# Enriching Exploratory Spatial Data Analysis with modern computer tools

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# Handling massive data sources with classical tools

# An intermediate kind of data

## Handling the recent massive data sources

### ~~"Big Data"~~

- Data that can't fit on a personnal computer
- Few evolutions in the last years
- Still the usual distributed computing solutions : Hadoop, Apache Spark
- Still hard to grasp for non computer scientists

### Traditionnal ~~large data~~

e.g. census data, territorial mesh data etc.

- Can be managed in most analysis softwares
- Often adapted for spreadsheets, GIS, GUI softwares (GeoDA...) etc.
- Can also be analyzed with CLI analysis tools like R or Python (cf. yesterday's workshop)

## What lies in-between these dataset types ?

# An intermediate kind of data

| Data | | | Storage and analysis | |
|---|---|---|---|---|
| Quantity | Memory size | Examples | Storage infrastructure | Analysis and visualization tools |
| Up to 1,000 rows | ~1 MB | Aggregated census data | Text file | Spreadsheets, GIS |
| 1,000-100,000 rows | ~1-50 MB | Detailed Census data | Text files | GIS, GUI software (GeoDA, Tableau…) etc. |
| 100,000 – a few million rows | ~50 MB – 1 GB | Individual data, time series of multiple sensors | Spreadsheet or binary files (SHP, geopackage…) | Interactive (GUI) statistical tool or Command-Line Interface (CLI) tools |
| 10 to 100 million rows | ~1 - 10 GB | Many new open datasets : equipments, user-generated content, VGI etc. | **???** | **???** |
| > 100 million rows | > 10s of GB | Spatio-temporal data, automated reporting, big companies datasets … | Distributed Databases | High-Performance Computing |

# Handling massive data

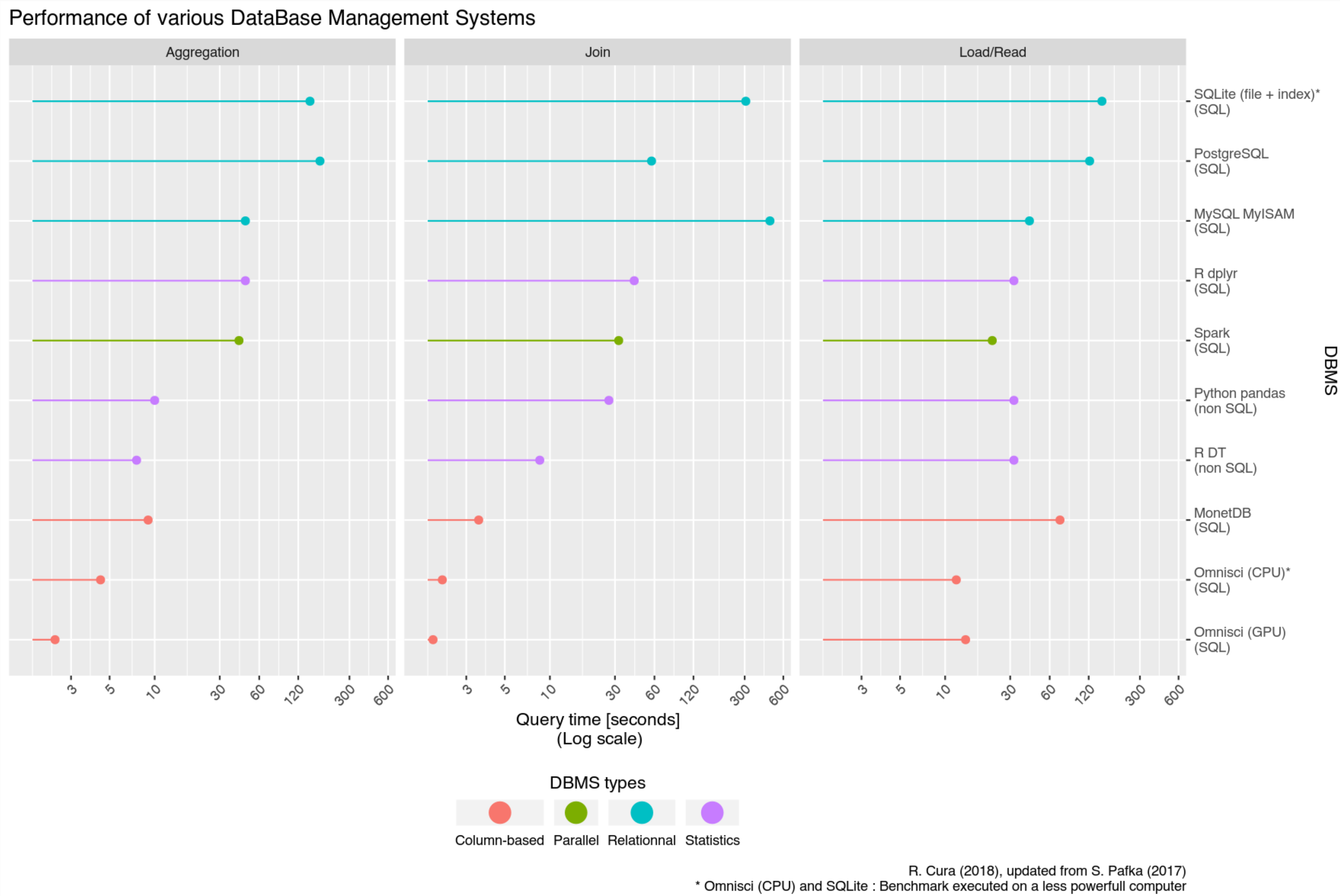
## It's not really a new problem

- Traditionnal handling : relational DMBS, e.g. MySQL, PostgreSQL, SQLite
  - Great for :
    - archiving large data
    - multiple users and concurrent queries
    - updatability
    - diversity of types and queries
    - customisation
    - universality through SQL
  - Issues with : **speed**
    - install/setup : can't be setup in a few minutes
    - data import : made for updating, slow for massive imports
    - queries : row-based DMBS : slow for global data aggregates/joins

**Traditionnal relationnal DBMS are not that good a fit for Exploratory Data Analysis (EDA).**

- Mostly a single-user context, requiring many back and forth between global structure and peculiarities

# A few benchmarks



# Using the new generation of colum-based DBMS

## Advantages :

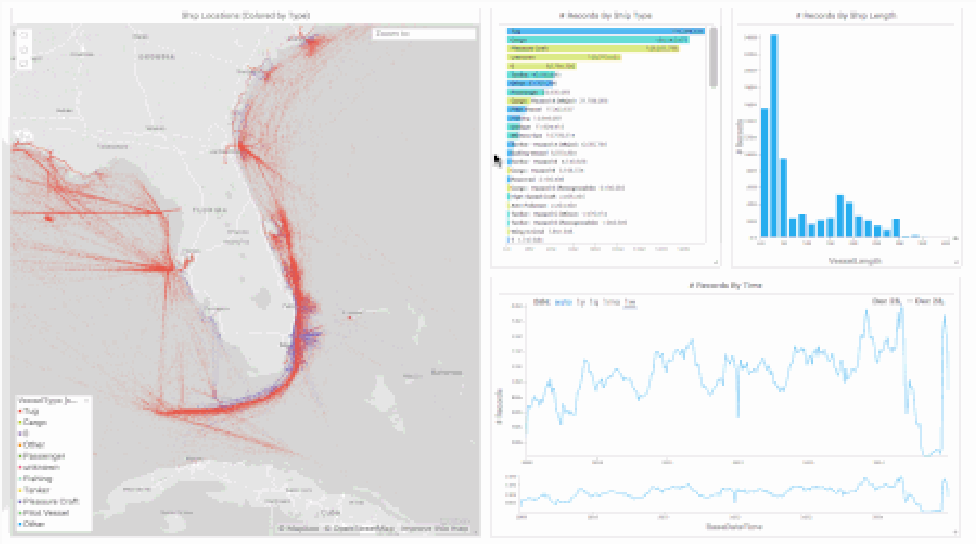
- Easy to setup
- Fast for data insert
- Fast (extremely) for column-based operations : agregation, joins
- Can be queried through SQL (at least some of them)

## Weaknesses :

- Not performant for upserts and data updates
- Not as mature as relational DBMS : still the state of the art, although used a lot by big tech companies
- Less operators/flexibility on queries (especially spatial queries : nothing can reach PostGIS spatial queries)

## Presenting the example of Omnisci (former MapD), an open-source* columnar DBMS

- A DBMS made for GPU processing :
  - Can query hundreds of billions of rows in a blink
  - When it is run on an adapted hardware configurations : high-end GPUs etc.
  - Check www.omnisci.com/demos :



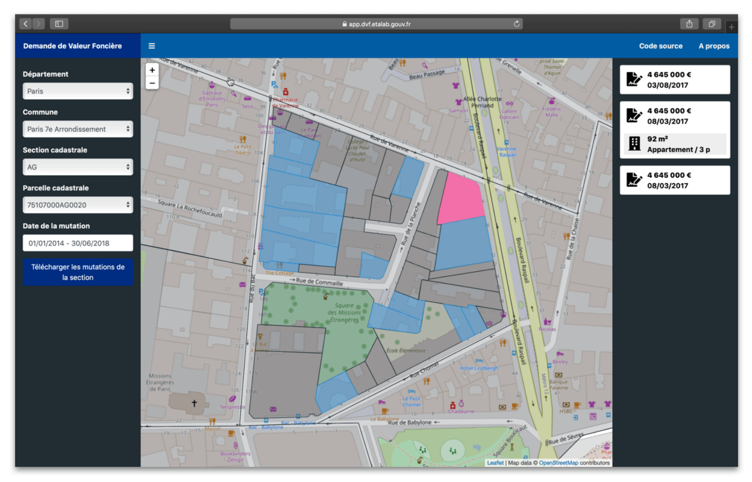
- Still works very well for $10^6$-$10^8$ rows-data on an aging personnal computer without GPU

# Illustrating an EDA approach using Omnisci

## Example dataset :

The recent governement opendataset on real estate transactions : the DVF ("Demande de Valeurs Foncières")

- Logs all (public and private) real estate transactions on *almost* all of France
- Detailed geolocation : cadastral parcel (e.g. big as a building)
- Detailed price for each transaction, with the corresponding informations on the real estate types, area and composition
- Yearly, since 2014




- 1 year : ~ 3M rows : easy to manage through CLI
- 5 years (2014-2018) : ~15M rows, doesn't fit in memory
- A good candidate for a quick test/demo

# Illustrating an EDA approach using Omnisci

## Preparing the DBMS :

- Run through Docker container : `docker run -name testdb -d -v $HOME/omnisci-docker-storage:/omnisci-storage -p 6273-6280:6273-6280 omnisci/core-os-cpu`
- Prepare the database :
    - Log to Omnisci container : `docker container exec -ti testdb /bin/bash`
    - Run the sql shell and create the table :

```
CREATE TABLE dvf ( id_mutation TEXT, annee SMALLINT, [ … ]);
```

    - Populate the table : `COPY dvf FROM '/data/dvf_2014-2018.csv.gz';` (~couple minutes)
    - Verify that the data looks correct (sub-seconds query)

```
omnisql> SELECT COUNT(*) AS n_rows FROM dvf;
> n_rows
> 13 255 975
```

## The full DB infrastructure can be setup in a few lines and ready in a few minutes

# Exploring the database with R

## Omnisci has a SQL interface, through ODBC/JDBC

-> It can be interactively queried from both R (using `RJDBC`) and from Python (`pymapd`)
-> Here, examples using R and tidyverse-style piped queries through the common database connection `DBI`

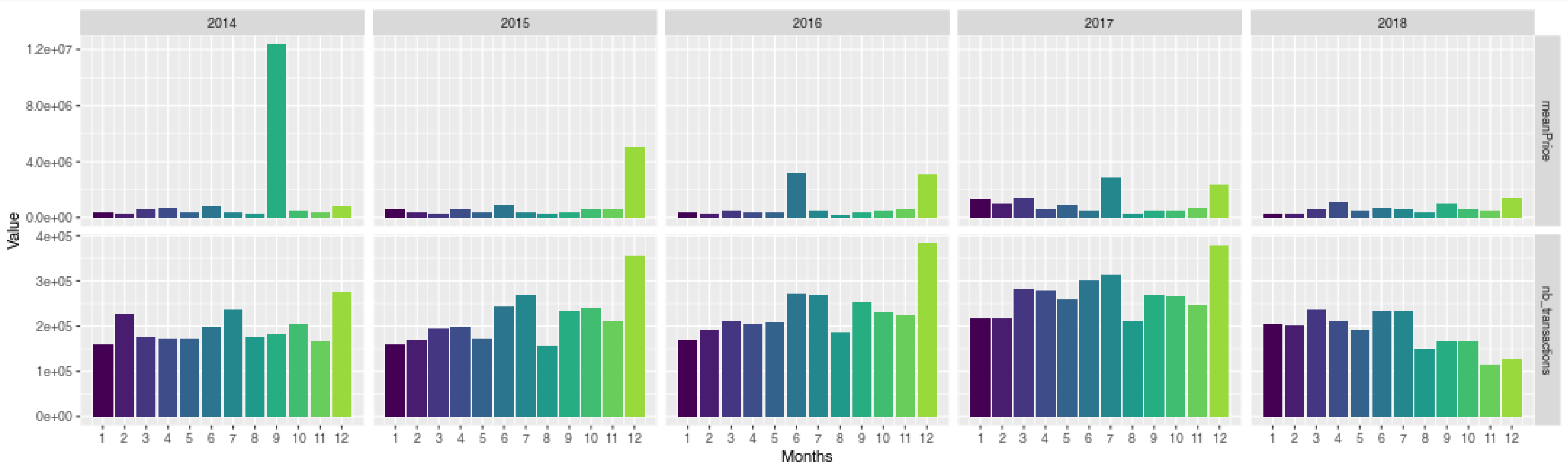
```
# Connecting to the DB
db_connection <- DBI::dbConnect(drv = db_driver, [credentials],
                                url = "jdbc:omnisci:localhost:6274:omnisci")
# Loading the table
dvf_data <- tbl(src = db_connection, "dvf")
dvf_data
```

```
## # Source:   table<dvf> [?? x 22]
## # Database: JDBCConnection
##    id_mutation annee date_mutation dept  code_commune section id_parcelle nature_mutation valeur_fonciere nombre_lots type_local surface_reelle_…
##    <chr>       <dbl> <chr>         <chr> <chr>        <chr>   <chr>       <chr>                     <dbl>       <dbl> <chr>                 <dbl>
##  1 2018-1       2018 2018-01-03    01    01053        010530… 01053000AN… Vente                    109000           1 Dépendance               NA
##  2 2018-1       2018 2018-01-03    01    01053        010530… 01053000AN… Vente                    109000           2 Apparteme…               73
##  3 2018-2       2018 2018-01-04    01    01095        010950… 01095000AH… Vente                    239300           0 Maison                  163
##  4 2018-2       2018 2018-01-04    01    01095        010950… 01095000AH… Vente                    239300           0 Maison                   51
##  5 2018-2       2018 2018-01-04    01    01095        010950… 01095000AH… Vente                    239300           0 Maison                   51
##  6 2018-2       2018 2018-01-04    01    01095        010950… 01095000AH… Vente                    239300           0 Maison                  163
##  7 2018-3       2018 2018-01-04    01    01343        013430… 01343000ZR… Vente                     90000           0 NA                       NA
##  8 2018-3       2018 2018-01-04    01    01343        013430… 01343000ZR… Vente                     90000           0 Maison                  150
##  9 2018-3       2018 2018-01-04    01    01343        013430… 01343000ZR… Vente                     90000           0 NA                       NA
## 10 2018-6       2018 2018-01-04    01    01053        010530… 01053000BD… Vente                     67000           1 Apparteme…               45
## # … with more rows, and 10 more variables: nombre_pieces_principales <dbl>, nature_culture <chr>, nature_culture_speciale <chr>,
## #   surface_terrain <dbl>, latitude <dbl>, longitude <dbl>, surface2 <dbl>, type_surface <chr>, prix_surface <dbl>, mois <dbl>
```

## Basic EDA

```r
dvf_data %>% group_by(annee, mois) %>%
  summarise(nb_transactions = n(), meanPrice = mean(valeur_fonciere, na.rm = TRUE)) %>%
  ungroup() %>% arrange(annee, mois) %>%
  collect() %>%  # Run computations inside the DB , retrieve the results locally
  gather(Var, Value, -annee, -mois) %>%
  ggplot() + aes(mois, Value, fill = mois) +geom_col() +
  facet_grid(Var~annee, scales = "free_y")
```

**Mean transaction price and number of transaction through months and years**



# Handling massive data sources with classical tools

- Many new-generations DBMS (NoSQL, graph DB, collection/document DB etc.)
- Among these, the relational column-based DBMS can offer a known and almost-universal interface (SQL) and integrate very easily our already existing workflows for EDA
- This allows to scale up, for a few order of magnitudes, the amount of data that *any* quantitativist geographer can now analyse
- Omnisci (but likewise Yandex's ClickHouse, MonetDB, Amazon Redshift, DuckDB, Uber's AresDB (soon) etc.) offers a quick-to-setup interface to managing such data

What about spatial data visualisation ?

# What about spatial data visualisation ?

## Often requires visualization of the spatial data

- Huge historical strength of GIS
  - Very good interaction with DBMS (e.g. QGIS was conceived as a PostGIS viewer)
  - Still disruptive inside an EDA CLI-based workflow
- CLI (Python/R) :
  - Many static visualisations : plot(SPDF), matplotlib, geoPandas.plot, ggplot2(sf) etc.
  - Yet, Shneiderman's mantra : *"Overview First, Zoom and Filter, Then Details-on-Demand"*
- For a few years, domination of Leaflet :
  - Vectorial data allows powerfull interactions
  - Limited in data quantities
  - Use of raster- (or vector-) tiles to handle larger data
  - Lacks of interactivity

# What about spatial data visualisation ?

**Main problem : Leaflet can't support CLI-size data :**

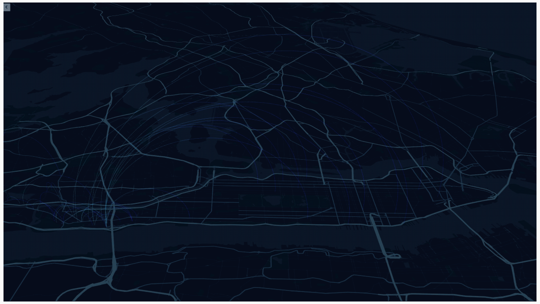
- Hard to display/interact with more than a few hundreds polygons (~ a few thousands points)

**A very simple example of the limits :**

- The DVF dataset cannot be rpresented at France's scale, only at the "département" level
- To add simple spatial visualisations of the DB-stored DVF dataset, we would need to use a GIS...

**At the same time**

- Many new technologies allow for webGUI-based analysis : MapboxGL, DeckGL, KeplerGL etc...
- As much / more performant than GIS or any local software



# What about spatial data visualisation ?

## Both R and Python can use performant visualisation solutions :

- PyOpenGL
- PyViz stack (Bokeh, Holoviews, hvPlot...)
- Plotly
- mapboxgl-jupyter

- RGL
- Plotly
- mapdeck
- leafgl

## Focus on leafgl (R)

- The versatility of leaflet (a wrapper around the Leaflet.glify JS library)
- Ability to interact with thousands of spatial entities
- Without leaving the CLI environment

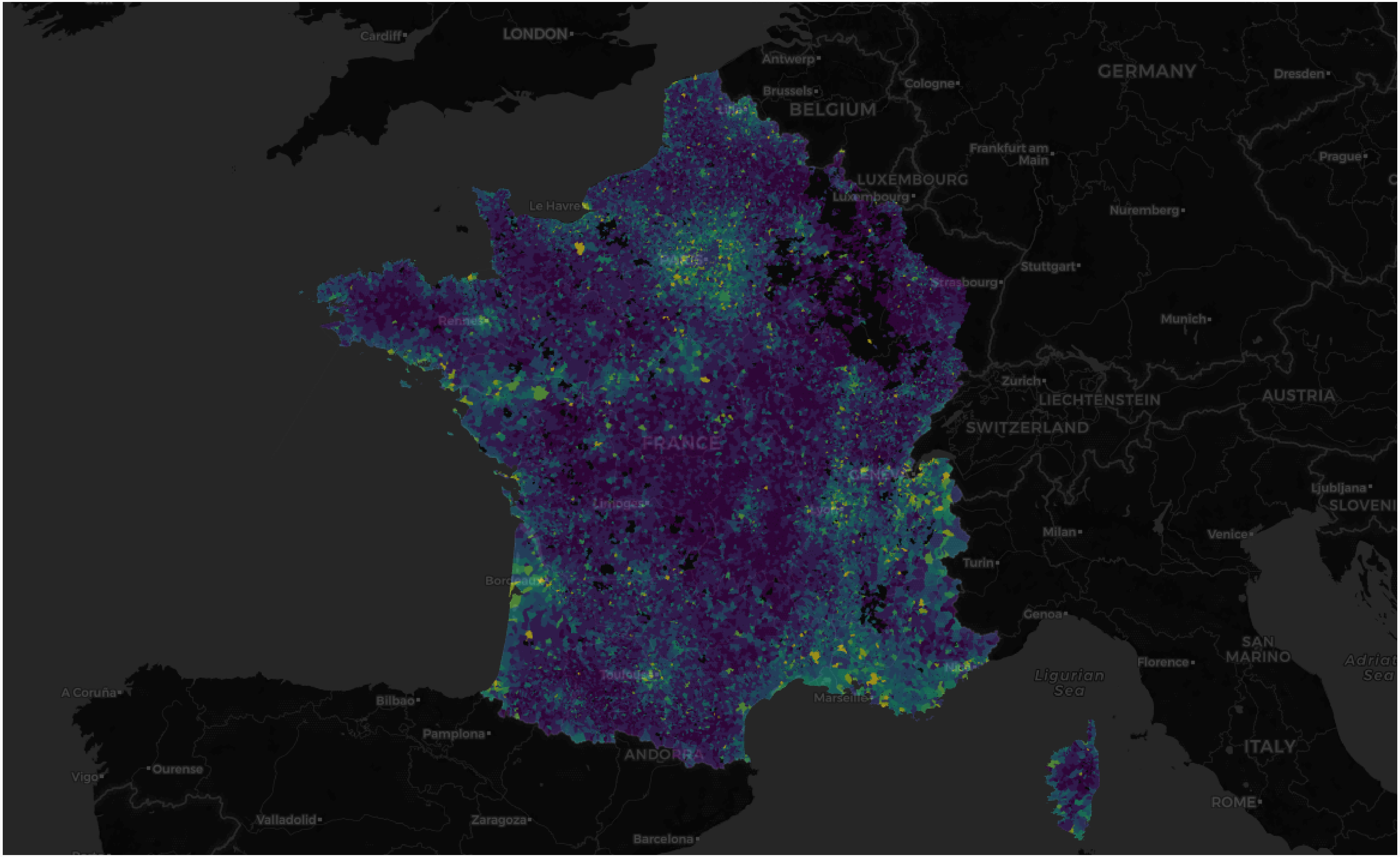
## An example with our DVF dataset :

- Aggregation on the ~36000 "communes"-scale
- Computing the mean square-meter price of the transaction for all years

*N.B.* : it can also be integrated inside more complete and ad-hoc applications (Shiny, Dash, Bokeh…)

```
# [ ... ] Preparing the data and loading the usual spatial packages
# [ ... ] Discretizing the values
# Making the map
leaflet() %>%
    addProviderTiles(provider = providers$CartoDB.DarkMatter) %>%
    addGlPolygons(data = map_data, color = communes_colors) # replaces leaflet::addPolygons
```

# Example


Cardiff
LONDON
Antwerp
Brussels
BELGIUM
Cologne
GERMANY
Dresden
Frankfurt am Main
Prague
LUXEMBOURG
Luxembourg
Nuremberg
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Stuttgart
Strasbourg
Munich
Zurich
LIECHTENSTEIN
AUSTRIA
SWITZERLAND
FRANCE
Limoges
Ljubljana
Milan
Venice
Turin
Genoa
SAN MARINO
Florence
Ligurian Sea
Marseille
A Coruña
Bilbao
Pamplona
Ourense
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# Conclusion :

- Intermediate solutions for intermediate data quantities exist
- Easy to setup/understand, doesn't require much computer science skills or computing power
- Just one small step ahead what you saw at yesterday's workshop
- Don't get blocked by data that are "a bit too big"