# Data exploration toolkit for cultural data

Stefano Rapisarda & Barbara Romero Ferron (RDM, UU)

2024-03-13

# Table of contents

# Welcome!

Welcome to the Cultural Data Exploration Toolkit! Throughout this workshop, you'll explore the nuances of data-driven analysis, from constructing your dataset and formulating research inquiries to learning data visualisation techniques. Along this journey, you'll contemplate the creation of personalised data models tailored to your research queries, navigate potential biases within datasets, and, importantly, learn how to effectively interrogate, explore, and analyse gathered information to generate visualisations.

# Schedule

| Time | Activity |
|---|---|
| 13:00 | Welcome - Icebreaker |
| 13:15 | Group activity: structuring data |
| 13:45 | Discussion |
| 14:00 | Introduction to data toolkit |
| 14:20 | Data Analysis part 1 |
| **15:00** | **Coffee break** |
| 15:15 | Data Analysis part 2 |
| 16:40 | Recap & Questions |

# Part I

# Preparation

# Setting up

## Running the analysis locally on your own computer

1. Install python and jupyter notebook. For installation and setup we point at the "Introduction to Python & Data" Installation & Setup page;
2. Create an empty directory called "cultural_data_analysis" (or any other name you prefer);
3. Inside the just created directory, create another directory called "data";
4. Click on this link, this will open a GitHub page. On the toolbar (on the right of the buttons "Raw" and copy), you will find the button for downloading the .csv file containing the data we used during our workshop. Download the file inside the just created data directory;
5. Click on this link, this will open the Jupyter-notebook in one of the instructor google colab environment containing the full analysis performed during the workshop. You can access the file only if you followed the workshop. At this point, you will just need to click on the "File" tab, select "download" (almost at the very end of the menu), select the "Download .ipynb" option, and download the file inside your project directory (the one also containing the data directory);
6. Open the jupyter notebook and have fun!

***!!! WARNING !!!*** In the first cell of the Jupyter-notebook you downloaded, the instructors wrote specific Python instructions to make the notebook work in their Google colab environment. In your case, the only thing you need to do is to find out the full path of your project directory (the one containing the notebook and the data directory you just created) and writing this path instead of "working_directory", as described in the comments of the first cell.

## Running the analysis from remote in your Google colab

1. In your personal Google Drive page, create a new directory called "cultural_data_analysis" (or any other name you prefer). For doing that, click on the "New" button on the top left corner of your browser (just below the Drive icon) and select directory;

2. Go inside the just created directory and create another directory called “data”;

3. Click on this link, this will open a GitHub page. On the toolbar (on the right of the buttons “Raw” and copy), you will find the button for downloading the .csv file containing the data we used during our workshop. Download the file inside the just created data directory;

4. Click on this link, this will open the Jupyter-notebook in google colab containing the full analysis performed during the workshop. You can access the file only if you followed the workshop. At this point, you will just need to click on the “File” tab, then click on “download” (almost at the very end of the menu), select the “Download .ipynb” option, and download the file inside your project directory (the one also containing the data directory). Alternatively, if you want to start from scratch creating a black jupyter notebook, click again on the “New” button, select “others”, and then Google collaboratory. Be sure that the just created jupyter notebook is in your project directory (the one containing your data directory);

***!!! WARNING !!!*** In the first cell of the Jupyter-notebook you downloaded, the instructors wrote specific instructions to make the notebook work in their Google colab environment. In your case, the only thing you need to do is to change the value of the variable `work_dir` in the first cell from ‘/det_cultural_data’ to ‘/your_dir_name’. If the name of your directory is det_cultural_data, you do not need to change anything.

# Part II

# Data Workflow

# 1 Organising your data

# 2 Reading data

The first thing we need to do is loading the data. This means opening the file where the data is currently stored and transfer that data here, in our working environment. As we are working with Python in this Jupyter notebook environment, this means transfering all the data into a Python object. Which object? There are Python libraries (Python code written by other developers) that have been specifically designed to perform the task of data analysis. One of these libraries, or ("Pythonically" speaking) **packages**, is called `pandas`. We will use one of the many `pandas` functions to read our `.csv` (coma separated values file) file and we will store the information into a pandas `DataFrame`.

```
<IPython.core.display.HTML object>
```

```python
import pandas as pd
data_file = 'data/data.csv'
df = pd.read_csv(data_file)
print(type(df))
```

```
<class 'pandas.core.frame.DataFrame'>
```

We managed to transfer our data into a Python object, specifically a `pandas.core.frame.DataFrame`, or simply (from now on) a DataFrame. However, a lot of things can go wrong when going from one format to another, so it is a good idea to have a first look at the data.

```
<IPython.core.display.HTML object>
```

```python
df.head(10)
```

| | Year of arrival at port of disembarkation | Voyage ID | Vessel name | Voyage itinerary imputed port |
|---|---|---|---|---|
| 0 | 1714.0 | 16109 | Freeke Gally | Bristol |
| 1 | 1713.0 | 16110 | Greyhound Gally | Bristol |
| 2 | 1714.0 | 16111 | Jacob | Bristol |

| | Year of arrival at port of disembarkation | Voyage ID | Vessel name | Voyage itinerary imputed port |
|---|---|---|---|---|
| 3 | 1714.0 | 16112 | Jason Gally | Bristol |
| 4 | 1713.0 | 16113 | Lawford Gally | Bristol |
| 5 | 1714.0 | 16114 | Mercy Gally | Bristol |
| 6 | 1714.0 | 16115 | Mermaid Gally | Bristol |
| 7 | 1713.0 | 16116 | Morning Star | Bristol |
| 8 | 1714.0 | 16117 | Peterborough | Bristol |
| 9 | 1713.0 | 16118 | Resolution | Bristol |

Comparing what we see here with our .csv file it seems that everything went well. We have the data organised in rows and columns. Each column has a name and each row and index. Looking at our data, some values are numbers, some are names and places, some contain htmlo tags, some are NaN. It is not time yet to run data analysis, after having loaded the data we still need to correctly interpret the information it contains, then we need to "clean" it, and after that, finally, we can proceed with some data analysis. This is just the beginning, but the best is yet to come!

# 3 Exploring data

## Previous steps

```
import pandas as pd
data_file = 'data/data.csv'
df = pd.read_csv(data_file)
```

```
df.head(5)
```

| | Year of arrival at port of disembarkation | Voyage ID | Vessel name | Voyage itinerary imputed port |
|---|---|---|---|---|
| 0 | 1714.0 | 16109 | Freeke Gally | Bristol |
| 1 | 1713.0 | 16110 | Greyhound Gally | Bristol |
| 2 | 1714.0 | 16111 | Jacob | Bristol |
| 3 | 1714.0 | 16112 | Jason Gally | Bristol |
| 4 | 1713.0 | 16113 | Lawford Gally | Bristol |

Now that we correctly loaded our data in our working environment, it is time to figure out what the data contains. It is always a good idea to look at the dataset documentation (or metadata) to understand where the data comes from, what is the source of all the different records, how data has been collected, and any other possible data related caveat. Diving into the data documentation is up to you, in this chapter what we want to do is understanding as much as we can from the data itself, looking at its columns, rows, and values. Every dataset tells a story. You may think about it like a person with a long experience, but not really willing to talk (well, some datasets "talk" more easily than others). It is your role in this case to "interrogate" the data, let it to talk, to tell a story and to dive into the details of that story, getting as much information as you can. This also depends on how much you need to know: will you be satisfied by a small "chat" or you need to know all kind of details? Let's formulate some questions to begin with.

```
<IPython.core.display.HTML object>
```

```
df.shape
```

```
(36151, 9)
```

```
solution = 'Our DataFrame contains data distributed in 36151 rows and 9 columns. '
question_box(solution=solution)
```

```
<IPython.core.display.HTML object>
```

It is a quite big dataset. Shall we care about how big is our dataset? We should as this may affect our analysis. For example, if we implement a scientific analysis that requires 1 second per row to produce an output, such program would take about 10hrs to analyse the entire dataset, and that is something we should keep in mind. That is why, in general, it is a good idea to test large analysis programs on a small sub-set of data and then, once verified that everything runs smoothly, to perform the analysis on the entire dataset.

Let's continue exploring our DataFrame. We have 9 columns, we saw them displayed in our notebook and, luckily enough, their names are pretty descriptive, therefore, in this case, it is quite intuitive to understand what kind of information they contain. It could be useful to store the column names inside a Python variable and to display their names with a corresponding index (this will be useful later).

```
<IPython.core.display.HTML object>
```

```
column_names = df.columns
print(column_names)
i=0
print("Index ) Column name")
for name in column_names:
    print(i,")",name)
    i = i + 1
```

```
Index(['Year of arrival at port of disembarkation', 'Voyage ID', 'Vessel name',
       'Voyage itinerary imputed port where began (ptdepimp) place',
       'Voyage itinerary imputed principal place of slave purchase (mjbyptimp) ',
       'Voyage itinerary imputed principal port of slave disembarkation (mjslptimp) place',
       'VOYAGEID2', 'Captives arrived at 1st port', 'Captain's name'],
      dtype='object')
Index ) Column name
```

```
0 ) Year of arrival at port of disembarkation
1 ) Voyage ID
2 ) Vessel name
3 ) Voyage itinerary imputed port where began (ptdepimp) place
4 ) Voyage itinerary imputed principal place of slave purchase (mjbyptimp)
5 ) Voyage itinerary imputed principal port of slave disembarkation (mjslptimp) place
6 ) VOYAGEID2
7 ) Captives arrived at 1st port
8 ) Captain's name
```

Now we have the column names nicely listed from top to bottom and with their corresponding index assigned to them. You might be tempted to start the indexing from 1, but as in Python the first element of a list (or any other series of elements) has index 0, we started counting from zero. You can obtain the same result with less lines of code, try it out!

```
print("Index) Column name")
for i,name in enumerate(column_names):
    print(f"{i}) {name}")
```

```
Index) Column name
0) Year of arrival at port of disembarkation
1) Voyage ID
2) Vessel name
3) Voyage itinerary imputed port where began (ptdepimp) place
4) Voyage itinerary imputed principal place of slave purchase (mjbyptimp)
5) Voyage itinerary imputed principal port of slave disembarkation (mjslptimp) place
6) VOYAGEID2
7) Captives arrived at 1st port
8) Captain's name
```

It is now time to figure out what are the rows about. Looking at the column names, we notice that the second one (index 1) is called “Voyage ID”. This indicates that this column contains a specific identifier for the ship voyage, implying that each row contains specific information about a single trip. To verify that each row corresponds to a single voyage, we need to check if all the values of the Voyage ID column are different, i.e. if they are unique.

```
<IPython.core.display.HTML object>
```

```
voyage_id = df.iloc[:,1]
print(voyage_id.is_unique)
```

```
True
```

We verified that all the values of the Voyage ID column are unique, this means that each of the rows of our DataFrame refers to a single ship voyage. Looking at the other columns, we also notice that information where the voyage began, the port where slaves have been purchased, and the port where slaves have been desembarked is provided. Looking in particular at the fifth column (index 4, “Voyage itinerary imputed principal place of slave purchase”), we notice it contains several NaNs. NaN stands for “Not a Number”, it is a value that appears when something goes wrong in one of the processes ran by our program. If something went wrong, why did not our program stop or told us something about an occuring problem? Because problems may happen more often than you think and if our program stops working everytime it encounters a situation it cannot handle, it would most probably never finish running! In this case, most probably the record does not exist so the data set cell has been filled by NaN, either in our original .csv file or by the `pandas` method `.read_csv()`. NaN are not necesseraly something bad, as they can be easily identified and eventually corrected (or simply ignored). Incorrect or missing data may be much harder to spot and correct. In any case, the presence of NaNs or any other missing value can severely affect our data analysis, for this reason before starting analysing the data we need to find and get rid of those values. This process is usually called “data cleaning” and that is exactly what we are going to do in the next chapter.

# 4 Cleaning data

## Previous steps

```
import pandas as pd
data_file = 'data/data.csv'
df = pd.read_csv(data_file)
print(df.shape)
```

```
(36151, 9)
```

```
column_names = df.columns
df.head(5)
```

| | Year of arrival at port of disembarkation | Voyage ID | Vessel name | Voyage itinerary imputed port |
|---|---|---|---|---|
| 0 | 1714.0 | 16109 | Freeke Gally | Bristol |
| 1 | 1713.0 | 16110 | Greyhound Gally | Bristol |
| 2 | 1714.0 | 16111 | Jacob | Bristol |
| 3 | 1714.0 | 16112 | Jason Gally | Bristol |
| 4 | 1713.0 | 16113 | Lawford Gally | Bristol |

Now that we got some familiarity with our dataset, it is time to clean our data, i.e. to get rid of all those NaN values and anything else that might effect our data analysis. Where to start? Well, inspecting the DataFrame by eye, we see several NaNs in the first 5 rows of our DataFrame. The first column we see NaNs is "Voyage itinerary imputed principal place of slave purchase", the fourth column (index 5). It would be nice to check if also other column have NaNs. Let's start with the first column, "Year of arrival at port of disembarkation" (index 0), let's check if this column contains any NaN and then we will repeat the same process for all the other columns.

```
<IPython.core.display.HTML object>
```

```
arr_year = df.iloc[:,0]
arr_year_na = arr_year.isna()
print(arr_year_na)
print('Total number of NaNs in the first column:',arr_year_na.sum())
```

```
0        False
1        False
2        False
3        False
4        False
         ...
36146    False
36147    False
36148    False
36149    False
36150    False
Name: Year of arrival at port of disembarkation, Length: 36151, dtype: bool
Total number of NaNs in the first column: 1
```

```
solution = 'The first column contains 1 NaN value'
question_box(solution=solution)
```

```
<IPython.core.display.HTML object>
```

In this way we found our that the first column has 1 NaN (or na) value, that would have been quite hard to spot by eye scrolling 36151 lines! It is great that we found 1 NaN in the first column, but where exactly it is located? What's the corresponding Voyage ID of that value?

```
<IPython.core.display.HTML object>
```

```
df[arr_year_na]
```

| | Year of arrival at port of disembarkation | Voyage ID | Vessel name | Voyage itinerary imputed port w |
|---|---|---|---|---|
| 32248 | NaN | 91909 | Kitty | Liverpool |

```
<IPython.core.display.HTML object>
```

In this way we can inspect NaNs one by one and we can make a decision about how to handle them. In our DataFrame there are thousands of NaNs (as you will see in a minute) and going through ALL of them one by one is not a good idea. Let's first try to figure out if the other columns have also NaNs and how many are they. The process will be quite straightforward as we already did it for one of the columns, so what we need to do now is to repeat the same procedure for all the other columns.

```
<IPython.core.display.HTML object>
```

```python
for column_name in column_names:
    selected_column = df[column_name]
    selected_column_na = selected_column.isna()
    n_nan = selected_column_na.sum()
    print(column_name,'has',n_nan,'NaN')
```

```
Year of arrival at port of disembarkation has 1 NaN
Voyage ID has 0 NaN
Vessel name has 1614 NaN
Voyage itinerary imputed port where began (ptdepimp) place has 4508 NaN
Voyage itinerary imputed principal place of slave purchase (mjbyptimp)  has 2210 NaN
Voyage itinerary imputed principal port of slave disembarkation (mjslptimp) place has 4191 Na
VOYAGEID2 has 36101 NaN
Captives arrived at 1st port has 17743 NaN
Captain's name has 4028 NaN
```

and if we want to keep in mind the column index of each column…

```python
for i,column_name in enumerate(column_names): \
    print(f"{i}) {column_name} has {df[column_name].isna().sum()} NaN")
```

```
0) Year of arrival at port of disembarkation has 1 NaN
1) Voyage ID has 0 NaN
2) Vessel name has 1614 NaN
3) Voyage itinerary imputed port where began (ptdepimp) place has 4508 NaN
4) Voyage itinerary imputed principal place of slave purchase (mjbyptimp)  has 2210 NaN
5) Voyage itinerary imputed principal port of slave disembarkation (mjslptimp) place has 419
6) VOYAGEID2 has 36101 NaN
7) Captives arrived at 1st port has 17743 NaN
8) Captain's name has 4028 NaN
```

```
<IPython.core.display.HTML object>
```

At this point we have a general idea of the amount of data missing in our DataFrame. The following question is how to deal with this missing data? There are several things we can do, the easiest option would be just exclude it from our DataFrame. However, in order to answer a research question, we often do not need to use or explore ALL the available information and we would usually be interested in some parameters more than others. In this case our data selection could be performed looking at one or more specific columns. What to do with the rest of the NaNs? We can either leave them as they are and trying to figure out how our analysis program will "digest" these values or find good substitute for them. The value of this substitute will depend on the data type of the columns containing the NaN and on our decision. For example the NaN in the columns containing a descriptive string, like the vessel name or the starting port, could be substituted by the string "unknown". NaNs in the "Captives arrived […]" column could be left as they are (you may be tempted to change them to 0, but zero captives is quite different from unknown number of captives) or substituted by, for example, the average of captives during the same year. Each choice will have different implications to our final results, the most important thing in this stage is to clearly document our criteria for filtering NaN. In our specific case we will be mostly interested in the data containing the number of captives, so we want to filter our all those rows where the number of captives is NaN. We will then exclude the columns VOYAGEID2 as we already have a voyage ID and it is not listed in the data variable description. To resume, here there are our cleaning criteria: - All the rows not containing data about the number of captives have been removed; - All the NaN values in columns with descriptive information (e.g. names) have been substituted with "unknown"; - The column VOYAGEID2 has been removed from the DataFrame.

```
<IPython.core.display.HTML object>
```

```python
# Display the name of the columns first
print(df.columns)

# Select our target columns for clearning the data
column_to_remove = 'VOYAGEID2'
column_to_remove_nan = 'Captives arrived at 1st port'

# Perform Data Cleaning visualising the result step by step
# step1, removing column VOYAGEID2 from the DataFrame
cleaned_df_step1 = df.drop(column_to_remove,axis=1)
cleaned_df_step1.head(5)
```

```
Index(['Year of arrival at port of disembarkation', 'Voyage ID', 'Vessel name',
       'Voyage itinerary imputed port where began (ptdepimp) place',
```

```
 'Voyage itinerary imputed principal place of slave purchase (mjbyptimp) ',
 'Voyage itinerary imputed principal port of slave disembarkation (mjslptimp) place',
 'VOYAGEID2', 'Captives arrived at 1st port', 'Captain's name'],
dtype='object')
```

| | Year of arrival at port of disembarkation | Voyage ID | Vessel name | Voyage itinerary imputed port |
|---|---|---|---|---|
| 0 | 1714.0 | 16109 | Freeke Gally | Bristol |
| 1 | 1713.0 | 16110 | Greyhound Gally | Bristol |
| 2 | 1714.0 | 16111 | Jacob | Bristol |
| 3 | 1714.0 | 16112 | Jason Gally | Bristol |
| 4 | 1713.0 | 16113 | Lawford Gally | Bristol |

```
# step2, removing all the rows haveing NaN in the "Captives arrived at 1st port" column
cleaned_df_step2 = cleaned_df_step1.dropna(subset=[column_to_remove_nan])
cleaned_df_step2.head(5)
```

| | Year of arrival at port of disembarkation | Voyage ID | Vessel name | Voyage itinerary imputed port wl |
|---|---|---|---|---|
| 0 | 1714.0 | 16109 | Freeke Gally | Bristol |
| 2 | 1714.0 | 16111 | Jacob | Bristol |
| 3 | 1714.0 | 16112 | Jason Gally | Bristol |
| 5 | 1714.0 | 16114 | Mercy Gally | Bristol |
| 6 | 1714.0 | 16115 | Mermaid Gally | Bristol |

```
# step3, changing all the other NaN into unknown
cleaned_df = cleaned_df_step2.fillna("unknown")
cleaned_df.head(5)
```

| | Year of arrival at port of disembarkation | Voyage ID | Vessel name | Voyage itinerary imputed port wl |
|---|---|---|---|---|
| 0 | 1714.0 | 16109 | Freeke Gally | Bristol |
| 2 | 1714.0 | 16111 | Jacob | Bristol |
| 3 | 1714.0 | 16112 | Jason Gally | Bristol |
| 5 | 1714.0 | 16114 | Mercy Gally | Bristol |
| 6 | 1714.0 | 16115 | Mermaid Gally | Bristol |

```
# step4, checking how much data we filtered out
print(cleaned_df.shape)
```

```
n_filtered_rows = len(df)-len(cleaned_df)
per_cent = (n_filtered_rows/len(df))*100
print('We filtered out: ',len(df)-len(cleaned_df),', corresponding to about', round(per_ce
```

```
(18408, 8)
We filtered out:  17743 , corresponding to about 49 % of our initial data
```

It seems that because of our filtering, almost half of our data will be excluded from the analysis. This is a quite large percent and we may decide to re-think our filtering criteria to include more data. For example, we could substitue the missing value in the Captives column with an avarage number of captived per trip. For the purpose of our workshop, we will keep the current filtering criteria and keep our filtered DataFrame as it is.

At this point we obtained a "clean" DataFrame, `cleaned_df`, containing 18408 rows with values organised in 8 columns. We can now start diving deep in the analysis of our DataFrame, we are ready to interrogate this dataset and see which kind of story it is going to tell us.

# 5 Analysing data

## Previous steps

```
import pandas as pd
data_file = 'data/data.csv'
df = pd.read_csv(data_file)
cleaned_df = df.drop('VOYAGEID2',axis=1).dropna(subset=['Captives arrived at 1st port']).f
cleaned_col_names = cleaned_df.columns
cleaned_df.head(10)
```

| | Year of arrival at port of disembarkation | Voyage ID | Vessel name | Voyage itinerary imputed |
|---|---|---|---|---|
| 0 | 1714.0 | 16109 | Freeke Gally | Bristol |
| 2 | 1714.0 | 16111 | Jacob | Bristol |
| 3 | 1714.0 | 16112 | Jason Gally | Bristol |
| 5 | 1714.0 | 16114 | Mercy Gally | Bristol |
| 6 | 1714.0 | 16115 | Mermaid Gally | Bristol |
| 8 | 1714.0 | 16117 | Peterborough | Bristol |
| 9 | 1713.0 | 16118 | Resolution | Bristol |
| 10 | 1714.0 | 16119 | Richard and William | Bristol |
| 11 | 1713.0 | 16120 | Rotchdale Gally | Bristol |
| 12 | 1714.0 | 16121 | Tunbridge Gally | Bristol |

```
print("Index) Column name")
for i,name in enumerate(cleaned_df.columns):
    print(i,")",name)
```

```
Index) Column name
0 ) Year of arrival at port of disembarkation
1 ) Voyage ID
2 ) Vessel name
3 ) Voyage itinerary imputed port where began (ptdepimp) place
4 ) Voyage itinerary imputed principal place of slave purchase (mjbyptimp)
```

```
5 ) Voyage itinerary imputed principal port of slave disembarkation (mjslptimp) place
6 ) Captives arrived at 1st port
7 ) Captain's name
```

# Data Analysis

It is finally time to ask questions to our data. Let's start with some simple ones regaring the time span of our dataset.

```
<IPython.core.display.HTML object>
```

```
arrival_year = cleaned_df.iloc[:,0]
first_year = min(arrival_year)
last_year = max(arrival_year)
year_span = last_year-first_year

print(first_year)
print(last_year)
print(year_span)
```

```
1520.0
1866.0
346.0
```

```
arrival_year_raw = df.iloc[:,0]
first_year_raw = min(arrival_year_raw)
last_year_raw = max(arrival_year_raw)
year_span_raw = last_year_raw-first_year_raw

print(first_year_raw)
print(last_year_raw)
print(year_span_raw)
```

```
1514.0
1866.0
352.0
```

```
<IPython.core.display.HTML object>
```

We can keep asking questions about numerical values. We focused on time in our last question, let's focus on the number of captives this time.

```
<IPython.core.display.HTML object>
```

```
n_captives = cleaned_df.iloc[:,6]
tot_captives = sum(n_captives)
ave_cap_per_voyage = tot_captives/len(cleaned_df)
ave_cap_per_year = tot_captives/year_span
print('Total n. of captives:',tot_captives)
print('Average captives per voyage',round(ave_cap_per_voyage))
print('Average captives per year',round(ave_cap_per_year))
```

```
Total n. of captives: 5082756.0
Average captives per voyage 276
Average captives per year 14690
```

```
filtered_rows = len(df)-len(cleaned_df)
tot_captives_ext = tot_captives + ave_cap_per_voyage*filtered_rows
ave_cap_per_year_adj = tot_captives_ext/year_span_raw
print('Extimated total n. of captives',round(tot_captives_ext))
print('Adjusted average captives per year', round(ave_cap_per_year_adj))
```

```
Extimated total n. of captives 9981894
Adjusted average captives per year 28358
```

```
<IPython.core.display.HTML object>
```

So far we computed numbers, but data can be most effectively described using visualization. In our DataFrame we have information about three different locations: the place where the voyage started, the principal port of slave purchase, and the principal port of slave disembarkation. Let's have a closer look at these locations.

```
<IPython.core.display.HTML object>
```

```
start_port = cleaned_df.iloc[:,3]
start_port_counts = start_port.value_counts()
```

```python
print(type(start_port_counts))
start_port_counts
```

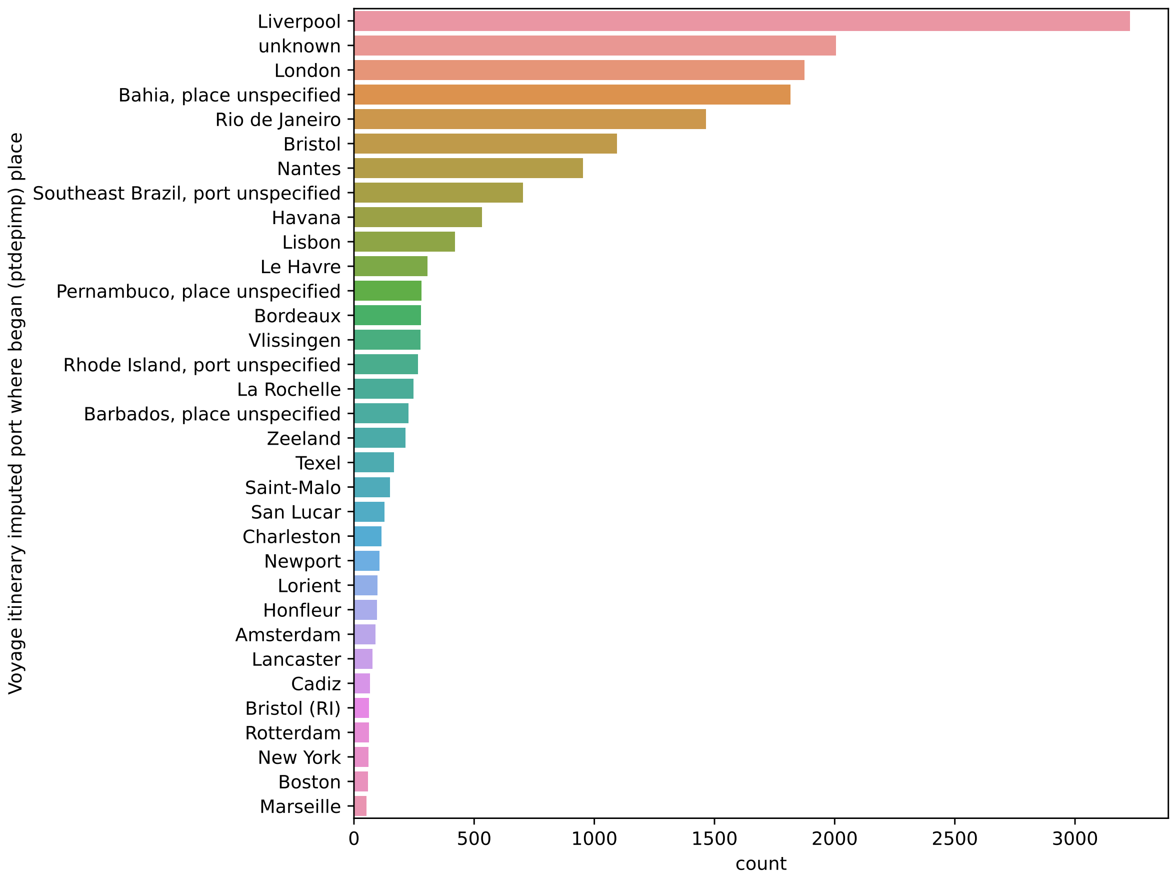
```
<class 'pandas.core.series.Series'>
```

```
Voyage itinerary imputed port where began (ptdepimp) place
Liverpool                        3227
unknown                          2005
London                           1874
Bahia, place unspecified         1815
Rio de Janeiro                   1464
                                 ...
Mangaratiba                         1
Mediterranean coast (France)        1
Canasí                              1
Santa Catarina                      1
Portland                            1
Name: count, Length: 176, dtype: int64
```

```python
import seaborn as sns
import matplotlib.pyplot as plt

fig, new_ax = plt.subplots(nrows=1,ncols=1,figsize=(8,8))
filter = start_port_counts > 50
x_data = start_port_counts[filter]
y_data = start_port_counts.index[filter]
sns.barplot(ax=new_ax,x=x_data,y=y_data)
```

```
<Axes: xlabel='count', ylabel='Voyage itinerary imputed port where began (ptdepimp) place'>
```



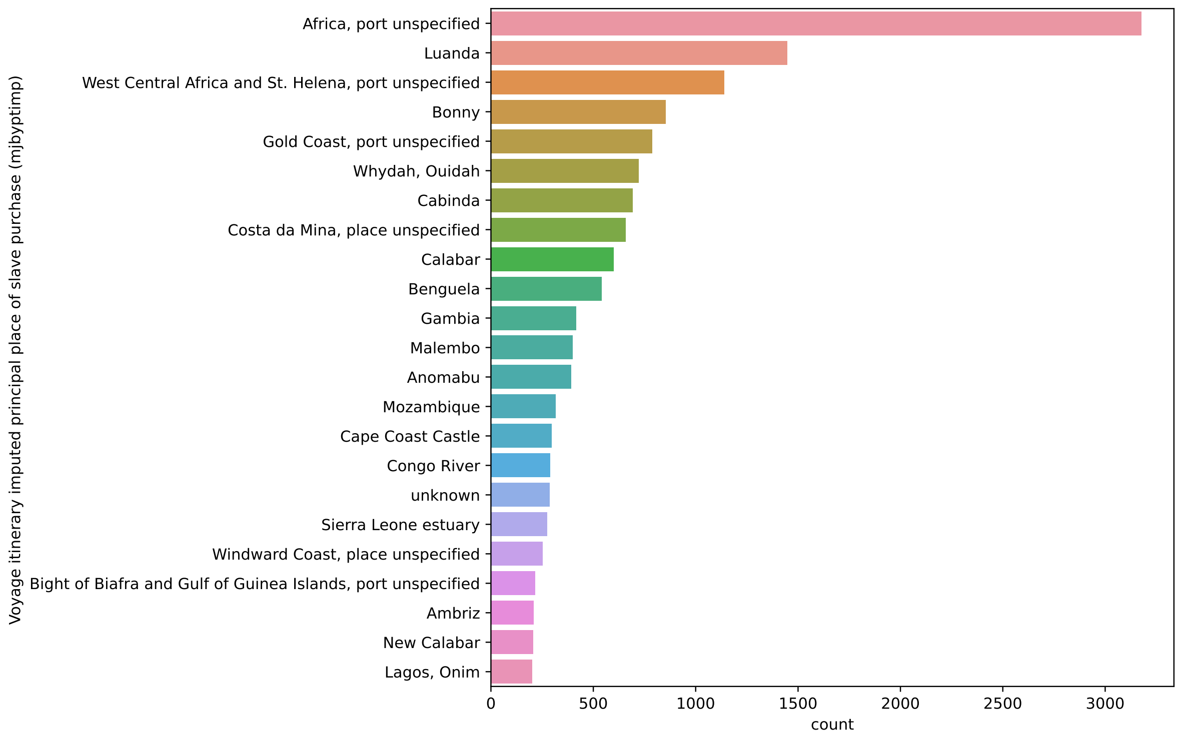

```
main_pur_port = cleaned_df.iloc[:,4]
main_pur_counts = main_pur_port.value_counts()
main_pur_counts
```

```
Voyage itinerary imputed principal place of slave purchase (mjbyptimp)
Africa, port unspecified                                    3177
Luanda                                                      1447
West Central Africa and St. Helena, port unspecified        1139
Bonny                                                        853
Gold Coast, port unspecified                                 787
                                                            ...
Petit Mesurado                                                 1
Eva                                                            1
Pokesoe (Princes Town)                                         1
Sassandra                                                      1
Sugary (Siekere)                                               1
```

```
Name: count, Length: 161, dtype: int64
```

```
fig, ax = plt.subplots(1,1,figsize=(8,8))
filter = main_pur_counts > 200
sns.barplot(ax=ax,x=main_pur_counts[filter],y=main_pur_counts.index[filter])
```

```
<Axes: xlabel='count', ylabel='Voyage itinerary imputed principal place of slave purchase (mj
```



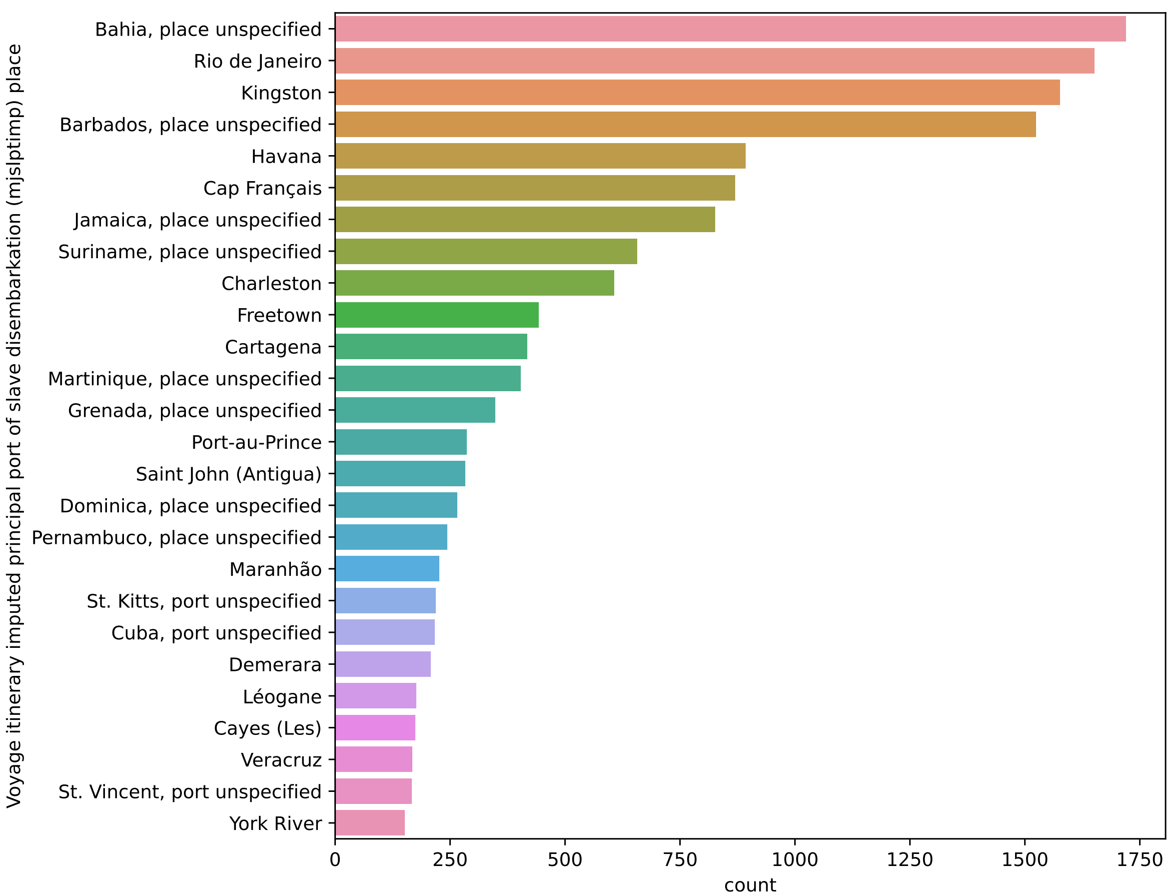

```
main_dis_port = cleaned_df.iloc[:,5]
main_dis_counts = main_dis_port.value_counts()
main_dis_counts
```

```
Voyage itinerary imputed principal port of slave disembarkation (mjslptimp) place
Bahia, place unspecified       1720
Rio de Janeiro                 1651
Kingston                       1576
Barbados, place unspecified    1524
```

```
Havana                           893
                               ...
France, place unspecified          1
Santa Marta                        1
Dois Rios                          1
Maceió                             1
Bonny                              1
Name: count, Length: 240, dtype: int64
```

```
fig, ax = plt.subplots(1,1,figsize=(8,8))
filter = main_dis_counts > 150
sns.barplot(ax=ax,x=main_dis_counts[filter],y=main_dis_counts.index[filter])
```

```
<Axes: xlabel='count', ylabel='Voyage itinerary imputed principal port of slave disembarkati
```



<IPython.core.display.HTML object>

Let's try to make now a different type of visualization, a time series, i.e. a plot where we see how parameters change over time

<IPython.core.display.HTML object>

```
col_to_group = 'Year of arrival at port of disembarkation'
col_to_sum = 'Captives arrived at 1st port'
df_per_year = cleaned_df.groupby(col_to_group)[col_to_sum].sum()
print(df_per_year.shape)
df_per_year
```

```
(298,)
```

```
Year of arrival at port of disembarkation
1520.0       44.0
1526.0      115.0
1527.0       46.0
1532.0      589.0
1534.0      354.0
            ...
1862.0    11407.0
1863.0     6739.0
1864.0     3298.0
1865.0      795.0
1866.0      700.0
Name: Captives arrived at 1st port, Length: 298, dtype: float64
```

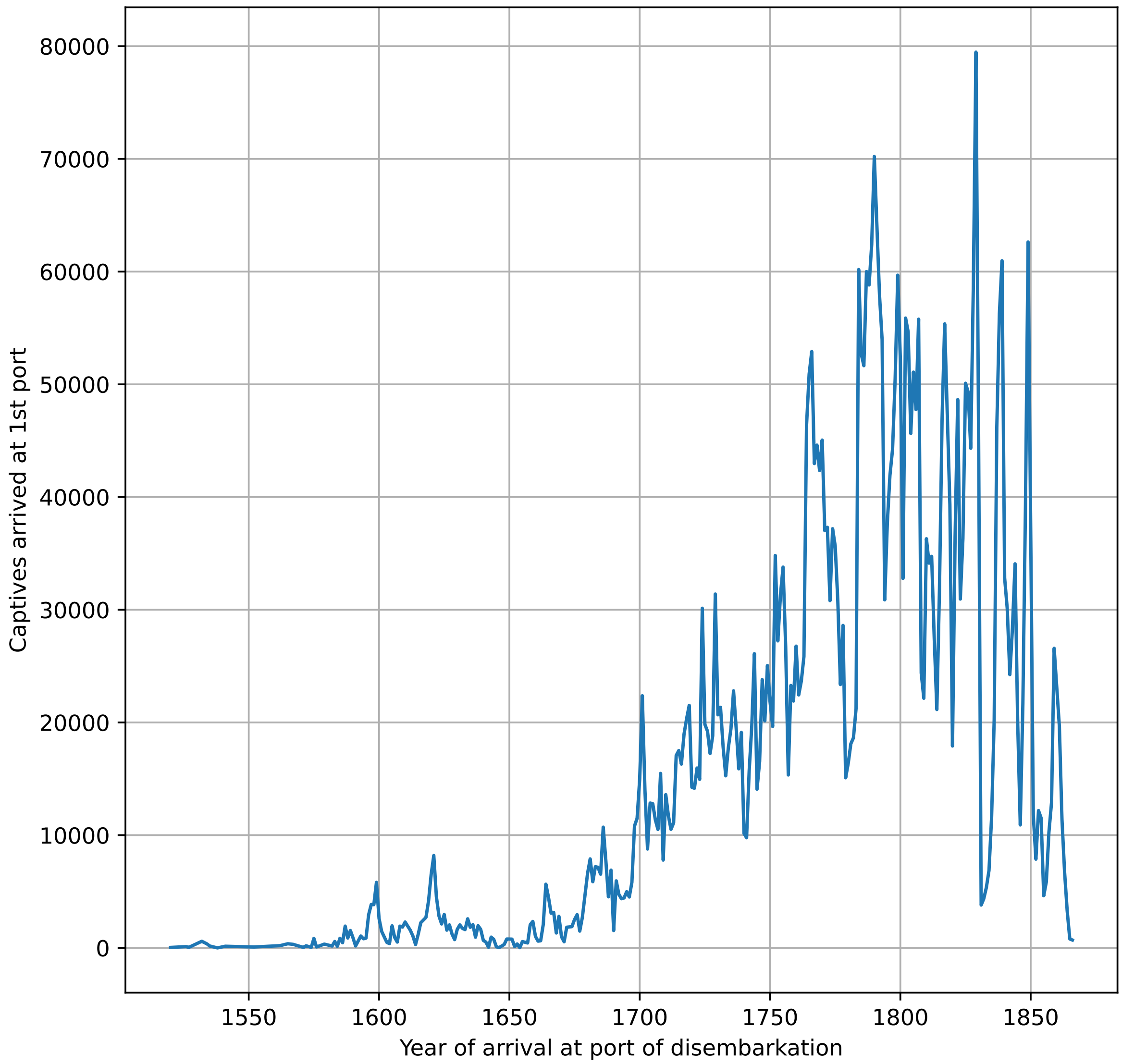
```
fig, ax = plt.subplots(1,1,figsize=(8,8))
sns.lineplot(ax=ax,x=df_per_year.index,y=df_per_year)
plt.grid()
```

```
/Users/xizg0003/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1119: FutureWarni

use_inf_as_na option is deprecated and will be removed in a future version. Convert inf valu

/Users/xizg0003/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1119: FutureWarni

use_inf_as_na option is deprecated and will be removed in a future version. Convert inf valu
```




```
max_index = df_per_year.idxmax()
min_index = df_per_year.idxmin()
min_year = df_per_year[min_index]
max_year = df_per_year[max_index]

print('Min. n. of captives per year:', min_year,'on',min_index)
print('Max. n. of captives per year:', max_year,'on',max_index)
```

```
Min. n. of captives per year: 2.0 on 1538.0
```

```
Max. n. of captives per year: 79472.0 on 1829.0
```

```
solution = 'The total number of captives is almost constant up to 1650, with the exception
and 1622. The number increases steadily up to 1800 and decreases afterwords. The times ser
by low and high peek. The number of captives per year reaches its maximum on 1829 with alm
that year. The minimum is 2 captives on 1538.'
question_box(solution=solution)
```

```
<IPython.core.display.HTML object>
```

Time series are very interesting to describe the trends of phenomema at different scale. Our plot ticks are separated by 50 years, this is fine to visualise trends over centuries, but we cannot see what's happening on decades.

```
<IPython.core.display.HTML object>
```

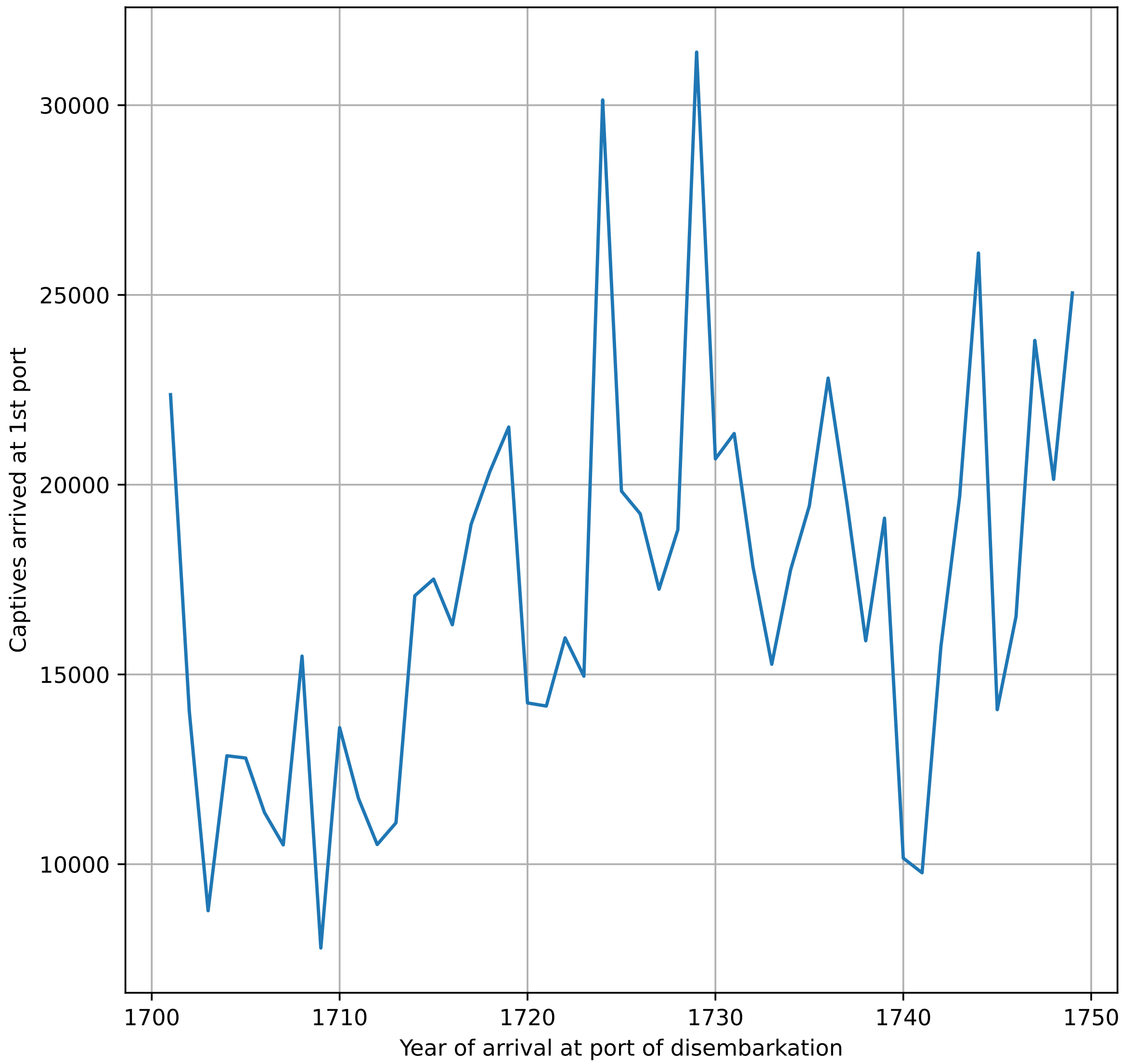
```
time_filter = (df_per_year.index > 1700) & (df_per_year.index < 1750)
fig, ax = plt.subplots(1,1,figsize=(8,8))
x_data = df_per_year.index[time_filter]
y_data = df_per_year[time_filter]
sns.lineplot(ax=ax,x=x_data,y=y_data)
plt.grid()
```

```
/Users/xizg0003/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1119: FutureWarni

use_inf_as_na option is deprecated and will be removed in a future version. Convert inf valu

/Users/xizg0003/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1119: FutureWarni

use_inf_as_na option is deprecated and will be removed in a future version. Convert inf valu
```



Captives arrived at 1st port
30000
25000
20000
15000
10000
1700
1710
1720
1730
1740
1750
Year of arrival at port of disembarkation

# Summary

## Databases and Data Analysis

In the first part of the workshop, we conducted an interactive exercise to experience the main challenges associated with converting unstructured data into structured, organized, tabular (and generally more mathematical) data. Having structured, machine-readable data is essential for proper data analysis. It is important to note that database creation, which marks the beginning of every data analysis process, can be affected by errors, missing data, and biases driven by human decisions.

In the second part of the workshop, we focused on data analysis. Data analysis is often only considered in relation to programming tools. However, we aimed to emphasize the fundamental principles of data analysis, emphasizing that analyzing data essentially involves querying a dataset. While some information may be easy to retrieve, other information may be hidden or require assumptions and speculation. Python (or any other programming language) is simply a tool to translate our questions into a machine-readable form.

Regardless of our data analysis process and the tools we use, it is crucial to describe and document our choices so that other researchers can reproduce the entire workflow that led to our conclusions.

## General data analysis workflow

1. **Define a Research question:**
    - Understand the problem or question you are trying to address;
    - Clearly define the goals, objectives, and sub-task to answer a research question.
2. **Collect/Organise Data:**
    - Collect relevant data from various sources;
    - Ensure data quality, address any missing or inconsistent data, ensure proper data structure.
3. **Clean Data:**
    - Clean and preprocess the data to handle missing values, outliers, and errors;

- Standardize or normalize data formats if necessary.

4. **Explore Data:**
   - Explore the data using statistical and visual methods;
   - Identify patterns, trends, and relationships in the data.

5. **(Model):**
   - Select appropriate models based on the analysis goals;
   - Evaluate the model's performance using metrics relevant to the analysis;
   - Fine-tune the model if necessary.

6. **Interpret Data:**
   - Interpret the results of the analysis in the context of the initial research question;
   - Draw conclusions and make recommendations based on the findings.

7. **Visualization and Reporting:**
   - Create visualizations to communicate key findings;
   - Prepare a comprehensive report summarizing the analysis process, results, and insights.

# What's next?

Congratulations! If you are reading these few lines you survived our workshop on analysing cultural data (and you even went through the documentation!). Our workshop was only an introduction, it would have been impossible to cover everything related to analysing cultural data in only four hours, but we hope you now have a general overview of how data analysis is performed and of all the caveats related to data base creation and analysis.

What's next? You can build on top of what we have discussed during the workshop. Here there is a list of possible further steps, good luck!

- **More data**: try to obtain more data in .csv form and perform the data analysis on this new data. You can either get new data in the SlaveVoyages website or download any data in .csv format. Just remember to download it in the "data" directory and to change `data_file` into "data/your_file.csv". You can also use data in a different format (like excel sheet for example) and read it with the corresponding `pandas` tool;
- **Learning more about Python**: if you know nothing about programming and Python, you might consider to invest some time for learning about it. The Utrecht University Library and the Centre for Digital Humanities (CDH) offer free Python courses: have a look at the Research Data Management (RDM) workshop page and at the CDH workshop page;
- **More data questioning**: you can ask your own questions to data and find a way to implement that in Python (or any other programming language you are going to use)

# Glossaries

## Data Glossary

### Controlled vocabularies

Standardised sets of terms or phrases used to ensure consistency and accuracy in categorising and retrieving information.

### Data cleaning

The process of identifying and correcting errors, inconsistencies, and inaccuracies in a dataset to improve its quality and reliability.

### Data harmonisation

The process of integrating and standardising data from different sources or formats to ensure consistency and compatibility for analysis or other purposes.

### Data models

Abstract representations defining the structure, relationships, and constraints of data within a system or database.

### Enrichment

The process of enhancing or augmenting existing data with additional information to improve its quality, usability, or value.

### Graph database

A database structured around graph theory, where data entities are represented as nodes and their relationships as edges, facilitating complex and interconnected data querying.

### ID

Identification or identifier used to uniquely distinguish an entity within a system.

### Normalisation

The process of organising data in a database to reduce redundancy and dependency by dividing large tables into smaller ones and defining relationships between them.

### Relational database

A type of database management system (DBMS) organised around tables and relationships, adhering to the principles of the relational model.

## Programming glossary

### Code

Code is like a set of instructions that tells the computer what to do. It's similar to a recipe for the computer. The instructions for a specific task may very according to the programming language you use, that is why you also usually specify the language you are using (e.g. "Python code").

#### csv

CSV (coma separated values) is a way to store information, like making lists. It's a simple way to organize data, like names and ages, using commas. A file containing data organised in this way, has usually the extention ".csv". Even if the word "coma" is present in the acronym, data can be also separated by other symbols such as ";" or ":" and still be contained in a .csv file.

### DataFrame

A DataFrame is a Python object included in the pandas library. It is basically a table where information is organised in rows and columns. Every DataFrame row has an index that can be either a numeric value or a string (i.e. a label)

### Initialisation

Initialise basically means getting things ready. It's the starting point before using something in a program. Initialising a variable, in particular, means assigning a value to it for the first time:

```
# We initialise the variable name and age for the first time with a string (a word) and a
name = 'Stefano'
age = 28
```

### Library

See package

### Loop

A loop is like a computer doing something over and over again. It's a way to repeat a task multiple times.

### Object

An object is like a thing in the computer's world. It has characteristics and things it can do. For example, a dog can have a name and bark.

### Package

A library or package is like a toolbox with ready-made tools. It's a collection of helpful code (objects and functions) that programmers can use to make their work easier. Packages are made by the programming community and are usually organised according to certain specific tasks. You may find packages specific for time series analysis, text analysis, satellite image analysis, etc. The advantage of using a package is that you do not have to spend time and energy in finding solutions to problems already tackled by other people. Packages do not usually come automatically with the basic programming language installation (so to optimize space), but need to first be downloaded and imported. You may think at packages as building tools. Downloading a package would be similar to buying them from the shop and importing them is similar to get them ready to work (you do not need all your tools ALL the time for ANY house job, right?)

### Series

A Series is a DataFrame with a single column. Like DataFrames, a Series is an object belonging to the pandas library. Series rows, like in a DataFrame, have indices that can be either values or labels.

### Variable

A variable is like a box where you can keep and change information. It is a container for numbers or words.

# Resources

## Datasets

- SlaveVoyages website;
- CSV exports of the Getty Provenance Index GitHub page;
- National Gallery of Art Open Data GitHub page.

## Programming

- Python webpage;
- Pandas (Python Data Analysis package) webpage;
- Matplotlib (Python visualization package) webpage;
- Seaborn webpage (Python visualization package) webpage.