Engel, C. (2019). R for Geospatial Analysis and Mapping. The Geographic Information Science & Technology Body of Knowledge (1st Quarter 2019 Edition), John P. Wilson (Ed.). DOI:10.22224/gistbok/2019.1.3.

For a quick introduction to all things geo check out map school.

Acknowledgements

Some of the materials for this tutorial are adapted from http://datacarpentry.org

Chapter 1

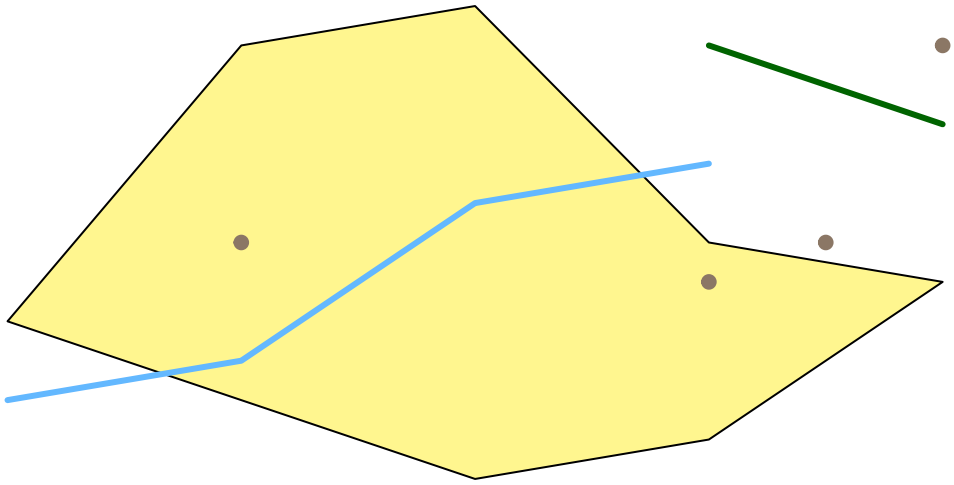
Introduction to spatial data in R

Learning Objectives

- Create point, line, and polygon shapefiles as `sp` and `sf` objects.
- Read shapefiles into `sp` and `sf` objects
- Examine `sp` and `sf` objects
- Read GeoTiff single and multiband into a `raster` object.
- Examine `raster` objects

1.1 Conceptualizing spatial vector objects in R

In vector GIS we deal with, points, lines, and polygons, like so:



Challenge

Discuss with your neighbor: What information do we need to store in order to define points, lines, polygons in geographic space?

There are currently two main approaches in R to handle geographic vector data:

1.1.1 The sp package

The first general package to provide classes and methods for spatial data types that was developed for R is called `sp`[1]. Development of the `sp` package began in the early 2000s in an attempt to standardize how spatial data would be treated in R and to allow for better interoperability between different analysis packages that use spatial data. The package (first release on CRAN in 2005) provides classes and methods to create *points*, *lines*, *polygons*, and *grids* and to operate on them. About 350 of the spatial analysis packages use the spatial data types that are implemented in `sp` i.e. they "depend" on the `sp` package and many more are indirectly dependent.

The foundational structure for any spatial object in `sp` is the `Spatial` class. It has two "slots" (new-style S4 class objects in R have pre-defined components called slots):

- a **bounding box**
- a **CRS class object** to define the Coordinate Reference System

This basic structure is then extended, depending on the characteristics of the spatial object (point, line, polygon).

To manually build up a spatial object in `sp` we could follow these steps:

I. Create geometric objects (topology)

Points (which may have 2 or 3 dimensions) are the most basic spatial data objects. They are generated out of either a single coordinate or a set of coordinates, like a two-column matrix or a dataframe with a column for latitude and one for longitude.
Lines are generated out of `Line` objects. A `Line` object is a spaghetti collection of 2D coordinates[2] and is generated out of a two-column matrix or a dataframe with a column for latitude and one for longitude. A `Lines` object is a **list** of one or more `Line` objects, for example all the contours at a single elevation.
Polygons are generated out of `Polygon` objects. A `Polygon` object is a spaghetti collection of 2D coordinates with equal first and last coordinates and is generated out of a two-column matrix or a dataframe with a column for latitude and one for longitude. A `Polygons` object is a **list** of one or more `Polygon` objects, for example islands belonging to the same country.

II. Create spatial objects `Spatial*` object (`*` stands for Points, Lines, or Polygons).

This step adds the bounding box (automatically) and the slot for the Coordinate Reference System or CRS (which needs to be filled with a value manually). `SpatialPoints` can be directly generated out of the coordinates. `SpatialLines` and `SpatialPolygons` objects are generated using lists of `Lines` or `Polygons` objects respectively (more below).

III. Add attributes (*Optional*:)

Add a data frame with attribute data, which will turn your `Spatial*` object into a `Spatial*DataFrame` object. The points in a `SpatialPoints` object may be associated with a row of attributes to create a `SpatialPointsDataFrame` object. The coordinates and attributes may, but do not have to be keyed to each other using ID values.
`SpatialLinesDataFrame` and `SpatialPolygonsDataFrame` objects are defined using `SpatialLines` and `SpatialPolygons` objects and data frames. The ID fields are here required to match the data frame row names.

If, for example we wanted to build up an `sp` Object that would contain highways we would do the following.

First we would create a `Line` object that holds one highway. We use a matrix with two columns of arbitrary numbers, for x and y coordinates.

[1] R Bivand (2011) Introduction to representing spatial objects in R
[2] Coordinates should be of type double and will be promoted if not.

```
ln1 <- Line(matrix(runif(6), ncol=2))
str(ln1)
```

```
#> Formal class 'Line' [package "sp"] with 1 slot
#>   ..@ coords: num [1:3, 1:2] 0.478 0.353 0.406 0.234 0.821 ...
```

Note the `@ coords` slot which holds the coordinates.

Ok, let's create another `Line` object for another highway:

```
ln2 <- Line(matrix(runif(6), ncol=2))
```

Now we combine the two highways to a `Lines` object. Note how we add a unique ID for each highway. This step allows to combine generate multiple line strings, so we could add more lines under the same ID.

```
lns1 <- Lines(list(ln1), ID = c("hwy1"))
lns2 <- Lines(list(ln2), ID = c("hwy2"))
str(lns1)
```

```
#> Formal class 'Lines' [package "sp"] with 2 slots
#>   ..@ Lines:List of 1
#>   .. ..$ :Formal class 'Line' [package "sp"] with 1 slot
#>   .. .. .. ..@ coords: num [1:3, 1:2] 0.478 0.353 0.406 0.234 0.821 ...
#>   ..@ ID   : chr "hwy1"
```

The `Line` objects are now in a list and we have an additional `ID` slot, which uniquely identifies each `Line` object.

Now we turn this into a geospatial object by creating a `SpatialLines` object:

```
sp_lns <- SpatialLines(list(lns1, lns2))
str(sp_lns)
```

```
#> Formal class 'SpatialLines' [package "sp"] with 3 slots
#>   ..@ lines      :List of 2
#>   .. ..$ :Formal class 'Lines' [package "sp"] with 2 slots
#>   .. .. .. ..@ Lines:List of 1
#>   .. .. .. .. ..$ :Formal class 'Line' [package "sp"] with 1 slot
#>   .. .. .. .. .. .. ..@ coords: num [1:3, 1:2] 0.478 0.353 0.406 0.234 0.821 ...
#>   .. .. .. ..@ ID   : chr "hwy1"
#>   .. ..$ :Formal class 'Lines' [package "sp"] with 2 slots
#>   .. .. .. ..@ Lines:List of 1
#>   .. .. .. .. ..$ :Formal class 'Line' [package "sp"] with 1 slot
#>   .. .. .. .. .. .. ..@ coords: num [1:3, 1:2] 0.357 0.354 0.547 0.205 0.439 ...
#>   .. .. .. ..@ ID   : chr "hwy2"
#>   ..@ bbox       : num [1:2, 1:2] 0.353 0.205 0.547 0.888
#>   .. ..- attr(*, "dimnames")=List of 2
#>   .. .. ..$ : chr [1:2] "x" "y"
#>   .. .. ..$ : chr [1:2] "min" "max"
#>   ..@ proj4string:Formal class 'CRS' [package "sp"] with 1 slot
#>   .. .. ..@ projargs: chr NA
```

Note how this adds the `@ bbox` with the bounding box coordinates and `@ proj4string` to hold the Coordinate Reference System - in our case `NA` as we have not assigned any projection.

Finally we create some attributes to each highway and create a `SpatialLinesDataframe`. The way we do this is that we create a regular `data.frame` and join it to the spatial object via the unique ID.

```
dfr <- data.frame(id = c("hwy1", "hwy2"), # note how we use the same IDs from above!
                  cars_per_hour = c(78, 22))
sp_lns_dfr <- SpatialLinesDataFrame(sp_lns, dfr, match.ID = "id")
str(sp_lns_dfr)
```

```
#> Formal class 'SpatialLinesDataFrame' [package "sp"] with 4 slots
#>   ..@ data       :'data.frame':  2 obs. of  2 variables:
#>   .. ..$ id           : Factor w/ 2 levels "hwy1","hwy2": 1 2
#>   .. ..$ cars_per_hour: num [1:2] 78 22
#>   ..@ lines      :List of 2
#>   .. ..$ :Formal class 'Lines' [package "sp"] with 2 slots
#>   .. .. .. ..@ Lines:List of 1
#>   .. .. .. .. ..$ :Formal class 'Line' [package "sp"] with 1 slot
#>   .. .. .. .. .. .. ..@ coords: num [1:3, 1:2] 0.478 0.353 0.406 0.234 0.821 ...
#>   .. .. .. ..@ ID   : chr "hwy1"
#>   .. ..$ :Formal class 'Lines' [package "sp"] with 2 slots
#>   .. .. .. ..@ Lines:List of 1
#>   .. .. .. .. ..$ :Formal class 'Line' [package "sp"] with 1 slot
#>   .. .. .. .. .. .. ..@ coords: num [1:3, 1:2] 0.357 0.354 0.547 0.205 0.439 ...
#>   .. .. .. ..@ ID   : chr "hwy2"
#>   ..@ bbox       : num [1:2, 1:2] 0.353 0.205 0.547 0.888
#>   .. ..- attr(*, "dimnames")=List of 2
#>   .. .. ..$ : chr [1:2] "x" "y"
#>   .. .. ..$ : chr [1:2] "min" "max"
#>   ..@ proj4string:Formal class 'CRS' [package "sp"] with 1 slot
#>   .. .. ..@ projargs: chr NA
```

Note the additional `@ data` slot here, where we find the attribute information.

There are a number of spatial methods are available for the object classes in `sp`. Among the ones I use more frequently are:

function	and what it does
`bbox()`	returns the bounding box coordinates
`proj4string()`	sets or retrieves projection attributes as object of the `CRS` class.
`CRS()`	creates an object of class of coordinate reference system arguments
`spplot()`	plots a separate map of all the attributes unless specified otherwise
`coordinates()`	set or retrieve the spatial coordinates. For spatial polygons it returns the centroids.
`over(a, b)`	used for example to retrieve the polygon or grid indices on a set of points
`spsample()`	sampling of spatial points within the spatial extent of objects

1.1.2 The `sf` package

The second package, first released on CRAN in late October 2016, is called `sf`[3]. It implements a formal standard called "Simple Features" that specifies a storage and access model of spatial geometries (point, line, polygon). A feature geometry is called simple when it consists of points connected by straight line pieces, and does not intersect itself. This standard has been adopted widely, not only by spatial databases such as PostGIS, but also more recent standards such as GeoJSON.

If you work with PostGis or GeoJSON you may have come across the WKT (well-known text) format (Fig 1.1 and 1.2)

[3]E. Pebesma & R. Bivand (2016)Spatial data in R: simple features and future perspectives

Geometry primitives (2D)

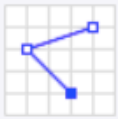
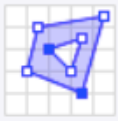
Type	Examples	
Point		`POINT (30 10)`
LineString		`LINESTRING (30 10, 10 30, 40 40)`
Polygon		`POLYGON ((30 10, 40 40, 20 40, 10 20, 30 10))`
		`POLYGON ((35 10, 45 45, 15 40, 10 20, 35 10), (20 30, 35 35, 30 20, 20 30))`

Figure 1.1: Well-Known-Text Geometry primitives (wikipedia)

Multipart geometries (2D)

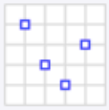
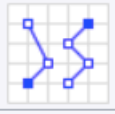
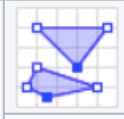
Type	Examples	
MultiPoint		`MULTIPOINT ((10 40), (40 30), (20 20), (30 10))`
		`MULTIPOINT (10 40, 40 30, 20 20, 30 10)`
MultiLineString		`MULTILINESTRING ((10 10, 20 20, 10 40), (40 40, 30 30, 40 20, 30 10))`
MultiPolygon		`MULTIPOLYGON (((30 20, 45 40, 10 40, 30 20)), ((15 5, 40 10, 10 20, 5 10, 15 5)))`
		`MULTIPOLYGON (((40 40, 20 45, 45 30, 40 40)), ((20 35, 10 30, 10 10, 30 5, 45 20, 20 35), (30 20, 20 15, 20 25, 30 20)))`

Figure 1.2: Well-Known-Text Multipart geometries (wikipedia)

`sf` implements this standard natively in R. Data are structured and conceptualized very differently from the `sp` approach.

In `sf` spatial objects are stored as a simple data frame with a special column that contains the information for the geometry coordinates. That special column is a list with the same length as the number of rows in the data frame. Each of the individual list elements then can be of any length needed to hold the coordinates that correspond to an individual feature.

To create a spatial `sf` object manually the basic steps would be:

I. Create geometric objects (topology)

Geometric objects (simple features) can be created from a numeric vector, matrix or a list with the coordinates. They are called `sfg` objects for Simple Feature Geometry.b Similarly to `sp` there are functions that help create simple feature geometries, like `st_point()`, `st_linestring()`, `st_polygon()` and more.

II. Combine all individual single feature objects for the special column.

The feature geometries are then combined into a Simple Feature Collection with `st_sfc()`. which is nothing other than a simple feature geometry list-column. The `sfc` object also holds the bounding box and the projection information.

III. Add attributes.

Lastly, we add the attributes to the the simple feature collection with the `st_sf()` function. This function extends the well known data frame in R with a column that holds the simple feature collection.

So if we created the same highway object from above as `sf` object we would first generate LINESTRINGs as simple feature geometries out of a matrix with coordinates:

```
lnstr_sfg1 <- st_linestring(matrix(runif(6), ncol=2))
lnstr_sfg2 <- st_linestring(matrix(runif(6), ncol=2))
class(lnstr_sfg1)
```

```
#> [1] "XY"         "LINESTRING" "sfg"
```

We would then combine this into a simple feature collection :

```
(lnstr_sfc <- st_sfc(lnstr_sfg1, lnstr_sfg2)) # just one feature here
```

```
#> Geometry set for 2 features
#> geometry type:  LINESTRING
#> dimension:      XY
#> bbox:           xmin: 0.1538548 ymin: 0.0949929 xmax: 0.9989873 ymax: 0.9816153
#> epsg (SRID):    NA
#> proj4string:    NA
#> LINESTRING (0.6232523 0.8006577, 0.9429675 0.26...
#> LINESTRING (0.1848177 0.2227957, 0.9989873 0.98...
```

And lastly use our data frame from above to generate the `sf` object:

```
(lnstr_sf <- st_sf(dfr , lnstr_sfc))
```

```
#> Simple feature collection with 2 features and 2 fields
#> geometry type:  LINESTRING
#> dimension:      XY
#> bbox:           xmin: 0.1538548 ymin: 0.0949929 xmax: 0.9989873 ymax: 0.9816153
#> epsg (SRID):    NA
#> proj4string:    NA
#>     id cars_per_hour                       lnstr_sfc
#> 1 hwy1            78 LINESTRING (0.6232523 0.800...
```

```
#> 2 hwy2            22 LINESTRING (0.1848177 0.222...
```

There are many methods available in the `sf` package, to find out use

```
methods(class="sf")
```

```
#>  [1] [                    [[<-                 $<-
#>  [4] aggregate            anti_join            arrange
#>  [7] as.data.frame        cbind                coerce
#> [10] dbDataType           dbWriteTable         distinct
#> [13] extent               extract              filter
#> [16] full_join            group_by             identify
#> [19] initialize           inner_join           left_join
#> [22] mask                 merge                mutate
#> [25] plot                 print                raster
#> [28] rasterize            rbind                rename
#> [31] right_join           sample_frac          sample_n
#> [34] select               semi_join            show
#> [37] slice                slotsFromS3          st_agr
#> [40] st_agr<-             st_area              st_as_sf
#> [43] st_bbox              st_boundary          st_buffer
#> [46] st_cast              st_centroid          st_collection_extract
#> [49] st_convex_hull       st_coordinates       st_crop
#> [52] st_crs               st_crs<-             st_difference
#> [55] st_geometry          st_geometry<-        st_intersection
#> [58] st_is                st_line_merge        st_nearest_points
#> [61] st_node              st_point_on_surface  st_polygonize
#> [64] st_precision         st_segmentize        st_set_precision
#> [67] st_simplify          st_snap              st_sym_difference
#> [70] st_transform         st_triangulate       st_union
#> [73] st_voronoi           st_wrap_dateline     st_write
#> [76] st_zm                summarise            transmute
#> [79] ungroup
#> see '?methods' for accessing help and source code
```

Here are some of the other highlights of `sf` you might be interested in:

- provides **fast** I/O, particularly relevant for large files
- spatial fuctions that rely on GEOS and GDAL and PROJ external libraries are directluy linked into the package, so no need to load additional external packages (like in `sp`)
- `sf` objects can be plotted directly with `ggplot`
- `sf` directly reads from and writes to spatial **databases** such as PostGIS
- `sf` is compatible with the `tidyvderse` approach, (but see some pitfalls here)

Note that `sp` and `sf` are not the only way spatial objects are conceptualized in R. Other spatial packages may use their own class definitions for spatial data (for example `spatstat`).

There are packages specifically for the GeoJSON and for that reason are more lightweight, for example:

- `geojson` and
- `geoops` - (demo)

Usuallly you can find functions that convert objects to and from these formats.

Challenge

Similarly to the example above generate a Point object in R. Use both, the `sp` and the `sf` "approach".

1. Create a matrix `pts` of random numbers with two columns and as many rows as you like. These are your points.
2. Create a dataframe `attrib_df` with the same number of rows as your `pts` matrix and a column that holds an attribute. You can make up any attribute.
3. Use the appropriate commands and `pts` to create

- a `SpatialPointsDataFrame` and
- an `sf` object with a gemoetry column of class `sfc_POINT`.

4. Try to subset your spatial object using the attribute you have added and the way you are used to from regular data frames.
5. How do you determine the bounding box of your spatial object?

1.2 Creating a spatial object from a lat/lon table

Often in your research might have a spreadsheet that contains latitude, longitude and perhaps some attribute values. You know how to read the spreadsheet into a data frame with `read.table` or `read.csv`. We can then very easily convert the table into a spatial object in R.

1.2.1 With `sf`

An `sf` object can be created from a data frame in the following way. We take advantage of the `st_as_sf()` function which converts any foreign object into an `sf` object. Similarly to above, it requires an argument `coords`, which in the case of point data needs to be a vector that specifies the data frame's columns for the longitude and latitude (x,y) coordinates.

```
my_sf_object <- st_as_sf(myDataframe, coords)
```

`st_as_sf()` creates a new object and leaves the original data frame untouched.

We use `read.csv()` to read `philly_homicides.csv` into a dataframe in R and name it `philly_homicides_df`.

```
philly_homicides_df <- read.csv("data/philly_homicides.csv")
str(philly_homicides_df )
```

```
#> 'data.frame':    3883 obs. of  10 variables:
#>  $ DC_DIST          : int  22 1 1 1 1 1 1 1 1 1 ...
#>  $ SECTOR           : Factor w/ 30 levels "1","2","3","4",..: 1 6 6 6 9 10 6 14 14 5 ...
#>  $ DISPATCH_DATE    : Factor w/ 2228 levels "2006-01-01","2006-01-02",..: 2139 10 62 90 125 132 133 1
#>  $ DISPATCH_TIME    : Factor w/ 1263 levels "00:00:00","00:01:00",..: 799 1 804 561 633 981 1224 86 1
#>  $ LOCATION_BLOCK   : Factor w/ 3305 levels " 100 E CHAMPLOST AVE",..: 595 745 3135 806 828 588 579 8
#>  $ UCR_GENERAL      : int  100 100 100 100 100 100 100 100 100 100 ...
#>  $ OBJ_ID           : int  1 1 1 1 1 1 1 1 1 1 ...
#>  $ TEXT_GENERAL_CODE: Factor w/ 4 levels "Homicide - Criminal",..: 1 1 1 1 1 2 1 1 1 1 ...
#>  $ POINT_X          : num  -75.2 -75.2 -75.2 -75.2 -75.2 ...
#>  $ POINT_Y          : num  40 39.9 39.9 39.9 39.9 ...
```

We convert the `philly_homicides_df` data frame into an `sf` object with `st_as_sf()`

```
philly_homicides_sf <- st_as_sf(philly_homicides_df, coords = c("POINT_X", "POINT_Y"))
str(philly_homicides_sf)
```

```
#> Classes 'sf' and 'data.frame':   3883 obs. of  9 variables:
```

```
#>  $ DC_DIST          : int  22 1 1 1 1 1 1 1 1 ...
#>  $ SECTOR           : Factor w/ 30 levels "1","2","3","4",..: 1 6 6 6 9 10 6 14 14 5 ...
#>  $ DISPATCH_DATE    : Factor w/ 2228 levels "2006-01-01","2006-01-02",..: 2139 10 62 90 125 132 133 1
#>  $ DISPATCH_TIME    : Factor w/ 1263 levels "00:00:00","00:01:00",..: 799 1 804 561 633 981 1224 86 1
#>  $ LOCATION_BLOCK   : Factor w/ 3305 levels " 100 E CHAMPLOST AVE",..: 595 745 3135 806 828 588 579 8
#>  $ UCR_GENERAL      : int  100 100 100 100 100 100 100 100 100 100 ...
#>  $ OBJ_ID           : int  1 1 1 1 1 1 1 1 1 1 ...
#>  $ TEXT_GENERAL_CODE: Factor w/ 4 levels "Homicide - Criminal",..: 1 1 1 1 1 2 1 1 1 1 ...
#>  $ geometry         :sfc_POINT of length 3883; first list element:  'XY' num  -75.2 40
#>  - attr(*, "sf_column")= chr "geometry"
#>  - attr(*, "agr")= Factor w/ 3 levels "constant","aggregate",..: NA NA NA NA NA NA NA NA
#>   ..- attr(*, "names")= chr  "DC_DIST" "SECTOR" "DISPATCH_DATE" "DISPATCH_TIME" ...
```

Note the additional **geometry** list-column which now holds the simple feature collection with the coordinates of all the points.

To make it a complete geographical object we assign the WGS84 projection, which has the EPSG code 4326:

```
st_crs(philly_homicides_sf)
```

```
#> Coordinate Reference System: NA
```

```
st_crs(philly_homicides_sf) <- 4326 # we can use EPSG as numeric here
st_crs(philly_homicides_sf)
```

```
#> Coordinate Reference System:
#>   EPSG: 4326
#>   proj4string: "+proj=longlat +datum=WGS84 +no_defs"
```

We will save this object as a shapefile on our hard drive for later use. (Note that by default `st_write` checks if the file already exists, and if so it will not overwrite it. If you need to force it to overwrite use the option `delete_layer = TRUE`.)

```
st_write(philly_homicides_sf, "data/PhillyHomicides", driver = "ESRI Shapefile")
# to force the save:
st_write(philly_homicides_sf, "data/PhillyHomicides", driver = "ESRI Shapefile", delete_layer = TRUE)
```

1.2.2 With sp

A `SpatialPointsDataFrame` object can be created directly from a table by specifying which columns contain the coordinates. This can be done in one step by using the `coordinates()` function. As mentioned above this function can be used not only to retrieve spatial coordinates but also to set them, which is done in R fashion with:

```
coordinates(myDataframe) <- value
```

`value` can have different forms – in this context needs to be a character vector which specifies the data frame's columns for the longitude and latitude (x,y) coordinates.

If we use this on a data frame it automatically converts the data frame object into a `SpatialPointsDataFrame` object.

Below, we convert the `philly_homicides_df` data frame into a spatial object with using the `coordinates` function and check with `class(philly_homicides_df)`again to examine which object class the table belongs to now. Note that the `coordinates()` function if used in this way **replaces the original data frame.**

```
coordinates(philly_homicides_df) <- c("POINT_X", "POINT_Y")
class(philly_homicides_df) # !!
```

```
#> [1] "SpatialPointsDataFrame"
#> attr(,"package")
#> [1] "sp"
```

Assigning the projection:

```
is.projected(philly_homicides_df) # see if a projection is defined
```

```
#> [1] NA
```

```
proj4string(philly_homicides_df) <- CRS("+init=epsg:4326") # this is WGS84
is.projected(philly_homicides_df) # voila! hm. wait a minute..
```

```
#> [1] FALSE
```

To save the `sp` object out as a shapefile we need to load another library, called `rgdal` (more on this below.)

```
# to save out using writeOGR from rgdal
library(rgdal)

# note that we need to save the philly_homicides_df, which we converted to sp object!
writeOGR(philly_homicides_df, "data/PhillyHomicides", "PhillyHomcides", driver = "ESRI Shapefile")
# to force save:
writeOGR(philly_homicides_df, "data/PhillyHomicides", "PhillyHomcides", driver = "ESRI Shapefile", overw
```

1.3 Loading shape files into R

1.3.1 How to do this in `sf`

`sf` relies on the powerful GDAL library, which is automatically linked in when loading `sf`. We can use `st_read()`, which simply takes the path of the directory with the shapefile as argument.

```
# read in
philly_sf <- st_read("data/Philly/")
```

```
#> Reading layer `PhillyTotalPopHHinc' from data source `/Users/cengel/Anthro/R_Class/R_Workshops/R-spat
#> Simple feature collection with 384 features and 17 fields
#> geometry type:  MULTIPOLYGON
#> dimension:      XY
#> bbox:           xmin: 1739497 ymin: 457343.7 xmax: 1764030 ymax: 490544.9
#> epsg (SRID):    NA
#> proj4string:    +proj=aea +lat_1=29.5 +lat_2=45.5 +lat_0=37.5 +lon_0=-96 +x_0=0 +y_0=0 +ellps=GRS80 +
```

```
# take a look at what we've got
str(philly_sf) # note again the geometry column
```

```
#> Classes 'sf' and 'data.frame':   384 obs. of  18 variables:
#>  $ STATEFP10 : Factor w/ 1 level "42": 1 1 1 1 1 1 1 1 1 1 ...
#>  $ COUNTYFP10: Factor w/ 1 level "101": 1 1 1 1 1 1 1 1 1 1 ...
#>  $ TRACTCE10 : Factor w/ 384 levels "000100","000200",..: 347 350 353 329 326 345 46 82 173 15 ...
#>  $ GEOID10   : Factor w/ 384 levels "42101000100",..: 347 350 353 329 326 345 46 82 173 15 ...
#>  $ NAME10    : Factor w/ 384 levels "1","10.01","10.02",..: 281 284 287 262 259 279 299 354 86 3 ...
#>  $ NAMELSAD10: Factor w/ 384 levels "Census Tract 1",..: 281 284 287 262 259 279 299 354 86 3 ...
#>  $ MTFCC10   : Factor w/ 1 level "G5020": 1 1 1 1 1 1 1 1 1 1 ...
#>  $ FUNCSTAT10: Factor w/ 1 level "S": 1 1 1 1 1 1 1 1 1 1 ...
#>  $ ALAND10   : num  2322732 4501110 1004313 1271533 1016206 ...
```

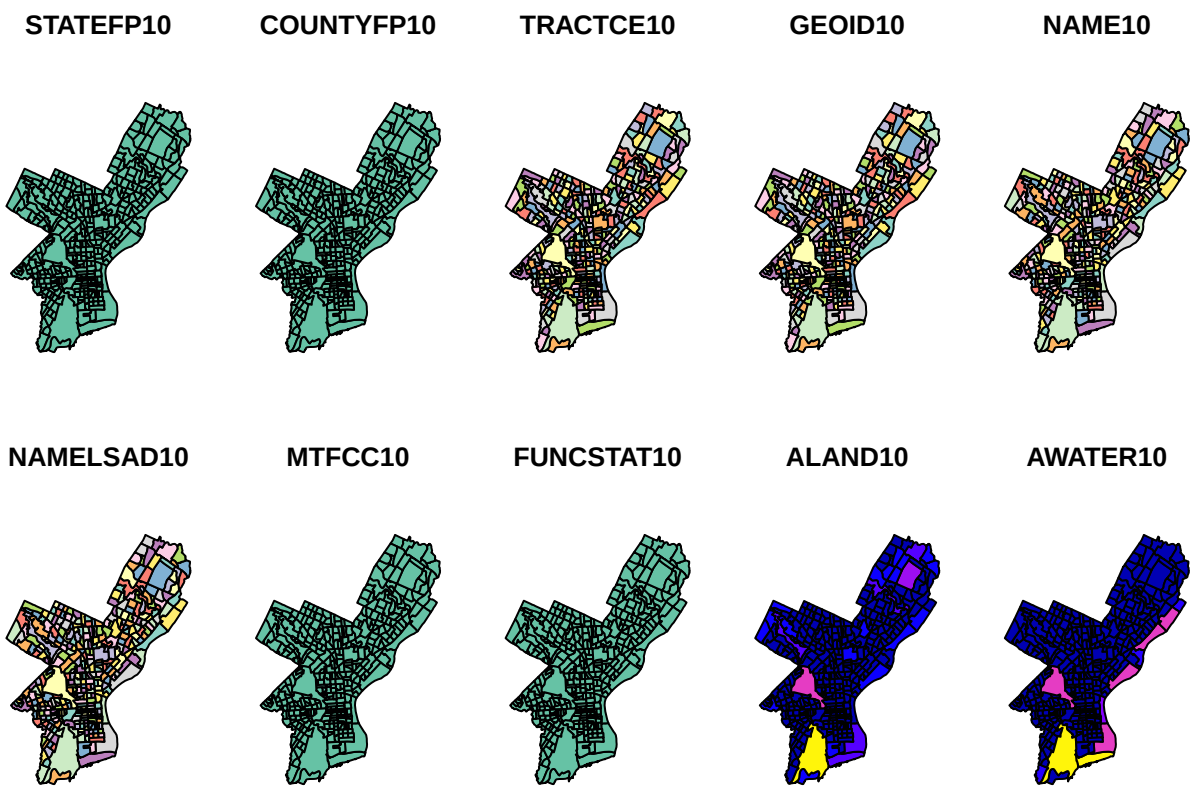
```
#>  $ AWATER10  : num  66075 8014 1426278 8021 0 ...
#>  $ INTPTLAT10: Factor w/ 384 levels "+39.8798897",..: 369 380 68 333 325 368 16 93 188 63 ...
#>  $ INTPTLON10: Factor w/ 384 levels "-074.9667387",..: 1 5 137 14 27 4 272 367 119 147 ...
#>  $ GISJOIN   : Factor w/ 384 levels "G4201010000100",..: 347 350 353 329 326 345 46 82 173 15 ...
#>  $ Shape_area: num  2388806 4509124 2430591 1279556 1016207 ...
#>  $ Shape_len : num  6851 10567 9257 4928 5920 ...
#>  $ medHHinc  : num  54569 NA 130139 56667 69981 ...
#>  $ totalPop  : num  3695 703 1643 4390 3807 ...
#>  $ geometry  :sfc_MULTIPOLYGON of length 384; first list element: List of 1
#>   ..$ :List of 1
#>   .. ..$ : num [1:55, 1:2] 1763647 1763473 1763366 1763378 1763321 ...
#>   ..- attr(*, "class")= chr  "XY" "MULTIPOLYGON" "sfg"
#>  - attr(*, "sf_column")= chr "geometry"
#>  - attr(*, "agr")= Factor w/ 3 levels "constant","aggregate",..: NA NA NA NA NA NA NA NA NA NA ...
#>   ..- attr(*, "names")= chr  "STATEFP10" "COUNTYFP10" "TRACTCE10" "GEOID10" ...
```

Two more words about the geometry column: You can name this column any way you wish. Secondly, you can remove this column and revert to a regular, non-spatial data frame at any dime wiht `st_drop_geometry()`.

The default `plot` of an `sf` object is a multi-plot of the first attributes, with a warning if not all can be plotted:

```
plot(philly_sf)
```

```
#> Warning: plotting the first 10 out of 17 attributes; use max.plot = 17 to
#> plot all
```



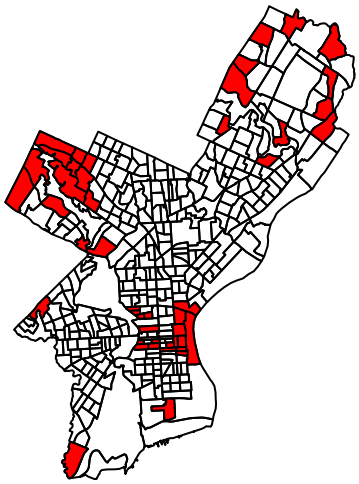
In order to only plot the polygon boundaries we need to directly use the geometry column. We use the `st_geometry()` function to extract it:

```
plot(st_geometry(philly_sf))
```

Let's add a subset of polygons with only the census tracts where the median houshold income is more than $60,000. We can extract elements from an `sf` object based on attributes using your prefered method of subsetting data frames.

```
# subset the familar way
philly_sf_rich <- philly_sf[philly_sf$medHHinc > 60000, ]
# or
philly_sf_rich <- subset(philly_sf, medHHinc > 60000)

plot(st_geometry(philly_sf_rich), add=T, col="red")
```



Piping works as well!

```
library(dplyr)
philly_sf %>%
  filter(medHHinc > 60000) %>%
  st_geometry() %>%
  plot(col="red", add=T)
```

1.3.2 How to work with rgdal and sp

In order to read spatial data into R and turn them into Spatial* family objects we require the rgdal package, which provides bindings to GDAL[4].

We can read in and write out spatial data using:

```
readOGR() and writeOGR() (for vector)
readGDAL() and writeGDAL() (for raster/grids)
```

The parameters provided for each function vary depending on the exact spatial file type you are reading. We will take an ESRI shapefile as an example. A shapefile - as you know - consists of various files of the same name, but with different extensions. They should all be in one directory and that is what R expects.

When reading in a shapefile, readOGR() requires the following two arguments:

```
datasource name (dsn)  # the path to the folder that contains the files
                       # this is a path to the folder, not a filename!
layer name (layer)     # the shapefile name WITHOUT extension
                       # this is not a path but just the name of the file!
```

Setting these arguments correctly can be cause of much headache for beginners, so let me spell it out:

- Firstly, you obviously need to know the name of shapefile.
- Secondly, you need to know the name and location of the folder that contains all the shapefile parts.
- Lastly, readOGR only reads the file and dumps it on your screen. But similarly when reading csv tables you want to actually work with the file, so you need to assign it to an R object.

Now let's do this.

We load the rgdal package and read PhillyTotalPopHHinc into an object called philly by using the readOGR function[5]. We can also examine the object and confirm what it is with class().

```
library(rgdal)
philly_sp <- readOGR("data/Philly/", "PhillyTotalPopHHinc")
```

```
#> OGR data source with driver: ESRI Shapefile
#> Source: "/Users/cengel/Anthro/R_Class/R_Workshops/R-spatial/data/Philly", layer: "PhillyTotalPopHHinc
#> with 384 features
#> It has 17 fields
```

```
class(philly_sp)
```

```
#> [1] "SpatialPolygonsDataFrame"
#> attr(,"package")
#> [1] "sp"
```

Very similarly to the above we can create a simple plot of the polygons with the plot command, which directly understands the SpatialPolygonsDatafame object and then plot a subset of polygons with a median household income (medHHinc) of over $60,000 on top of the plot of the entire city.

```
plot(philly_sp)
philly_sp_rich <- subset(philly_sp, medHHinc > 60000)
plot(philly_sp_rich, add=T, col="red")
```

[4]GDAL supports over 200 raster formats and vector formats. Use ogrDrivers() and gdalDrivers() (without arguments) to find out which formats your rgdal install can handle.

[5]Unlike read.csv readOGR does not understand the ~ as valid element of a path. This (on Mac) will not work: philly_sp <- readOGR("~/Desktop/data/Philly/", "PhillyTotalPopHHinc")

1.4 Raster data in R

Raster files, as you might know, have a much more compact data structure than vectors. Because of their regular structure the coordinates do not need to be recorded for each pixel or cell in the rectangular extent. A raster is defined by:

- a CRS
- coordinates of its origin
- a distance or cell size in each direction
- a dimension or numbers of cells in each direction
- an array of cell values

Given this structure, coordinates for any cell can be computed and don't need to be stored.

The `raster` package[6] is a major extension of spatial data classes to access large rasters and in particular to process very large files. It includes object classes for `RasterLayer`, `RasterStacks`, and `RasterBricks`, functions for converting among these classes, and operators for computations on the raster data. Conversion from `sp` type objects into `raster` type objects is possible.

If we wanted to do create a raster object from scratch we would do the following:

```
# specify the RasterLayer with the following parameters:
# - minimum x coordinate (left border)
# - minimum y coordinate (bottom border)
# - maximum x coordinate (right border)
# - maximum y coordinate (top border)
# - resolution (cell size) in each dimension
r <- raster(xmn=-0.5, ymn=-0.5, xmx=4.5, ymx=4.5, resolution=c(1,1))
r
```

```
#> class       : RasterLayer
#> dimensions  : 5, 5, 25  (nrow, ncol, ncell)
#> resolution  : 1, 1  (x, y)
#> extent      : -0.5, 4.5, -0.5, 4.5  (xmin, xmax, ymin, ymax)
#> coord. ref. : +proj=longlat +datum=WGS84 +ellps=WGS84 +towgs84=0,0,0
```

Note that this raster object **has a CRS defined!** If the crs argument is missing when creating the Raster object, the x coordinates are within -360 and 360 and the y coordinates are within -90 and 90, the WGS84 projection is used by default!

Good to know.

To add some values to the cells we could the following.

```
class(r)
```

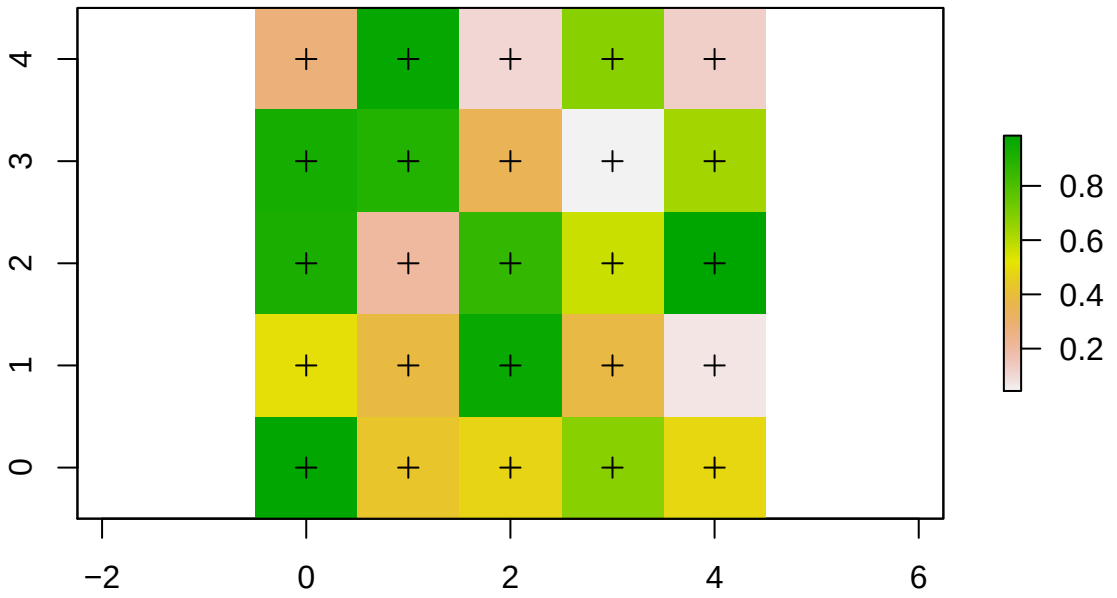
```
#> [1] "RasterLayer"
#> attr(,"package")
#> [1] "raster"
```

```
r <- setValues(r, runif(25))
class(r)
```

```
#> [1] "RasterLayer"
#> attr(,"package")
#> [1] "raster"
```

[6] Note that `sp` also allows to work with raster structures. The `GridTopology` class is the key element of raster representations. It contains: (a) the center coordinate pair of the south-west raster cell, (b) the two cell sizes in the metric of the coordinates, giving the step to successive centres, and (c) the numbers of cells for each dimension. There is also a `SpatialPixels` object which stores grid topology and coordinates of the actual points.

```
plot(r); points(coordinates(r), pch=3)
```



(See the `rasterVis` package for more advanced plotting of `Raster*` objects.)

RasterLayer objects can also be created from a matrix.

```
class(volcano)
```

```
#> [1] "matrix"
```

```
volcano.r <- raster(volcano)
class(volcano.r)
```

```
#> [1] "RasterLayer"
#> attr(,"package")
#> [1] "raster"
```

And to read in a raster file we can use the `raster()` function. This raster is generated as part of the NEON Harvard Forest field site.

```
library(raster)
HARV <- raster("data/HARV_RGB_Ortho.tif")
```

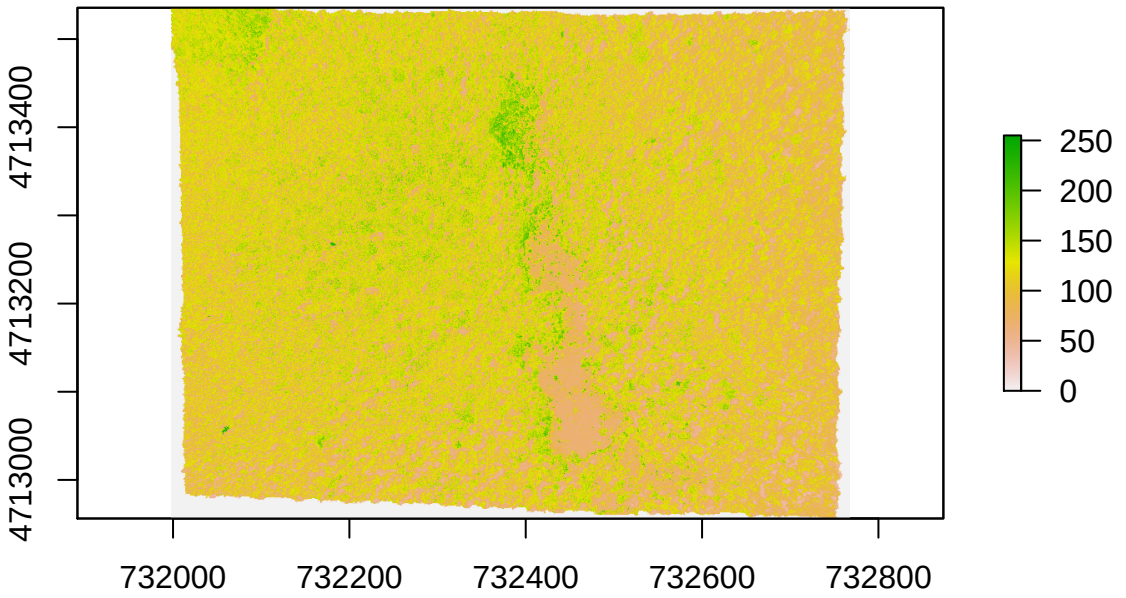
Typing the name of the object will give us what's in there:

```
HARV
```

```
#> class       : RasterLayer
#> band        : 1  (of  3  bands)
#> dimensions  : 2317, 3073, 7120141  (nrow, ncol, ncell)
#> resolution  : 0.25, 0.25  (x, y)
#> extent      : 731998.5, 732766.8, 4712956, 4713536  (xmin, xmax, ymin, ymax)
#> coord. ref. : +proj=utm +zone=18 +datum=WGS84 +units=m +no_defs +ellps=WGS84 +towgs84=0,0,0
#> data source : /Users/cengel/Anthro/R_Class/R_Workshops/R-spatial/data/HARV_RGB_Ortho.tif
#> names       : HARV_RGB_Ortho
#> values      : 0, 255  (min, max)
```

We can plot it like this:

```
plot(HARV)
```



We can find out about the Coordinate Reference System with this:

```
crs(HARV)
```

```
#> CRS arguments:
#>  +proj=utm +zone=18 +datum=WGS84 +units=m +no_defs +ellps=WGS84
#> +towgs84=0,0,0
```

See what you can do with such an object:

```
methods(class=class(HARV))
```

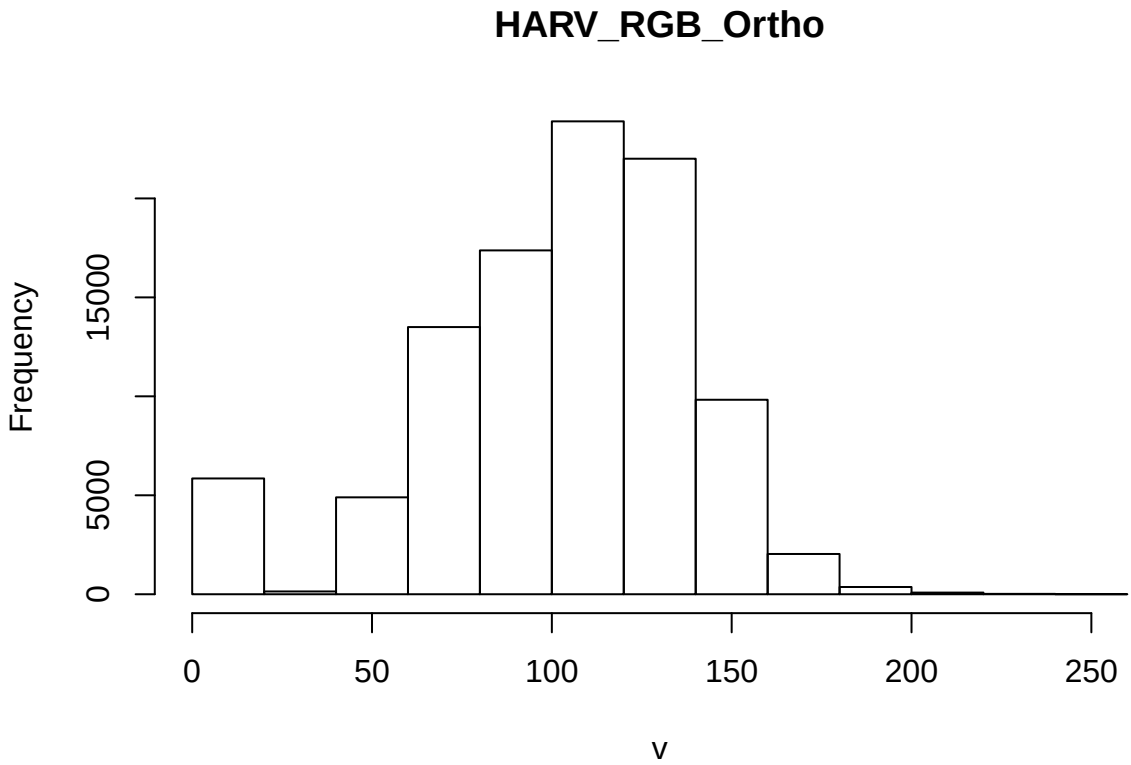
```
#>   [1] !                 !=                [                 [[
#>   [5] [<-               %in%              ==                $
#>   [9] $<-               addLayer          adjacent          aggregate
#>  [13] all.equal         area              Arith             as.array
#>  [17] as.character      as.data.frame     as.factor         as.integer
#>  [21] as.list           as.logical        as.matrix         as.raster
#>  [25] as.vector         asFactor          atan2             bandnr
#>  [29] barplot           bbox              boundaries        boxplot
#>  [33] brick             buffer            calc              cellFromRowCol
#>  [37] cellFromXY        cellStats         clamp             click
#>  [41] clump             coerce            colFromCell       colFromX
#>  [45] colSums           Compare           contour           coordinates
#>  [49] corLocal          cover             crop              crosstab
#>  [53] crs<-             cut               cv                density
#>  [57] dim               dim<-             direction         disaggregate
#>  [61] distance          extend            extent            extract
#>  [65] flip              focal             freq              getValues
#>  [69] getValuesBlock    getValuesFocal    gridDistance      head
#>  [73] hist              image             interpolate       intersect
#>  [77] is.factor         is.finite         is.infinite       is.na
#>  [81] is.nan            isLonLat          KML               labels
#>  [85] layerize          length            levels            levels<-
#>  [89] lines             localFun          log               Logic
```

```
#>  [93] mask             match            Math             Math2
#>  [97] maxValue         mean             merge            minValue
#> [101] modal            mosaic           names            names<-
#> [105] ncell            ncol             ncol<-           nlayers
#> [109] nrow             nrow<-           origin           origin<-
#> [113] overlay          persp            plot             predict
#> [117] print            proj4string      proj4string<-    quantile
#> [121] raster           rasterize        readAll          readStart
#> [125] readStop         reclassify       res              resample
#> [129] RGB              rotate           rowColFromCell   rowFromCell
#> [133] rowFromY         rowSums          sampleRandom     sampleRegular
#> [137] sampleStratified scale            select           setMinMax
#> [141] setValues        shift            show             spplot
#> [145] stack            stackSelect      subs             subset
#> [149] Summary          summary          t                tail
#> [153] text             trim             unique           update
#> [157] values           values<-         Which            which.max
#> [161] which.min        writeRaster      writeStart       writeStop
#> [165] writeValues      xFromCell        xFromCol         xmax
#> [169] xmin             xres             xyFromCell       yFromCell
#> [173] yFromRow         ymax             ymin             yres
#> [177] zonal            zoom
#> see '?methods' for accessing help and source code
```

We can explore the distribution of values contained within our raster using the hist() function which produces a histogram. Histograms are often useful in identifying outliers and bad data values in our raster data.

```
hist(HARV)
```

```
#> Warning in .hist1(x, maxpixels = maxpixels, main = main, plot = plot, ...):
#> 1% of the raster cells were used. 100000 values used.
```



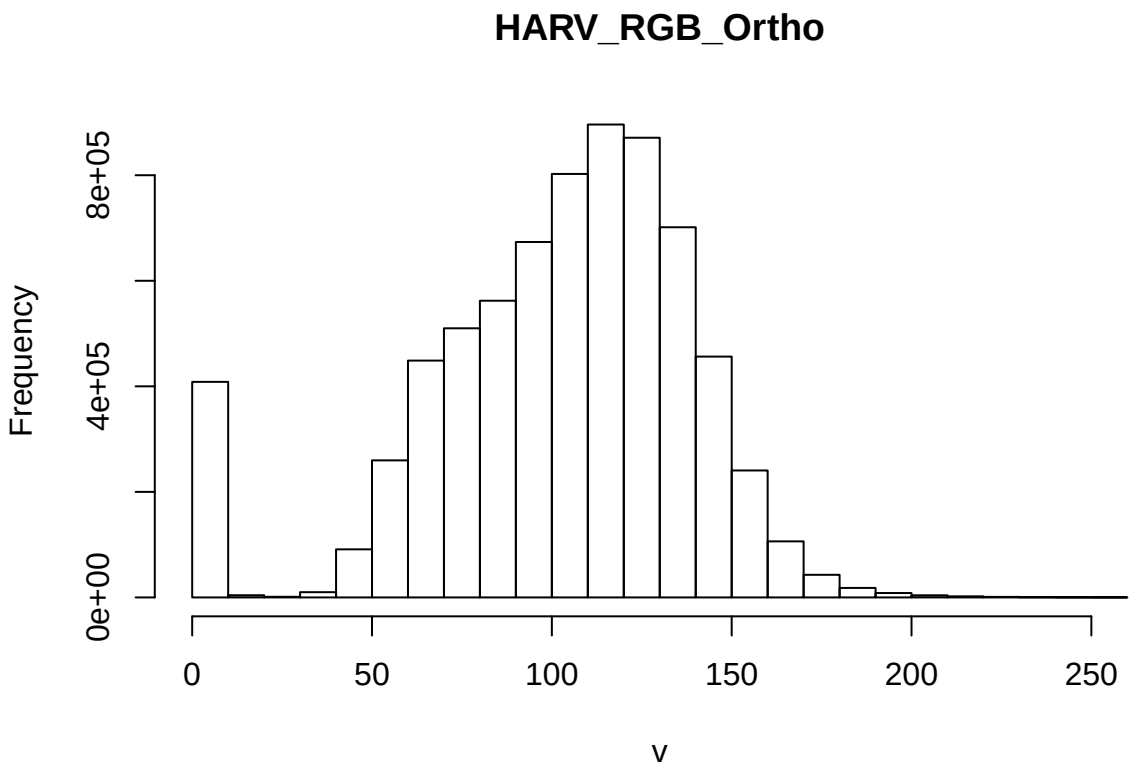
Notice that a warning message is produced when R creates the histogram.

This warning is caused by the default maximum pixels value of 100,000 associated with the hist function. This maximum value is to ensure processing efficiency as our data become larger! We can force the `hist` function to use all cell values.

```
ncell(HARV)
```

```
#> [1] 7120141
```

```
hist(HARV, maxpixels = ncell(HARV))
```



At times it may be useful to explore raster metadata before loading them into R. This can be done with:

```
GDALinfo("path-to-raster-here")
```

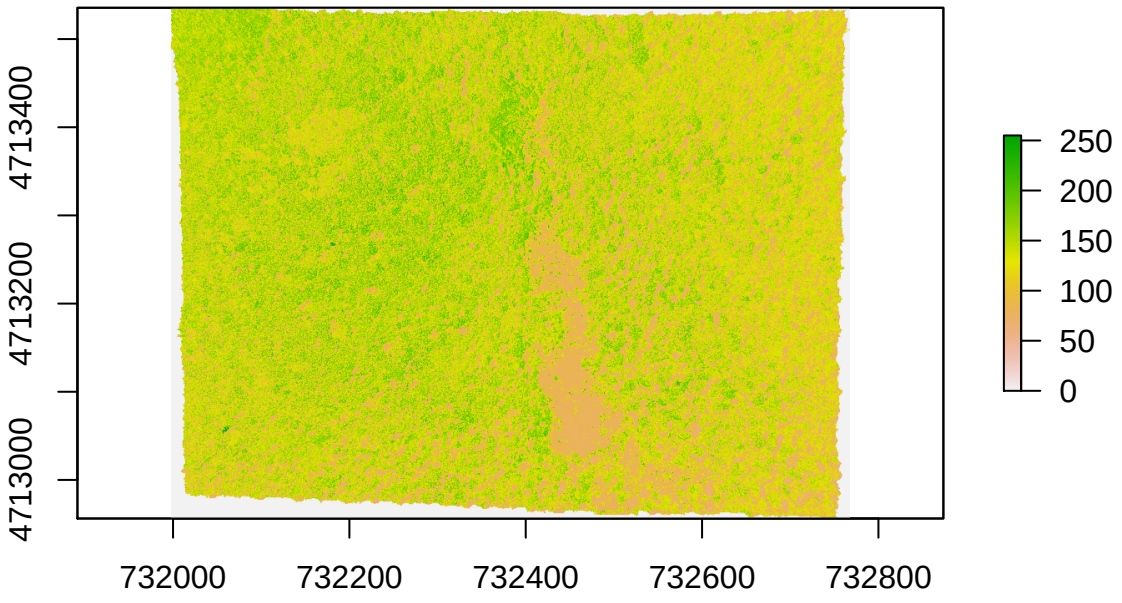
A raster dataset can contain one or more bands. We can view the number of bands in a raster using the `nlayers()` function.

```
nlayers(HARV)
```

```
#> [1] 1
```

We can use the `raster()` function to import one single band from a *single* **OR** from a *multi-band* raster. For multi-band raster, we can specify which band we want to read in.

```
HARV_Band2 <- raster("data/HARV_RGB_Ortho.tif", band = 2)
plot(HARV_Band2)
```



To bring in all bands of a multi-band raster, we use the `stack()` function.

```
HARV_stack <- stack("data/HARV_RGB_Ortho.tif")

# how many layers?
nlayers(HARV_stack)
```

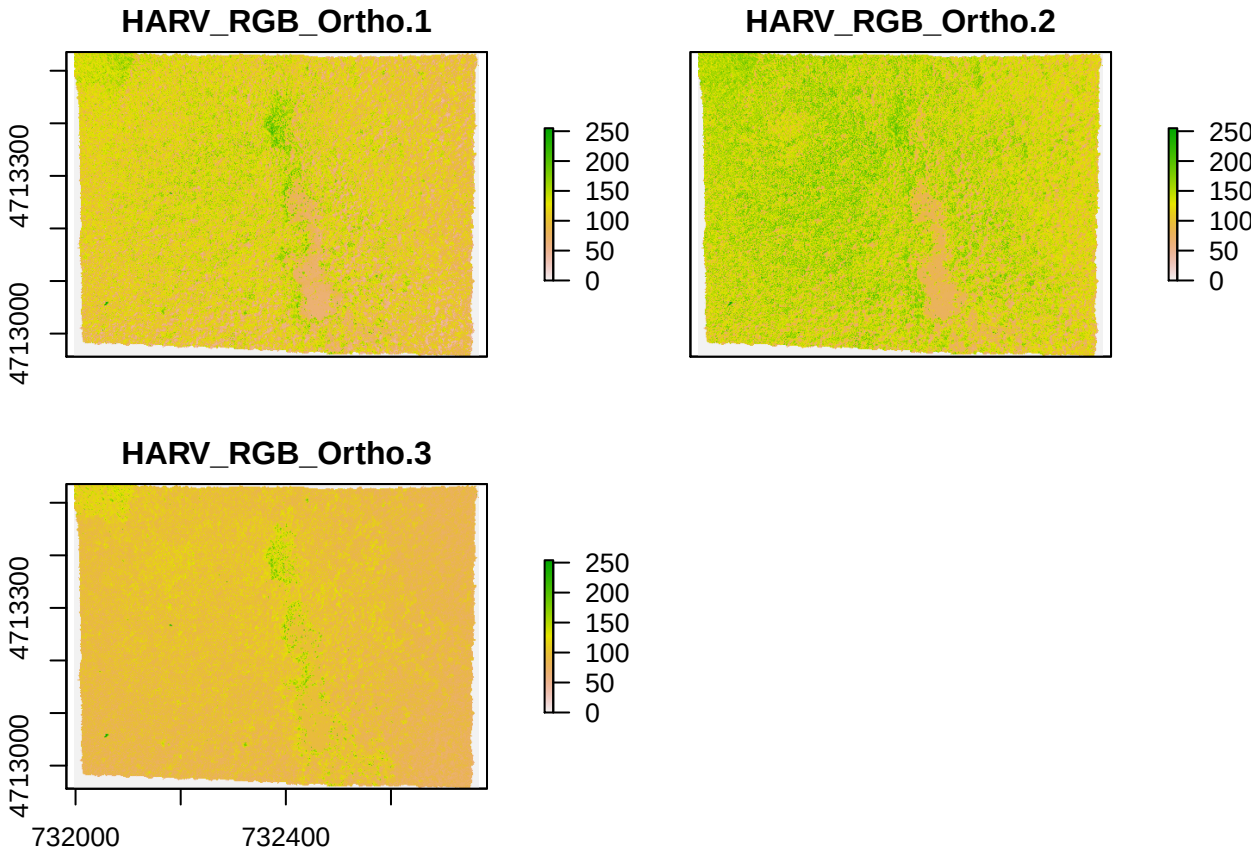
```
#> [1] 3
```

```
# view attributes of stack object
HARV_stack
```

```
#> class       : RasterStack
#> dimensions  : 2317, 3073, 7120141, 3  (nrow, ncol, ncell, nlayers)
#> resolution  : 0.25, 0.25  (x, y)
#> extent      : 731998.5, 732766.8, 4712956, 4713536  (xmin, xmax, ymin, ymax)
#> coord. ref. : +proj=utm +zone=18 +datum=WGS84 +units=m +no_defs +ellps=WGS84 +towgs84=0,0,0
#> names       : HARV_RGB_Ortho.1, HARV_RGB_Ortho.2, HARV_RGB_Ortho.3
#> min values  :                 0,                 0,                 0
#> max values  :               255,               255,               255
```

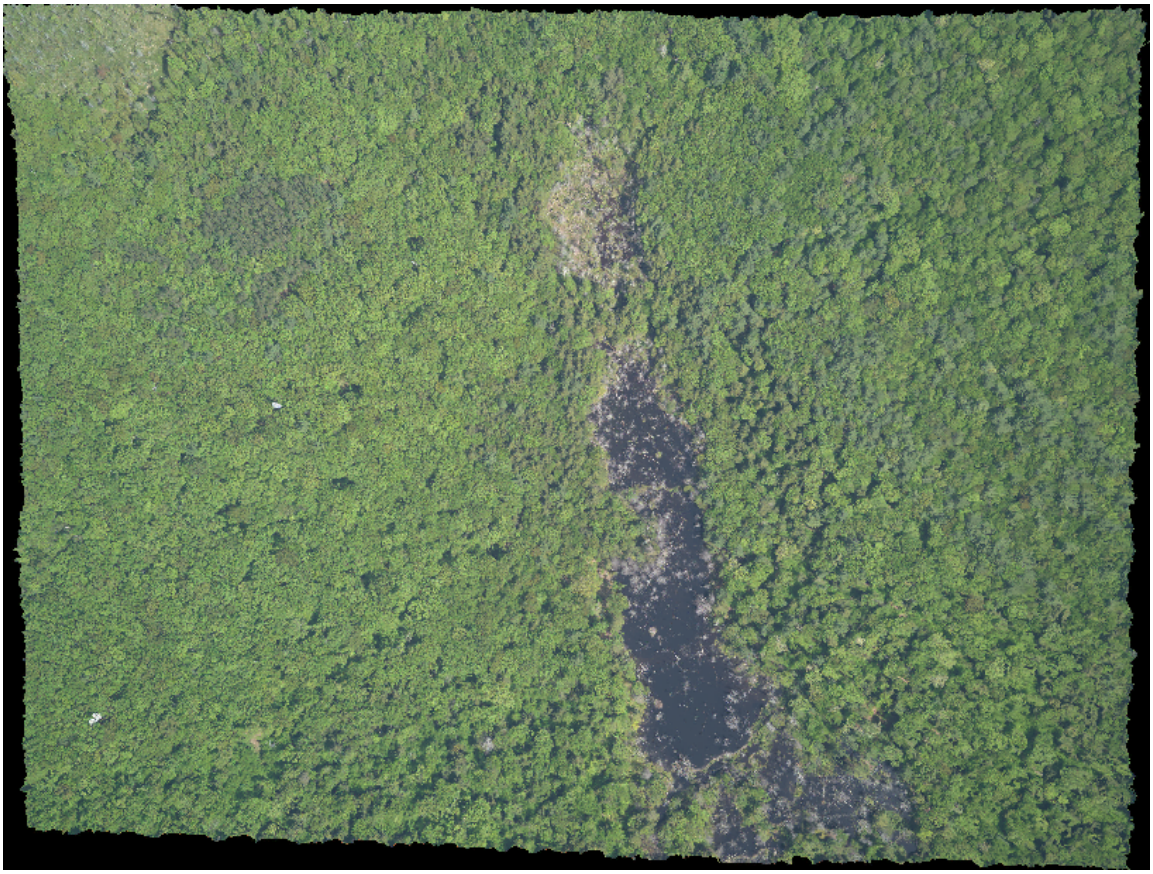
What happens when we plot?

```
plot(HARV_stack)
```



If we know that it is an RGB multiband raster we can plot them all in one

```
plotRGB(HARV_stack)
```



1.4.1 RasterStack vs RasterBrick

The R `RasterStack` and `RasterBrick` object types can both store multiple bands. However, how they store each band is different. The bands in a `RasterStack` are stored as links to raster data that is located somewhere on our computer. A `RasterBrick` contains all of the objects stored within the actual R object. Since in the `RasterBrick`, all of the bands are stored within the actual object its object size is much larger than the `RasterStack` object.

In most cases, we can work with a `RasterBrick` in the same way we might work with a `RasterStack`. However, a `RasterBrick` is often more efficient and faster to process - which is important when working with larger files.

We can turn a `RasterStack` into a `RasterBrick` in R by using `brick(StackName)`. Use the `object.size()` function to compare stack and brick R objects.

```
object.size(HARV_stack)
```

```
#> 44248 bytes
```

```
HARV_brick <- brick(HARV_stack)
object.size(HARV_brick)
```

```
#> 170897168 bytes
```

Going back to the `sp` package, a simple grid can be built like this:

```
# specify the grid topology with the following parameters:
# - the smallest coordinates for each dimension, here: 0,0
```

```
# - cell size in each dimension, here: 1,1
# - number of cells in each dimension, here: 5,5
gtopo <- GridTopology(c(0,0), c(1,1), c(5,5)) # create the grid
datafr <- data.frame(runif(25)) # make up some data
SpGdf <- SpatialGridDataFrame(gtopo, datafr) # create the grid data frame
summary(SpGdf)
```

```
#> Object of class SpatialGridDataFrame
#> Coordinates:
#>       min max
#> [1,] -0.5 4.5
#> [2,] -0.5 4.5
#> Is projected: NA
#> proj4string : [NA]
#> Grid attributes:
#>   cellcentre.offset cellsize cells.dim
#> 1                 0        1         5
#> 2                 0        1         5
#> Data attributes:
#>    runif.25.
#>  Min.   :0.008003
#>  1st Qu.:0.260418
#>  Median :0.494006
#>  Mean   :0.446363
#>  3rd Qu.:0.576674
#>  Max.   :0.885643
```

Chapter 2

Spatial data manipulation in R

Learning Objectives

- Join attribute data to a polygon vector file
- Reproject a vector file
- Select polygons of a vector by location

There are a wide variety of spatial, topological, and attribute data operations you can perform with R. Lovelace et al's recent publication[1] goes into great depth about this and is highly recommended.

In this section we will look at just a few examples for libraries and commands that allow us to process spatial data in R and perform a few commonly used operations.

2.1 Attribute Join

An attribute join on vector data brings tabular data into a geographic context. It refers to the process of joining data in tabular format to data in a format that holds the geometries (polygon, line, or point)[2].

If you have done attribute joins of shapefiles in GIS software like *ArcGIS* or *QGis* you know that you need a **unique identifier** in both the attribute table of the shapefile and the table to be joined.

First we will load the CSV table `PhiladelphiaEduAttain.csv` into a dataframe in R and name it `ph_edu`.

```
ph_edu <- read.csv("data/PhiladelphiaEduAttain.csv")
names(ph_edu)
```

2.1.1 How to do this in `sf`

If you don't have the object still loaded read the the `PhillyTotalPopHHinc` shapefile into an object named `philly_sf`. Check out the column names of `philly_sf` and of `ph_edu` to determine which one might contain the unique identifier for the join.

```
## sf ##
# if you need to read in again:
```

[1] Lovelace, R., Nowosad, J., & Muenchow, J. (2019). Geocomputation with R. CRC Press.

[2] Per the ESRI specification a shapefile must have an attribute table, so when we read it into R with the `readOGR` command from the `sp` package it automatically becomes a `Spatial*Dataframe` and the attribute table becomes the dataframe.

```
# philly_sf <- st_read("data/Philly/")
names(philly_sf)
```

To join the ph_edu data frame with philly_sf we can use merge like this:

```
philly_sf_merged <- merge(philly_sf, ph_edu, by.x = "GEOID10", by.y = "GEOID")
names(philly_sf_merged)
```

```
#>  [1] "GEOID10"         "STATEFP10"       "COUNTYFP10"
#>  [4] "TRACTCE10"       "NAME10"          "NAMELSAD10"
#>  [7] "MTFCC10"         "FUNCSTAT10"      "ALAND10"
#> [10] "AWATER10"        "INTPTLAT10"      "INTPTLON10"
#> [13] "GISJOIN"         "Shape_area"      "Shape_len"
#> [16] "medHHinc"        "totalPop"        "NAME"
#> [19] "fem_bachelor"    "fem_doctorate"   "fem_highschool"
#> [22] "fem_noschool"    "fem_ovr_25"      "male_bachelor"
#> [25] "male_doctorate"  "male_highschool" "male_noschool"
#> [28] "male_ovr_25"     "pop_ovr_25"      "geometry"
```

We see the new attribute columns added, as well as the geometry column.

2.1.2 The same with sp

In sp we have a Spatial*Dataframe that contains the geometries and an identifying index variable for each. We combine it with a dataframe, that includes the same index variable with additional variables.

The sp package has a merge command which extends the base merge command to work with Spatial* objects as argument[3].

```
## sp ##
# if you need to read in again:
# philly_sp <- readOGR("data/Philly/", "PhillyTotalPopHHinc")

# this is sp::merge()
philly_sp_merged <- merge(philly_sp, ph_edu, by.x = "GEOID10", by.y = "GEOID")
names(philly_sp_merged) # no geometry column here
```

(You may come across alternative suggestions for joins that operate on the data slot @data of the Spatial* object. While they may work, we don't suggest them here, as good practice suggests not to use the slot explicitly if at all possible.)

2.2 Topological Subsetting: Select Polygons by Location

For the next example our goal is to select all Philadelphia census tracts within a range of 2 kilometers from the city center.

Think about this for a moment – what might be the steps you'd follow?

```
## How about:

# 1. Get the census tract polygons.
# 2. Find the Philadelphia city center coordinates.
```

[3]The geo_join() command from the tigris package also provides a convenient way to merge a data frame to a spatial data frame.

```
# 3. Create a buffer around the city center point.
# 4. Select all census tract polygons that intersect with the center buffer
```

2.2.1 Using the sf package

We will use `philly_sf` for the census tract polygons.

In addition, we need to create a `sf` Point object with the Philadelphia city center coordinates:

$$x = 1750160$$

$$y = 467499.9$$

These coordinates are in the *USA Contiguous Albers Equal Area Conic* projected CRS and the EPSG code is 102003.

With this information, we create a object that holds the coordinates of the city center. Since we don't have attributes we will just create it as a simple feature collection, `scf`.

```
# if you need to read in again:
# philly_sf <- st_read("data/Philly/", quiet = T)

# make a simple feature point with CRS
philly_ctr_sfc <- st_sfc(st_point(c(1750160, 467499.9)), crs = 102003)
```

For the spatial operations we can recur to the suite of geometric operations that come with the `sf` package.

We create a 2km buffer around the city center point:

```
philly_buf_sf <- st_buffer(philly_ctr_sfc, 2000)
```

Ok. Now we can use that buffer to select all census tract polygons that intersect with the center buffer. In order to determine the polygons we use `st_intersects`, a geometric binary which returns a vector of logical values, which we we can use for subsetting. Note the difference to `st_intersection`, which performs a geometric operation and creates a new sf object which cuts out the area of the buffer from the polygons a like cookie cutter.

Let us try this:

```
philly_buf_intersects <- st_intersects(philly_buf_sf, philly_sf)

#> Error in st_geos_binop("intersects", x, y, sparse = sparse, prepared = prepared) :
#>   st_crs(x) == st_crs(y) is not TRUE
```

Oh, what happened? Are these projections not the same?

```
st_crs(philly_sf)
```

```
#> Coordinate Reference System:
#>   No EPSG code
#>   proj4string: "+proj=aea +lat_1=29.5 +lat_2=45.5 +lat_0=37.5 +lon_0=-96 +x_0=0 +y_0=0 +ellps=GRS80 +
```

```
st_crs(philly_buf_sf)
```

```
#> Coordinate Reference System:
#>   EPSG: 102003
#>   proj4string: "+proj=aea +lat_1=29.5 +lat_2=45.5 +lat_0=37.5 +lon_0=-96 +x_0=0 +y_0=0 +datum=NAD83 +
```

Ah. The difference seems to be that there is no EPSG code for `philly_sf`. Poking around the documentation we see that :

> …`st_read` typically reads the coordinate reference system as `proj4string`, but not the EPSG (SRID). GDAL cannot retrieve SRID (EPSG code) from proj4string strings, and, **when needed, it has to be set by the user**…

Ok, so we need to fix this.

```
st_crs(philly_sf) <- 102003
```

```
#> Warning: st_crs<- : replacing crs does not reproject data; use st_transform
#> for that
```

This warning is ok, we know what we are doing. So now try again:

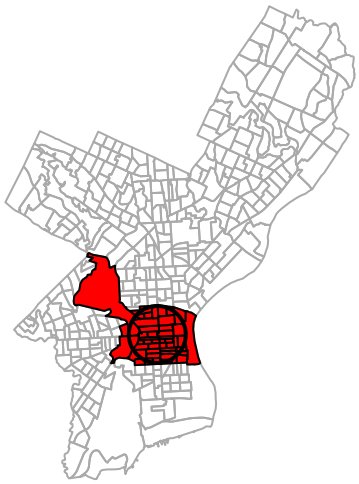
```
philly_buf_intersects <- st_intersects(philly_buf_sf, philly_sf)
class(philly_buf_intersects)
```

```
#> [1] "sgbp"
```

We have created a `sgbp` object, which is a "Sparse Geomtry Binary Predicate". It is a so called sparse matrix, which is a list with integer vectors only holding the indices for each polygon that intersects. In our case we only have one vector, because we only intersect with one buffer polygon, so we can extract this first vector with `philly_buf_intersects[[1]]` and use it for subsetting:

```
philly_sel_sf <- philly_sf[philly_buf_intersects[[1]],]

# plot
plot(st_geometry(philly_sf), border="#aaaaaa", main="Census tracts that fall within 2km of city center")
plot(st_geometry(philly_sel_sf), add=T, col="red")
plot(st_geometry(philly_buf_sf), add=T, lwd = 2)
```



2.2.2 Using the sp package

In order to perform those operations on an `sp` object we will need to make use of an additional package, called `rgeos`. Make sure you have it loaded.

```
library(rgeos)
# if you need to read it in again
# philly_sp <- readOGR("data/Philly/", "PhillyTotalPopHHinc", verbose = F)
```

We will use `philly_sp` for the census tract polygons.

Create a `SpatialPoints` object with the Philadelphia city center coordinates named `philly_ctr_sp`.

```
coords <- data.frame(x = 1750160, y = 467499.9) # set the coordinates
prj <- CRS("+proj=aea +lat_1=29.5 +lat_2=45.5 +lat_0=37.5 +lon_0=-96 +x_0=0 +y_0=0 +datum=NAD83 +units=m
philly_ctr_sp <- SpatialPoints(coords, proj4string = prj) # create the spatialPoints
```

Next, we create a buffer around the city center point.
Here is where we will use the `gBuffer()` function from the `rgeos` package. For this purpose we will need to provide two arguments: the **sp object** and the **width** of the buffer, which is assumed to be in map units. The function returns a `SpatialPolygons` object to you with the buffer.

```
philly_buf_sp <- gBuffer(philly_ctr_sp, width=2000)  # create buffer around center
```

We will use the `gIntersects()` function from the `rgeos` package to select all census tract polygons that intersect with the center buffer. The function tests if two geometries (let's name them *spgeom1* and *spgeom2*) have points in common or not. `gIntersects` returns TRUE if *spgeom1* and *spgeom2* have at least one point in common.

Here is where we determine if the census tracts fall within the buffer. In addition to our two `sp` objects (`philly_buf` and `philly_sp`) we need to provide one more argument, `byid`. It determines if the function should be applied across ids (TRUE) or the entire object (FALSE) for *spgeom1* and *spgeom2*. The default setting is FALSE. Since we want to compare *every single* census tract polygon in our `philly_sp` object we need to set it to TRUE. Then we subset the object with the census tract polygons.

```
philly_buf_intersects <-  gIntersects (philly_buf_sp, philly_sp, byid=TRUE)

# what kind of object is this?
class(philly_buf_intersects)

# subset
philly_sel_sp <- philly_sp[as.vector(philly_buf_intersects),]

# plot
plot (philly_sp, border="#aaaaaa")
plot (philly_sel_sp, add=T, col="red")
plot (philly_buf_sp, add=T, lwd = 2)
```

2.3 Reprojecting

Occasionally you may have to change the coordinates of your spatial object into a new Coordinate Reference System (CRS). Functions to transform, or *reproject* spatial objects typically take the following two arguments:

- the spatial object to reproject
- a CRS object with the new projection definition

You can reproject

- a `sf` object with `st_transform()`

- a `Spatial*` object with `spTransform()`
- a `raster` object with `projectRaster()`

The perhaps trickiest part here is to determine the definition of the projection, which needs to be a character string in proj4 format. You can look it up online. For example for UTM zone 33N (EPSG:32633) the string would be:

```
+proj=utm +zone=33 +ellps=WGS84 +datum=WGS84 +units=m +no_defs
```

You can retrieve the CRS:

- from an `sf` object with `st_crs()`
- from an existing `Spatial*` object with `proj4string()`
- from a `raster` object with `crs()`

Let us go back to the `"PhillyHomicides"` shapefile we exported earlier. Let's read it back in and reproject it so it matches the projection of the Philadelphia Census tracts.

Now let us check the CRS for both files.

```
#If you need to read the file back in:
#philly_homicides_sf <- st_read("data/PhillyHomicides/")

st_crs(philly_sf)
```

```
#> Coordinate Reference System:
#>   EPSG: 102003
#>   proj4string: "+proj=aea +lat_1=29.5 +lat_2=45.5 +lat_0=37.5 +lon_0=-96 +x_0=0 +y_0=0 +datum=NAD83 +
```

```
st_crs(philly_homicides_sf)
```

```
#> Coordinate Reference System:
#>   EPSG: 4326
#>   proj4string: "+proj=longlat +datum=WGS84 +no_defs"
```

We see that the CRS are different: we have `+proj=aea...` and `+proj=longlat....` AEA refers to USA Contiguous Albers Equal Area Conic which is a projected coordinate system with numeric units. We will need this below for our spatial operations, so we will make sure both files are in that same CRS.

We use `st_transform` and assign the result to a new object. Note how we also use `str_crs` to extract the projection defitition from `philly_sf`, so we don't have to type it out.

```
philly_homicides_sf_aea <- st_transform(philly_homicides_sf, st_crs(philly_sf))
```

We can use the `range()` command from the R base package to compare the coordinates before and after reprojection and confirm that we actually have transformed them. `range()` returns the *min* and *max* value of a vector of numbers.

```
range(st_coordinates(philly_homicides_sf))
```

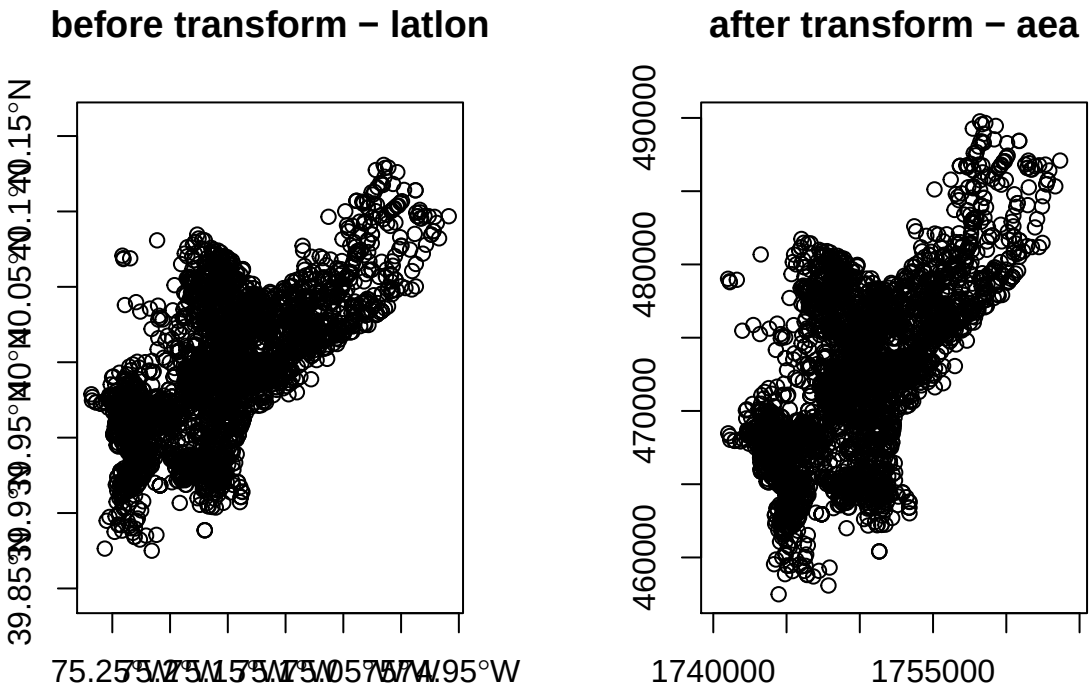
```
#> [1] -75.26809  40.13086
```

```
range(st_coordinates(philly_homicides_sf_aea))
```

```
#> [1]  457489.7 1763671.8
```

We can also compare them visually with:

```
par(mfrow=c(1,2))
plot(st_geometry(philly_homicides_sf), axes=TRUE, main = "before transform - latlon")
plot(st_geometry(philly_homicides_sf_aea), axes=TRUE, main = "after transform - aea")
```



Lastly, let us save the reprojected file as `PhillyHomicides_aea` shapefile, as we will use it later on.

```
st_write(philly_homicides_sf_aea, "data/PhillyHomicides_aea", driver = "ESRI Shapefile")
```

2.3.1 For sp

Below is the equivalent for `sp` objects. This is very similar, except that we wrap the `CRS` function ariound the result of `proj4string`, because `spTransform` requires a CRS object.

```
ph_homic_sp <- readOGR("data/PhillyHomicides/", "PhillyHomicides")
proj4string(philly_sp)
proj4string(philly_homicides_sp)
philly_homicides_sp_aea <- spTransform(philly_homicides_sp, CRS(proj4string(philly_sp)))

## check the coordinates ##
range(coordinates(ph_homic_aea_sp))
range(coordinates(ph_homic_sp))

## write out
writeOGR(philly_homicides_sp_aea, "data/PhillyHomicides_AEA", "PhillyHomcides_AEA", driver = "ESRI Shap
```

2.3.2 Raster reprojection

Here is what it would look like to reproject the HARV raster used earlier to a WGS84 projection. We see that the original projection is in UTM.

```
# if you need to load again:
#HARV <- raster("data/HARV_RGB_Ortho.tif")
crs(HARV)
```

```
#> CRS arguments:
#>  +proj=utm +zone=18 +datum=WGS84 +units=m +no_defs +ellps=WGS84
```

```
#> +towgs84=0,0,0
```

```
HARV_WGS84 <- projectRaster(HARV, crs="+init=epsg:4326")
```

Let's look at the coordinates to see the effect:

```
extent(HARV)
```

```
#> class       : Extent
#> xmin        : 731998.5
#> xmax        : 732766.8
#> ymin        : 4712956
#> ymax        : 4713536
```

```
extent(HARV_WGS84)
```

```
#> class       : Extent
#> xmin        : -72.17505
#> xmax        : -72.16544
#> ymin        : 42.53393
#> ymax        : 42.5394
```

```
ncell(HARV)
```

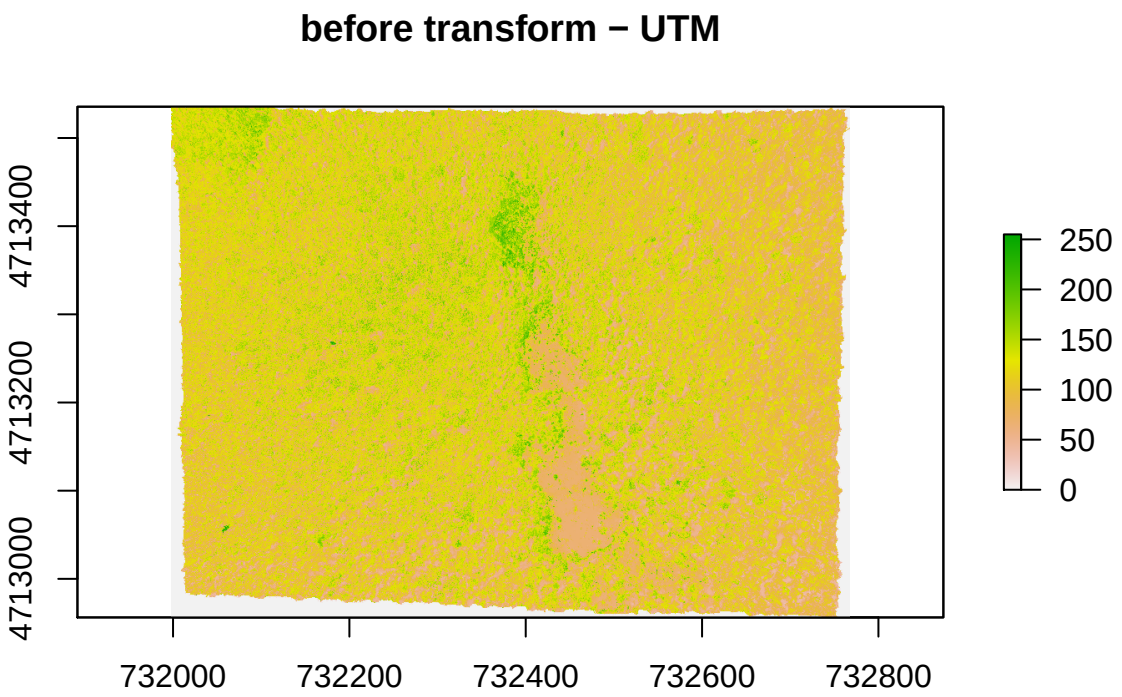
```
#> [1] 7120141
```

```
ncell(HARV_WGS84)
```

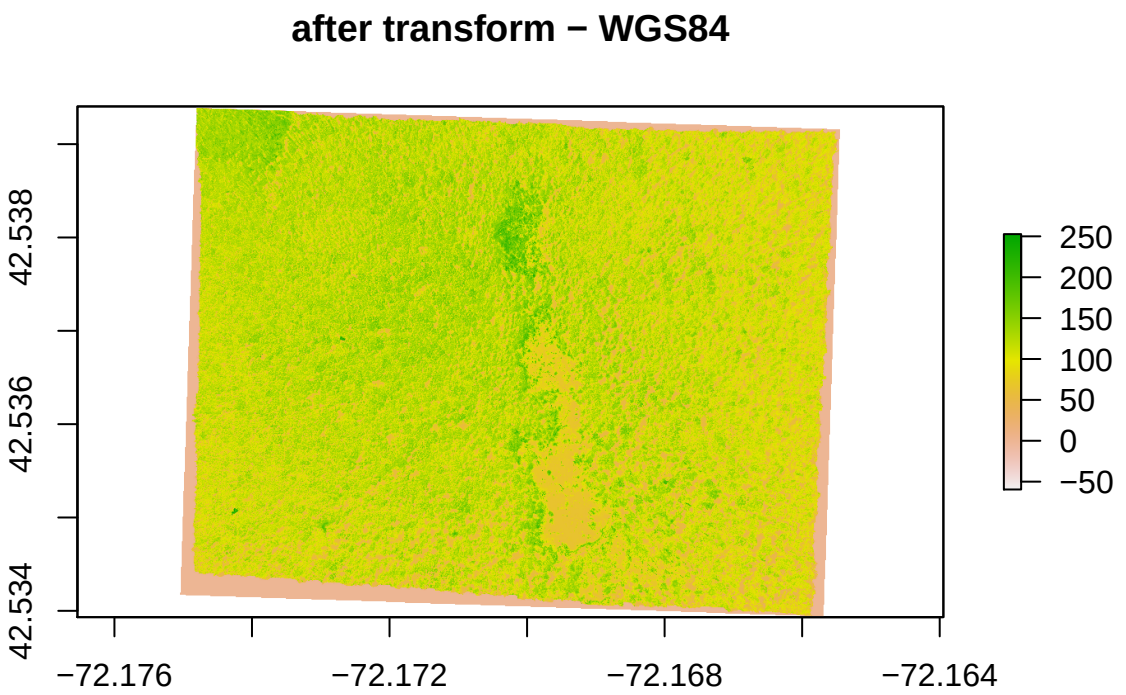
```
#> [1] 7687552
```

And here is the visual proof:

```
plot(HARV, main = "before transform - UTM")
```




```
plot(HARV_WGS84, main = "after transform - WGS84")
```



2.4 Spatial Aggregation: Points in Polygons

Now that we have both homicides and census tracts in the same projection we will forge ahead and ask for the density of homicides for **each census tract** in Philadelphia: $\frac{homicides}{area}$

To achieve this this we join the points of homicide incidence to the census tract polygon and count them up for each polygon. You might be familiar with this operation from other GIS packages.

2.4.1 With `sf`

We will use piping and build up our object in the following way. First we calculate the area for each tract. We use the `st_area` function on the geometry column and add the result.

```
philly_sf %>%
  mutate(tract_area = st_area(geometry)) %>%
  head()
```

Next, we use st_join to perform a spatial join with the points:

```
philly_sf %>%
  mutate(tract_area = st_area(geometry)) %>%
  st_join(philly_homicides_sf_aea) %>%
  head()
```

Now we can group by a variable that uiquely identifies the census tracts, (we choose *GEOID10*) and use `summarize` to count the points for each tract and calculate the homicide rate. Since our units are in sq meter. multiply by by 1000000 to get sq km. We also need to carry over the area, which I do using `unique`.

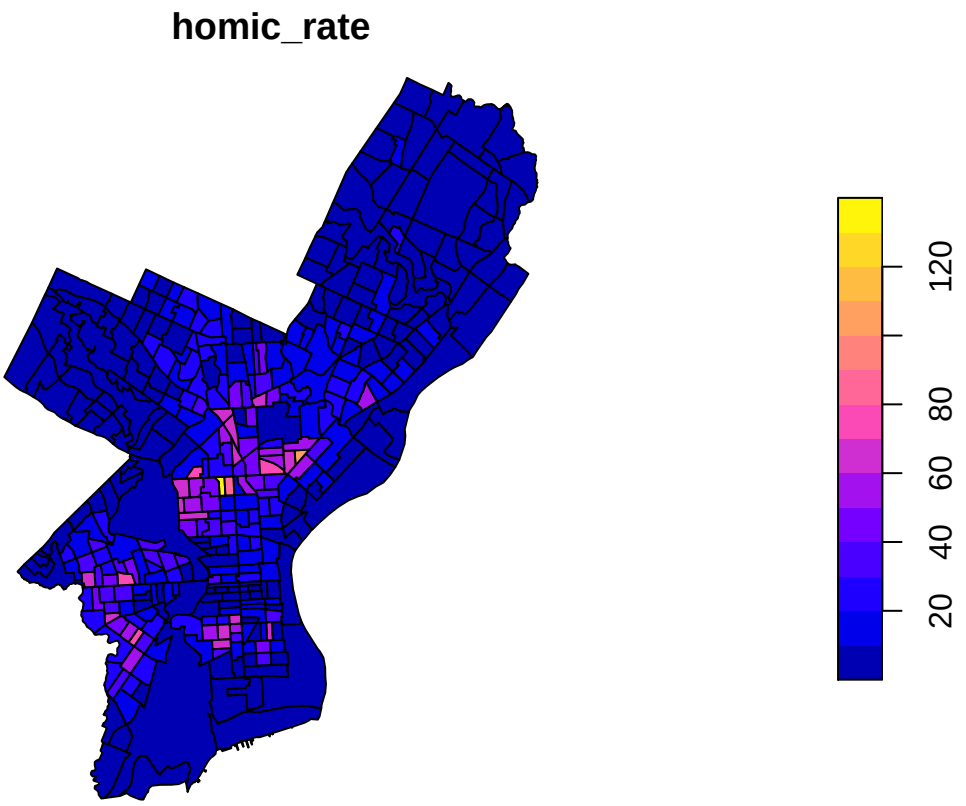
We also assign the output to a new object `crime_rate`.

```
crime_rate <- philly_sf %>%
      mutate(tract_area = st_area(geometry)) %>%
```

```
      st_join(philly_homicides_sf_aea) %>%
      group_by(GEOID10) %>%
      summarize(n_homic = n(),
                tract_area = unique(tract_area),
                homic_rate = n_homic/tract_area * 1e6)
```

And here is a simple plot:

```
plot(crime_rate["homic_rate"])
```



Finally, we write this out for later:

```
st_write(crime_rate, "data/PhillyCrimerate", driver = "ESRI Shapefile")
```

2.4.2 With sp

For `sp` objects we can use the `aggregate()` function[4]. Here are the arguments that it needs:

- the `SpatialPointDataframe`with the homicide incidents as point locations,
- the `SpatialPolygonDataframe` with the census tract polygons to aggregate on, and
- an aggregate function. Since we are interested in counting the points (i.e. the rows of all the points that belong to a certain polygon), we can use length (of the respective vectors of the aggregated data).

To count homicides per census tract we can use any field from `ph_homic_aea` for homicide incidents (we chose `OBJ_ID`) and `philly` polygons to aggregate on and save the result as `ph_hom_count`. Use `length` as aggregate function.

[4]There is also an `aggregate()` function in the `stats` package that comes with the R standard install. Note that `sp` extends this function so it can take `Spatial*` objects and aggregate over the geometric features.

```
ph_hom_count_sp <- aggregate(x = ph_homic_aea_sp["OBJ_ID"], by = philly_sp, FUN = length)
# make sure we understand this error message:
# aggregate(x = ph_homic_sp, by = philly_sp, FUN = length)
```

Now let us investigate the object we created.

```
class(ph_hom_count_sp)
names(ph_hom_count_sp)
head(ph_hom_count_sp)
```

Now we can calculate the density of homicides in Philadelphia, normalized over the area for each census tract.

We use `gArea()` from the `rgeos` library. `gArea`, when given a `SpatialPolygon`, calculates the size of the area covered. If we need that calculation for each polygon, we set `byid = TRUE`. Units are in map units.

```
library(rgeos)
# we multiply by by 1000000 to get sq km.
ph_hom_count_sp$homic_dens <- 1e6 * (ph_hom_count_sp$OBJ_ID/gArea(ph_hom_count_sp, byid = FALSE))

hist(ph_hom_count_sp$homic_dens)
```

We will write it out for later. (Note that this will produce an error if the file already exists. You can force it to write out with the option `overwrite_layer = TRUE`)

```
writeOGR(ph_hom_count_sp, "data/PhillyCrimerate", "PhillyCrimerate", driver = "ESRI Shapefile")
```

There might be other instances where we don't want to aggregate, but might only want to know which polygon a point falls into. In that case we can use `over()`. In fact, the `aggregate()` function used above makes use of `over()`. See https://cran.r-project.org/web/packages/sp/vignettes/over.pdf for more details on the over-methods. `point.in.poly()` from the `spatialEco` package intersects point and polygons and adds polygon attributes to points. There is also `point.in.polygon()` from the `sp` package which tests if a point or set of points fall in a given polygon.

2.4.3 `sp` - `sf` comparison

how to..	for `sp` objects	for `sf` objects
join attributes	`sp::merge()`	`dplyr::*_join()` (also `sf::merge()`)
reproject	`spTransform()`	`st_transform()`
retrieve (or assign) CRS	`proj4string()`	`st_crs()`
count points in polygons	`over()`	`st_within` and `aggregate()`
buffer	`rgeos::gBuffer()` (separate package)	`st_buffer()`
select by location	`g*` functions from `rgeos`	st_* geos functions in `sf`

Here are some additional packages that use vector data:

- `stplanr`: Functionality and data access tools for transport planning, including origin-destination analysis, route allocation and modelling travel patterns.
- `bikedata`: Data from public hire bicycle systems,including London, New York, Chicago, Washington DC, Boston, Los Angeles, and Philadelphia

2.5 `raster` operations

to come

Some helpful packages that deal with raster data:

- `landscapetools` provides utility functions to complete tasks involved in common landscape analysis.
- `getlandsat`: Get Landsat 8 Data from Amazon Public Data Sets
- `MODIStsp`: automates the creation of time series of rasters derived from MODIS Land Products data
- `FedData`: Download geospatial Data from federated data sources, including the The National Elevation Dataset digital elevation models, the Global Historical Climatology Network, the National Land Cover Database, and more.

Chapter 3

Making Maps in R

In the works.
