GEOG0114 Principles of Spatial Analysis

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> **Note**
>
> This GitHub page contains the material for Week 07 (Geodemographics) and Week 08 (Transport network analysis) of **Principles of Spatial Analysis** 2023-2024. The content for 2022-2023 has been archived and can be found here: [Link]

1 Geodemographics

This week we will see how we can use socio-demographic and socio-economic data to characterise neighbourhoods using **geodemographics**. Geodemographics is the "*analysis of people by where they live (Harris et al. 2005) and as such entails representing the individual and collective identities that are manifest in observable neighbourhood structure*" (Longley 2012). We will look at geodemographics by focusing on an existing geodemographic classification known as the Internet User Classification.

1.1 Lecture slides

You can download the slides of this week's lecture here: [Link].

1.2 Reading list

Essential readings

- Longley, P. A. 2012. Geodemographics and the practices of geographic information science. *International Journal of Geographical Information Science* 26(12): 2227-2237. [Link]
- Martin, D., Gale, C., Cockings, S. *et al.* 2018. Origin-destination geodemographics for analysis of travel to work flows. *Computers, Environment and Urban Systems* 67: 68-79. [Link]
- Singleton, A., Alexiou, A. and Savani, R. 2020. Mapping the geodemographics of digital inequality in Great Britain: An integration of machine learning into small area estimation. *Computers, Environment and Urban Systems* 82: 101486. [Link]
- Singleton, A. and Spielman, S. 2014. The past, present, and future of geodemographic research in the United States and United Kingdom. *The Professional Geographer* 66(4): 558-567. [Link]

Suggested readings

- Goodman, A., Wilkinson, P., Stafford, M. *et al.* 2011. Characterising socio-economic inequalities in exposure to air pollution: A comparison of socio-economic markers and scales of measurement. *Health & Place* 17(3): 767-774. [Link]

1.3 Geodemographics

The CDRC Internet User Classification (IUC) is a bespoke geodemographic classification that describes how people residing in different parts of Great Britain interact with the Internet. For every Lower Super Output Area (LSOA) in England and Wales and Data Zone (DZ) (2011 Census Geographies), the IUC provides aggregate population estimates of Internet use and provides insights into the geography of the digital divide in the United Kingdom:

> "Digital inequality is observable where access to online resources and those opportunities that these create are non-egalitarian. As a result of variable rates of access and use of the Internet between social and spatial groups (..), this leads to digital differentiation, which entrenches difference and reciprocates digital inequality over time" (Singleton *et al.* 2020).

1.3.1 Internet User Classification I

For the first part of this week's practical material, we will be looking at the Internet User Classification (IUC) for Great Britain in more detail by mapping it.

Our first step is to download the IUC data set:

- Open a web browser and go to the data portal of the CDRC.
- Register if you need to, or if you are already registered, make sure you are logged in.
- Search for **Internet User Classification**.
- Scroll down and choose the download option for the *IUC 2018 (CSV)*.
- Save the `iuc_gb_2018.csv` file in an appropriate folder.

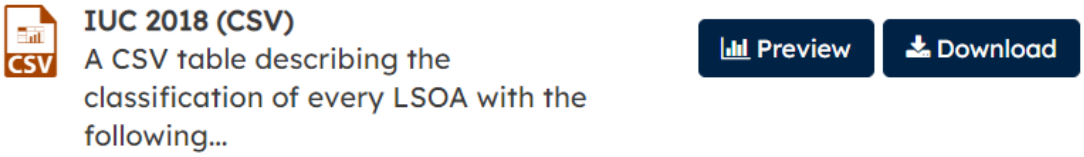
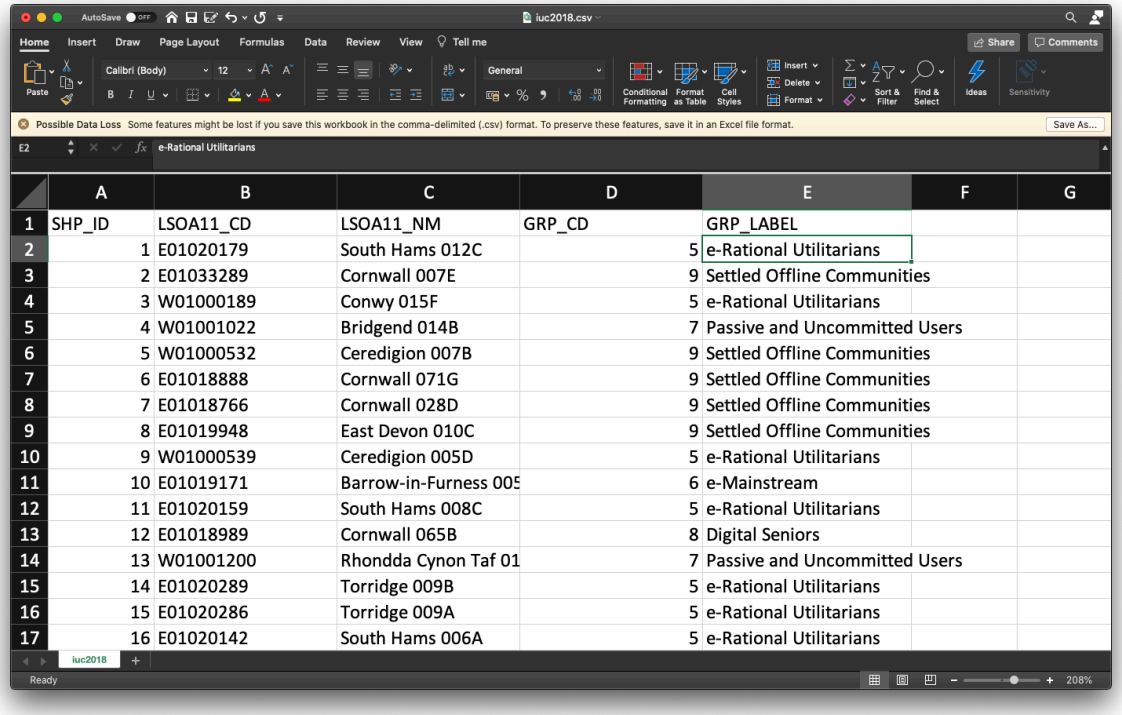


Figure 1.1: Download the GB IUC 2018

Start by inspecting the data set in MS Excel, or any other spreadsheet software such as Apache OpenOffice Calc or Numbers. Also, have a look at the IUC 2018 User Guide that provides the **pen portraits** of every cluster, including plots of cluster centres and a brief summary of the methodology.

> **Tip**
>
> It is always a good idea to inspect your data prior to analysis to find out how your data look like. Of course, depending on the type of data, you can choose any tool you like to do this inspection (ArcGIS, R, QGIS, Microsoft Excel, etc.).



	A	B	C	D	E	F	G
1	SHP_ID	LSOA11_CD	LSOA11_NM	GRP_CD	GRP_LABEL		
2	1	E01020179	South Hams 012C	5	e-Rational Utilitarians		
3	2	E01033289	Cornwall 007E	9	Settled Offline Communities		
4	3	W01000189	Conwy 015F	5	e-Rational Utilitarians		
5	4	W01001022	Bridgend 014B	7	Passive and Uncommitted Users		
6	5	W01000532	Ceredigion 007B	9	Settled Offline Communities		
7	6	E01018888	Cornwall 071G	9	Settled Offline Communities		
8	7	E01018766	Cornwall 028D	9	Settled Offline Communities		
9	8	E01019948	East Devon 010C	9	Settled Offline Communities		
10	9	W01000539	Ceredigion 005D	5	e-Rational Utilitarians		
11	10	E01019171	Barrow-in-Furness 005	6	e-Mainstream		
12	11	E01020159	South Hams 008C	5	e-Rational Utilitarians		
13	12	E01018989	Cornwall 065B	8	Digital Seniors		
14	13	W01001200	Rhondda Cynon Taf 01	7	Passive and Uncommitted Users		
15	14	E01020289	Torridge 009B	5	e-Rational Utilitarians		
16	15	E01020286	Torridge 009A	5	e-Rational Utilitarians		
17	16	E01020142	South Hams 006A	5	e-Rational Utilitarians		

Figure 1.2: GB IUC 2018 in Excel

```
# A tibble: 41,729 x 5
   SHP_ID LSOA11_CD LSOA11_NM              GRP_CD GRP_LABEL
    <dbl> <chr>     <chr>                   <dbl> <chr>
 1      1 E01020179 South Hams 012C             5 e-Rational Utilitarians
 2      2 E01033289 Cornwall 007E               9 Settled Offline Communities
 3      3 W01000189 Conwy 015F                  5 e-Rational Utilitarians
 4      4 W01001022 Bridgend 014B               7 Passive and Uncommitted Users
```

Listing 1.1 R code

```
# load libraries
library(tidyverse)
library(tmap)

# load data
iuc <- read_csv("data/index/iuc-gb-2018.csv")


# inspect
iuc
```

```
 5      5 W01000532 Ceredigion 007B             9 Settled Offline Communities
 6      6 E01018888 Cornwall 071G               9 Settled Offline Communities
 7      7 E01018766 Cornwall 028D               9 Settled Offline Communities
 8      8 E01019948 East Devon 010C             9 Settled Offline Communities
 9      9 W01000539 Ceredigion 005D             5 e-Rational Utilitarians
10     10 E01019171 Barrow-in-Furness 005E      6 e-Mainstream
# ... with 41,719 more rows
```

Listing 1.2 R code

```
# inspect data types
str(iuc)
```

```
spc_tbl_ [41,729 x 5] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
 $ SHP_ID   : num [1:41729] 1 2 3 4 5 6 7 8 9 10 ...
 $ LSOA11_CD: chr [1:41729] "E01020179" "E01033289" "W01000189" "W01001022" ...
 $ LSOA11_NM: chr [1:41729] "South Hams 012C" "Cornwall 007E" "Conwy 015F" "Bridgend 014B" .
 $ GRP_CD   : num [1:41729] 5 9 5 7 9 9 9 9 5 6 ...
 $ GRP_LABEL: chr [1:41729] "e-Rational Utilitarians" "Settled Offline Communities" "e-Ratio
 - attr(*, "spec")=
  .. cols(
  ..   SHP_ID = col_double(),
  ..   LSOA11_CD = col_character(),
  ..   LSOA11_NM = col_character(),
```

```
  ..   GRP_CD = col_double(),
  ..   GRP_LABEL = col_character()
  .. )
 - attr(*, "problems")=<externalptr>
```

Now the data are loaded we can move to acquiring our spatial data. As the IUC is created at the level of the Lower layer Super Output Area Census geography, we need to download its administrative borders. As the data set for the entire country is quite large, we will focus on Liverpool.

- Go to the UK Data Service Census support portal and select **Boundary Data Selector**.
- Set Country to *England*, Geography to *Statistical Building Block*, dates to *2011 and later*, and click **Find**.
- Select *English Lower Layer Super Output Areas, 2011* and click **List Areas**.
- Select *Liverpool* from the list and click **Extract Boundary Data**.
- Wait until loaded and download the `BoundaryData.zip` file.
- Unzip and save the file.

> **Note**
>
> You could also have downloaded the shapefile with the data already joined to the LSOA boundaries directly from the CDRC data portal, but this is the national data set and is quite large (75MB). Also, as we will be looking at Liverpool today we do not need all LSOAs in Great Britain..

Now we got the administrative boundary data, we can prepare the IUC map by joining our `csv` file with the IUC classification to the `shapefile`.

Listing 1.3 `R code`

```r
# load libraries
library(sf)
library(tmap)

# load spatial data
liverpool <- st_read("data/boundaries/england_lsoa_2011.shp")
```

```
Reading layer `england_lsoa_2011' from data source
  `/Users/justinvandijk/Library/CloudStorage/Dropbox/UCL/Web/jtvandijk.github.io/GEOG0114Q/da
  using driver `ESRI Shapefile'
Simple feature collection with 298 features and 3 fields
```

```
Geometry type: POLYGON
Dimension:     XY
Bounding box:  xmin: 332390.2 ymin: 379748.5 xmax: 345636 ymax: 397980.1
Projected CRS: OSGB36 / British National Grid
```

```r
# inspect
tm_shape(liverpool) + tm_polygons()
```

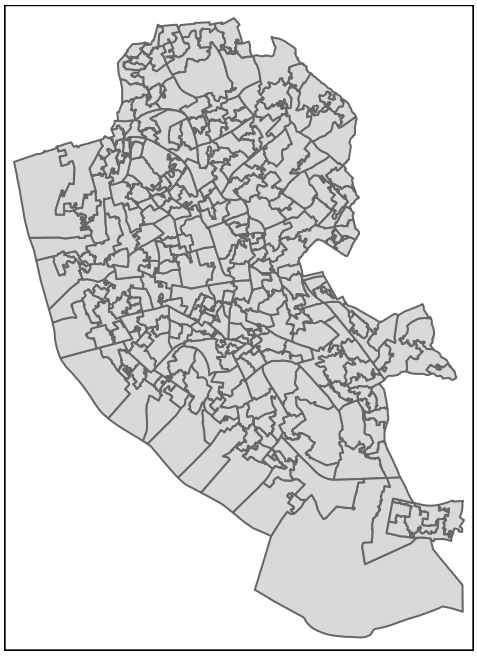


Figure 1.3: LSOAs Liverpool

Listing 1.4 `R code`

```r
# join data
liv_iuc <- left_join(liverpool, iuc, by = c(code = "LSOA11_CD"))

# inspect
liv_iuc
```

```
Simple feature collection with 298 features and 7 fields
```

```
Geometry type: POLYGON
Dimension:     XY
Bounding box:  xmin: 332390.2 ymin: 379748.5 xmax: 345636 ymax: 397980.1
Projected CRS: OSGB36 / British National Grid
First 10 features:
                         label           name      code SHP_ID      LSOA11_NM
1  E08000012E02006934E01033755 Liverpool 062D E01033755  25097 Liverpool 062D
2  E08000012E02006932E01033758 Liverpool 060B E01033758  24070 Liverpool 060B
3  E08000012E02001356E01033759 Liverpool 010F E01033759  26845 Liverpool 010F
4  E08000012E02006932E01033762 Liverpool 060E E01033762  26866 Liverpool 060E
5  E08000012E02001396E01032505 Liverpool 050F E01032505  27848 Liverpool 050F
6  E08000012E02001396E01032506 Liverpool 050G E01032506   2429 Liverpool 050G
7  E08000012E02001396E01032507 Liverpool 050H E01032507  24242 Liverpool 050H
8  E08000012E02001373E01032508 Liverpool 027G E01032508  28413 Liverpool 027G
9  E08000012E02001373E01032509 Liverpool 027H E01032509  24339 Liverpool 027H
10 E08000012E02001354E01032510 Liverpool 008F E01032510  25167 Liverpool 008F
   GRP_CD                     GRP_LABEL                       geometry
1       2               e-Professionals POLYGON ((334276.7 391012.8...
2       4         Youthful Urban Fringe POLYGON ((335723 391178, 33...
3       7 Passive and Uncommitted Users POLYGON ((338925 394476, 33...
4       1           e-Cultural Creators POLYGON ((334612.4 391111.7...
5       7 Passive and Uncommitted Users POLYGON ((335894.7 387448.3...
6       6                  e-Mainstream POLYGON ((336256.7 387691.8...
7       3                    e-Veterans POLYGON ((336803.5 387432.7...
8      10                   e-Withdrawn POLYGON ((339299 391470, 33...
9       7 Passive and Uncommitted Users POLYGON ((338901 391308, 33...
10      7 Passive and Uncommitted Users POLYGON ((338018.2 395716.4...
```

Listing 1.5 `R code`

```r
# inspect
tm_shape(liv_iuc) + tm_fill(col = "GRP_LABEL") +
 ↪  tm_layout(legend.outside = TRUE)
```

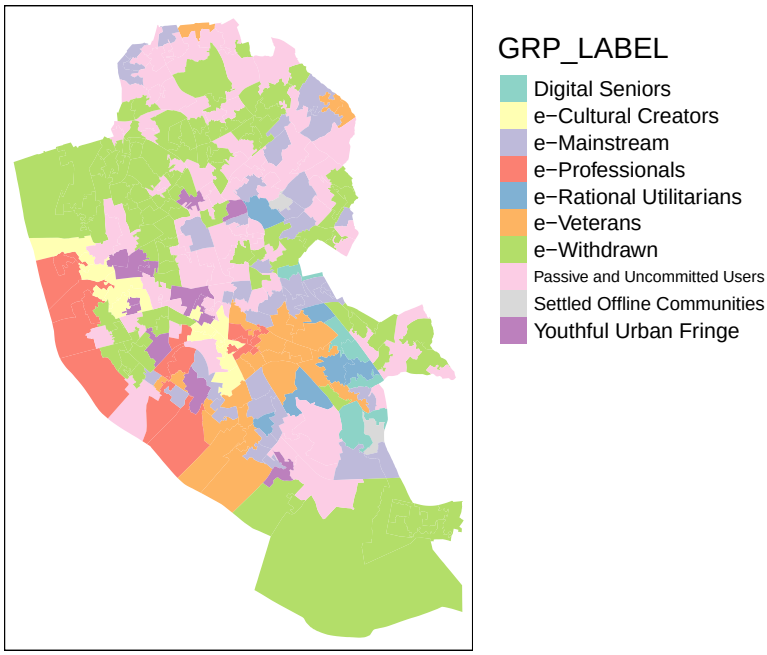


Figure 1.4: Internet User Classification Liverpool

Let's use the same colours as used on CDRC mapmaker by specifying the **hex** colour codes for each of our groups. Note the order of the colours is important: the colour for group 1 is first, group 2 second and so on.

Listing 1.6 `R code`

```
# define palette
iuc_colours <- c("#dd7cdc", "#ea4d78", "#d2d1ab", "#f36d5a", "#a5cfbc",
 ↪  "#e4a5d0",
    "#8470ff", "#79cdcd", "#808fee", "#ffd39b")

# plot pretty
tm_shape(liv_iuc) + tm_fill(col = "GRP_LABEL", palette = iuc_colours) +
 ↪  tm_layout(legend.outside = TRUE)
```

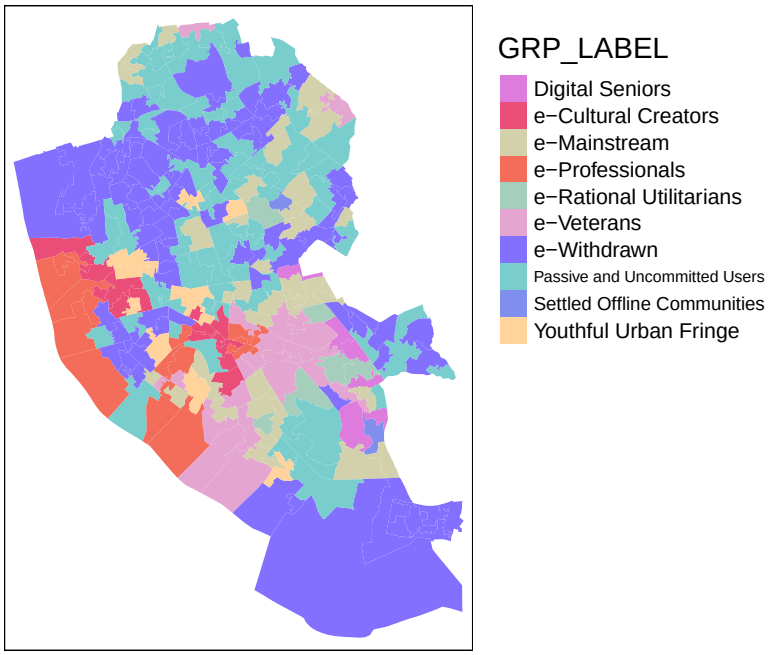


Figure 1.5: Internet User Classification Liverpool with mapmaker colours

1.3.2 Tutorial task I

Now we have these cluster classifications, how can we link them to people? Try using the **Mid-Year Population Estimates 2019** that you can download below to:

- calculate the total number of people associated with each cluster group **for England and Wales as a whole**; and
- create a pretty data visualisation showing the results (no map!).

File download

File	Type	Link
LSOA-level Mid-Year Population Estimates England and Wales 2019	`csv`	Download
Lower-layer Super Output Areas Great Britain 2011	`shp`	Download

1.3.3 k-means clustering

In several cases, including the 2011 residential-based area classifications and the Internet User Classification, a technique called **k-means clustering** is used in the creation of a geodemographic classification. K-means clustering aims to partition a set of observations into a number of clusters (k), in which each observation will be assigned to the cluster with the nearest mean. As such, a cluster refers to a collection of data points aggregated together because of certain similarities (i.e. standardised scores of your input data). In order to run a **k-means clustering**, you first define a target number k of clusters that you want. The k-means algorithm subsequently assigns every observation to one of the clusters by finding the solution that minimises the total within-cluster variance. For the second part of this week's practical material, we will be replicating part of the Internet User Classification for Great Britain. For this we will be using an MSOA-level input data set containing various socio-demographic and socio-economic variables that you can download below together with the MSOA administrative boundaries.

The data set contains the following variables:

Variable	Definition
`msoa11cd`	MSOA Code
`age_total`, `age0to4pc`, `age5to14pc`, `age16to24pc`, `age25to44pc`, `age45to64pc`, `age75pluspc`	Percentage of people in various age groups
`nssec_total`, `1_higher_managerial`, `2_lower_managerial`, `3_intermediate_occupations`, `4_employers_small_org`, `5_lower_supervisory`, `6_semi_routine`, `7_routine`, `8_unemployed`	Percentage of people in selected operational categories and sub-categories classes drawn from the National Statistics Socio-economic Classification (NS-SEC)
`avg_dwn_speed`, `avb_superfast`, `no_decent_bband`, `bband_speed_under2mbs`, `bband_speed_under10mbs`, `bband_speed_over30mbs`	Measures of broadband use and internet availability

File download

File	Type	Link
Middle-layer Super Output Areas Great Britain 2011	`shp`	Download
MSOA-level input variables for IUC	`csv`	Download

Listing 1.7 R code

```
# load data
iuc_input <- read_csv("data/index/msoa-iuc-input.csv")

# inspect
head(iuc_input)
```

```
# A tibble: 6 x 23
  msoa11cd  age_total age0to4pc age5to~1 age16~2 age25~3 age45~4 age75~5 nssec~6
  <chr>         <dbl>     <dbl>    <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
1 E02000001      7375    0.032    0.0388  0.0961   0.407   0.273  0.0607    5816
2 E02000002      6775    0.0927   0.122   0.113    0.280   0.186  0.0980    3926
3 E02000003     10045    0.0829   0.102   0.118    0.306   0.225  0.0646    6483
4 E02000004      6182    0.0590   0.102   0.139    0.254   0.250  0.0886    4041
5 E02000005      8562    0.0930   0.119   0.119    0.299   0.214  0.0501    5368
6 E02000007      8791    0.103    0.125   0.129    0.285   0.197  0.0688    5158
# ... with 14 more variables: `1_higher_managerial` <dbl>,
#   `2_lower_managerial` <dbl>, `3_intermediate_occupations` <dbl>,
#   `4_employers_small_org` <dbl>, `5_lower_supervisory` <dbl>,
#   `6_semi_routine` <dbl>, `7_routine` <dbl>, `8_unemployed` <dbl>,
#   avg_dwn_speed <dbl>, avb_superfast <dbl>, no_decent_bband <dbl>,
#   bband_speed_under2mbs <dbl>, bband_speed_under10mbs <dbl>,
#   bband_speed_over30mbs <dbl>, and abbreviated variable names ...
```

Before running our **k-means** clustering algorithm, we need to extract the data which we want to use; i.e. we need to remove all the columns with data that we do not want to include in the clustering process.

Listing 1.8 R code

```
# column names
names(iuc_input)
```

```
 [1] "msoa11cd"                  "age_total"
 [3] "age0to4pc"                 "age5to14pc"
 [5] "age16to24pc"               "age25to44pc"
 [7] "age45to64pc"               "age75pluspc"
 [9] "nssec_total"               "1_higher_managerial"
```

```
[11] "2_lower_managerial"          "3_intermediate_occupations"
[13] "4_employers_small_org"       "5_lower_supervisory"
[15] "6_semi_routine"              "7_routine"
[17] "8_unemployed"                "avg_dwn_speed"
[19] "avb_superfast"               "no_decent_bband"
[21] "bband_speed_under2mbs"       "bband_speed_under10mbs"
[23] "bband_speed_over30mbs"
```

```r
# extract columns by index
cluster_data <- iuc_input[, c(3:8, 10:17, 18:20)]

# inspect
head(cluster_data)
```

```
# A tibble: 6 x 17
  age0to4pc age5to14pc age16to~1 age25~2 age45~3 age75~4 1_hig~5 2_low~6 3_int~7
      <dbl>      <dbl>     <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
1    0.032      0.0388    0.0961   0.407   0.273  0.0607  0.385    0.339  0.0781
2    0.0927     0.122     0.113    0.280   0.186  0.0980  0.0568   0.171  0.143
3    0.0829     0.102     0.118    0.306   0.225  0.0646  0.0818   0.208  0.182
4    0.0590     0.102     0.139    0.254   0.250  0.0886  0.0678   0.206  0.191
5    0.0930     0.119     0.119    0.299   0.214  0.0501  0.0494   0.166  0.156
6    0.103      0.125     0.129    0.285   0.197  0.0688  0.0564   0.163  0.136
# ... with 8 more variables: `4_employers_small_org` <dbl>,
#   `5_lower_supervisory` <dbl>, `6_semi_routine` <dbl>, `7_routine` <dbl>,
#   `8_unemployed` <dbl>, avg_dwn_speed <dbl>, avb_superfast <dbl>,
#   no_decent_bband <dbl>, and abbreviated variable names 1: age16to24pc,
#   2: age25to44pc, 3: age45to64pc, 4: age75pluspc, 5: `1_higher_managerial`,
#   6: `2_lower_managerial`, 7: `3_intermediate_occupations`
```

We also need to rescale the data so all input data are presented on a comparable scale: the average download speed data (i.e. `avg_dwn_speed`) is very different to the other data that, for instance, represent the percentage of the population by different age groups.

```
     age0to4pc age5to14pc age16to24pc age25to44pc age45to64pc age75pluspc
[1,] -1.7579913 -2.8680309 -0.36823669   2.1768529   0.2561260  -0.6039803
[2,]  1.9519376  1.6403191 -0.05766949   0.1671857  -1.5639740   0.6215590
[3,]  1.3549320  0.5475394  0.02888699   0.5773908  -0.7424464  -0.4769094
[4,] -0.1050147  0.5938501  0.40759191  -0.2402277  -0.2247116   0.3136111
[5,]  1.9687596  1.5173858  0.05639359   0.4733916  -0.9785969  -0.9539525
```

Listing 1.9 `R code`

```r
# rescale
cluster_data <- scale(cluster_data)

# inspect
head(cluster_data)
```

```
[6,]  2.6064366  1.8434062  0.22116720   0.2379171  -1.3168781  -0.3384050
     1_higher_managerial 2_lower_managerial 3_intermediate_occupations
[1,]           4.4185012          1.8391416                 -2.2291104
[2,]          -0.8510113         -0.9272602                  0.1031344
[3,]          -0.4499409         -0.3266302                  1.5123844
[4,]          -0.6741298         -0.3469851                  1.8104058
[5,]          -0.9705088         -1.0065195                  0.5809449
[6,]          -0.8571773         -1.0674213                 -0.1494470
     4_employers_small_org 5_lower_supervisory 6_semi_routine   7_routine
[1,]           -1.02298662         -2.53130431    -2.49888739 -1.81145433
[2,]            0.39745656         -0.67859270     1.05051667  0.08877827
[3,]            0.28308676         -0.37987493    -0.05595897 -0.52802287
[4,]            0.13591535          0.24587683    -0.15093353 -0.07008362
[5,]            0.09942212          0.42532220     0.76747039  0.35318453
[6,]           -0.18786941          0.05518013     0.56442659  0.57156979
     8_unemployed avg_dwn_speed avb_superfast no_decent_bband
[1,]   -0.5139854    -1.6561653    -5.2186970      -0.3797659
[2,]    1.1777334     0.7915882     0.5093876      -0.2031415
[3,]    0.7615830     0.6354463     0.5222597      -0.3797659
[4,]    0.2898589     0.9477301     0.5480039      -0.2472976
[5,]    0.8482656     0.4701196     0.2648177       0.2384195
[6,]    1.5510655     0.6813704     0.4965155      -0.1589854
```

Now our data are all on the same scale, we will start by creating an elbow plot. The elbow method is a visual aid that can help in determining the number of clusters in a data set. Remember: this is important because with a **k-means** clustering you need to specify the numbers of clusters *a priori*!

The elbow method can help as it plots the total explained variation ('Within Sum of Squares') in your data as a function of the number of cluster. The idea is that you pick the number of clusters at the 'elbow' of the curve as this is the point in which the additional variation that would be explained by an additional cluster is decreasing. Effectively this means you are

actually running the **k-means** clustering multiple times before running the actual **k-means** clustering algorithm.

Listing 1.10 `R code`

```
# create empty list to store the within sum of square values
wss_values <- list()

# execute a k-means clustering for k=1, k=2, ..., k=15
for (i in 1:15) {

}   wss_values[i] <- sum(kmeans(cluster_data, centers = i, iter.max =
 ↪  30)$withinss)
# inspect
```

```
wss_values
```

```
[[1]]
[1] 144143

[[2]]
[1] 110934.1

[[3]]
[1] 100058.1

[[4]]
[1] 82701.63

[[5]]
[1] 73974.97

 [ reached getOption("max.print") -- omitted 10 entries ]
```

Listing 1.11 `R code`

```r
# vector to dataframe
wss_values <- as.data.frame(wss_values)

# transpose
wss_values <- as.data.frame(t(wss_values))


# add cluster numbers
wss_values$cluster <- seq.int(nrow(wss_values))
names(wss_values) <- c("wss", "cluster")

# plot using ggplot2

ggplot(data = wss_values, aes(x = cluster, y = wss)) + geom_point() +
 ↪  geom_path() +
    scale_x_continuous(breaks = seq(1, 15)) + xlab("Number of clusters")
     ↪  + ylab("Within sum of squares") +
    theme_minimal()
```

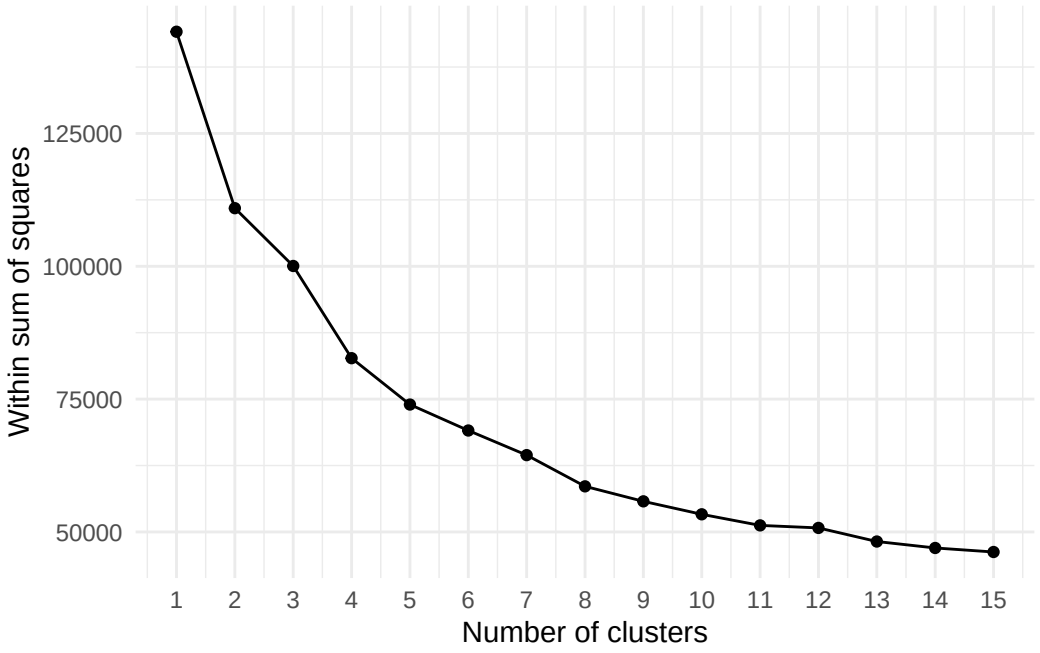


Figure 1.6: Within sum of squares by number of clusters

Based on the elbow plot, we can now choose the number of clusters and it looks like **7** clusters would be a reasonable choice.

> **Note**
>
> The interpretation of an elbow plot can be quite subjective and often multiple options would be justified: **6**, **8**, and perhaps **9** clusters also do not look unreasonable. You would need to try the different options and see what output you get to determine the 'optimal' solution. However, at very least, the elbow plot does give you an idea of what would potentially be an adequate number of clusters.

Now we have decided on the number of clusters (i.e. **7** clusters), we can run our cluster analysis. We will be running this analysis 10 times because there is an element of randomness within the clustering, and we want to make sure we get the optimal clustering output.

```
[1] "starting run: 1"
[1] "starting run: 2"
[1] "starting run: 3"
[1] "starting run: 4"
[1] "starting run: 5"
[1] "starting run: 6"
[1] "starting run: 7"
[1] "starting run: 8"
[1] "starting run: 9"
[1] "starting run: 10"
```

```
# inspect
clusters
```

```
K-means clustering with 7 clusters of sizes 2053, 2039, 740, 186, 1107, 1814, 541

Cluster means:
     age0to4pc  age5to14pc age16to24pc age25to44pc age45to64pc age75pluspc
  1_higher_managerial 2_lower_managerial 3_intermediate_occupations
  4_employers_small_org 5_lower_supervisory 6_semi_routine  7_routine
  8_unemployed avg_dwn_speed avb_superfast no_decent_bband
 [ reached getOption("max.print") -- omitted 7 rows ]

Clustering vector:
[1] 3 5 2 2 5
 [ reached getOption("max.print") -- omitted 8475 entries ]
```

```
Within cluster sum of squares by cluster:
[1] 11736.830 11471.872  7786.692  3401.821  9429.647
 [ reached getOption("max.print") -- omitted 2 entries ]
 (between_SS / total_SS =  56.3 %)

Available components:

[1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
 [ reached getOption("max.print") -- omitted 4 entries ]
```

We now have to execute a bit of post-processing to extract some useful summary data for each cluster: the cluster size (`size`) and mean values for each cluster.

```
[1] 2053 2039  740  186 1107
 [ reached getOption("max.print") -- omitted 2 entries ]
```

```r
# mean values for each variable in each cluster
kfit_mean <- as_tibble(aggregate(cluster_data, by = list(kfit$cluster),
 ↪  FUN = mean))
names(kfit_mean)[1] <- "cluster"

# inspect
kfit_mean
```

```
# A tibble: 7 x 18
  cluster age0to4pc age5to14pc age16to~1 age25~2 age45~3 age75~4 1_hig~5 2_low~6
    <int>     <dbl>      <dbl>     <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
1       1  -0.00815    -0.0824   -0.0526 -0.158   0.0919   0.164 -0.837   -0.849
2       2   0.0162      0.118    -0.172   0.0189  0.202   -0.103 -0.0481   0.211
3       3   0.326      -0.923     0.209   2.05   -1.23    -0.927  1.50     1.26
4       4  -1.52       -2.68      5.42    0.113  -2.62    -1.28   0.870    0.223
5       5   1.56        1.14      0.381   0.626  -1.13    -0.954 -0.906   -1.26
6       6  -0.679      -0.0412   -0.465  -0.773   0.765    0.856  0.845    0.893
7       7  -0.880      -0.148    -0.523  -0.998   1.22     0.554  0.0251   0.225
# ... with 9 more variables: `3_intermediate_occupations` <dbl>,
#   `4_employers_small_org` <dbl>, `5_lower_supervisory` <dbl>,
#   `6_semi_routine` <dbl>, `7_routine` <dbl>, `8_unemployed` <dbl>,
#   avg_dwn_speed <dbl>, avb_superfast <dbl>, no_decent_bband <dbl>, and
#   abbreviated variable names 1: age16to24pc, 2: age25to44pc, 3: age45to64pc,
#   4: age75pluspc, 5: `1_higher_managerial`, 6: `2_lower_managerial`
```

Figure 1.7: Mean variable values by cluster

> **Warning**
>
> Your values may be slightly different due to the random choice of initial cluster centres.

Looking at the table with the mean values for each cluster and the barplot, we can see that variables contribute differently to the different clusters. The graph is a little busy, so you might want to look at the cluster groups or variables individually to get a better picture of each cluster.

Figure 1.8: Mean variable values for cluster 1

We can also show the results of our geodemographic classification on a map.

```
Reading layer `gb_msoa11_sim' from data source
  `/Users/justinvandijk/Library/CloudStorage/Dropbox/UCL/Web/jtvandijk.github.io/GEOG0114Q/da
  using driver `ESRI Shapefile'
Simple feature collection with 8480 features and 3 fields
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: 5513 ymin: 5342.7 xmax: 655604.7 ymax: 1220302
Geodetic CRS:  WGS 84
```

```r
# set projection
st_crs(msoa) = 27700

# simplify for speedier plotting
msoa <- st_simplify(msoa, dTolerance = 100)

# join
cluster_data <- cbind(iuc_input, kfit$cluster)
msoa <- left_join(msoa, cluster_data, by = c(geo_code = "msoa11cd"))
```

```
# plot
tm_shape(msoa) + tm_fill(col = "kfit$cluster") +
 ↪  tm_layout(legend.outside = TRUE)
```

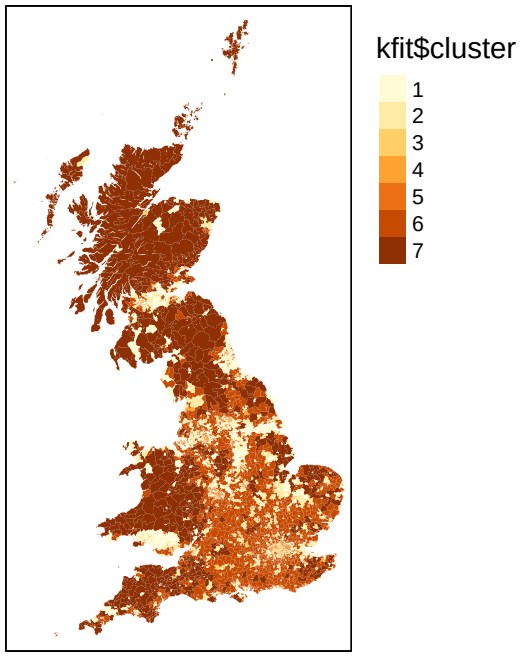


Figure 1.9: Spatial pattern of our geodemographic classification

> **Warning**
>
> Your map might look different as the cluster numbers are not consistently assigned and therefore colours can be map onto the cluster numbers differently.

1.3.4 Tutorial task II

The creation of a geodemographic classification is an **iterative process** of trial and error that involves the addition and removal of variables as well as experimentation with different numbers of clusters. It also might be, for instances, that some clusters are very focused on one group of data (e.g. age) and it could be an idea to group some ages together. If you want to make changes to the clustering solution, you can simply re-run the analysis with a different set of variables or with a different number of clusters by updating the code. However, it would be even simpler if you could automate some of the process.

Try to create a **R function** that:

1. takes *at least* the following three arguments: **a data frame that contains your input data**, **the number of clusters that you want**, and **a list of input variables**;
2. executes a **k-means** clustering on the input variables and the specified number of clusters; and,
3. produces a `csv` file that contains the **table of means** of the solution.

> **Note**
>
> 1. Your function could look something like: `run-kmeans(dataframe,number_of_clusters,input_variab`
> 2. The list of input variables does not have to be a list of *names*, but can also be a list containing the index values of the columns.
> 3. Have a look at Hadley Wickhams explanation of functions in R.

1.4 Before you leave

Having finished this tutorial, you should now understand the basics of a geodemographic classification. In addition, you should have written a simple function. Although you have now reached the end of this week's content, you could try and improve your function. Consider:

1. Including *maps* or *graphs* in the code that get automatically saved.
2. Ensuring that the `csv` outcome does **not** get overwritten every time you run you function.
3. Including optional arguments in your function with **default values** if certain values are not specified.

Listing 1.12 `R code`

```
# create empty list to store the results of the clustering
clusters <- list()

# create empty variable to store fit
fit <- NA

# run the k-means 10 times
for (i in 1:10) {

    # keep track of the runs
    print(paste0("starting run: ", i))

    # run the k-means clustering algorithm to extract 7 clusters
    clust7 <- kmeans(x = cluster_data, centers = 7, iter.max = 1e+06,
 ↪  nstart = 1)

    # get the total within sum of squares for the run and
    fit[i] <- clust7$tot.withinss

    # update the results of the clustering if the total within sum of
     ↪  squares
    # for the run is lower than any of the runs that have been executed
     ↪  so far
    if (fit[i] < min(fit[1:(i - 1)])) {
        clusters <- clust7
    }
}
```

Listing 1.13 R code

```
# assign to new variable for clarity
kfit <- clusters

# cluster sizes
kfit_size <- kfit$size

# inspect
kfit_size
```

Listing 1.14 R code

```
# transform shape to tidy format
kfit_mean_long <- pivot_longer(kfit_mean, cols = (-cluster))

# plot using ggplot2

ggplot(kfit_mean_long, aes(x = cluster, y = value, fill = name)) +
 ↪  geom_bar(stat = "identity") + scale_x_continuous(breaks = seq(1, 7, by = 1))
    ylab("Mean value") + xlab("Cluster") + theme_minimal() + theme(legend.title =
     ↪  element_blank(),

    legend.position = "bottom")
```

Listing 1.15 R code

```
# plot using ggplot2
ggplot(kfit_mean_long[kfit_mean_long$cluster == 1, ], aes(x = cluster, y
 ↪  = value,
    fill = name)) + geom_bar(stat = "identity", position = "dodge") +
     ↪  xlab("Cluster") +
    ylab("Mean value") + theme_minimal() + theme(legend.title =
     ↪  element_blank(),
    legend.position = "bottom")
```

Listing 1.16 `R code`

```
# read shape
msoa <- st_read("data/boundaries/gb_msoa11_sim.shp")
```

2 Transport Network Analysis

This week we will cover a different type of data: network data. We will take a look at how we can use network data to measure accessibility using the `dodgr` R library. We will calculate the network distances between combinations of locations (i.e. a set of origins and a set of destinations). These distances can then, for instance, be used to calculate the number of a resource (e.g. fast-food outlets) within a certain distance of a Point of Interest (e.g. a school or population-weighted centroid).

2.1 Lecture slides

You can download the slides of this week's lecture here: [Link].

2.2 Reading list

Essential readings

- Geurs, K., Van Wee, B. 2004. Accessibility evaluation of land-use and transport strategies: review and research directions. *Journal of Transport Geography* 12(2): 127-140. [Link]
- Higgins, C., Palm, M. DeJohn, A. *et al.* 2022. Calculating place-based transit accessibility: Methods, tools and algorithmic dependence. *Journal of Transport and Land Use* 15(1): 95-116. [Link]
- Neutens, T. Schwanen, T. and Witlox, F. 2011. The prism of everyday life: Towards a new research agenda for time geography. *Transport Reviews* 31(1): 25-47. [Link]

Suggested readings

- Schwanen, T. and De Jong, T. 2008. Exploring the juggling of responsibilities with space-time accessibility analysis. *Urban Geography* 29(6): 556-580. [Link]
- Van Dijk, J., Krygsman, S. and De Jong, T. 2015. Toward spatial justice: The spatial equity effects of a toll road in Cape Town, South Africa. *Journal of Transport and Land Use* 8(3): 95-114. [Link]

- Van Dijk, J. and De Jong, T. 2017. Post-processing GPS-tracks in reconstructing travelled routes in a GIS-environment: network subset selection and attribute adjustment. *Annals of GIS* 23(3): 203-217. [Link]

2.3 Transport Network Analysis

The term network analysis covers a wide range of analysis techniques ranging from complex network analysis to social network analysis, and from link analysis to transport network analysis. What the techniques have in common is that they are based on the concept of a **network**. A network or network graph is constituted by a collection of vertices that are connected to one another by edges. Note, vertices may also be called nodes or points, whilst edges may be called links or lines. Within social network analysis, you may find the terms actors (the vertices) and ties or relations (the edges) also used.

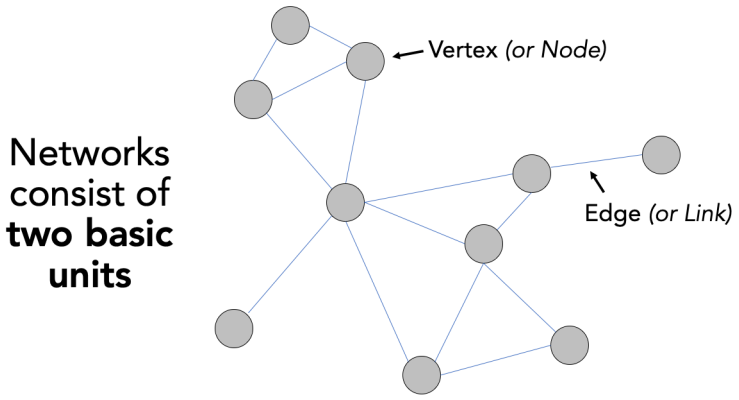


Figure 2.1: Visualising networks with vertices and edges.

2.3.1 Accessibility in Portsmouth

For this week's practical, we will be using Portsmouth in the UK as our area of interest for our analysis. One prominent topic within the city is the issue of public health and childhood obesity. According to figures released in March 2020 by Public Health England, more than one in three school pupils are overweight or obese by the time they finish primary school within the city; this is much higher than the national average of one in four. One potential contributor to the health crisis is the ease and availability of fast-food outlets in the city. In the following, we will measure the accessibility of fast-food outlets within specific walking distances of all school in Portsmouth starting at 400m, then 800m and finally a 1km walking distance. We will then

aggregate these results to Lower Super Output Areas (LSOA) and overlay these results with some socio-economic variables.

To execute this analysis, we will need to first calculate the distances between our schools and fast-food outlets. This involves calculating the shortest distance a child would walk between a school and a fast-food outlet, using roads or streets. We will use the `dodgr` R package to conduct this transport network analysis.

> **Note**
>
> All calculations within the `dodgr` library currently need to be run in WGS84/4236. This is why we will not transform the CRS of our data in this practical.

2.3.2 Acquiring network data

The first dataset we need to download will help with the visualisation of our results: boundary data that contains an outline of Portsmouth.

File	File Type	Link
Major towns and cities boundaries 2015	`shp`	Download

We can now load the required libraries as well as the major towns and cities boundaries `shapefile`.

Listing 2.1 `R code`

```
# libraries
library(tidyverse)
library(sf)
library(tmap)
library(osmdata)
library(dodgr)

# load major towns and cities, filter Portsmouth
portsmouth_city <-
 ↪  st_read("data/outline/Major_Towns_and_Cities__December_2015__Boundaries.shp",
    stringsAsFactors = FALSE) %>%
    filter(tcity15nm == "Portsmouth")
```

```
Reading layer `Major_Towns_and_Cities__December_2015__Boundaries' from data source `/Users/ju
  using driver `ESRI Shapefile'
Simple feature collection with 112 features and 5 fields
Geometry type: MULTIPOLYGON
Dimension:     XY
Bounding box:  xmin: -4.204842 ymin: 50.34101 xmax: 1.378014 ymax: 55.03117
Geodetic CRS:  WGS 84
```

To create our network and Origin-Destination dataset, we will need data on schools, fast-food outlets, and a streetnetwork. Today we will be using OpenStreetMap for this. If you have never come across OpenStreetMap (OSM) before, it is a free editable map of the world.

> **Note**
>
> OpenStreetMap's spatial coverage is still unequal across the world - plus, as you will find if you use the data, the accuracy and quality of the data can often be quite questionable or simply missing attribute details that we would like to have, e.g. types of roads and their speed limits, to complete specific types of spatial analysis.

Whilst there are various approaches to downloading data from OpenStreetMap, we will use the `osmdata` library to directly extract our required OpenStreetMap (OSM) data into a variable. The `osmdata` library grants access within R to the Overpass API that allows us to run queries on OSM data and then import the data as spatial objects. These queries are at the heart of these data downloads.

We will go ahead and start with downloading and extracting our road network data. To OSM data using the `osmdata` library, we can use the `add_osm_feature()` function. To use the function, we need to provided it with either a *bounding box* of our area of interest (AOI) or a set of points, from which the function will create its own bounding box. You can find out more about this and details on how to construct your own queries in the data vignette.

To use the library (and API), we need to know how to write and run a query, which requires identifying the `key` and `value` that we need within our query to select the correct data. Essentially every map element (whether a point, line or polygon) in OSM is **tagged** with different attribute data. These `keys` and `values` are used in our queries to extract only map elements of that feature type - to find out how a feature is tagged in OSM is simply a case of reading through the OSM documentation and becoming familiar with their keys and values.

To download our road network dataset, we first define a variable to store our bounding box coordinates, `p_bbox()`. We then use this within our OSM query to extract specific types of road segments within that bounding box - the results of our query are then stored in an `osmdata` object. We will select all OSM features with the `highway` tag that are likely to be used by pedestrians (e.g. not `motorways`).

Listing 2.2 `R code`

```
# define our bbox coordinates for Portsmouth

p_bbox <- c(-1.113197, 50.775781, -1.026508, 50.859941)



# pass bounding box coordinates into the OverPassQuery (opq) function
#↪download only features that are not classified as motorway

osmdata <- opq(bbox = p_bbox) %>%

    add_osm_feature(key = "highway", value = c("primary", "secondary",
     ↪  "tertiary",
        "residential", "path", "footway", "unclassified",
    osmdata_sf()      ↪  "living_street", "pedestrian")) %>%
```

> **Note**
>
> In some instances the OSM query will return an error, especially when several people from the same location are executing the exact same query. If this happens, you can just read through the instructions and download a prepared copy of the data that contains **all** required OSM Portsmouth data instead: [Link].
> You can load these downloaded data as follows into R:
>
> **Listing 2.3** `R code`
>
> ```
> load("../path/to/file/ports_ff.RData")
> load("../path/to/file/ports_roads_edges.RData")
> load("../path/to/file/ports_schools.RData")
> ```
>
> After loading your data, you can continue with the analysis in the Measuring Accessiblity section below, starting with the creation of a network graph with the 'foot weighting' profile.

The `osmdata` object contains the bounding box of your query, a time-stamp of the query, and then the spatial data as `osm_points`, `osm_lines`, `osm_multilines` and `osm_polgyons` (which

are listed with their respective fields also detailed). Some of the spatial features maybe empty, depending on what you asked your query to return. Our next step therefore is to extract our spatial data from our `osmdata` object to create our road network data set. This is in fact incredibly easy, using the traditional `$` R approach to access these spatial features from our object.

Deciding what to extract is probably the more complicated aspect of this - mainly as you need to understand how to represent your road network, and this will usually be determined by the library/functions you will be using it within. Today, we want to extract the **edges** of the network, i.e. the lines that represent the roads, as well as the **nodes** of the network, i.e. the points that represent the locations at which the roads start, end, or intersect. For our points, we will only keep the `osm_id` data field, just in case we need to refer to this later. For our lines, we will keep a little more information that we might want to use within our transport network analysis, including the type of road, the maximum speed, and whether the road is one-way or not.

Listing 2.4 `R code`

```
# extract the `p`oints, with their osm_id.
ports_roads_nodes <- osmdata$osm_points[, "osm_id"]

# extract the lines, with their osm_id, name, type of highway, max speed
 ↪  and
# oneway attributes
ports_roads_edges <- osmdata$osm_lines[, c("osm_id", "name", "highway",
 ↪  "maxspeed",
    "oneway")]
```

To check our data set, we can quickly plot the edges of our road network using the `plot()` function:

Listing 2.5 `R code`

```
# inspect
plot(ports_roads_edges, max.plot = 1)
```

Figure 2.2: OSM road network

Because we are focusing on walking, we will overwrite the `oneway` variable by suggesting that none of the road segments are restricted to one-way traffic which may affect our analysis as well as the general connectivity of the network.

Listing 2.6 `R code`

```
# overwrite one-way default
ports_roads_edges$oneway <- "no"
```

Now we have the network edges, we can turn this into a graph-representation that allows for the calculation of network-based accessibility statistics.

2.3.3 Measuring accessibility

Before we can construct our full network graph for the purpose of accessibility analysis, we need to also provide our **Origin** and **Destination** points, i.e. the data points we wish to calculate the distances between. According to the `dodgr` documentation, these points need to be in either a vector or matrix format, containing the two coordinates for each point for the origins and for the destinations.

As for our Portsmouth scenario we are interested in calculating the shortest distances between schools and fast-food outlets, we need to try and download these datasets - again we will turn to OpenStreetMap. Following a similar structure to our query above, we will use our knowledge of OpenStreetMap `keys` and `values` to extract the points of Origins (schools) and Destinations (fast-food outlets) we are interested in:

Listing 2.7 `R code`

```r
# download schools from OSM
schools <- opq(bbox = p_bbox) %>%
    add_osm_feature(key = "amenity", value = "school") %>%
    osmdata_sf()

# download fast-food outlets
ff_outlets <- opq(bbox = p_bbox) %>%
    add_osm_feature(key = "amenity", value = "fast_food") %>%
    osmdata_sf()
```

We also need to then extract the relevant data from the `osmdata` object:

Listing 2.8 `R code`

```r
# extract school points
ports_schools <- schools$osm_points[, c("osm_id", "name")]

# extract fast-food outlet points
ports_ff <- ff_outlets$osm_points[, c("osm_id", "name")]
```

We now have our road network data and our Origin-Destination (OD) points in place and we can now move to construct our network graph and run our transport network analysis.

> **Note**
>
> In this analysis, we are highly reliant on the use of OpenStreetMap to provide data for both our Origins and Destinations. Whilst in the UK OSM provides substantial coverage, its quality is not always guaranteed. As a result, to improve on our current methodology in future analysis, we should investigate into a more official school data set or at least validate the number of schools against City Council records. The same applies to our fast-food outlets.

With any network analysis, the main data structure is a **graph**, constructed by our nodes and edges. To create a graph for use within `dodgr`, we pass our `ports_roads_edges()` into the `weight_streetnet()` function. The `dodgr` library also contains weighting profiles, that you can customise, for use within your network analysis. These weighting profiles contain weights based on the type of road, determined by the type of transportation the profile aims to model. Here we will use the weighting profile **foot**, as we are looking to model walking accessibility.

Listing 2.9 `R code`

```
# create network graph with the foot weighting profile
graph <- weight_streetnet(ports_roads_edges, wt_profile = "foot")
```

Once we have our graph, we can then use this to calculate our network distances between our OD points. One thing to keep in mind is that potentially not all individual components in the network that we extracted are connected, for instance, because the bounding box cut off the access road of a cul-de-sac. To make sure that our entire extracted network is connected, we now extract the **largest connected component** of the graph. You can use `table(graph$component)` to examine the sizes of all individual subgraphs. You will notice that most subgraphs consist of a very small number of edges.

> **Note**
>
> The `dodgr` package documentation explains that components are numbered in order of decreasing size, with `$component = 1` always denoting the largest component. Always inspect the resulting subgraph to make sure that its coverage is adequate for analysis.

Listing 2.10 `R code`

```
# extract the largest connected graph component
graph_connected <- graph[graph$component == 1, ]

# inspect number of remaining road segments
nrow(graph_connected)
```

```
[1] 56364
```

```
# inspect
plot(dodgr_to_sf(graph_connected), max.plot = 1)
```

Figure 2.3: Largest graph component

> **Warning**
>
> OpenStreetMap is a living dataset, meaning that changes are made on a continuous basis; as such it may very well possible that the number of remaining road segments as shown above may be slighlty different when you run this analysis.

Now we have our connected subgraph, will can use the `dodgr_distances()` function to calculate the network distances between every possible Origin and Destination. In the `dodgr_distances()` function, we first pass our `graph`, then our Origin points (schools), in the `from` argument, and then our Destination points (fast-food outlets), in the `to` argument. One thing to note is our addition of the `st_coordinates()` function as we pass our two point data sets within the `from` and `to` functions as we need to supplement our Origins and Destinations in a matrix format. For all Origins and Destinations, `dodgr_distances()` will map the points to the **closest network points**, and return corresponding shortest-path distances.

The result of this computation is a distance-matrix that contains the network distances between all Origins (i.e. schools) and all Destinations (i.e. fast-food outlets). Let's inspect the first row of our output. Do you understand what the values mean?

```
1        2        3        4        5        6        7        8
```

Listing 2.11 R code

```
# create a distance matrix between schools and fast-food stores
sch_to_ff_calc <- dodgr_distances(graph_connected, from =
 ↪  st_coordinates(ports_schools),
    to = st_coordinates(ports_ff), shortest = TRUE, pairwise = FALSE,
     ↪  quiet = FALSE)
```

Listing 2.12 R code

```
# inspect

head(sch_to_ff_calc, n = 1)
```

```
1 4000.016 2090.485 6549.779 9356.08 10903.62 2231.919 11845.44 2292.263
         9       10       11       12       13       14       15       16
1 1676.805 1680.043 1697.416 1676.805 2090.485 2090.485 2060.898 4000.016
        17       18       19       20       21       22       23       24
1 2324.454 4000.016 4000.016 3338.83 1700.179 581.0582 7277.651 3610.322
        25       26       27       28       29       30       31       32
1 1359.146 3321.374 340.8823 1102.226 10796.81 2963.157 2720.491 3508.267
        33       34       35       36       37       38       39       40
1 2330.386 2818.121 2920.565 2920.565 736.0556 3399.756 844.6083 6231.901
        41       42       43       44       45       46       47       48
1 3394.397 9171.192 9372.628 9238.263 9481.949 1629.029 3525.506 2400.918
        49       50       51       52       53       54       55       56
1 7173.413 8978.739 9403.034 9329.926 6483.465 6483.465 6470.802 6470.802
        57       58       59       60       61       62       63       64
1 804.5849 763.0434 2526.807 1067.907 1010.408 1010.408 1967.697 1418.767
        65       66       67       68       69       70       71       72
1 2818.121 1245.823 2157.02 688.8672 2162.922 2205.285 2119.323 11755.26
        73       74       75       76       77       78       79       80
1 4829.051 2738.124 844.6083 615.1102 788.7212 2586.476 2667.125 728.4882
        81       82       83       84       85       86       87       88
1 11845.44 11845.44 11845.44 11934.59 11934.59 11934.59 11845.44 11845.44
        89       90       91       92       93       94       95       96
1 11845.44 11845.44 11845.44 11845.44 11845.44 11339.91 6545.668 6589.917
        97       98       99      100      101      102      103      104
1 6589.917 6442.566 4000.016 4000.016 4234.432 5929.469 3841.384 581.0582
```

```
       105      106      107      108      109      110      111      112
1 597.3575 2654.314 5119.621 5317.048 5058.497 375.2084 926.0127 5058.497
       113      114      115      116      117      118      119      120      121
1 4045.705 753.752 556.5173 713.536 622.6949 597.3575 1225.66 3339.134 3295.758
       122      123      124      125      126      127      128      129
1 5469.038 6670.481 6634.905 6634.905 6626.71 6634.905 6634.905 6626.71
       130      131      132      133      134      135      136      137
1 6670.481 6670.481 6626.71 6670.481 6670.481 6670.481 6670.481 6670.481
       138      139      140      141      142      143      144      145
1 12348.71 9528.601 9528.601 5522.227 9339.459 9339.459 9291.034 8563.944
       146      147      148      149      150      151      152      153
1 9291.034 9339.459 12026.51 12026.51 12033.8 12026.11 9548.47 3586.662
       154      155      156      157      158      159      160      161
1 2300.121 815.5434 3467.049 5708.154 905.8238 905.8238 905.8238 4950.036
       162      163      164      165      166      167      168      169
1 4968.988 858.9023 3216.085 3397.074 11419.74 4879.532 1813.109 9160.3
       170      171      172      173      174      175      176      177
1 1666.407 9599.24 9659.195 4687.627 3177.171 3467.049 3118.594 5973.195
       178      179      180      181      182      183      184      185
1 9633.051 9659.195 5299.098 3966.434 9219.851 6041.409 5972.696 8905.439
       186      187      188      189      190      191      192      193
1 6656.006 5895.308 10772.24 1505.914 4995.748 11489.11 1574.826 5478.182
       194      195      196      197      198      199      200      201
1 1804.091 3107.774 9102.648 4738.493 4968.988 4041.569 13159.31 5478.182
       202      203      204      205      206      207      208      209
1 3295.758 3295.758 556.5173 788.7212 10113.11 5101.577 9633.051 9633.051
       210      211      212      213      214      215      216      217
1 9633.051 9520.773 9520.773 9520.773 9520.773 9633.051 9633.051 6001.071
      218      219      220      221      222      223      224      225
1 5606.02 4718.064 4041.569 4887.462 4885.475 1543.604 1510.665 1559.537
       226      227      228      229      230      231      232      233
1 5317.388 11646.67 4944.579 4949.291 4188.983 3525.506 6046.467 5452.211
       234      235      236      237      238      239      240      241
1 5317.048 5317.048 5317.048 5317.048 5317.048 5317.048 5317.048 4963.868
       242      243      244      245      246      247      248      249
1 6272.114 5376.342 4738.493 5818.335 6634.905 4925.352 11559.4 11584.02
       250      251      252      253      254      255      256      257
1 5058.497 5058.497 5058.497 5058.497 5101.577 5131.313 5101.577 5131.313
       258      259      260      261      262      263      264      265
1 5131.313 5125.567 11845.44 6549.779 6549.779 6529.533 6549.779 6549.779
       266      267      268      269      270      271      272      273
1 6529.533 4808.089 4968.988 11845.44 4774.109 4361.855 1129.672 1302.289
       274      275      276      277      278      279      280      281
```

```
1 1302.289 1320.727 3344.664 4341.78 1332.226 1122.057 5297.203 11934.59
       282      283      284      285      286      287      288      289
1 12026.51 3002.79 6483.465 5784.828 3383.088 3166.965 11584.02 2920.565
      290      291      292      293      294      295      296      297
1 1677.06 2312.611 5837.072 5735.345 5737.21 5837.072 5837.072 4958.337
       298      299      300      301      302      303      304      305
1 1128.534 9233.39 2059.118 7701.615 1114.85 1092.164 1092.164 1122.057
       306      307      308      309      310      311      312      313
1 1092.164 4661.76 2205.285 3361.814 2738.453 3026.324 3508.075 3522.959
       314      315      316      317      318      319      320      321
1 3522.959 3610.322 3610.322 3639.371 3377.222 3522.959 2724.716 597.3575
       322      323      324      325      326
1 3532.616 7376.95 7338.052 7338.052 7376.95
```

Our output shows the calculations for the first school - and the distances between the school and every fast-food outlet. Because we manually overwrote the values for all one-way streets as well as that we extracted the larges connected graph only, we currently should not have any `NA` values.

> **Tip**
>
> The `dodgr` vignette notes that a distance matrix obtained from running `dodgr_distances` on `graph_connected` should generally contain no `NA` values, although some points may still be effectively unreachable due to one-way connections (or streets). Thus, routing on the largest connected component of a directed graph ought to be expected to yield the minimal number of `NA` values, which may sometimes be more than zero. Note further that spatial routing points (expressed as from and/or to arguments) will in this case be mapped to the nearest vertices of `graph_connected`, rather than the potentially closer nearest points of the full graph.

The next step of processing all depends on what you are trying to assess - here we want to understand which schools have a higher accessibility of fast-food outlets compared to others, quantified by how many outlets are within walking distance of specific distances. We will therefore look to count how many outlets are with walking distance from each school and store this as a new column within our `ports_school` data frame.

2.3.4 Tutorial task

Now you have calculated the number of fast-food outlets within specific distances from every school in Portsmouth, your task is to estimate the accessibility of fast-food outlets at the LSOA scale and compare this to the 2019 Index of Multiple Deprivation.

Listing 2.13 `R code`

```r
# fastfood outlets within 400m
ports_schools$ff_within_400m <- rowSums(sch_to_ff_calc <= 400)

# fastfood outlets within 800m
ports_schools$ff_within_800m <- rowSums(sch_to_ff_calc <= 800)

# fastfood outlets within 1000m

ports_schools$ff_within_1km <- rowSums(sch_to_ff_calc <= 1000)
```

> **Tip**
>
> This skills and steps required for this analysis are not just based on this week's practical, but you will have to combine all your knowledge of coding and spatial analysis you have gained over the past weeks.

One way of doing this, is by taking some of the following steps:

- Download and extract the 2011 LSOA boundaries of Portsmouth.
- Download the 2019 Index of Multiple Deprivation scores.
- Decide on an accessibility measure, such as:
  - The average number of fast-food restaurants within `x` meters of a school within each LSOA.
  - The average distance a fast-food restaurant is from a school within each LSOA.
  - The (average) shortest distance a fast-food restaurant is from a school within each LSOA.
  - The minimum shortest distance a fast-food outlet is from a school within each LSOA.
- Create a choropleth map of aggregate accessibility to visualise the results.
- Join the 2019 Index of Multiple Deprivation data to your LSOA dataset.
- For each IMD decile, calculate the average for your chosen aggregate measure and produce a table.

Using your approach what do you think: are fast-food restaurants, on average, more accessible for students at schools that are located within LSOAs with a lower IMD decile when compared to students at schools that are located within LSOAs with a higher IMD decile?

2.4 Want more? [Optional]

We have now conducted some basic accessibility analysis, however, there is some additional fundamental challenges to consider in the context of transport network and accessibility analysis:

1. How do the different weight profiles of the `dodgr` package work? How would one go about creating your own weight profile? How would using a different weight profiles affect the results of your analysis?
2. Why do we have unconnected segments in the extracted transport network? How would you inspect these unconnected segments? Would they need to be connected? If so, how would one do this?
3. Why you think all Origins and Destinations are mapped onto the closest network points? Is this always the best option? What alternative methods could you think of and how would you implement these?

> Tip
>
> If you want to take a deepdive into accessibility analysis, there is a great resource that got published recently: Introduction to urban accessibility: a practical guide in R.

2.5 Before you leave

Having finished this tutorial on transport network analysis and, hopefully, having been able to independently conduct some further area-profiling using IMD deciles, you have now reached the end of this week's content. However, there is some additional fundamental challenges to consider in the context of transport network and accessibility analysis:

1. How do the different weight profiles of the `dodgr` package work? How would one go about creating your own weight profile? How would using a different weight profiles affect the results of your analysis?
2. Why do we have unconnected segments in the extracted transport network? How would you inspect these unconnected segments? Would they need to be connected? If so, how would one do this?
3. Why you think all Origins and Destinations are mapped onto the closest network points? Is this always the best option? What alternative methods could you think of and how would you implement these?