Hands-on Exercise 2: Geospatial Data Wrangling with R

In this hands-on exercise, you will learn how to handle geospatial data in R by using **sf** package.

Contents

Learning Outcome

By the end of this hands-on exercise, you should acquire the following competencies:

- importing geospatial data by using appropriate functions of **sf** package,
- importing aspatial data by using appropriate function of **readr** package,
- exploring the content of simple feature data frame by using appropriate **Base R** and **sf** functions,
- assigning or transforming coordinate systems by using using appropriate *sf* functions,
- converting an aspatial data into a sf data frame by using appropriate function of **sf** package,
- performing geoprocessing tasks by using appropriate functions of **sf** package,
- performing data wrangling tasks by using appropriate functions of **dplyr** package and
- performing Exploratory Data Analysis (EDA) by using appropriate functions from **ggplot2** package.

> *Note: Students are encouraged to read the reference guide of each function, especially the input data requirements, syntaxt and argument option before using them.*

Data Acquisition

Data are key to data analytics including geospatial analytics. Hence, before analysing, we need to assemble the necessary data. In this hands-on exercise, you are required to extract the necessary data sets from the following sources:

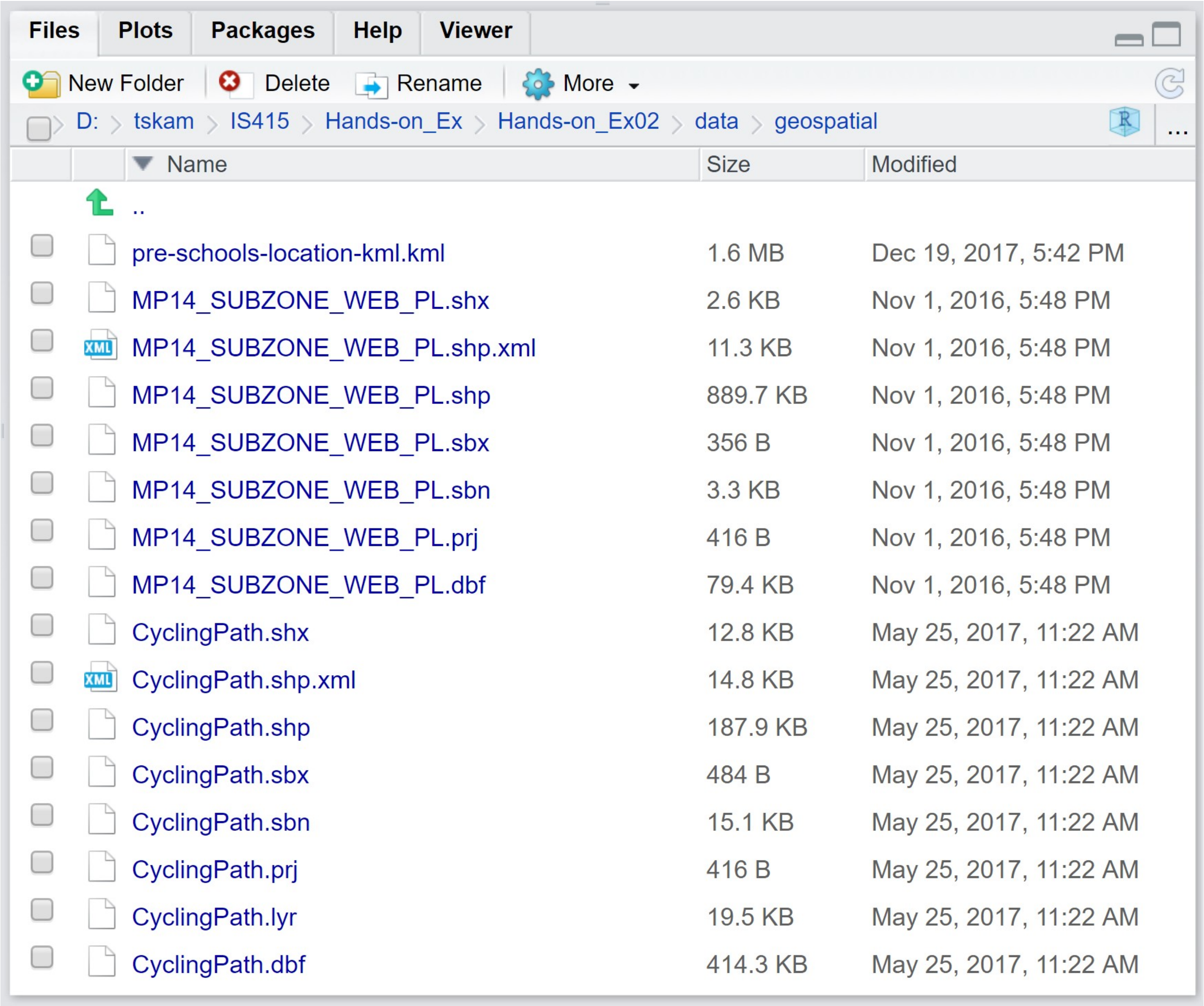
- Master Plan 2014 Subzone Boundary (Web) from data.gov.sg
- Pre-Schools Location from data.gov.sg
- Cycling Path from LTADataMall
- Singapore Airbnb listing data, 19 July 2021 from Inside Airbnb

> *Note: The purpose of this section is not merely extracting the necessary data sets. It also aims to introduce you to public available data sets. Students are encouraged to explore the rest of the available data sets in these three data sources.*

Extracting the geospatial data sets

Next, at the `Hands-on_Ex02` folder, create a sub-folder called `data`. Then, inside the `data` sub-folder, create two sub-folders and name them `geospatial` and `aspatial` respectively.

Place `Master Plan 2014 Subzone Boundary (Web)`, `Pre-Schools Location` and `Cycling Path` zipped files into `geospatial` sub-folder and unzipped them. Copy the unzipped files from their respective sub-folders and place them inside `geospatial` sub-folder. The file listing in `geospatial` sub-folder `should` look similar to the screenshot below.



Extracting the aspatial data set

Now, you will extract the downloaded `listing` data file. At `Downloads` folder, cut and paste `listing.csv` into `aspatial` sub-folder.

Getting Started

In this hands-on exercise, two R packages will be used. They are:

- **sf** for importing, managing, and processing geospatial data, and
- **tidyverse** for performing data science tasks such as importing, wrangling and visualising data.

Tidyverse consists of a family of R packages. In this hands-on exercise, the following packages will be used:

- **readr** for importing csv data,

- **readxl** for importing Excel worksheet,
- **tidyr** for manipulating data,
- **dplyr** for transforming data, and
- **ggplot2** for visualising data

Type the following code chunk.

```
packages = c('sf', 'tidyverse')
for (p in packages) {
  if(!require(p, character.only = T)) {
    install.packages(p)
  }
  library(p, character.only = T)
}
```

What we can learn from the code chunk above:

- A packaging list call `packages` will be created. It consists of all the R packages required to accomplish this hands-on exercise.
- Next, the code chunk will check if the R packages on `package` have been installed in R. If they have yet been installed, they will be installed.
- After all the R packages have been installed, they will be launched in RStudio environment.

Importing Geospatial Data

In this section, you will learn how to import the following geospatial data into R by using *st_read()* of **sf** package:

- `MP14_SUBZONE_WEB_PL`, a polygon feature layer in ESRI shapefile format,
- `CyclingPath`, a line feature layer in ESRI shapefile format, and
- `PreSchool`, a point feature layer in kml file format.

Importing polygon feature data in shapefile format

The code chunk below uses *st_read()* function of **sf** package to import `MP14_SUBZONE_WEB_PL` shapefile into R as a polygon feature data frame. Note that when the input geospatial data is in shapefile format, two arguments will be used, namely: `dsn` to define the data path and `layer` to provide the shapefile name. Also note that no extension such as .shp, .dbf, .prj and .shx are needed.

```
mpsz = st_read ( dsn = "data/geospatial",
                 layer = "MP14_SUBZONE_WEB_PL")
```

```
Reading layer `MP14_SUBZONE_WEB_PL' from data source
  `D:\tskam\IS415\Hands-on_Ex\Hands-On_ex02\data\geospatial'
  using driver `ESRI Shapefile'
Simple feature collection with 323 features and 15 fields
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: 2667.538 ymin: 15748.72 xmax: 56396.44 ymax: 50256.33
Projected CRS: SVY21
```

The message above reveals that the geospatial objects are multipolygon features. There are a total of 323 multipolygon features and 15 fields in `mpsz` simple feature data frame. `mpsz` is in **svy21** projected coordinates systems. The bounding box provides the x extend and y extend of the data.

Importing polyline feature data in shapefile form

The code chunk below uses *st_read()* function of **sf** package to import `CyclingPath` shapefile into R as line feature data frame.

```
cyclingpath = st_read ( dsn = "data/geospatial",
                        layer = "CyclingPath")
```

```
Reading layer `CyclingPath' from data source
  `D:\tskam\IS415\Hands-on_Ex\Hands-On_ex02\data\geospatial'
  using driver `ESRI Shapefile'
Simple feature collection with 1625 features and 2 fields
Geometry type: LINESTRING
Dimension:     XY
Bounding box:  xmin: 12711.19 ymin: 28711.33 xmax: 42626.09 ymax: 48948.15
Projected CRS: SVY21
```

The message above reveals that there are a total of 1625 features and 2 fields in `cyclingpath` linestring feature data frame and it is in **svy21** projected coordinates system too.

Importing GIS data in kml format

The `pre-schools-location-kml` is in kml format. The code chunk below will be used to import the kml into R. Notice that in the code chunk below, the complete path and the kml file extension were provided.

```
preschool = st_read ( "data/geospatial/pre-schools-location-kml.kml")
```

```
Reading layer `PRESCHOOLS_LOCATION' from data source
  `D:\tskam\IS415\Hands-on_Ex\Hands-On_ex02\data\geospatial\pre-schools-location-kml.kml'
  using driver `KML'
```

```
Simple feature collection with 1359 features and 2 fields
Geometry type: POINT
Dimension:     XYZ
Bounding box:  xmin: 103.6824 ymin: 1.248403 xmax: 103.9897 ymax: 1.462134
z_range:       zmin: 0 zmax: 0
Geodetic CRS:  WGS 84
```

The message above reveals that `preschool` is a point feature data frame. There are a total of 1359 features and 2 fields. Different from the previous two simple feature data frame, preschool is in **wgs84** coordinates system.

Checking the Content of A Simple Feature Data Frame

In this sub-section, you will learn different ways to retrieve information related to the content of a simple feature data frame.

Working with *st_geometry()*

The column in the sf data.frame that contains the geometries is a list, of class `sfc`. We can retrieve the geometry list-column in this case by mpsz$geom or mpsz[[1]], but the more general way uses *st_geometry()* as shown in the code chunk below.

```
st_geometry(mpsz)
```

```
Geometry set for 323 features
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: 2667.538 ymin: 15748.72 xmax: 56396.44 ymax: 50256.33
Projected CRS: SVY21
First 5 geometries:
```

Notice that the print only displays basic information of the feature class such as type of geometry, the geographic extent of the features and the coordinate system of the data.

Working with glimpse()

Beside the basic feature information, we also would like to learn more about the associated attribute information in the data frame. This is the time you will find *glimpse()* of **dplyr**. very handy as shown in the code chunk below.

```
glimpse(mpsz)
```

```
Rows: 323
Columns: 16
$ OBJECTID   <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15
```

```
$ OBJECTID   <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15~
$ SUBZONE_NO <int> 1, 1, 3, 8, 3, 7, 9, 2, 13, 7, 12, 6, 1, 5, 1, 1,~
$ SUBZONE_N  <chr> "MARINA SOUTH", "PEARL'S HILL", "BOAT QUAY", "HEN~
$ SUBZONE_C  <chr> "MSSZ01", "OTSZ01", "SRSZ03", "BMSZ08", "BMSZ03",~
$ CA_IND     <chr> "Y", "Y", "Y", "N", "N", "N", "N", "Y", "N", "N",~
$ PLN_AREA_N <chr> "MARINA SOUTH", "OUTRAM", "SINGAPORE RIVER", "BUK~
$ PLN_AREA_C <chr> "MS", "OT", "SR", "BM", "BM", "BM", "BM", "SR", "~
$ REGION_N   <chr> "CENTRAL REGION", "CENTRAL REGION", "CENTRAL REGI~
$ REGION_C   <chr> "CR", "CR", "CR", "CR", "CR", "CR", "CR", "CR", "~
$ INC_CRC    <chr> "5ED7EB253F99252E", "8C7149B9EB32EEFC", "C35FEFF0~
$ FMEL_UPD_D <date> 2014-12-05, 2014-12-05, 2014-12-05, 2014-12-05, ~
$ X_ADDR     <dbl> 31595.84, 28679.06, 29654.96, 26782.83, 26201.96,~
$ Y_ADDR     <dbl> 29220.19, 29782.05, 29974.66, 29933.77, 30005.70,~
$ SHAPE_Leng <dbl> 5267.381, 3506.107, 1740.926, 3313.625, 2825.594,~
$ SHAPE_Area <dbl> 1630379.3, 559816.2, 160807.5, 595428.9, 387429.4~
$ geometry   <MULTIPOLYGON [m]> MULTIPOLYGON (((31495.56 30..., MULT~
```

glimpse() report reveals the data type of each fields. For example `FMEL-UPD_D` field is in **date** data type and `X_ADDR`, `Y_ADDR`, `SHAPE_L` and `SHAPE_AREA` fields are all in **double-precision values**.

Working with *head()*

Sometimes we would like to reveal complete information of a feature object, this is the job of *head()* of Base R

```
head        (          mpsz      , n=          5          )
```

```
Simple feature collection with 5 features and 15 fields
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: 25867.68 ymin: 28369.47 xmax: 32362.39 ymax: 30435.54
Projected CRS: SVY21
  OBJECTID SUBZONE_NO      SUBZONE_N SUBZONE_C CA_IND      PLN_AREA_N
1        1          1   MARINA SOUTH    MSSZ01      Y    MARINA SOUTH
2        2          1   PEARL'S HILL    OTSZ01      Y          OUTRAM
3        3          3      BOAT QUAY    SRSZ03      Y SINGAPORE RIVER
4        4          8 HENDERSON HILL    BMSZ08      N     BUKIT MERAH
5        5          3        REDHILL    BMSZ03      N     BUKIT MERAH
  PLN_AREA_C       REGION_N REGION_C          INC_CRC FMEL_UPD_D
1         MS CENTRAL REGION       CR 5ED7EB253F99252E 2014-12-05
2         OT CENTRAL REGION       CR 8C7149B9EB32EEFC 2014-12-05
3         SR CENTRAL REGION       CR C35FEFF02B13E0E5 2014-12-05
4         BM CENTRAL REGION       CR 3775D82C5DDBEFBD 2014-12-05
5         BM CENTRAL REGION       CR 85D9ABEF0A40678F 2014-12-05
    X_ADDR   Y_ADDR SHAPE_Leng SHAPE_Area
1 31595.84 29220.19   5267.381  1630379.3
2 28679.06 29782.05   3506.107   559816.2
3 29654.96 29974.66   1740.926   160807.5
4 26782.83 29933.77   3313.625   595428.9
5 26201.96 30005.70   2825.594   387429.4
```

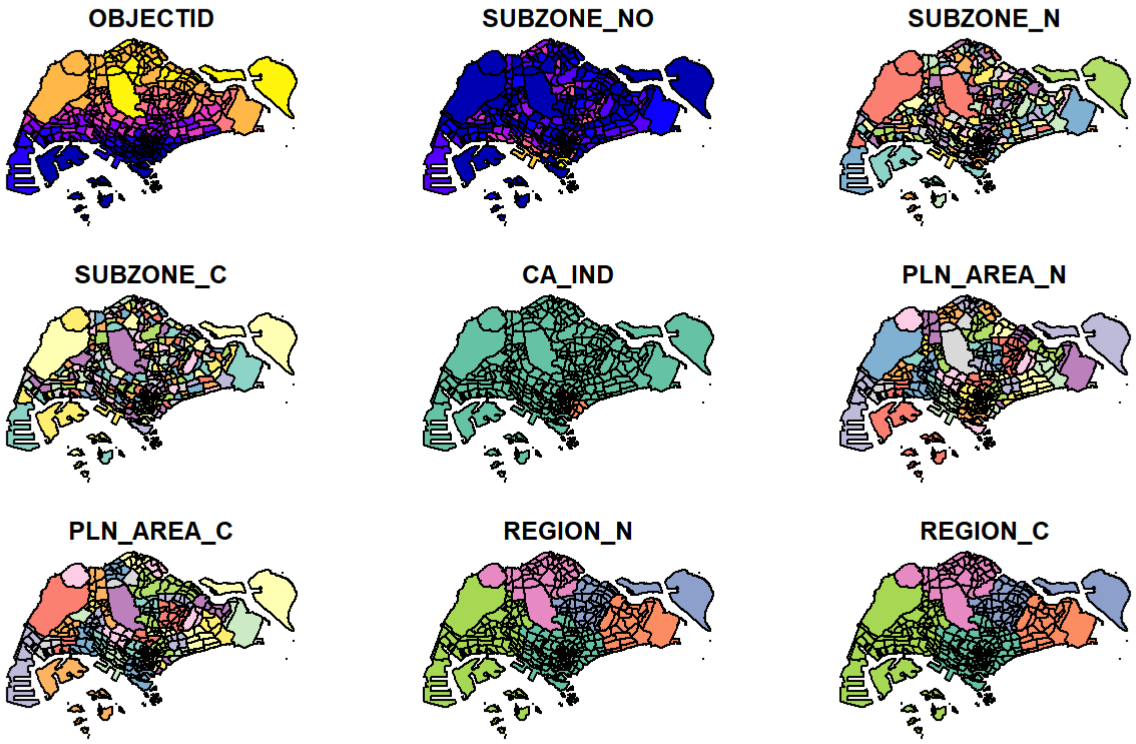
```
                       geometry
1 MULTIPOLYGON (((31495.56 30...
2 MULTIPOLYGON (((29092.28 30...
3 MULTIPOLYGON (((29932.33 29...
4 MULTIPOLYGON (((27131.28 30...
5 MULTIPOLYGON (((26451.03 30...
```

> *Note: One of the useful argument of head() is it allows user to select the numbers of record to display (i.e. the n argument).*

Plotting the Geospatial Data

In geospatial data science, by looking at the feature information is not enough. We are also interested to visualise the geospatial features. This is the time you will find *plot()* of R Graphic comes in very handy as shown in the code chunk below.

```
plot(mpsz)
```

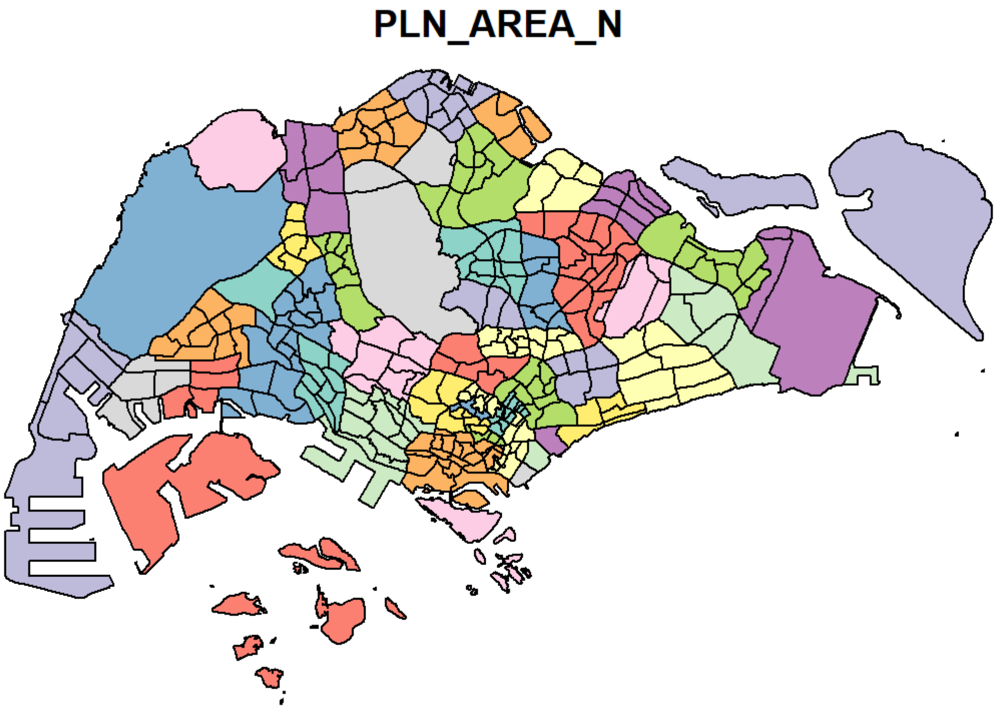


The default plot of an sf object is a multi-plot of all attributes, up to a reasonable maximum as shown above. We can, however, choose to plot only the geometry by using the code chunk below.

```
plot(st_geometry(mpsz))
```

Alternatively, we can also choose the plot the sf object by using a specific attribute as shown in the code chunk below.

```
plot(mpsz["PLN_AREA_N"])
```



> *Note: plot() is mean for plotting the geospatial object for quick look. For high cartographic quality plot, other R package such as tmap should be used.*

Working with Projection

Map projection is an important property of a geospatial data. In order to perform geoprocessing using two geospatial data, we need to ensure that both geospatial data are projected using similar coordinate system.

In this section, you will learn how to project a simple feature data frame from one coordinate system to another coordinate system. The technical term of this process is called **projection transformation**.

Assigning EPSG code to a simple feature data frame

One of the common issue that can happen during importing geospatial data into R is that the coordinate system of the source data was either missing (such as due to missing .proj for ESRI shapefile) or wrongly assigned during the importing process.

This is an example the coordinate system of `mpsz` simple feature data frame by using *st_crs()* of *sf* package as shown in the code chunk below.

```r
st_crs(mpsz)
```

```
Coordinate Reference System:
  User input: SVY21 
  wkt:
PROJCRS["SVY21",
    BASEGEOGCRS["SVY21[WGS84]",
        DATUM["World Geodetic System 1984",
            ELLIPSOID["WGS 84",6378137,298.257223563,
                LENGTHUNIT["metre",1]],
            ID["EPSG",6326]],
        PRIMEM["Greenwich",0,
            ANGLEUNIT["Degree",0.0174532925199433]]],
    CONVERSION["unnamed",
        METHOD["Transverse Mercator",
            ID["EPSG",9807]],
        PARAMETER["Latitude of natural origin",1.36666666666667,
            ANGLEUNIT["Degree",0.0174532925199433],
            ID["EPSG",8801]],
        PARAMETER["Longitude of natural origin",103.833333333333,
            ANGLEUNIT["Degree",0.0174532925199433],
            ID["EPSG",8802]],
        PARAMETER["Scale factor at natural origin",1,
            SCALEUNIT["unity",1],
            ID["EPSG",8805]],
        PARAMETER["False easting",28001.642,
            LENGTHUNIT["metre",1],
            ID["EPSG",8806]],
        PARAMETER["False northing",38744.572,
            LENGTHUNIT["metre",1],
            ID["EPSG",8807]]],
```

```
    CS[Cartesian,2],
        AXIS["(E)",east,
            ORDER[1],
            LENGTHUNIT["metre",1,
                ID["EPSG",9001]]],
        AXIS["(N)",north,
            ORDER[2],
            LENGTHUNIT["metre",1,
                ID["EPSG",9001]]]]
```

Although `mpsz` data frame is projected in svy21 but when we read until the end of the print, it indicates that the EPSG is 9001. This is a wrong EPSG code because the correct EPSG code for svy21 should be 3414.

In order to assign the correct EPSG code to `mpsz` data frame, *st_set_crs()* of **sf** package is used as shown in the code chunk below.

```
mpsz3414 <- st_set_crs(mpsz, 3414)
```

Now, let us check the CSR again by using the code chunk below.

```
st_crs(mpsz3414)
```

```
Coordinate Reference System:
  User input: EPSG:3414
  wkt:
PROJCRS["SVY21 / Singapore TM",
    BASEGEOGCRS["SVY21",
        DATUM["SVY21",
            ELLIPSOID["WGS 84",6378137,298.257223563,
                LENGTHUNIT["metre",1]]],
        PRIMEM["Greenwich",0,
            ANGLEUNIT["degree",0.0174532925199433]],
        ID["EPSG",4757]],
    CONVERSION["Singapore Transverse Mercator",
        METHOD["Transverse Mercator",
            ID["EPSG",9807]],
        PARAMETER["Latitude of natural origin",1.36666666666667,
            ANGLEUNIT["degree",0.0174532925199433],
            ID["EPSG",8801]],
        PARAMETER["Longitude of natural origin",103.833333333333,
            ANGLEUNIT["degree",0.0174532925199433],
            ID["EPSG",8802]],
        PARAMETER["Scale factor at natural origin",1,
            SCALEUNIT["unity",1],
            ID["EPSG",8805]],
        PARAMETER["False easting",28001.642,
            LENGTHUNIT["metre",1],
            ID["EPSG",8806]],
        PARAMETER["False northing",38744.572,
            LENGTHUNIT["metre",1],
            ID["EPSG",8807]]],
```

```
    CS[Cartesian,2],
        AXIS["northing (N)",north,
            ORDER[1],
            LENGTHUNIT["metre",1]],
        AXIS["easting (E)",east,
            ORDER[2],
            LENGTHUNIT["metre",1]],
    USAGE[
        SCOPE["Cadastre, engineering survey, topographic mapping."],

        AREA["Singapore - onshore and offshore."],
        BBOX[1.13,103.59,1.47,104.07]],
    ID["EPSG",3414]]
```

Notice that the EPSG code is 3414 now.

Transforming the projection of preschool from wgs84 to svy21.

In geospatial analytics, it is very common for us to transform the original data from geographic coordinate system to projected coordinate system. This is because geographic coordinate system is not appropriate if the analysis need to use distance or/and area measurements.

Let us take preschool simple feature data frame as an example. The print below reveals that it is in wgs84 coordinate system.

```
Geometry set for 1359 features
Geometry type: POINT
Dimension:     XYZ
Bounding box:  xmin: 103.6824 ymin: 1.248403 xmax: 103.9897 ymax: 1.462134
z_range:       zmin: 0 zmax: 0
Geodetic CRS:  WGS 84
First 5 geometries:
```

This is a scenario that *st_set_crs()* is not appropriate and *st_transform()* of sf package should be used. This is because we need to reproject `preschool` from one coordinate system to another coordinate system mathematically.

Let us perform the projection transformation by using the code chunk below.

```
preschool3414 <-         st_transform(        preschool,
                              crs =         3414      )
```

> *Note: In practice, we need find out the appropriate project coordinate system to use before performing the projection transformation.*

Next, let us display the content of preschool3414 sf data frame as shown below.

```
Geometry set for 1359 features
Geometry type: POINT
```

```
Geometry type: POINT
Dimension:     XYZ
Bounding box:  xmin: 11203.01 ymin: 25667.6 xmax: 45404.24 ymax: 49300.88
z_range:       zmin: 0 zmax: 0
Projected CRS: SVY21 / Singapore TM
First 5 geometries:
```

Notice that it is in svy21 projected coordinate system now. Furthermore, if you refer to *Bounding box:*, the values are greater than 0-360 range of decimal degree commonly used by most of the geographic coordinate systems.

Importing and Converting An Aspatial Data

In practice, it is not unusual that we will come across data such as `listing` of Inside Airbnb. We call this kind of data aspatial data. This is because it is not a geospatial data but among the data fields, there are two fields that capture the x- and y-coordinates of the data points.

In this section, you will learn how to import an aspatial data into R environment and save it as a tibble data frame. Next, you will convert it into a simple feature data frame.

For the purpose of this exercise, the `listings.csv` data downloaded from AirBnb will be used.

Importing the aspatial data

Since `listings` data set is in csv file format, we will use *read_csv()* of **readr** package to import `listing.csv` as shown the code chunk below. The output R object is called `listings` and it is a tibble data frame.

```
listings <- read_csv("data/aspatial/listings.csv")
```

After importing the data file into R, it is important for us to examine if the data file has been imported correctly.

The code chunk below shows *list()* of Base R instead of *glimpse()* is used to do the job.

```
list(listings)
```

```
[[1]]
# A tibble: 4,252 x 16
       id name         host_id host_name neighbourhood_g~ neighbourhood
    <dbl> <chr>          <dbl> <chr>     <chr>            <chr>
 1  50646 Pleasant R~  227796 Sujatha   Central Region   Bukit Timah
 2  71609 Ensuite Ro~  367042 Belinda   East Region      Tampines
 3  71896 B&B  Room ~  367042 Belinda   East Region      Tampines
 4  71903 Room 2-nea~  367042 Belinda   East Region      Tampines
 5 275343 Convenient~ 1439258 Joyce     Central Region   Bukit Merah
```

```
 6 275344 15 mins to~ 1439258 Joyce     Central Region   Bukit Merah
 7 294281 5 mins wal~ 1521514 Elizabeth Central Region   Newton
 8 301247 Nice room ~ 1552002 Rahul     Central Region   Geylang
 9 324945 20 Mins to~ 1439258 Joyce     Central Region   Bukit Merah
10 330089 Accomo@ RE~ 1439258 Joyce     Central Region   Bukit Merah
# ... with 4,242 more rows, and 10 more variables: latitude <dbl>,
#   longitude <dbl>, room_type <chr>, price <dbl>,
#   minimum_nights <dbl>, number_of_reviews <dbl>,
#   last_review <date>, reviews_per_month <dbl>,
#   calculated_host_listings_count <dbl>, availability_365 <dbl>
```

The output reveals that `listing` tibble data frame consists of 4252 rows and 16 columns. Two useful fields we are going to use in the next phase are `latitude` and `longitude`. Note that they are in decimal degree format. As a best guess, we will assume that the data is in **wgs84** Geographic Coordinate System.

Creating a simple feature data frame from an aspatial data frame

The code chunk below converts `listing` data frame into a simple feature data frame by using *st_as_sf()* of **sf** packages

```
listings_sf <- st_as_sf(listings,
                        coords = c("longitude", "latitude"),
                        crs=4326) %>%
  st_transform(crs = 3414)
```

Things to learn from the arguments above:

- *coords* argument requires you to provide the column name of the x-coordinates first then followed by the column name of the y-coordinates.
- *crs* argument requires you to provide the coordinates system in epsg format. EPSG: 4326 is wgs84 Geographic Coordinate System and EPSG: 3414 is Singapore SVY21 Projected Coordinate System. You can search for other country's epsg code by referring to epsg.io.
- *%>%* is used to nest *st_transform()* to transform the newly created simple feature data frame into svy21 projected coordinates system.

Let us examine the content of this newly created simple feature data frame.

```
glimpse(listings_sf)
```

```
Rows: 4,252
Columns: 15
$ id                             <dbl> 50646, 71609, 71896, 71903, 2~
$ name                           <chr> "Pleasant Room along Bukit Ti~
$ host_id                        <dbl> 227796, 367042, 367042, 36704~
$ host_name                      <chr> "Sujatha", "Belinda", "Belind~
$ neighbourhood_group            <chr> "Central Region", "East Regio~
$ neighbourhood                  <chr> "Bukit Timah", "Tampines", "T~
```

```
$ room_type                      <chr> "Private room", "Private room~
$ price                          <dbl> 80, 178, 81, 81, 52, 40, 72, ~
$ minimum_nights                 <dbl> 90, 90, 90, 90, 14, 14, 90, 8~
$ number_of_reviews              <dbl> 18, 20, 24, 48, 20, 13, 133, ~
$ last_review                    <date> 2014-07-08, 2019-12-28, 2014~
$ reviews_per_month              <dbl> 0.22, 0.28, 0.33, 0.67, 0.20,~
$ calculated_host_listings_count <dbl> 1, 4, 4, 4, 50, 50, 7, 1, 50,~
$ availability_365               <dbl> 365, 365, 365, 365, 353, 364,~
$ geometry                       <POINT [m]> POINT (22646.02 35167.9~
```

Table above shows the content of `listing_sf`. Notice that a new column called `geometry` has been added into the data frame. On the other hand, the `longitude` and `latitude` columns have been dropped from the data frame.

Geoprocessing with sf package

Besides providing functions to handling (i.e. importing, exporting, assigning projection, transforming projection etc) geospatial data, **sf** package also offers a wide range of geoprocessing (also known as GIS analysis) functions.

In this section, you will learn how to perform two commonly used geoprocessing functions, namely buffering and point in polygon count.

Buffering

The scenario:

The authority is planning to upgrade the exiting cycling path. To do so, they need to acquire 5 metres of reserved land on the both sides of the current cycling path. You are tasked to determine the extend of the land need to be acquired and their total area.

The solution:

Firstly, *st_buffer()* of **sf** package is used to compute the 5-meter buffers around cycling paths

```
buffer_cycling <- st_buffer(cyclingpath,
                            dist=5, nQuadSegs = 30)
```

This is followed by calculating the area of the buffers as shown in the code chunk below.

```
buffer_cycling$AREA <- st_area(buffer_cycling)
```

Lastly, sum() of Base R will be used to derive the total land involved

```
sum(buffer_cycling$AREA)
```

```
773143.9 [m^2]
```

Mission Accomplished!

Point-in-polygon count

The scenario:

A pre-school service group want to find out the numbers of pre-schools in each Planning Subzone.

The solution:

The code chunk below performs two operations at one go. Firstly, identify pre-schools located inside each Planning Subzone by using st_intersects(). Next, *length()* of Base R is used to calculate numbers of pre-schools that fall inside each planning subzone.

```
mpsz3414$`PreSch Count`<- lengths(st_intersects(mpsz3414, preschool3414))
```

> ***Warning***: *You should not confuse with st_intersection().*

You can check the summary statistics of the newly derived *PreSch Count* field by using *summary()* as shown in the code chunk below.

```
summary(mpsz3414$`PreSch Count`)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  0.000   0.000   2.000   4.207   6.000  37.000 
```

To list the planning subzone with the most number of pre-school, the *top_n()* of **dplyr** package is used as shown in the code chunk below.

```
top_n(mpsz3414, 1, `PreSch Count`)
```

```
Simple feature collection with 1 feature and 16 fields
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: 23449.05 ymin: 46001.23 xmax: 25594.22 ymax: 47996.47
Projected CRS: SVY21 / Singapore TM
  OBJECTID SUBZONE_NO      SUBZONE_N SUBZONE_C CA_IND PLN_AREA_N
1      290          3 WOODLANDS EAST    WDSZ03      N  WOODLANDS
  PLN_AREA_C     REGION_N REGION_C          INC_CRC FMEL_UPD_D
1         WD NORTH REGION       NR C90769E43EE6B0F2 2014-12-05
    X_ADDR   Y_ADDR SHAPE_Leng SHAPE_Area
1 24506.64 46991.63   6603.608    2553464
                        geometry PreSch Count
1 MULTIPOLYGON (((24786.75 46...           37
```

> ***DIY: Calculate the density of pre-school by planning subzone.***

The solution:

Firstly, the code chunk below uses *st_area()* of **sf** package to derive the area of each planning subzone.

```
mpsz3414$Area <- mpsz3414 %>%
  st_area()
```

Next, *mutate()* of **dplyr** package is used to compute the density by using the code chunk below.

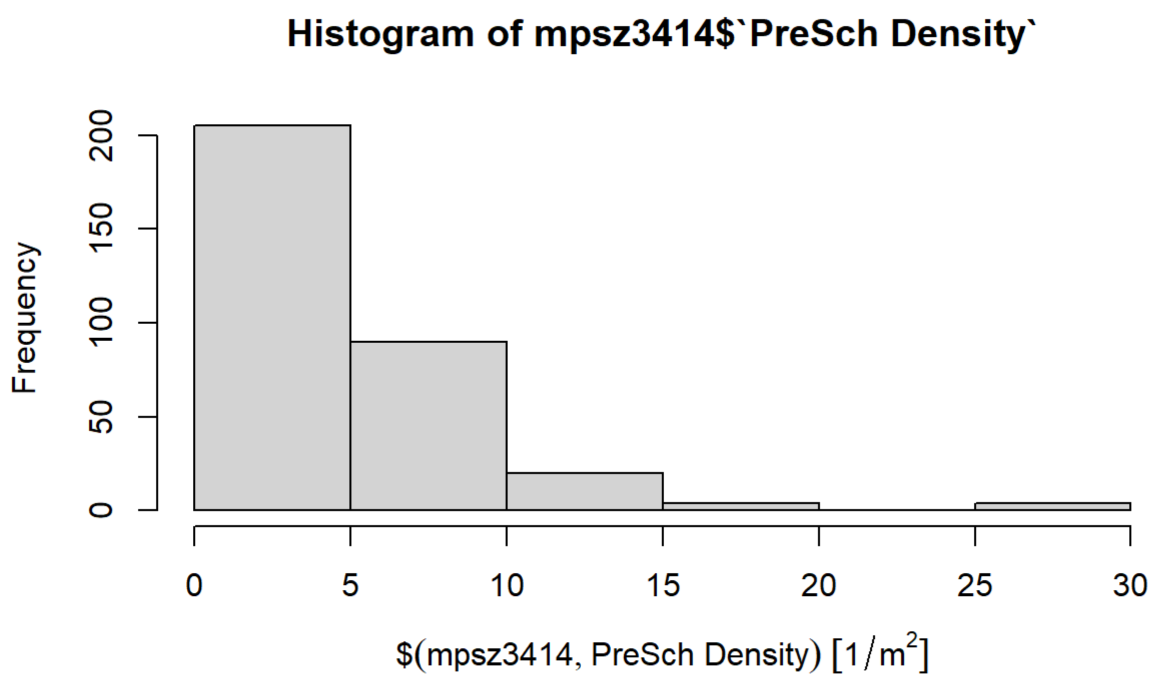
```
mpsz3414 <- mpsz3414 %>%
  mutate(`PreSch Density` = `PreSch Count`/Area * 1000000)
```

Explorotary Data Analysis (EDA)

In practice, many geospatial analytics start with Exploratory Data Analysis. In this section, you will learn how to use appropriate ggplot2 functions to create functional and yet truthful statistical graphs for EDA purposes.

Firstly, we will plot a histogram to reveal the distribution of `PreSch Density`. Conventionally, *hist()* of R Graphics will be used as shown in the code chunk below.

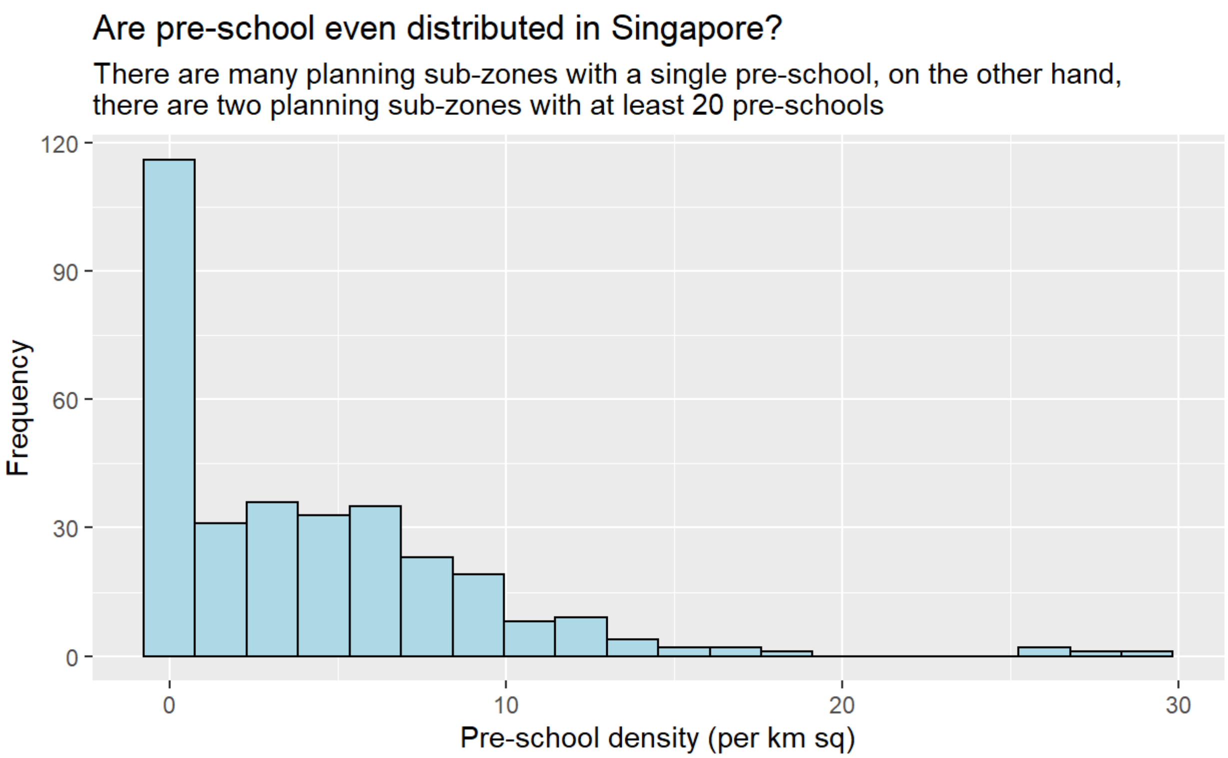
```
hist(mpsz3414$`PreSch Density`)
```



Although the syntax is very easy to use however the output is far from meeting publication quality. Furthermore, the function has limited room for further customisation.

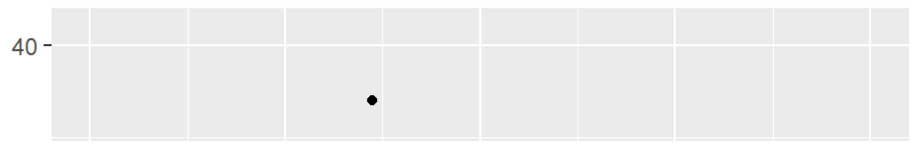
In the code chunk below, appropriate **ggplot2** functions will be used.

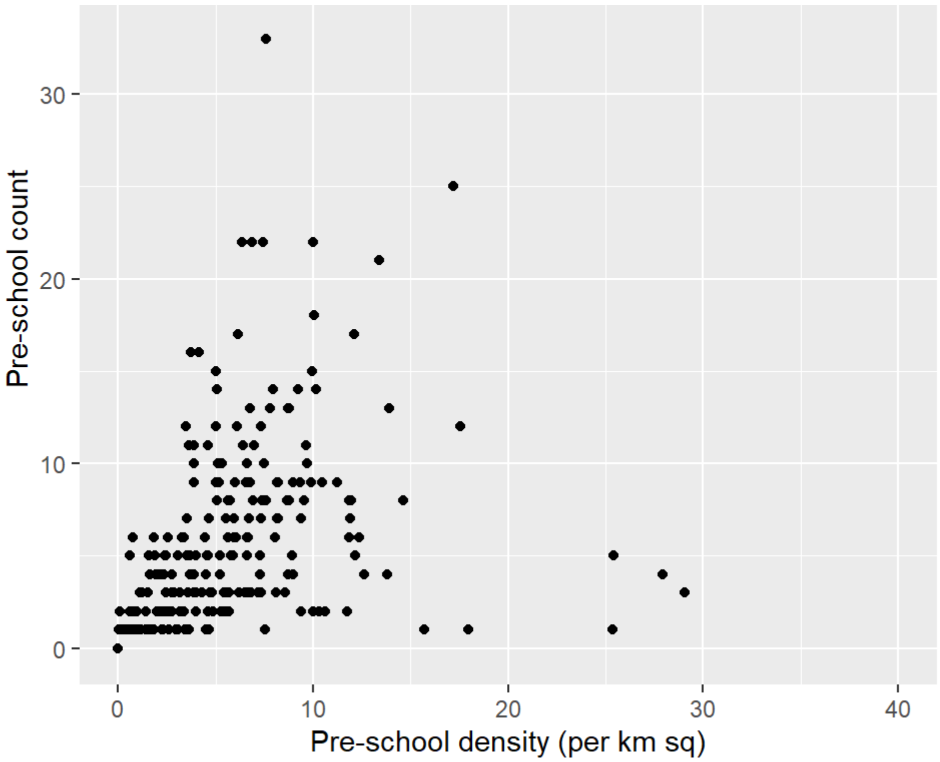
```
ggplot(data=mpsz3414,
       aes(x= as.numeric(`PreSch Density`)))+
  geom_histogram(bins=20,
                 color="black",
                 fill="light blue") +
  labs(title = "Are pre-school even distributed in Singapore?",
       subtitle= "There are many planning sub-zones with a single pre-school, on the other hand, \nthere are two planning sub-zones with at least 20 pre-schools",
       x = "Pre-school density (per km sq)",
       y = "Frequency")
```



> ***DIY: Using ggplot2 method, plot a scatterplot showing the relationship between Pre-school Density and Pre-school Count.***

The solution:





Pre-school count
Pre-school density (per km sq)
0
10
20
30
40