Practical 304

Stefano De Sabbata

2020-09-01

Exploratory data analysis

Stefano De Sabbata

Introduction

This practical showcases an exploratory analysis of the distribution of people aged 20 to 24 in Leicester, using the `u011` variable from the 2011 Output Area Classification (2011OAC) dataset. Create a new R project for this practical session and create a new RMarkdown document to replicate the analysis in this document.

Once the document is set up, start by adding the first R code snipped including the code below, which is loads the 2011OAC dataset and the libraries used for the practical session.

```
library(tidyverse)
library(knitr)
leicester_2011OAC <- read_csv("2011_OAC_Raw_uVariables_Leicester.csv")
```

GGlot2 recap

As seen in the practical session 401, the `ggplot2` library is part of the Tidyverse, and it offers a series of functions for creating graphics **declaratively**, based on the concepts outlined in the Grammar of Graphics. While the `dplyr` library offers functionalities that cover *data manipulation* and *variable transformations*, the `ggplot2` library offers functionalities that allow to specify elements, define guides, and apply scale and coordinate system transformations.

- **Marks** can be specified in `ggplot2` using the `geom_` functions.
- The mapping of variables (table columns) to **visual variables** can be specified in `ggplot2` using the `aes` element.
- Furthermore, the `ggplot2` library:
  - automatically adds all necessary **guides** using default table column names, and additional functions can be used to overwrite the defaults;
  - provides a wide range of `scale_` functions that can be used to control the **scales** of all visual variables;
  - provides a series of `coord_` fucntions that allow transforming the **coordinate system**.

Check out the `ggplot2` reference for all the details about the functions and options discussed below.

Data visualisation

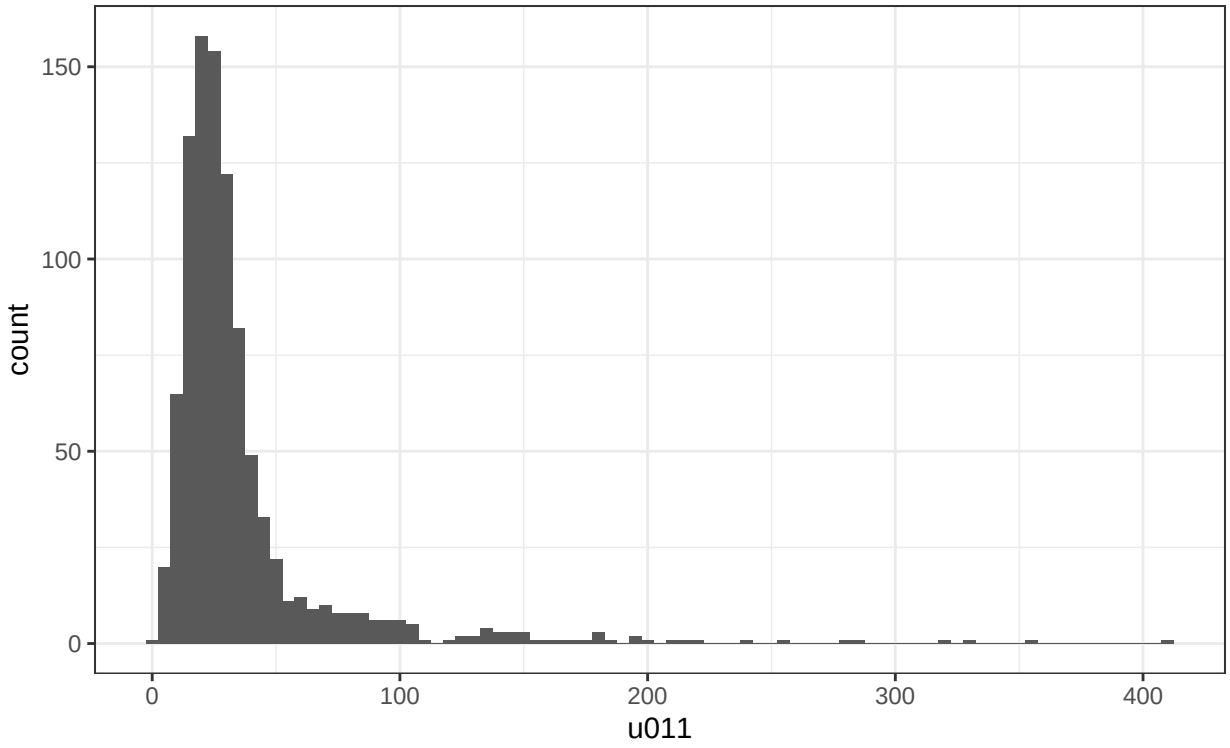
Distributions

We start the analysis with a simple histogram, to explore the distribution of the variable `u011`. RMarkdown allows specifying the height (as well as the width) of the figure as an option for the R snipped, as shown in the example typed out in plain text below.

````
```{r, echo=TRUE, message=FALSE, warning=FALSE, fig.height = 4}
leicester_2011OAC %>%
  ggplot(
    aes(
      x = u011
    )
  ) +
  geom_histogram(binwidth = 5) +
  theme_bw()
```
````

The snipped and barchart is included in output documents, as shown below.

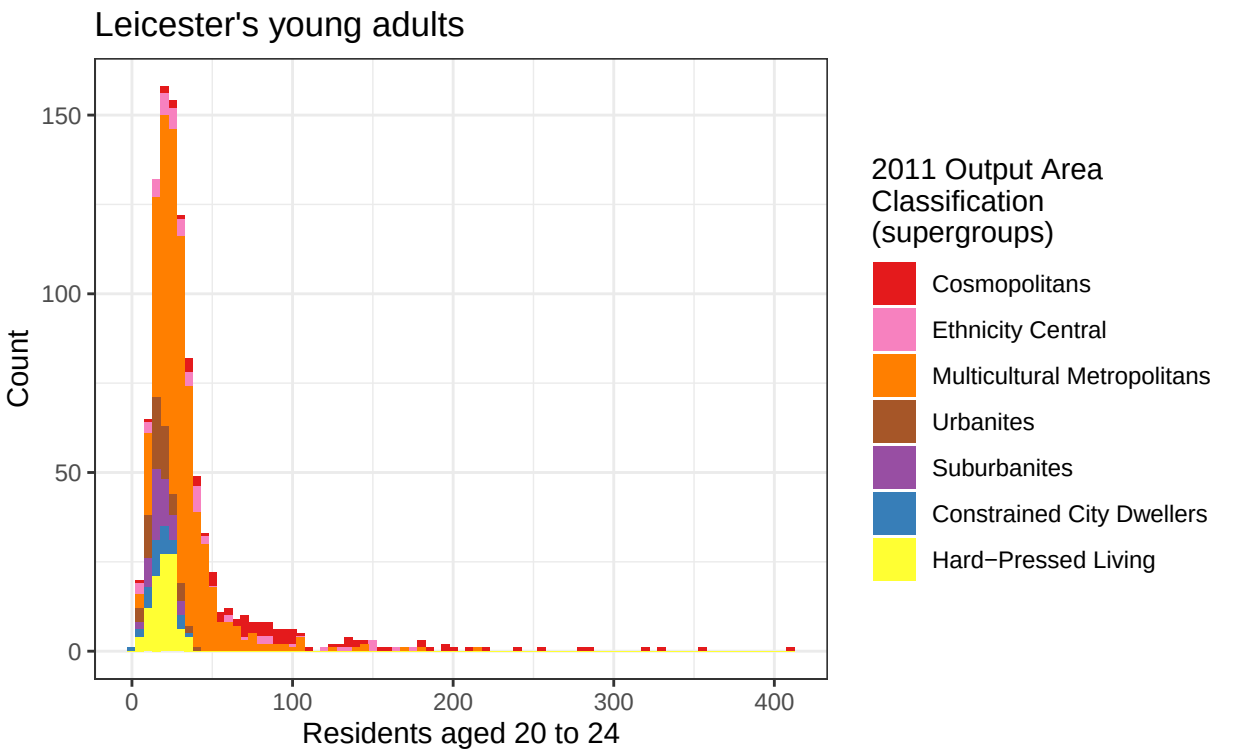
```
leicester_2011OAC %>%
  ggplot(
    aes(
      x = u011
    )
  ) +
  geom_histogram(binwidth = 5) +
  theme_bw()
```



If we aim to explore how that portion of the population is distributed among the different supergroups of the 2011OAC, there are a number of charts that would allow us to visualise that relationship.

For instance, the barchart above can be enhanced through the use of the visual variable colour and the `fill` option. The graphic below uses a few options seen in the practical session 401 to create a stacked barchart, where sections of each bar are filled with the colour associated with a 2011OAC supergroup.

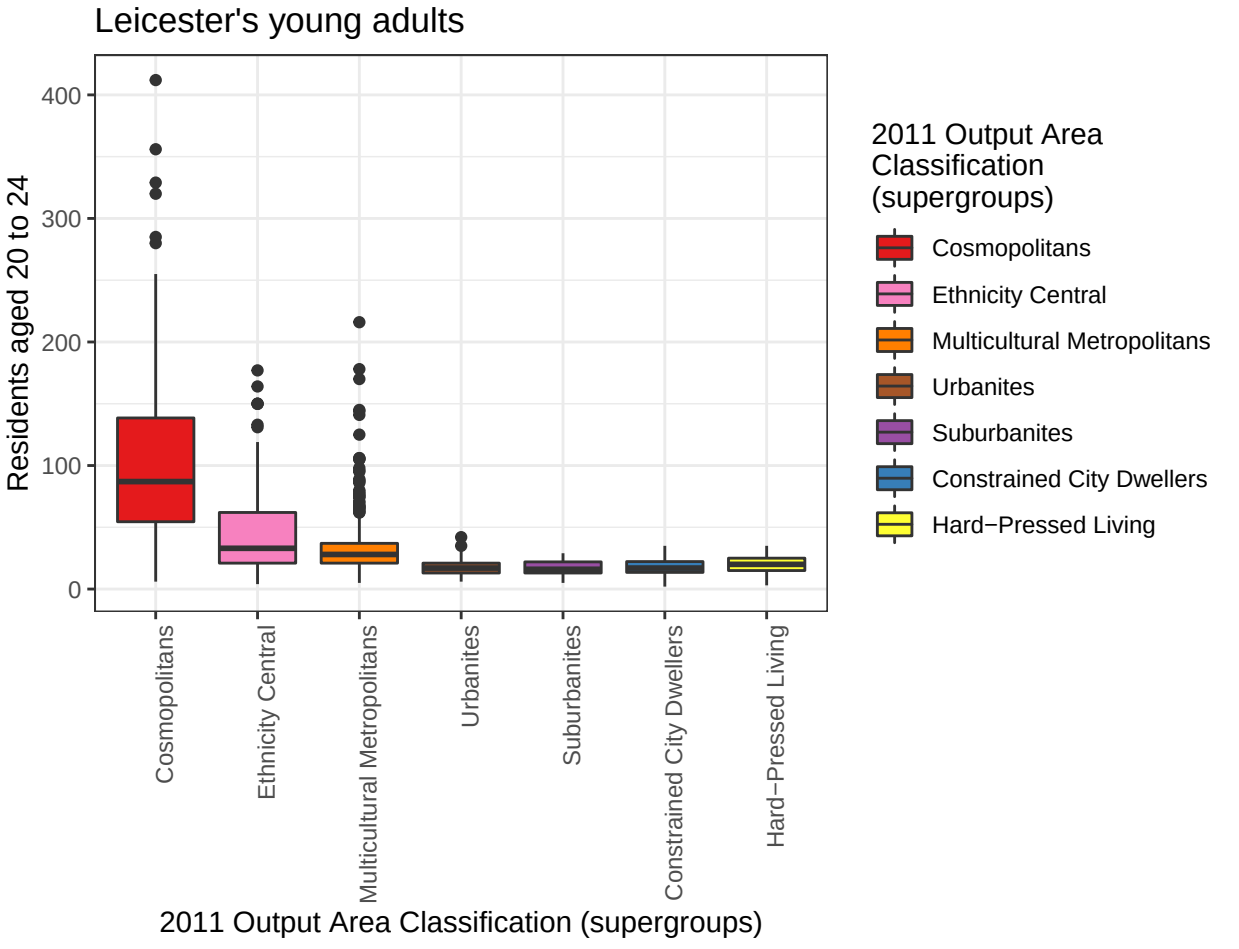
```
leicester_2011OAC %>%
  ggplot(
    aes(
      x = u011,
      fill = fct_reorder(supgrpname, supgrpcode)
    )
  ) +
  geom_histogram(binwidth = 5) +
  ggtitle("Leicester's young adults") +
  labs(
    fill = "2011 Output Area\nClassification\n(supergroups)"
  ) +
  xlab("Residents aged 20 to 24") +
  ylab("Count") +
  scale_fill_manual(
    values = c("#e41a1c", "#f781bf", "#ff7f00", "#a65628", "#984ea3", "#377eb8", "#ffff33")
  ) +
  theme_bw()
```



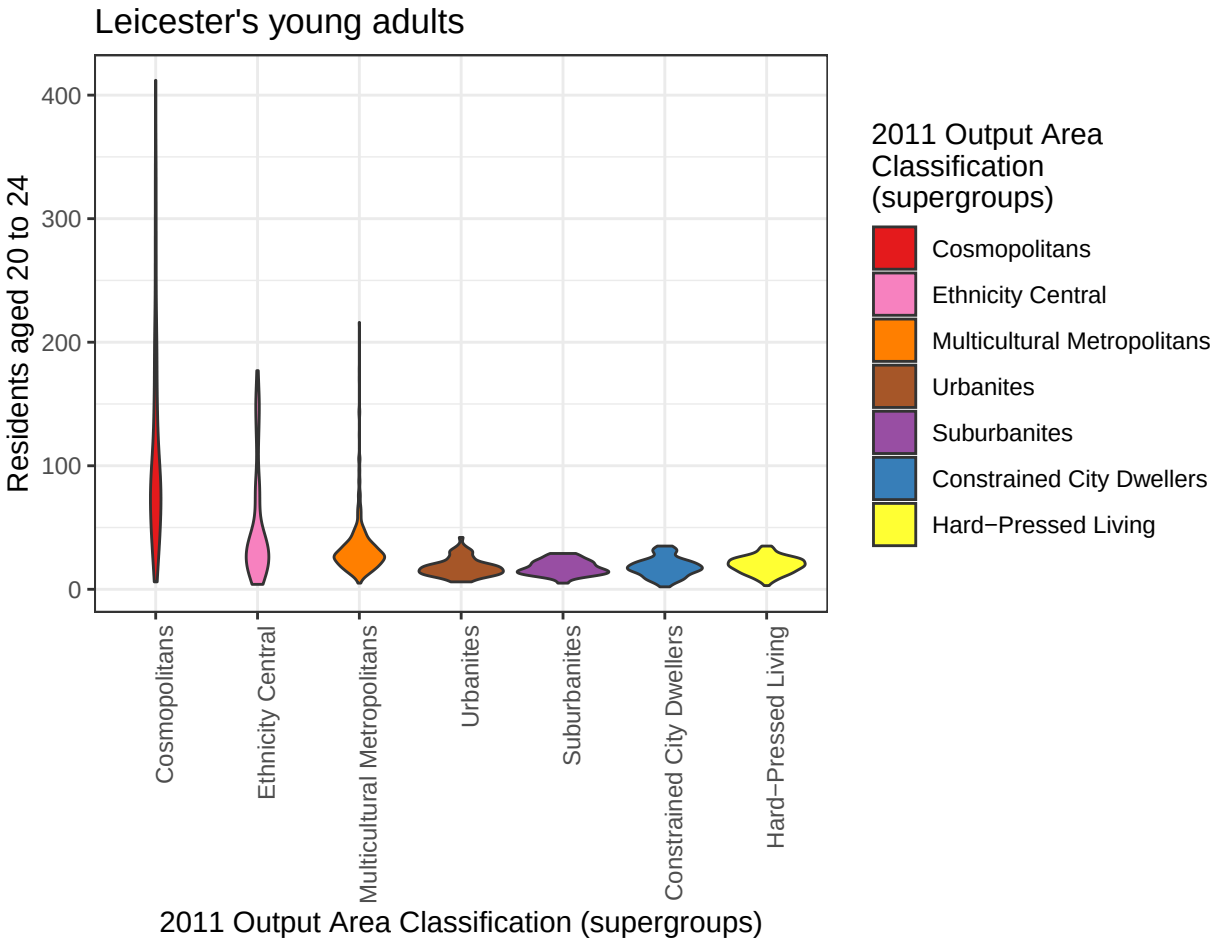
However, the graphic above is not extremely clear. A boxplot and a violin plot created from the same data are shown below. In both cases, the parameter `axis.text.x` of the function theme is set to `element_text(angle = 90, hjust = 1)` in order to orientate the labels on the x-axis vertically, as the supergroup names are rather long, and they would overlap one-another if set horizontally on the x-axis. In both cases, the option

`fig.height` of the R snippet in RMarkdown should be set to a higher value (e.g., `5`) to allow for sufficient room for the supergroup names.

```
leicester_2011OAC %>%
  ggplot(
    aes(
      x = fct_reorder(supgrpname, supgrpcode),
      y = u011,
      fill = fct_reorder(supgrpname, supgrpcode)
    )
  ) +
  geom_boxplot() +
  ggtitle("Leicester's young adults") +
  labs(
    fill = "2011 Output Area\nClassification\n(supergroups)"
  ) +
  xlab("2011 Output Area Classification (supergroups)") +
  ylab("Residents aged 20 to 24") +
  scale_fill_manual(
    values = c("#e41a1c", "#f781bf", "#ff7f00", "#a65628", "#984ea3", "#377eb8", "#ffff33")
  ) +
  theme_bw() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
```



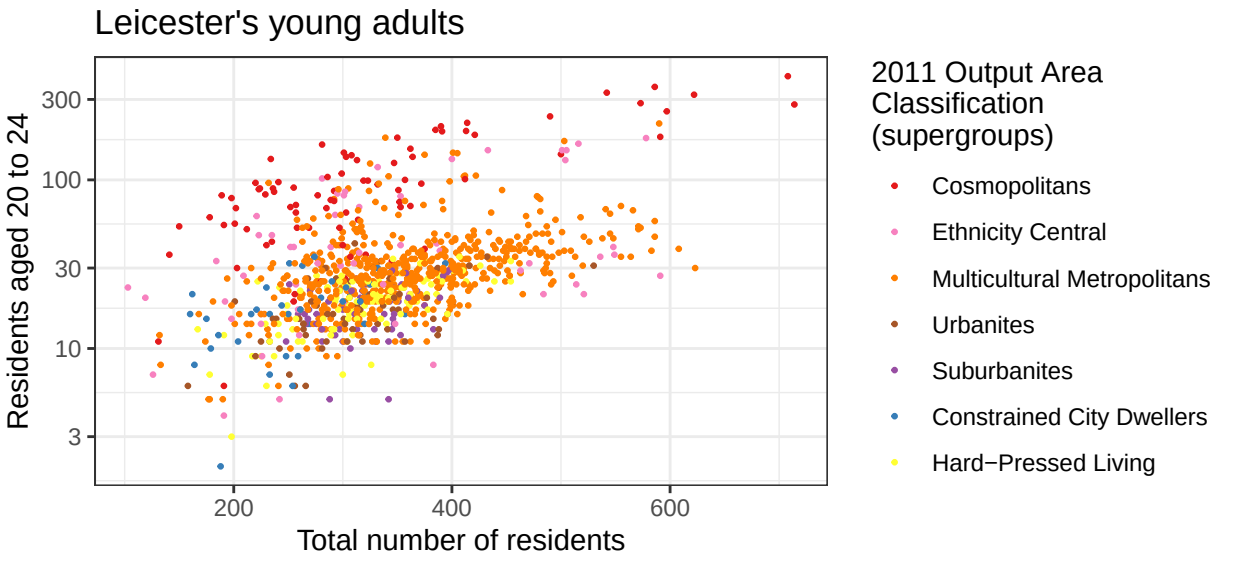
```r
leicester_2011OAC %>%
  ggplot(
    aes(
      x = fct_reorder(supgrpname, supgrpcode),
      y = u011,
      fill = fct_reorder(supgrpname, supgrpcode)
    )
  ) +
  geom_violin() +
  ggtitle("Leicester's young adults") +
  labs(
    fill = "2011 Output Area\nClassification\n(supergroups)"
  ) +
  xlab("2011 Output Area Classification (supergroups)") +
  ylab("Residents aged 20 to 24") +
  scale_fill_manual(
    values = c("#e41a1c", "#f781bf", "#ff7f00", "#a65628", "#984ea3", "#377eb8", "#ffff33")
  ) +
  theme_bw() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
```



Relationships

The first barchart above seems to illustrate that the distribution might be skewed towards the left, with most values seemingly below 50. However, that tells only part of the story about how people aged 20 to 24 are distributed in Leicester. In fact, each Output Area (OA) has a different total population. So, a higher number of people aged 20 to 24 living in an OA might be simply due to the OA been more populous than others. Thus, the next step is to compare `u011` to `Total_Population`, for instance, through a scatterplot such as the one seen in the practical session 401, reported below.

```
leicester_2011OAC %>%
  ggplot(
    aes(
      x = Total_Population,
      y = u011,
      colour = fct_reorder(supgrpname, supgrpcode)
    )
  ) +
  geom_point(size = 0.5) +
  ggtitle("Leicester's young adults") +
  labs(
    colour = "2011 Output Area\nClassification\n(supergroups)"
  ) +
  xlab("Total number of residents") +
  ylab("Residents aged 20 to 24") +
  scale_y_log10() +
  scale_colour_brewer(palette = "Set1") +
  scale_colour_manual(
    values = c("#e41a1c", "#f781bf", "#ff7f00", "#a65628", "#984ea3", "#377eb8", "#ffff33")
  ) +
  theme_bw()
```



Exercise 7.1

Question 7.1.1: Which one of the boxplot or violin plot above do you think better illustrate the different distributions, and what do the two graphics say about the distribution of people aged 20 to 24 in Leicester? Write a short answer in your RMarkdown document (max 200 words).

Question 7.1.2: Create a jittered points plot (see `geom_jitter`) visualisation illustrating the same data shown in the boxplot and violin plot above.

Question 7.1.3: Create the code necessary to calculate a new column named `perc_age_20_to_24`, which is the percentage of people aged 20 to 24 (i.e., `u011`) over total population per OA `Total_Population`, and create a boxplot visualising the distribution of the variable per 2011OAC supergroup.

Exploratory statistics

The graphics above provide preliminary evidence that the distribution of people aged 20 to 24 might, in fact, be different in different 2011 supergroups. In the remainder of the practical session, we are going to explore that hypothesis further. First, load the necessary statistical libraries.

The code below calculates the percentage of people aged 20 to 24 (i.e., `u011`) over total population per OA, but it also recodes (see recode) the names of the 2011OAC supergroups to a shorter 2-letter version, which is useful for the tables presented further below.

Only the OA code, the recoded 2011OAC supergroup name, and the newly created `perc_age_20_to_24` are retained in the new table `leic_2011OAC_20to24`. Such a step is sometimes useful as stepping stone for further analysis and can make the code easier to read further down the line. Sometimes it is also a necessary step when interacting with certain libraries, which are not fully compatible with Tidyverse libraries, such as `leveneTest`.

```
leic_2011OAC_20to24 <- leicester_2011OAC %>%
  mutate(
    perc_age_20_to_24 = (u011 / Total_Population) * 100,
    supgrpname = dplyr::recode(supgrpname,
      `Suburbanites` = "SU",
      `Cosmopolitans` = "CP",
      `Multicultural Metropolitans` = "MM",
      `Ethnicity Central` = "EC",
      `Constrained City Dwellers` = "CD",
      `Hard-Pressed Living` = "HP",
      `Urbanites` = "UR"
    )
  ) %>%
  select(OA11CD, supgrpname, perc_age_20_to_24)

leic_2011OAC_20to24 %>%
  top_n(5) %>%
  kable()
```

OA11CD	supgrpname	perc_age_20_to_24
E00169455	CP	57.65125
E00169481	CP	60.70111
E00169446	CP	60.75085
E00168096	CP	58.19209
E00169043	CP	56.83761

Descriptive statistics

The first step of any statistical analysis or modelling should be to explore the *"shape"* of the data involved, by looking at the descriptive statistics of all variables involved. The function `stat.desc` of the `pastecs` library provides three series of descriptive statistics.

- `base`:
  - `nbr.val`: overall number of values in the dataset;
  - `nbr.null`: number of `NULL` values – NULL is often returned by expressions and functions whose values are undefined;
  - `nbr.na`: number of `NA`s – missing value indicator;
- `desc`:
  - `min` (see also `min` function): **minimum** value in the dataset;
  - `max` (see also `max` function): **minimum** value in the dataset;
  - `range`: difference between `min` and `max` (different from `range()`);
  - `sum` (see also `sum` function): sum of the values in the dataset;
  - `median` (see also `median` function): **median**, that is the value separating the higher half from the lower half the values
  - `mean` (see also `mean` function): **arithmetic mean**, that is `sum` over the number of values not `NA`;
  - `SE.mean`: **standard error of the mean** – estimation of the variability of the mean calculated on different samples of the data (see also *central limit theorem*);
  - `CI.mean.0.95`: **95% confidence interval of the mean** – indicates that there is a 95% probability that the actual mean is within that distance from the sample mean;
  - `var`: **variance** (σ^2), it quantifies the amount of variation as the average of squared distances from the mean;
  - `std.dev`: **standard deviation** (σ), it quantifies the amount of variation as the square root of the variance;
  - `coef.var`: **variation coefficient** it quantifies the amount of variation as the standard deviation divided by the mean;
- `norm` (default is `FALSE`, use `norm = TRUE` to include it in the output):
  - `skewness`: **skewness** value indicates
    - positive: the distribution is skewed towards the left;
    - negative: the distribution is skewed towards the right;
  - `kurtosis`: **kurtosis** value indicates:
    - positive: heavy-tailed distribution;
    - negative: flat distribution;
  - `skew.2SE` and `kurt.2SE`: skewness and kurtosis divided by 2 standard errors. If greater than 1, the respective statistics is significant ($p < .05$);
  - `normtest.W`: test statistics for the **Shapiro–Wilk test** for normality;
  - `normtest.p`: significance for the **Shapiro–Wilk test** for normality.

The Shapiro–Wilk test compares the distribution of a variable with a normal distribution having the same mean and standard deviation. The null hypothesis of the Shapiro–Wilk test is that the sample is normally distributed, thus if `normtest.p` is lower than `0.01` (i.e., $p < .01$), the test indicates that the distribution is most probably not normal. The threshold to accept or reject a hypothesis is arbitrary and based on conventions, where $p < .01$ is the most commonly accepted threshold, or $p < .05$ for relatively small data sample (e.g., 30 cases).

The next step is thus to apply the `stat.desc` to the variable we are currently exploring (i.e., `perc_age_20_to_24`), including the `norm` section.

```
leic_2011OAC_20to24_stat_desc <- leic_2011OAC_20to24 %>%
  select(perc_age_20_to_24) %>%
  stat.desc(norm = TRUE)

leic_2011OAC_20to24_stat_desc %>%
  kable(digits = 3)
```

	perc_age_20_to_24
nbr.val	969.000
nbr.null	0.000
nbr.na	0.000
min	1.064
max	60.751
range	59.687
sum	10238.502
median	7.514
mean	10.566
SE.mean	0.304
CI.mean.0.95	0.596
var	89.386
std.dev	9.454
coef.var	0.895
skewness	2.710
skew.2SE	17.249
kurtosis	7.707
kurt.2SE	24.549
normtest.W	0.645
normtest.p	0.000

The table above tells us that all 969 OA in Leicester have a valid value for the variable `perc_age_20_to_24`, as no `NULL` nor `NA` value have been found. The values vary from about 1% to almost 61%, with an average value of 11% of the population in an OA aged between 20 and 24.

The short paragraph above is reporting on the values on the table, taking advantage of two features of RMarkdown. First, the output of the `stat.desc` function in the snippet further above is stored in the variable `leic_2011OAC_20to24_stat_desc`, which is then a valid variable for the rest of the document. Second, RMarkdown allows for in-line R snippets, that can also refer to variables defined in any snippet above the text. As such, the source of the paragraph above reads as below, with the in-line R snipped opened by a single grave accent (i.e., `` ` ``) followed by a lowercase `r` and closed by another single grave accent.

Having included all the code above into an RMarkdown document, copy the text below verbatim into the same RMarkdown document and make sure that you understand how the code in the in-line R snippets works.

```
The table above tells us that all ‘r leic_2011OAC_20to24_stat_desc["nbr.val",
"perc_age_20_to_24"] %>% round(digits = 0)‘ OA in Leicester have a valid
value for the variable ‘perc_age_20_to_24‘, as no ‘NULL‘ nor ‘NA‘ value have
been found.The values vary from about ‘r leic_2011OAC_20to24_stat_desc["min",
"perc_age_20_to_24"] %>% round(digits = 0)‘% to almost ‘r
leic_2011OAC_20to24_stat_desc["max", "perc_age_20_to_24"] %>% round(digits =
0)‘%, with an average value of ‘r leic_2011OAC_20to24_stat_desc["mean",
"perc_age_20_to_24"] %>% round(digits = 0)‘% of the population in an OA aged
between 20 and 24.
```

If the data described by statistics presented in the table above was a random sample of a population, the 95% confidence interval `CI.mean.0.95` would indicate that we can be 95% confident that the actual mean of the distribution is somewhere between 10.566 - 0.596 = 9.97% and 10.566 + 0.596 = 11.162%.

However, this is not a sample. Thus the statistical interpretation is not valid, in the same way that the `sum` values doesn't make sense, as it is the sum of a series of percentages.

Both `skew.2SE` and `kurt.2SE` are greater than `1`, which indicate that the `skewness` and `kurtosis` values are significant ($p < .05$). The `skewness` is positive, which indicates that the distribution is skewed towards the left (low values). The `kurtosis` is positive, which indicates that the distribution is heavy-tailed.

As such, `perc_age_20_to_24` having a heavy-tailed distribution skewed towards low values, it is not surprising that the `normtest.p` value indicates that the Shapiro–Wilk test is significant, which indicates that the distribution is not normal.

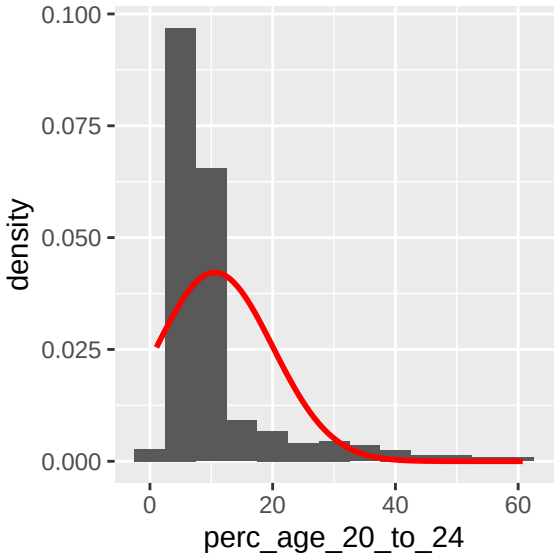
The code below present the output of the `shapiro.test` function, which only present the outcome of a Shapiro–Wilk test on the values provided as input. The output values are the same as the values reported by the `norm` section of `stat.desc`. Note that the `shapiro.test` function require the argument to be a numeric vector. Thus the `pull` function must be used to extract the `perc_age_20_to_24` column from `leic_2011OAC_20to24` as a vector, whereas using `select` with a single column name as the argument would produce as output a table with a single column.

```
leic_2011OAC_20to24 %>%
  pull(perc_age_20_to_24) %>%
  shapiro.test()
```

```
##
##  Shapiro-Wilk normality test
##
## data:  .
## W = 0.64491, p-value < 2.2e-16
```

The two code snippets below can be used to visualise a density-based histogram including the shape of a normal distribution having the same mean and standard deviation, and a Q-Q plot, to visually confirm the fact that `perc_age_20_to_24` is not normally distributed.

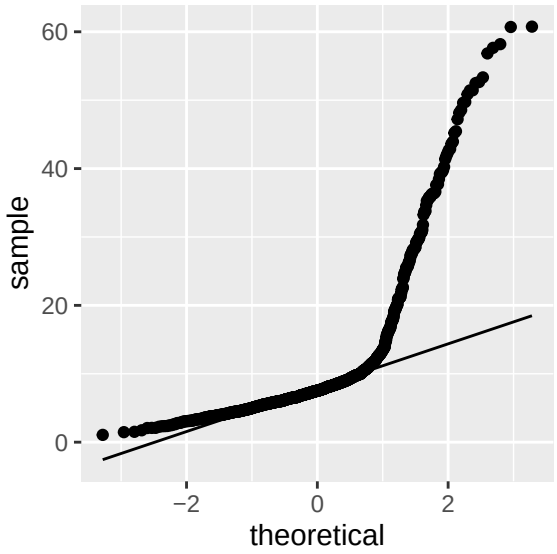
```
leic_2011OAC_20to24 %>%
  ggplot(
    aes(
      x = perc_age_20_to_24
    )
  ) +
  geom_histogram(
    aes(
      y =..density..
    ),
    binwidth = 5
  ) +
  stat_function(
    fun = dnorm,
    args = list(
      mean = leic_2011OAC_20to24 %>% pull(perc_age_20_to_24) %>% mean(),
      sd = leic_2011OAC_20to24 %>% pull(perc_age_20_to_24) %>% sd()
    ),
    colour = "red", size = 1
  )
```



A Q-Q plot in R can be created using a variety of functions. In the example below, the plot is created using the `stat_qq` and `stat_qq_line` functions of the `ggplot2` library. Note that the `perc_age_20_to_24` variable is mapped to a particular option of `aes` that is `sample`.

If `perc_age_20_to_24` had been normally distributed, the dots in the Q-Q plot would be distributed straight on the line included in the plot.

```
leic_2011OAC_20to24 %>%
  ggplot(
    aes(
      sample = perc_age_20_to_24
    )
  ) +
  stat_qq() +
  stat_qq_line()
```



Exercise 7.2

Create a new RMarkdown document, and add the code necessary to recreate the table `leic_2011OAC_20to24` used in the example above. Use the code below to re-shape the table `leic_2011OAC_20to24` by spreading the `perc_age_20_to_24` column to multiple columns using `supgrpname` as key.

```
leic_2011OAC_20to24_supgrp <- leic_2011OAC_20to24 %>%
  spread(
    key = supgrpname,
    value = perc_age_20_to_24
  )
```

That manipulation creates one column per supergroup, containing the `perc_age_20_to_24` if the OA is part of that supergroup, or an `NA` value if the OA is not part of the supergroup. The transformation is illustrated in the two tables below. The first shows an extract from the original `leic_2011OAC_20to24` dataset, followed by the wide version `leic_2011OAC_20to24_supgrp`.

```
leic_2011OAC_20to24 %>%
  top_n(10, OA11CD) %>%
  kable(digits = 3)
```

OA11CD	supgrpname	perc_age_20_to_24
E00169565	CD	8.571
E00169569	MM	6.533
E00169562	MM	6.630
E00169561	MM	7.500
E00169567	CP	49.738
E00169564	CP	30.457
E00169573	MM	6.477
E00169570	MM	4.337
E00169575	CP	42.714
E00169572	CP	40.249

```
leic_2011OAC_20to24_supgrp %>%
  top_n(10, OA11CD) %>%
  kable(digits = 3)
```

OA11CD	CD	CP	EC	HP	MM	SU	UR
E00169561	NA	NA	NA	NA	7.500	NA	NA
E00169562	NA	NA	NA	NA	6.630	NA	NA
E00169564	NA	30.457	NA	NA	NA	NA	NA
E00169565	8.571	NA	NA	NA	NA	NA	NA
E00169567	NA	49.738	NA	NA	NA	NA	NA
E00169569	NA	NA	NA	NA	6.533	NA	NA
E00169570	NA	NA	NA	NA	4.337	NA	NA
E00169572	NA	40.249	NA	NA	NA	NA	NA
E00169573	NA	NA	NA	NA	6.477	NA	NA
E00169575	NA	42.714	NA	NA	NA	NA	NA

Question 7.2.1: The code below uses the newly created `leic_2011OAC_20to24_supgrp` table to calculate the descriptive statistics calculated for the variable `leic_2011OAC_20to24` for each supergroup. Is `leic_2011OAC_20to24` normally distributed in any of the subgroups? If yes, which supergroups and based on which values do you justify that claim? (Write up to 200 words)

```
leic_2011OAC_20to24_supgrp %>%
  select(-OA11CD) %>%
  stat.desc(norm = TRUE) %>%
  kable(digits = 3)
```

	CD	CP	EC	HP	MM	SU	UR
nbr.val	36.000	83.000	57.000	101.000	573.000	54.000	65.000
nbr.null	0.000	0.000	0.000	0.000	0.000	0.000	0.000
nbr.na	933.000	886.000	912.000	868.000	396.000	915.000	904.000
min	1.064	3.141	2.066	1.515	2.490	1.462	2.256
max	12.963	60.751	36.299	11.261	52.507	9.562	13.505
range	11.899	57.609	34.233	9.746	50.018	8.100	11.249
sum	252.108	2646.551	838.415	619.266	5214.286	295.867	372.010
median	6.854	30.457	10.881	6.053	7.880	5.476	5.380
mean	7.003	31.886	14.709	6.131	9.100	5.479	5.723
SE.mean	0.471	1.574	1.373	0.172	0.230	0.233	0.264
CI.mean.0.95	0.956	3.131	2.751	0.341	0.452	0.467	0.528
var	7.983	205.556	107.523	2.980	30.285	2.929	4.545
std.dev	2.825	14.337	10.369	1.726	5.503	1.712	2.132
coef.var	0.403	0.450	0.705	0.282	0.605	0.312	0.372
skewness	0.322	0.067	0.633	0.124	3.320	0.005	1.042
skew.2SE	0.410	0.127	1.001	0.258	16.266	0.008	1.753
kurtosis	-0.142	-0.825	-1.009	0.220	15.143	-0.391	1.441
kurt.2SE	-0.093	-0.789	-0.810	0.231	37.156	-0.306	1.229
normtest.W	0.965	0.980	0.889	0.993	0.684	0.991	0.937
normtest.p	0.310	0.239	0.000	0.886	0.000	0.954	0.002

Question 7.2.2: Write the code necessary to test again the normality of `leic_2011OAC_20to24` for the supergroups where the analysis conducted for question 7.2.1 indicated they are normal, using the function `shapiro.test`, and draw the respective Q-Q plot.

Question 7.2.3: Observe the output of the Levene's test executed below. What does the result tell you about the variance of `perc_age_20_to_24` in supergroups?

```
leveneTest(leic_2011OAC_20to24$perc_age_20_to_24, leic_2011OAC_20to24$supgrpname)
```

```
## Levene's Test for Homogeneity of Variance (center = median)
##        Df F value    Pr(>F)
## group   6  62.011 < 2.2e-16 ***
##       962
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```