

Geographic Data Science

Welcome to Geographic Data Science, a course taught by Dr. Dani Arribas-Bel in the Autumn of 2020 at the University of Liverpool.

Contact

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Note

A PDF version of this course is available for download [here](#)

Overview

Aims

The module provides students with little or no prior knowledge core competences in Geographic Data Science (GDS). This includes the following:

- Advancing their statistical and numerical literacy.
- Introducing basic principles of programming and state-of-the-art computational tools for GDS.
- Presenting a comprehensive overview of the main methodologies available to the Geographic Data Scientist, as well as their intuition as to how and when they can be applied.
- Focusing on real world applications of these techniques in a geographical and applied context.

Learning outcomes

By the end of the course, students will be able to:

- Demonstrate advanced GIS/GDS concepts and be able to use the tools programmatically to import, manipulate and analyse spatial data in different formats.
- Understand the motivation and inner workings of the main methodological approaches of GDS, both analytical and visual.
- Critically evaluate the suitability of a specific technique, what it can offer and how it can help answer questions of interest.

- Apply a number of spatial analysis techniques and explain how to interpret the results, in a process of turning data into information.
- When faced with a new data-set, work independently using GIS/GDS tools programmatically to extract valuable insight.

Feedback strategy

The student will receive feedback through the following channels:

- Formal assessment of three summative assignments: two tests and a computational essay. This will be on the form of reasoning of the mark assigned as well as comments specifying how the mark could be improved. This will be provided no later than three working weeks after the deadline of the assignment submission.
- Direct interaction with Module Leader and demonstrators in the computer labs. This will take place in each of the scheduled lab sessions of the course.
- Online forum maintained by the Module Leader where students can contribute by asking and answering questions related to the module.

Key texts and learning resources

Access to materials, including lecture slides and lab notebooks, is centralized through the use of a course website available in the following url:

https://darribas.org/gds_course

Specific videos, (computational) notebooks, and other resources, as well as academic references are provided for each learning block.

In addition, the currently-in-progress book [*“Geographic Data Science with PySAL and the PyData stack”*](#) provides an additional resource for more in-depth coverage of similar content.

Syllabus

Week 1: Introduction

- Lecture: Geographic Data Science.
- Tutorial: Tools + Manipulating data in Python - Tidy Data.

Week 2: Modern Computational Environments

- Lecture: Modern Computational Environments.
- Tutorial: Manipulating data in Python - Advanced Tricks.

Week 3: Spatial Data

- Lecture: Spatial Data.
- Tutorial: Manipulating geospatial data in Python.

Week 4: (Geo)Visualization + Choropleths

- Lecture: (Geo)Visualization + Choropleths.
- Tutorial: Mapping deprivation.

Week 5: Spatial Weights

- Lecture: Spatial Weights.
- Tutorial:
 - [TEST 1](#) (1h): Thursday Oct. 24th
 - Spatial Weights with PySAL.

Week 6: ESDA

- Lecture: Exploratory Spatial Data Analysis (ESDA).
- Tutorial: ESDA in Python.

Week 7: Clustering

- Lecture: Clustering.
- Tutorial: Geodemographic analysis.

Week 8: Point Data

- Lecture: Point Data.
 - Tutorial: Exploring Twitter patterns.
-

Week 9

- Lecture: Assignment preparation.
- Tutorial:
 - [TEST 2](#) (1h): Thursday Nov. 21st
 - Assignment Clinic

Week 10: (Spatial) causal inference

- Lecture: Spatial causal inference.
- Tutorial: Assignment Clinic.

Week 11: Geographic Data Science in Action

- Lecture: Geographic Data Science *in the wild*.
- Tutorial: Assignment Clinic.

[ASSIGNMENT](#) due on Thursday, December 5th-2019.

Bibliography

[Don17]

David Donoho. 50 years of data science. *Journal of Computational and Graphical Statistics*, 26(4):745–766, 2017.

[McK12]

Wes McKinney. *Python for data analysis: Data wrangling with Pandas, NumPy, and IPython*. O’Reilly Media, Inc., 2012.

[RABWng]

Sergio J. Rey, Daniel Arribas-Bel, and Levi J. Wolf. *Geographic Data Science with PySAL and the PyData stack*. CRC press, forthcoming.

[SONeil13]

Rachel Schutt and Cathy O’Neil. *Doing data science: Straight talk from the frontline*. “O’Reilly Media, Inc.”, 2013.

[SAB19]

Alex Singleton and Daniel Arribas-Bel. Geographic data science. *Geographical Analysis*, 2019.

[Som18]

James Somers. The scientific paper is obsolete. *The Atlantic*, 2018.

[Wic14]

Hadley Wickham. Tidy data. *Journal of Statistical Software*, 59(10):??–??, 9 2014.
URL: <http://www.jstatsoft.org/v59/i10>.

Concepts

The concepts in this block are delivered through:

- Two video clips
- Accompanying slides
- **[Optional]** further readings for the interested and curious mind

This course

Let us start from the beginning, here is a snapshot of what this course is about! In the following clip, you will find out about the philosophy behind the course, how the content is structured, and why this is all designed like this. And, also, a little bit about the assessment...

What is *Geographic Data Science*?

Once it is clearer how this course is going to run, let’s dive right into why this course is necessary. In the following clip, you will learn about the background and context, which will hopefully help you understand a bit better what Geographic Data Science is.

Slides

The slides used in the clip are available at:

- [\[HTML\]](#).
- [\[PDF\]](#).

Further readings

To get a better picture, the following readings complement the overview provided above very well:

1. The introductory chapter to “Doing Data Science” [\[SONeil13\]](#), by Cathy O’Neil and Rachel Schutt is general overview of why we needed Data Science and where it came from.
2. A slightly more technical historical perspective on where Data Science came from and where it might go can be found in David Donoho’s recent overview [\[Don17\]](#).
3. A geographic take on Data Science, proposing more interaction between Geography and Data Science [\[SAB19\]](#).

Slides

The slides used in the clip are available at:

- [\[HTML\]](#).
- [\[PDF\]](#).

Bonus

The chapter is available free online [HTML](#) | [PDF](#)

Hands-on

In this first

Following this course interactively

Maybe use this for start up a notebook:

```
http://darribas.org/gds19/content/labs/begin.html
```

Video with walk through Jupyter Lab

Re-write this:

```
http://darribas.org/gds19/content/labs/lab_00.html
```

Software infrastructure for the course

- Point to available guides + install options

Files

Do-It-Yourself

To do:

- Make sure you have the setup installed and/or access to a campus computer to complete the course
- Launch JupyterLab, and explore

Concepts

The concepts in this block are delivered a few main references, totalling up about one and a half hours of your focused time. You are expected to read them all.

Open Science

The first part of this block is about setting the philosophical background. Why do we care about the processes and tools we use when we do computational work? Where do the current paradigm come from? Are we on the verge of a new model? For all of this, we have two reads to set the tone. Make sure to get those in first thing before moving on to the next bits.

- First half of Chapter 1 in “Geographic Data Science with PySAL and the PyData stack” [\[RABWng\]](#).
- The 2018 Atlantic piece “*The scientific paper is obsolete*” on computational notebooks, by James Somers [\[Som18\]](#).

Read the chapter [here](#). Estimated time: 15min.

Read the piece [here](#). Estimated time: 35min.

Modern Scientific Tools

Once we know a bit more about why we should care about the tools we use, let’s dig into those that will underpin much of this course. This part is interesting in itself, but will also valuable to better understand the practical aspects of the course. Again, we have two reads here to set the tone and complement the practical introduction we saw in the Hands-on and DIY parts of the previous block. We are closing the circle here:

- Second half of Chapter 1 in “Geographic Data Science with PySAL and the PyData stack” [\[RABWng\]](#).
- The chapter in the [GIS&T Book of Knowledge](#) on computational notebooks, by Geoff Boeing and Dani Arribas-Bel.

Read the chapter [here](#). Estimated time: 15min.

Hands-on

Once we know a bit about what computational notebooks are and why we should care about them, let’s jump to using them! This section introduces you to using Python for manipulating tabular data. Please read through it carefully and pay attention to how ideas about manipulating data are translated into Python code that “does stuff”. For this part, you can read directly from the course website, although it is recommended you follow the section interactively by running code on your own.

Once you have read through and have a bit of a sense of how things work, jump on the Do-It-Yourself section, which will provide you with a challenge to complete it on your own, and will allow you to put what you have already learnt to good use. Happy hacking!

Data munging

Real world datasets are messy. There is no way around it: datasets have “holes” (missing data), the amount of formats in which data can be stored is endless, and the best structure to share data is not always the optimum to analyze them, hence the need to [munge](#) them. As has been correctly pointed out in many outlets ([e.g.](#)), much of the time [spent](#) in what is called (Geo-)Data Science is related not only to sophisticated modeling and insight, but

has to do with much more basic and less exotic tasks such as obtaining data, processing, turning them into a shape that makes analysis possible, and exploring it to get to know their basic properties.

For how labor intensive and relevant this aspect is, there is surprisingly very little published on patterns, techniques, and best practices for quick and efficient data cleaning, manipulation, and transformation. In this session, you will use a few real world datasets and learn how to process them into Python so they can be transformed and manipulated, if necessary, and analyzed. For this, we will introduce some of the bread and butter of data analysis and scientific computing in Python. These are fundamental tools that are constantly used in almost any task relating to data analysis.

This notebook covers the basic and the content that is expected to be learnt by every student. We use a prepared dataset that saves us much of the more intricate processing that goes beyond the introductory level the session is aimed at. As a companion to this introduction, there is an additional notebook (see link on the website page for Lab 01) that covers how the dataset used here was prepared from raw data downloaded from the internet, and includes some additional exercises you can do if you want dig deeper into the content of this lab.

In this notebook, we discuss several patterns to clean and structure data properly, including tidying, subsetting, and aggregating; and we finish with some basic visualization. An additional extension presents more advanced tricks to manipulate tabular data.

Before we get our hands data-dirty, let us import all the additional libraries we will need, so we can get that out of the way and focus on the task at hand:

```
# This ensures visualizations are plotted inside the notebook
%matplotlib inline

import os           # This provides several system utilities
import pandas as pd  # This is the workhorse of data munging in Python
import seaborn as sns # This allows us to efficiently and beautifully plot
```

Dataset

We will be exploring some of the characteristics of the population in Liverpool. To do that, we will use a dataset that contains population counts, split by ethnic origin. These counts are aggregated at the [Lower Layer Super Output Area](#) (LSOA from now on). LSOAs are an official Census geography defined by the Office of National Statistics that is small enough to create variation within cities, but large enough also to preserve privacy. For that reason, many data products (Census, deprivation indices, etc.) use LSOAs as one of their main geographies.

Let us first set the path to the file where we store the data we will use:

```
# Important! You need to specify the path to the data in *your* machine
# If you have placed the data folder in the same directory as this notebook,
# you would do:
# f = 'liv_pop.csv'
f = 'data/liv_pop.csv' # Path to file containing the table
```

IMPORTANT: the path above might have look different in your computer. See this introductory notebook for more details about how to set your paths.

Alternatively, you can read this file from its web location too (do not run the following cell if you want to read the data locally or are currently offline):

```
f = 'http://darribas.org/gds19/content/labs/data/liv_pop.csv'
```

To read a “comma separated values” (**.csv**) file, we can run:

```
db = pd.read_csv(f, index_col='GeographyCode')    # Read the table in
```

Let us stop for a minute to learn how we have read the file. Here are the main aspects to keep in mind:

- We are using the method **read_csv** from the **pandas** library, which we have imported with the alias **pd**.
- In this form, all that is required is to pass the path to the file we want to read, which in this case we have created by concatenating two strings. We can see the full path we have used:

```
f
```

- The argument **index_col** is not strictly necessary but allows us to choose one of the columns as the index of the table. More on indices below.
- We are using **read_csv** because the file we want to read is in the **csv** format. However, **pandas** allows for many more formats to be read and write. A full list of formats supported may be found [here](#).

Data, sliced and diced

Now we are ready to start playing and interrogating the dataset! What we have at our fingertips is a table that summarizes, for each of the LSOAs in Liverpool, how many people live in each, by the region of the world where they were born. Now, let us learn a few cool tricks built into **pandas** that work out-of-the box with a table like ours.

- Inspecting what it looks like. We can check the top (bottom) X lines of the table by passing X to the method **head** (**tail**). For example, for the top/bottom five lines:

```
db.head()
```

```
db.tail()
```

- Getting an overview of the table:

```
db.info()
```



```
<class 'pandas.core.frame.DataFrame'>
Index: 298 entries, E01006512 to E01033768
Data columns (total 5 columns):
Europe                298 non-null int64
Africa                298 non-null int64
Middle East and Asia  298 non-null int64
The Americas and the Caribbean  298 non-null int64
Antarctica and Oceania  298 non-null int64
dtypes: int64(5)
memory usage: 14.0+ KB
```

- Getting an overview of the *values* of the table:

```
db.describe()
```

Note how the output is also a **DataFrame** object, so you can do with it the same things you would with the original table (e.g. writing it to a file).

In this case, the summary might be better presented if the table is “transposed”:

```
db.describe().T
```

- Equally, common descriptive statistics are also available:

```
# Obtain minimum values for each table
db.min()
```

```
# Obtain minimum value for the column `Europe`
db['Europe'].min()
```

Note here how we have restricted the calculation of the maximum value to one column only.

Similarly, we can restrict the calculations to a single row:

```
# Obtain standard deviation for the row `E01006512`,
# which represents a particular LSOA
db.loc['E01006512', :].std()
```

- Creation of new variables: we can generate new variables by applying operations on existing ones. For example, we can calculate the total population by area. Here is a couple of ways to do it:

```
# Longer, hardcoded
total = db['Europe'] + db['Africa'] + db['Middle East and Asia'] + \
        db['The Americas and the Caribbean'] + db['Antarctica and Oceania']
# Print the top of the variable
total.head()
```

```
# One shot
total = db.sum(axis=1)
# Print the top of the variable
total.head()
```

Note how we are using the command **sum**, just like we did with **max** or **min** before but, in this case, we are not applying it over columns (e.g. the max of each column), but over rows, so we get the total sum of populations by areas.

Once we have created the variable, we can make it part of the table:

```
db['Total'] = total
db.head()
```

- Assigning new values: we can easily generate new variables with scalars, and modify those.

```
# New variable with all ones
db['ones'] = 1
db.head()
```

And we can modify specific values too:

```
db.loc['E01006512', 'ones'] = 3
db.head()
```

- Permanently deleting variables is also within reach of one command:

```
del db['ones']
db.head()
```

- Index-based querying.

We have already seen how to subset parts of a **DataFrame** if we know exactly which bits we want. For example, if we want to extract the total and European population of the first four areas in the table, we use **loc** with lists:

```
eu_tot_first4 = db.loc[['E01006512', 'E01006513', 'E01006514', 'E01006515'], \
                        ['Total', 'Europe']]
eu_tot_first4
```

- Querying based on conditions.

However, sometimes, we do not know exactly which observations we want, but we do know what conditions they need to satisfy (e.g. areas with more than 2,000 inhabitants). For these cases, **DataFrames** support selection based on conditions. Let us see a few examples. Suppose we want to select...

... areas with more than 2,500 people in Total:

```
m5k = db.loc[db['Total'] > 2500, :]
m5k
```

... areas where there are no more than 750 Europeans:

```
nm5ke = db.loc[db['Europe'] < 750, :]
nm5ke
```

... areas with exactly ten person from Antarctica and Oceania:

```
oneOA = db.loc[db['Antarctica and Oceania'] == 10, :]
oneOA
```

Pro-tip: these queries can grow in sophistication with almost no limits. For example, here is a case where we want to find out the areas where European population is less than half the population:

```
eu_lth = db.loc[(db['Europe'] * 100. / db['Total']) < 50, :]
eu_lth
```

- Combining queries.

Now all of these queries can be combined with each other, for further flexibility. For example, imagine we want areas with more than 25 people from the Americas and Caribbean, but less than 1,500 in total:

```
ac25_1500 = db.loc[(db['The Americas and the Caribbean'] > 25) & \
                  (db['Total'] < 1500), :]\nac25_1500
```

- Sorting.

Among the many operations **DataFrame** objects support, one of the most useful ones is to sort a table based on a given column. For example, imagine we want to sort the table by total population:

```
db_pop_sorted = db.sort_values('Total', ascending=False)\ndb_pop_sorted.head()
```

If you inspect the help of **db.sort_values**, you will find that you can pass more than one column to sort the table by. This allows you to do so-called hierarchical sorting: sort first based on one column, if equal then based on another column, etc.

Visual exploration

The next step to continue exploring a dataset is to get a feel for what it looks like, visually. We have already learnt how to uncover and inspect specific parts of the data, to check for particular cases we might be interested in. Now we will see how to plot the data to get a sense of the overall distribution of values. For that, we will be using the Python library [seaborn](#).

- Histograms.

One of the most common graphical devices to display the distribution of values in a variable is a histogram. Values are assigned into groups of equal intervals, and the groups are plotted as bars rising as high as the number of values into the group.

A histogram is easily created with the following command. In this case, let us have a look at the shape of the overall population:

```
_ = sns.distplot(db['Total'], kde=False)
```

Note we are using **sns** instead of **pd**, as the function belongs to **seaborn** instead of **pandas**.

We can quickly see most of the areas contain somewhere between 1,200 and 1,700 people, approx. However, there are a few areas that have many more, even up to 3,500 people.

An additional feature to visualize the density of values is called **rug**, and adds a little tick for each value on the horizontal axis:

```
_ = sns.distplot(db['Total'], kde=False, rug=True)
```

- Kernel Density Plots

Histograms are useful, but they are artificial in the sense that a continuous variable is made discrete by turning the values into discrete groups. An alternative is kernel density estimation (KDE), which produces an empirical density function:

```
_ = sns.kdeplot(db['Total'], shade=True)
```

- Line and bar plots

Another very common way of visually displaying a variable is with a line or a bar chart. For example, if we want to generate a line plot of the (sorted) total population by area:

```
_ = db['Total'].sort_values(ascending=False).plot()
```

For a bar plot all we need to do is to change an argument of the call:

```
_ = db['Total'].sort_values(ascending=False).plot(kind='bar')
```

Note that the large number of areas makes the horizontal axis unreadable. We can try to turn the plot around by displaying the bars horizontally (see how it's just changing **bar** for **barh**). To make it readable, let us expand the plot's height:

```
_ = db['Total'].sort_values().plot(kind='barh', figsize=(6, 20))
```

Un/tidy data

Happy families are all alike; every unhappy family is unhappy in its own way.

Leo Tolstoy.

Once you can read your data in, explore specific cases, and have a first visual approach to the entire set, the next step can be preparing it for more sophisticated analysis. Maybe you are thinking of modeling it through regression, or on creating subgroups in the dataset with particular characteristics, or maybe you simply need to present summary measures that relate to a slightly different arrangement of the data than you have been presented with.

For all these cases, you first need what statistician, and general R wizard, Hadley Wickham calls “*tidy data*”. The general idea to “tidy” your data is to convert them from whatever structure they were handed in to you into one that allows convenient and standardized manipulation, and that supports directly inputting the data into what he calls “*tidy*” analysis tools. But, at a more practical level, what is exactly “*tidy data*”? In Wickham’s own words:

Tidy data is a standard way of mapping the meaning of a dataset to its structure. A dataset is messy or tidy depending on how rows, columns and tables are matched up with observations, variables and types.

He then goes on to list the three fundamental characteristics of “*tidy data*”:

1. Each variable forms a column.
2. Each observation forms a row.
3. Each type of observational unit forms a table.

If you are further interested in the concept of “*tidy data*”, I recommend you check out the [original paper](#) (open access) and the [public repository](#) associated with it.

Let us bring in the concept of “*tidy data*” to our own Liverpool dataset. First, remember its structure:

```
db.head()
```

Thinking through *tidy* lenses, this is not a tidy dataset. It is not so for each of the three conditions:

- Starting by the last one (*each type of observational unit forms a table*), this dataset actually contains not one but two observational units: the different areas of Liverpool, captured by **GeographyCode**; and subgroups of an area. To *tidy* up this aspect, we can create two different tables:

```
# Assign column `Total` into its own as a single-column table
db_totals = db[['Total']]
db_totals.head()
```

```
# Create a table `db_subgroups` that contains every column in `db` without `Total`
db_subgroups = db.drop('Total', axis=1)
db_subgroups.head()
```

Note we use **drop** to exclude “Total”, but we could also use a list with the names of all the columns to keep. Additionally, notice how, in this case, the use of **drop** (which leaves **db** untouched) is preferred to that of **del** (which permanently removes the column from **db**).

At this point, the table **db_totals** is tidy: every row is an observation, every table is a variable, and there is only one observational unit in the table.

The other table (**db_subgroups**), however, is not entirely tidied up yet: there is only one observational unit in the table, true; but every row is not an observation, and there are variable values as the names of columns (in other words, every column is not a variable). To obtain a fully tidy version of the table, we need to re-arrange it in a way that every row is a population subgroup in an area, and there are three variables: **GeographyCode**, population subgroup, and population count (or frequency).

Because this is actually a fairly common pattern, there is a direct way to solve it in **pandas**:

```
tidy_subgroups = db_subgroups.stack()
tidy_subgroups.head()
```

The method **stack**, well, “stacks” the different columns into rows. This fixes our “tidiness” problems but the type of object that is returning is not a **DataFrame**:

```
type(tidy_subgroups)
```

It is a **Series**, which really is like a **DataFrame**, but with only one column. The additional information (**GeographyCode** and population group) are stored in what is called an multi-index. We will skip these for now, so we would really just want to get a **DataFrame** as we know it out of the **Series**. This is also one line of code away:

```
# Unfold the multi-index into different, new columns
tidy_subgroupsDF = tidy_subgroups.reset_index()
tidy_subgroupsDF.head()
```

To which we can apply to renaming to make it look better:

```
tidy_subgroupsDF = tidy_subgroupsDF.rename(columns={'level_1': 'Subgroup', 0: 'Freq'})
tidy_subgroupsDF.head()
```

Now our table is fully tidied up!

Grouping, transforming, aggregating

One of the advantage of tidy datasets is they allow to perform advanced transformations in a more direct way. One of the most common ones is what is called “group-by” operations. Originated in the world of databases, these operations allow you to group observations in a table by one of its labels, index, or category, and apply operations on the data group by group.

For example, given our tidy table with population subgroups, we might want to compute the total sum of population by each group. This task can be split into two different ones:

- Group the table in each of the different subgroups.
- Compute the sum of **Freq** for each of them.

To do this in **pandas**, meet one of its workhorses, and also one of the reasons why the library has become so popular: the **groupby** operator.

```
pop_grouped = tidy_subgroupsDF.groupby('Subgroup')
pop_grouped
```

The object **pop_grouped** still hasn't computed anything, it is only a convenient way of specifying the grouping. But this allows us then to perform a multitude of operations on it. For our example, the sum is calculated as follows:

```
pop_grouped.sum()
```

Similarly, you can also obtain a summary of each group:

```
pop_grouped.describe()
```

We will not get into it today as it goes beyond the basics we want to convey, but keep in mind that **groupby** allows you to not only call generic functions (like **sum** or **describe**), but also your own functions. This opens the door for virtually any kind of transformation and aggregation possible.

Additional lab materials

The following provide a good “next step” from some of the concepts and tools covered in the lab and DIY sections of this block:

- This [NY Times article](#) does a good job at conveying the relevance of data “cleaning” and [munging](#).
- A good introduction to data manipulation in Python is Wes McKinney’s “Python for Data Analysis” [\[McK12\]](#).
- To explore further some of the visualization capabilities in at your fingertips, the Python library [seaborn](#) is an excellent choice. Its online [tutorial](#) is a fantastic place to start.
- A good extension is Hadley Wickham’ “Tidy data” paper [\[Wic14\]](#), which presents a very popular way of organising tabular data for efficient manipulation.

Do-It-Yourself

Warning

ToDo:

- Prepare dataset so it is easy for student to consume
- Publish as derivative from WikiLeaks’
- Introduce what is expected from the student more clearly

Practice your data tidying skills with a different dataset. For example, you can have a look at the Guardian’s version of [Wikileaks’ Afghanistan war logs](#). The table is stored on a GoogleDoc on the following address:

https://docs.google.com/spreadsheets/d/1EAX8_ksSCmoWW_SlhEyg2QrRn0FNNhcg1TtDFJzZRgc/edit?hl=en#gid=1

Follow these steps:

- Download the table as a [csv](#) file (File → Download as → .csv, current sheet).
- Read it into Python.
- Explore it by creating a few plots.
- Examine its level of tidiness and turn it into a fully tidy dataset.
- Obtain a monthly total count of casualties and create a line or a bar plot of them.

By Dani Arribas-Bel



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