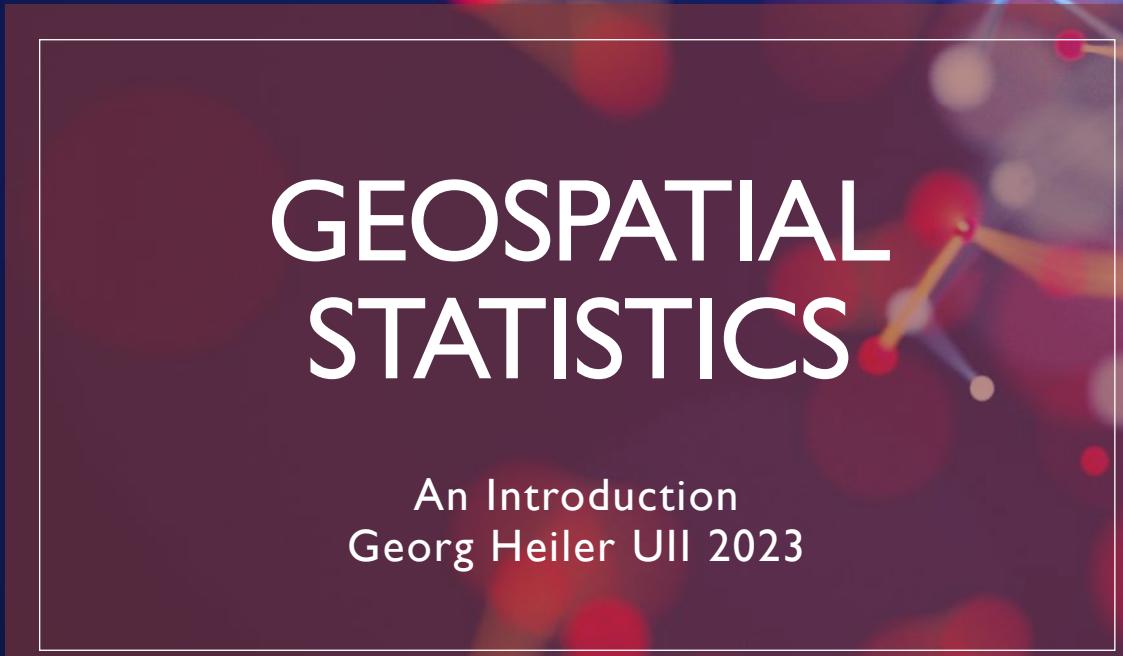


GEOSPATIAL STATISTICS

An Introduction
Georg Heiler UII 2023





Georg Heiler: georgheiler.com



Co-founder of startup for
time series prediction



Senior Software Engineer
with a specialization in data
@MagentaTelekom
big geospatial analytics



Lecturer (R-Summer school,
UII, DHBW)



Organizing data science
meetups in Vienna Data
Science Group (VDSG) &
board member



Post Doc Researcher
@Complexity Science Hub

Agenda

- Properties of spatial data
- Examples of spatial data
- Geospatial usecases
- Spatial analytics
- Scaling geospatial data handling
- Geo statistics





What is Geo processing?

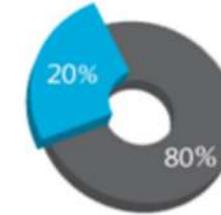
- Operations to manipulate spatial data
- Operations include **geographic feature overlay**, feature selection and analysis, **topology processing**, raster processing, and data conversion
- Geospatial statistics: statistics with spatiotemporal data

Geography matters: 60 % of all data is spatial

“

80% of the informational needs of local government are related to geographic location.

”



- 80 % of all data is spatial, is a commonly repeated myth (a phrase used for selling geospatial data to governments: Williams, 1987).
- However, after investigating, scientists have estimated that **approximately 60 %** of all the data is geospatially referenced
 - **Still, it's a lot**
 - With the same logic, one might reason that at least ~60 % of all Sustainable Development Goals and indicators have a geographical dimension in them, hence, spatial data science inherently has a lot to give for SDGs

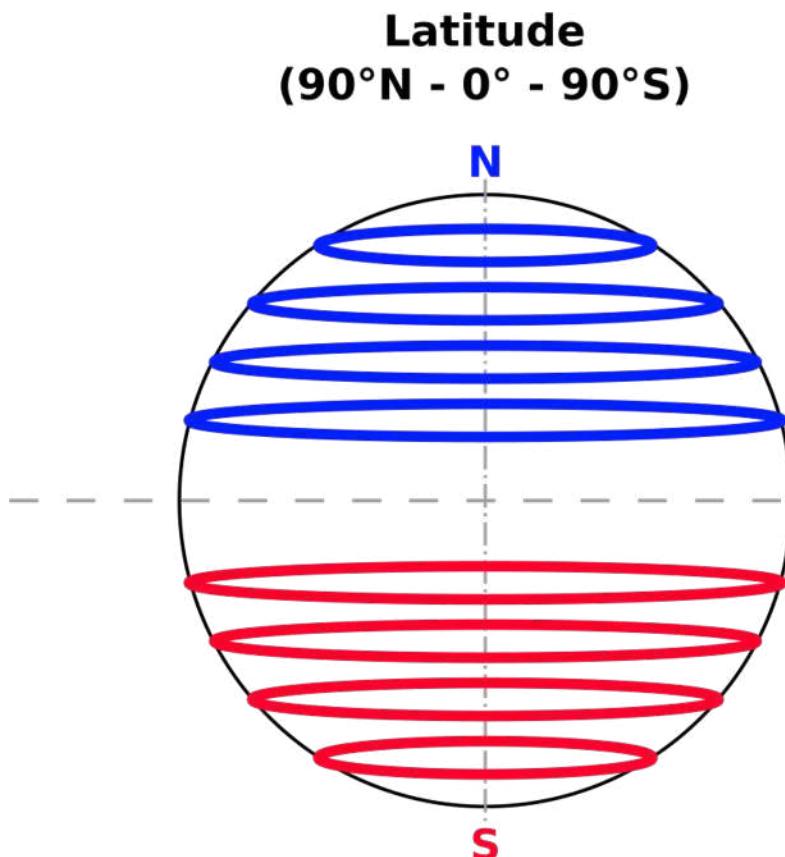
Properties of spatial data

Spatial data

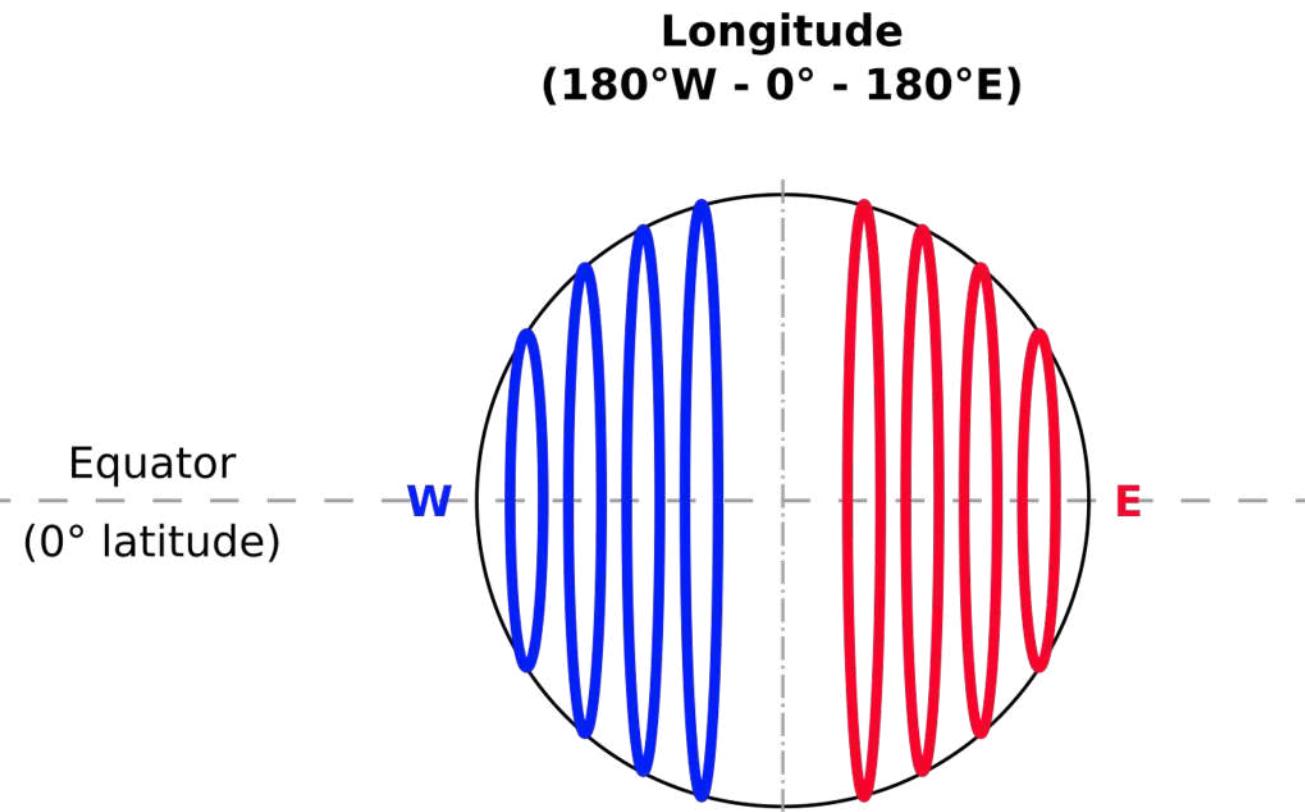
- Data for spatial reference
- Geometries (points, polygons, lines), 1D or 2D
- Often latitude, longitude as x, y spatial reference
- Point clouds (3D, 4D) of LIDAR scans

geometry	value	thing
POLYGON ((-97.019...)	31	Cumin
POLYGON ((-123.43...)	53	Wahkiaku
POLYGON ((-104.56...)	35	De Bac
POLYGON ((-96.910...)	31	Lancaste

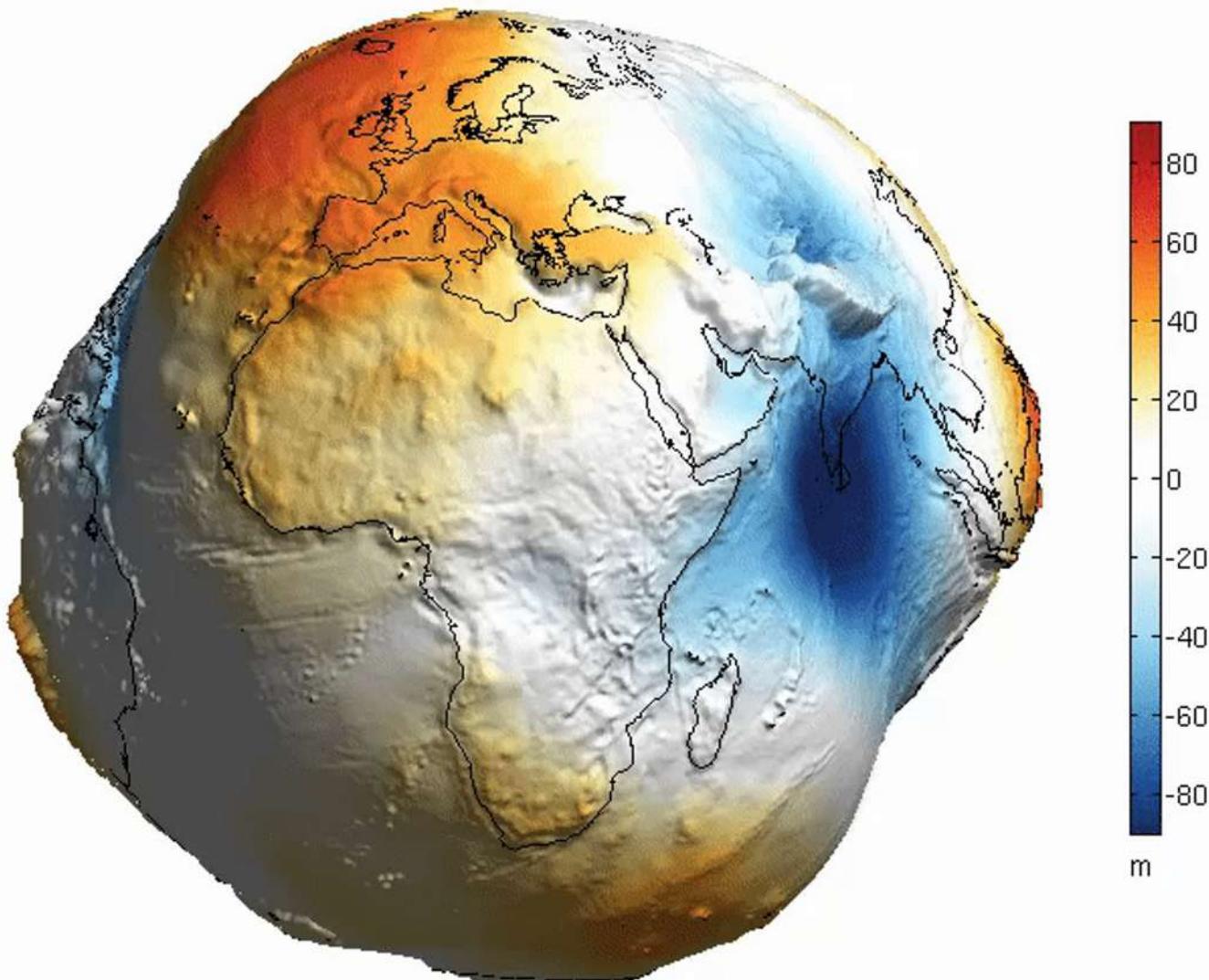
What is latitude and longitude?



Prime Meridian
(0° longitude)



Prime Meridian
(0° longitude)



Source: imgur.com

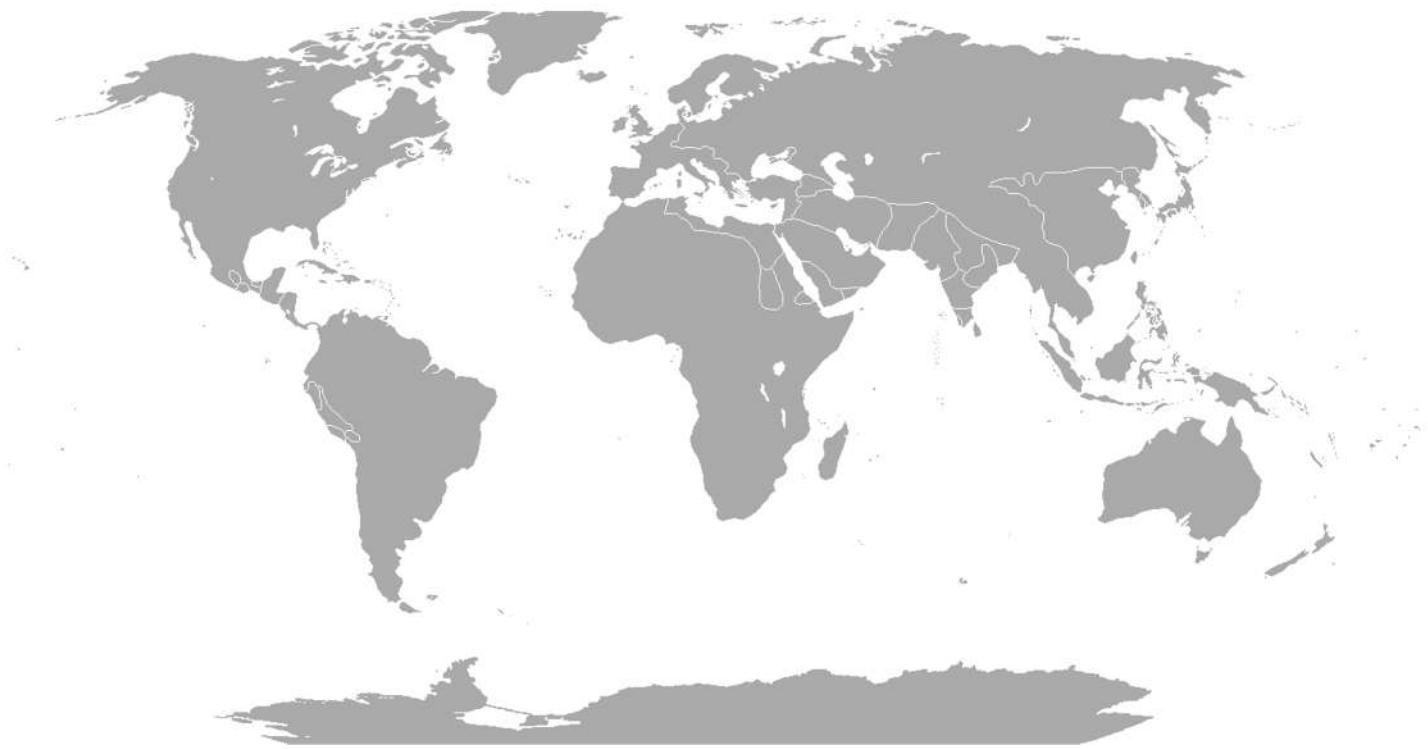
Geoid height (EGM2008, nmax=500)



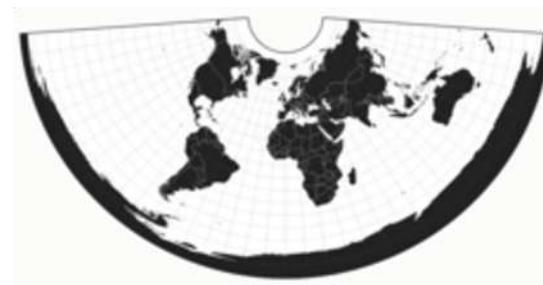
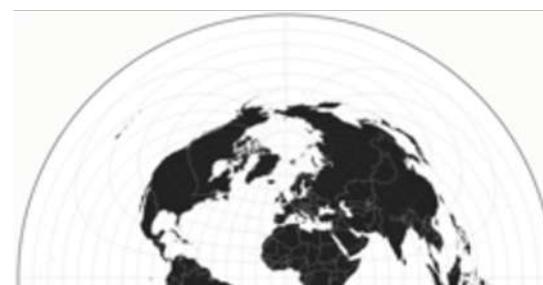
3D Coordinates

- Earth is not a perfect sphere!
- Can be approximated by a biaxial ellipsoid
- 3D coordinates need a reference ellipsoid
- Widely used is the **World Geodetic System (WGS84)** used by GPS
- Minimal positioning error on the surface

3D or 2D



Going to 2 Dimensions





2D Projections

- The earth cannot be displayed on a 2D map without distortion
- Mapping to the surface of other 3D Volumes
 - Cylindrical
 - Conical
 - Azimuthal

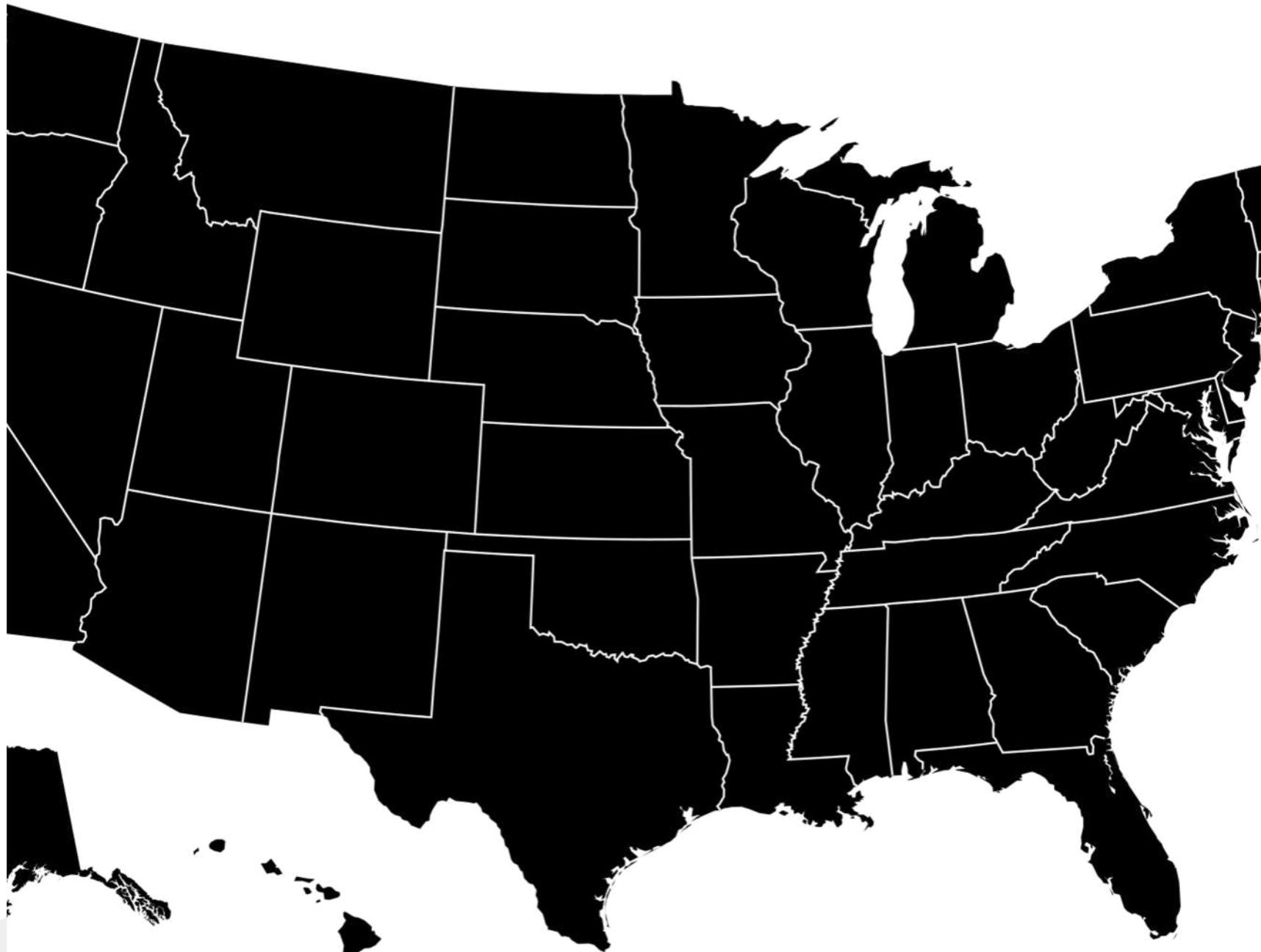


2D Projections

- The earth cannot be displayed on a 2D map without distortion
- Every mapping has its tradeoff
 - Length Preserving (Equidistant)
 - Area Preserving (Equal Area)
 - Angle Preserving (Conformal)

2D Projections

- Commonly used in Austria: MGI Austria Lambert (equal area)
- Commonly used in the US: Albers USA projection (equal area)





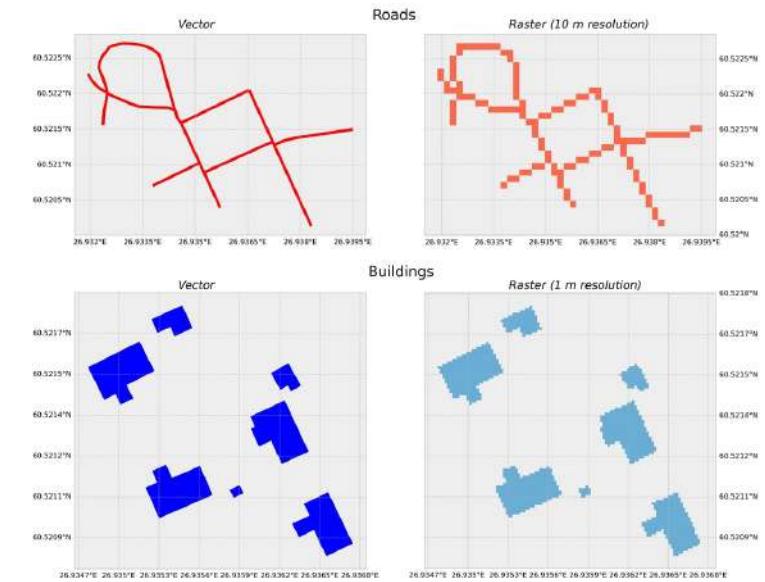
Projections

- Remember different coordinate systems
- Make sure all data sets use the same CRS!!!
 - If not apply reprojection

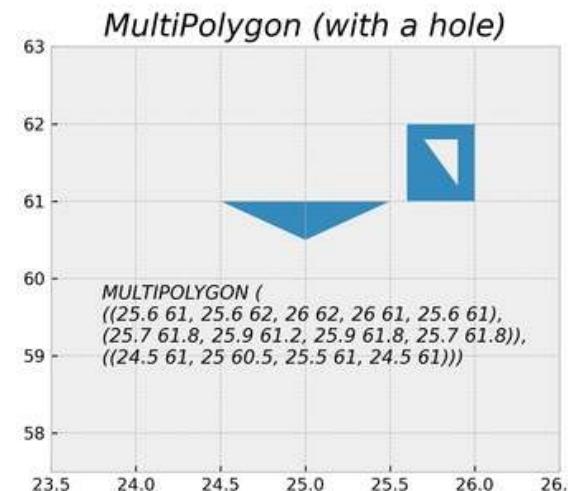
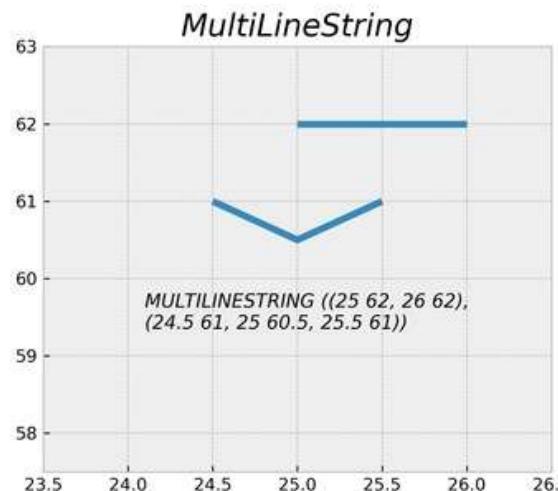
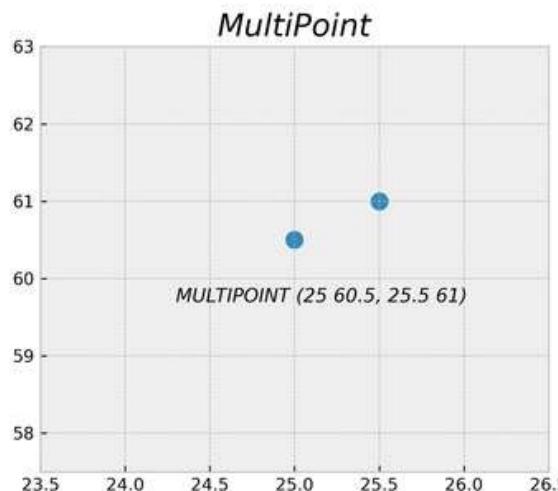
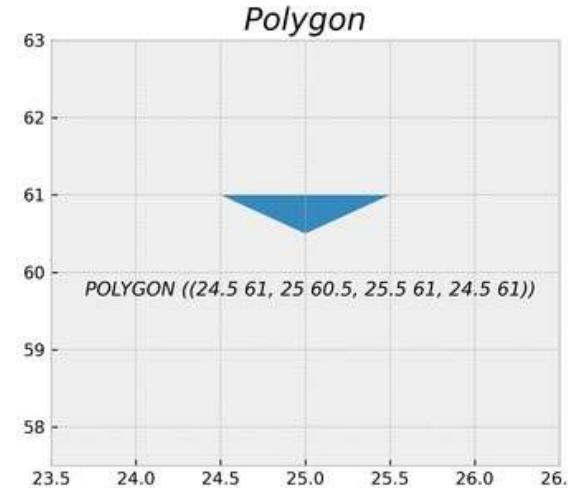
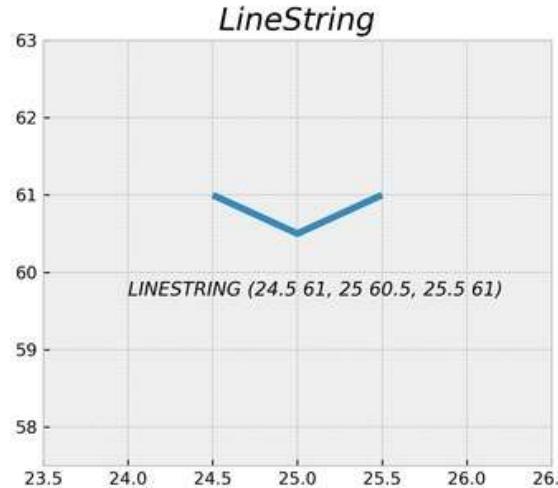
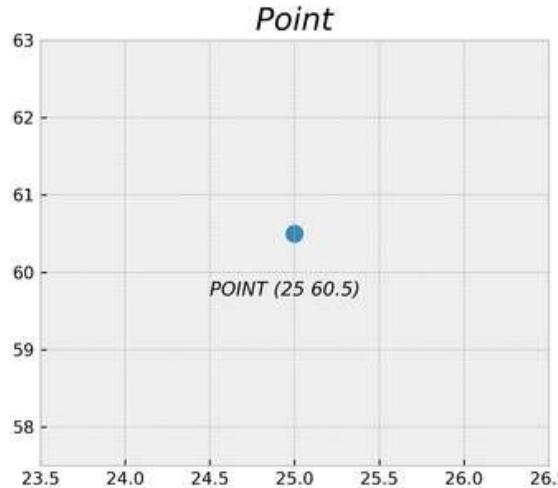
Data formats

- Make the data format readable by your tool of choice
- Vector
 - Well Known Text
 - GeoJson
 - Shapefile
 - Geodatabase (file)
 - Points
 - Geoparquet
- Raster
 - GeoTiff
- 3D
 - LIDAR data

There is a huge variety of formats! <https://pro.arcgis.com/de/pro-app/help/data/imagery/supported-raster-dataset-file-formats.htm> you will probably need to convert data from different sources to a single shared format
<https://pythongis.org/part2/chapter-05/nb/01-introduction-to-geographic-data-in-python.html>



Geometry types





GDAL - Transform Shapefiles to CSV

```
ogr2ogr -f CSV output.csv \  
input.shp \  
-lco GEOMETRY=AS_WKT \  
-lco SEPARATOR=SEMICOLON \  
-oo ENCODING=UTF-8
```



GDAL - Use spatial queries

```
ogr2ogr -sql "SELECT A.* FROM shape1 A,  
shape2 B WHERE ST_Intersects(A.geo, B.geo)"  
\  
-dialect SQLITE \  
data input_dir \  
-nln output.shp
```

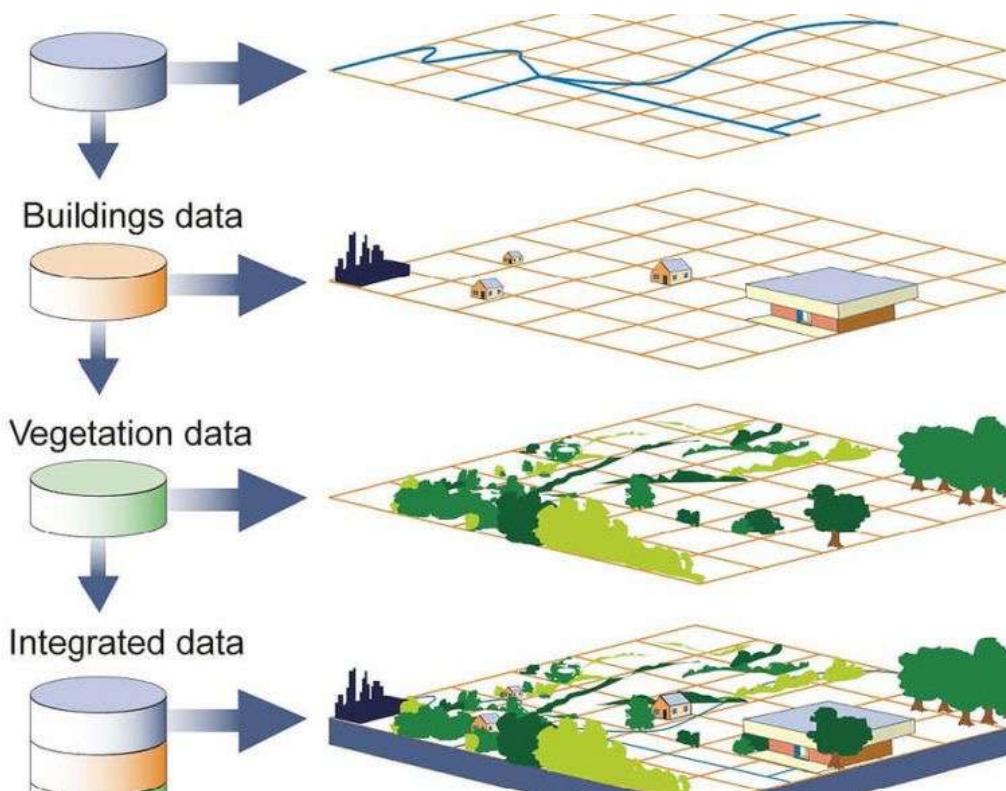


More complex preprocessing

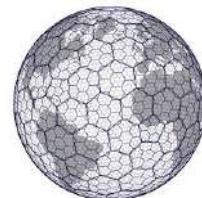
- Custom scripts with geospatial libraries of choice in programming language of choice
 - Python (scripts, exploratory analytics)
 - JVM based (production pipeline)

Examples for spatial data

Geospatial Information System



- Government published open data
- Geo-marketing
- Raster
 - Topology (federal states, municipality, postal codes)
 - Mathematical. (S3, H3, geoHash)

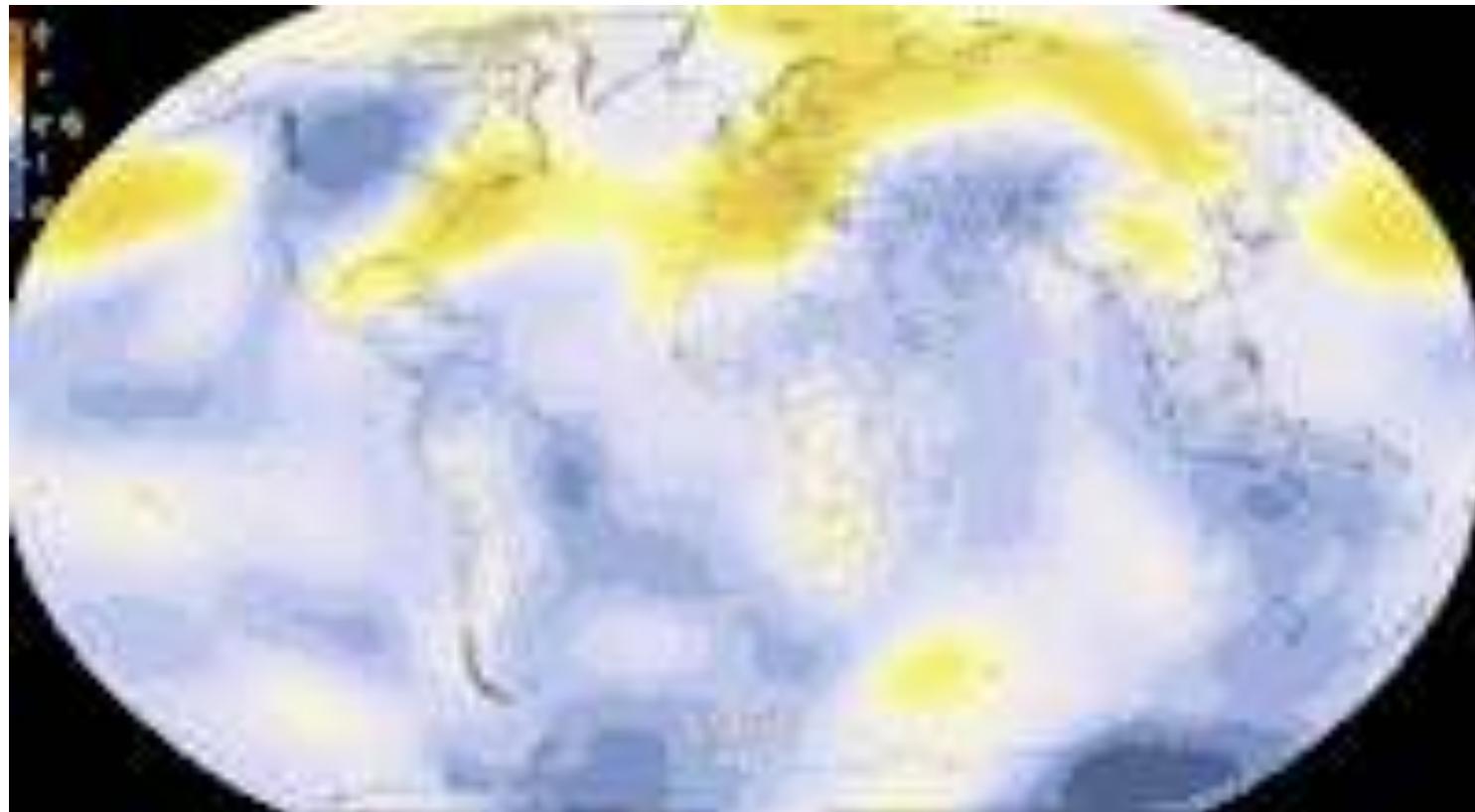


Global Positioning System



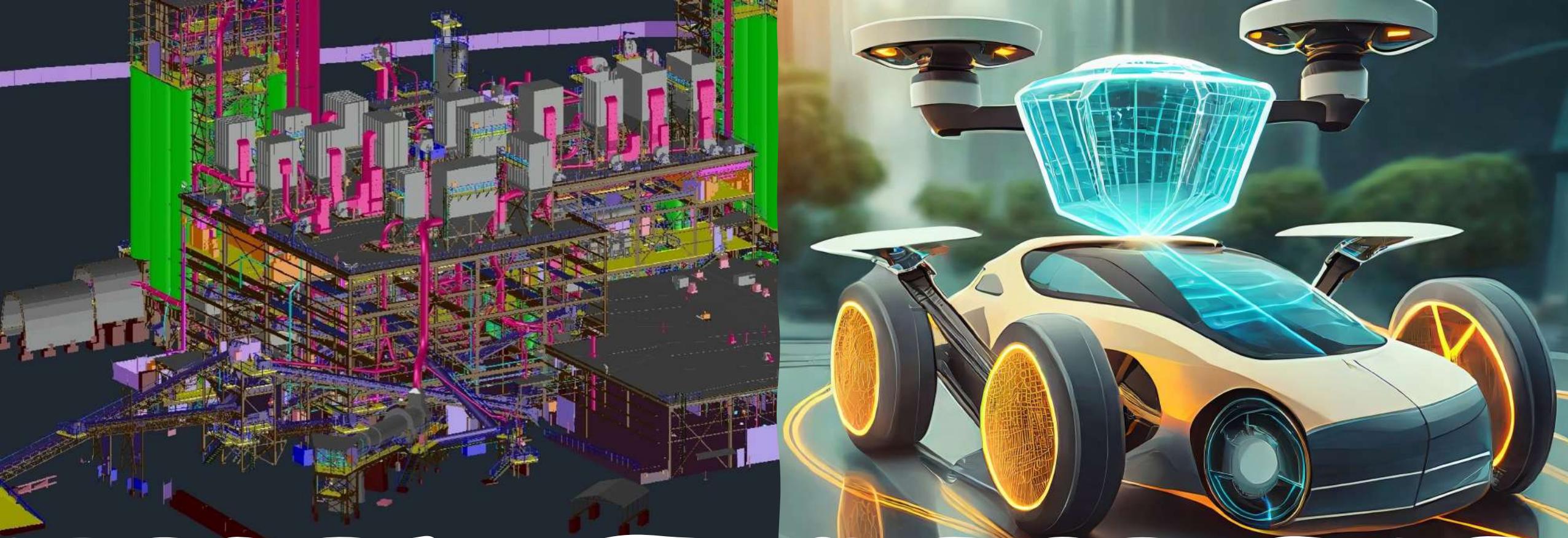
Remote sensing satellite data

Spatiotemporal data: Track over Time, Potentially Forecast the Future



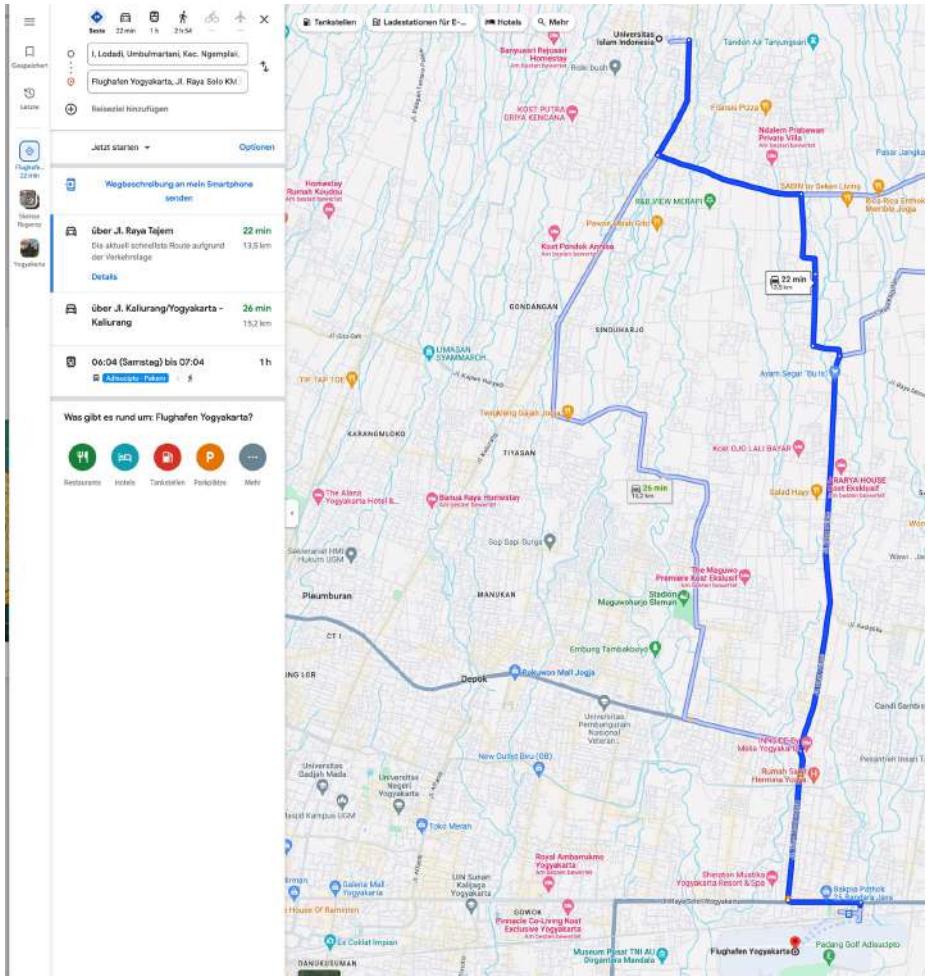
A photograph of two firefighters in full protective gear, including helmets and oxygen tanks, spraying a powerful stream of water from a hose onto a grassy area. Water droplets are visible in the air around them. In the background, a fire truck is partially visible.

REALTIME STREAM OF IOT DATA



LIDAR Scan

- Self driving cars
- Drones
- Maintenance of industry plants



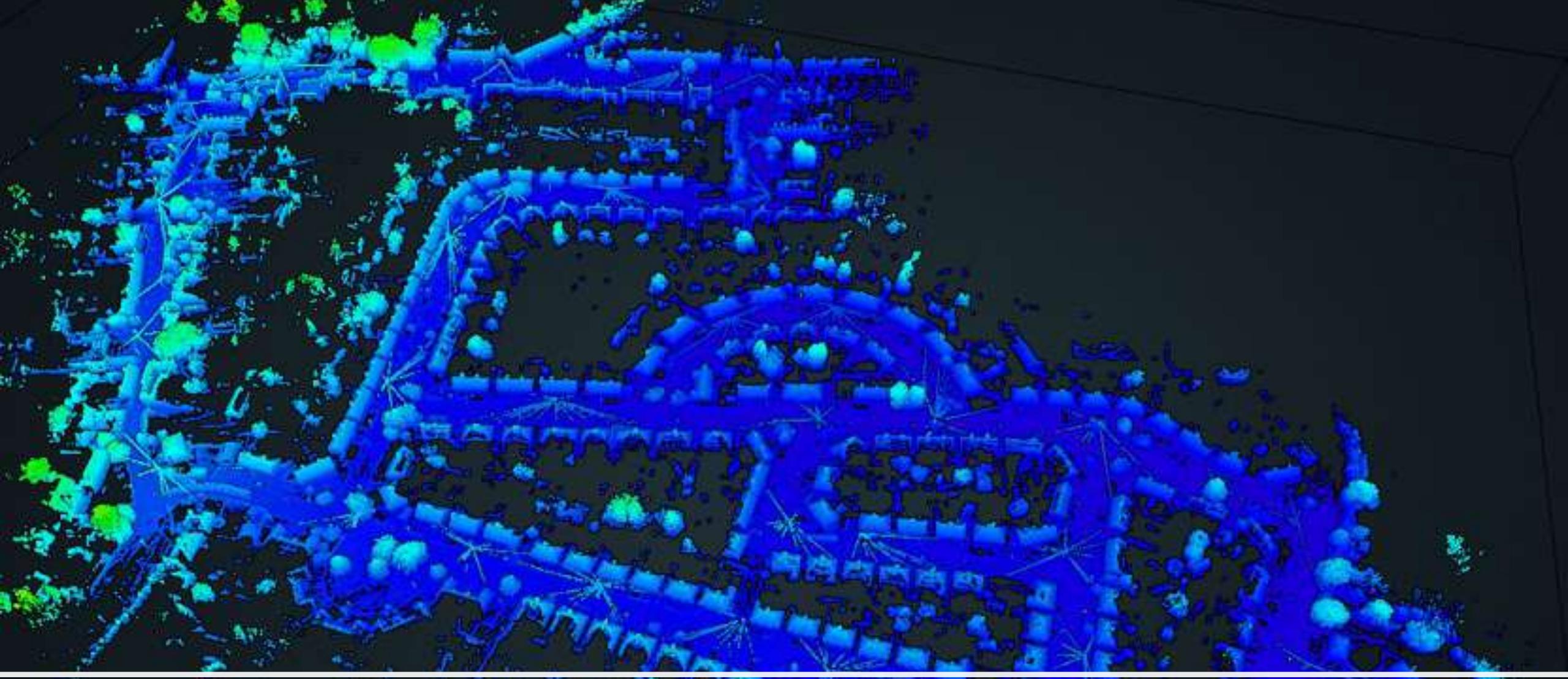
Topological data (routing)

Spatial usecases

Disaster recovery

- Awareness
- Mitigation
- Recovery





Urban planning

An aerial photograph of a tractor spraying a field with a red liquid. Overlaid on the field is a detailed agricultural map showing soil nutrient levels or crop health in various colors from green to red. The map highlights specific areas of the field, suggesting where more fertilizer or pesticides are needed.

Agriculture precision farming

<https://www.agrifac.com/sustainable-farming/precision-farming/>

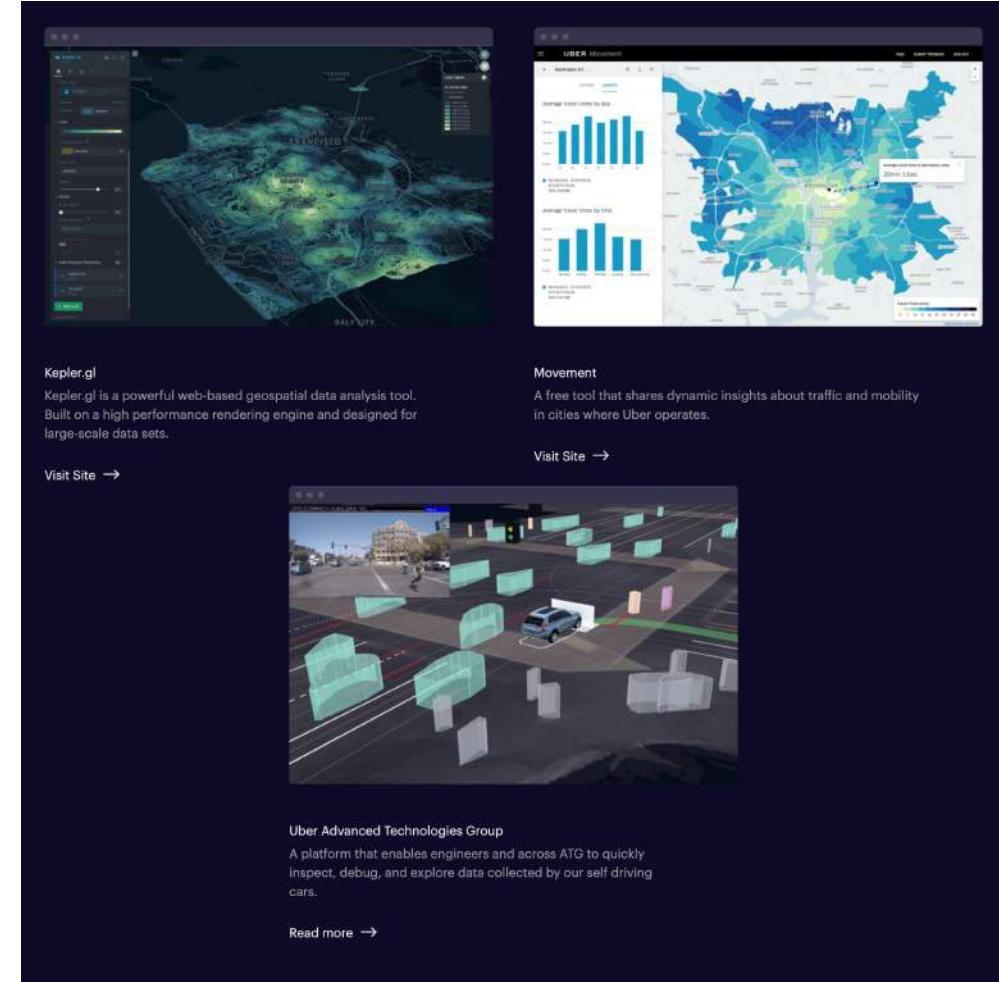
Use Case: Geo Processing @ telecommunications

- Network traffic analysis and optimization
- Signal performance along railway tracks
- Analysis of network coverage
- Footfall analytics



Use Case: Trips Analysis @ Uber

- What do trips look like?
- How can we reduce wait time and make more trips?
- Are there new products we should introduce?
- <https://vis.gl/showcases>



Source: slideshare.net, <https://eng.uber.com/rethinking-gps/>

Use Case: Traffic Jam Prediction based on GPS/FCD

- Estimate average speed of cars on road
- Compare to the max speed on each street
- Use public traffic jam data as ground truth
- Train a model to predict traffic jams

FLEET Analysis (Spark SQL)



Travel times from raw FCD from Hilton Danube to Wr. Staatsoper

```
tt: org.apache.spark.sql.DataFrame = [tripId: int, departure: timestamp ... 3 more fields]
```

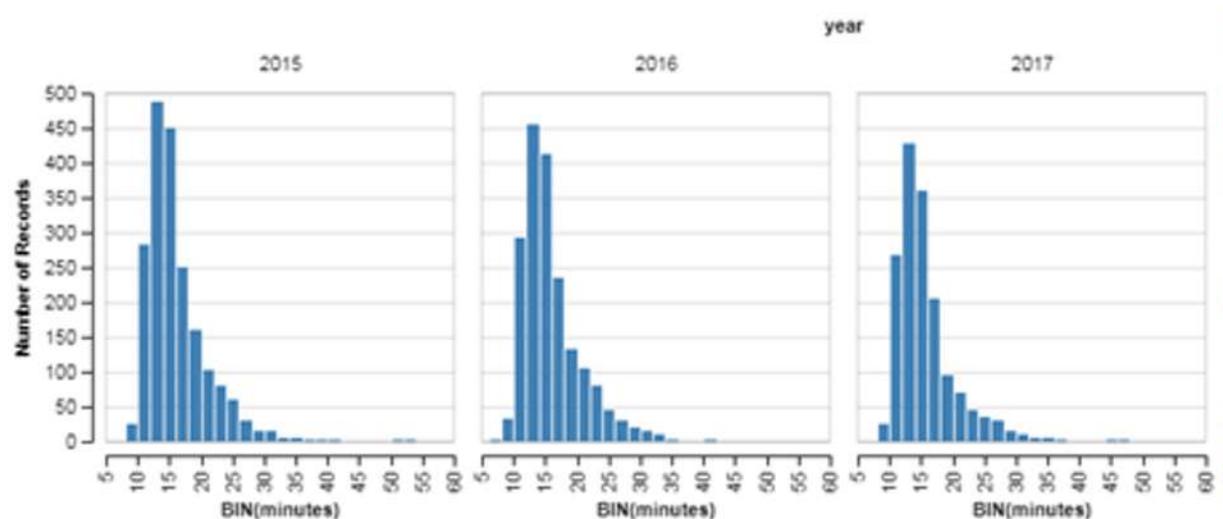
```
+-----+-----+-----+-----+
|tripId|departure|arrival|year|minutes |
+-----+-----+-----+-----+
|174754894|2015-02-05 19:39:27.0|2015-02-05 20:34:57.0|2015|55.500000|
|179786839|2015-04-29 11:50:39.0|2015-04-29 12:15:50.0|2015|25.183333|
|180317262|2015-05-07 21:30:21.0|2015-05-07 21:47:15.0|2015|16.900000|
|181847725|2015-06-01 10:23:54.0|2015-06-01 10:43:21.0|2015|19.450000|
|182419313|2015-06-10 19:43:59.0|2015-06-10 20:13:17.0|2015|29.300000|
|182619821|2015-06-13 12:54:20.0|2015-06-13 13:04:50.0|2015|10.500000|

```

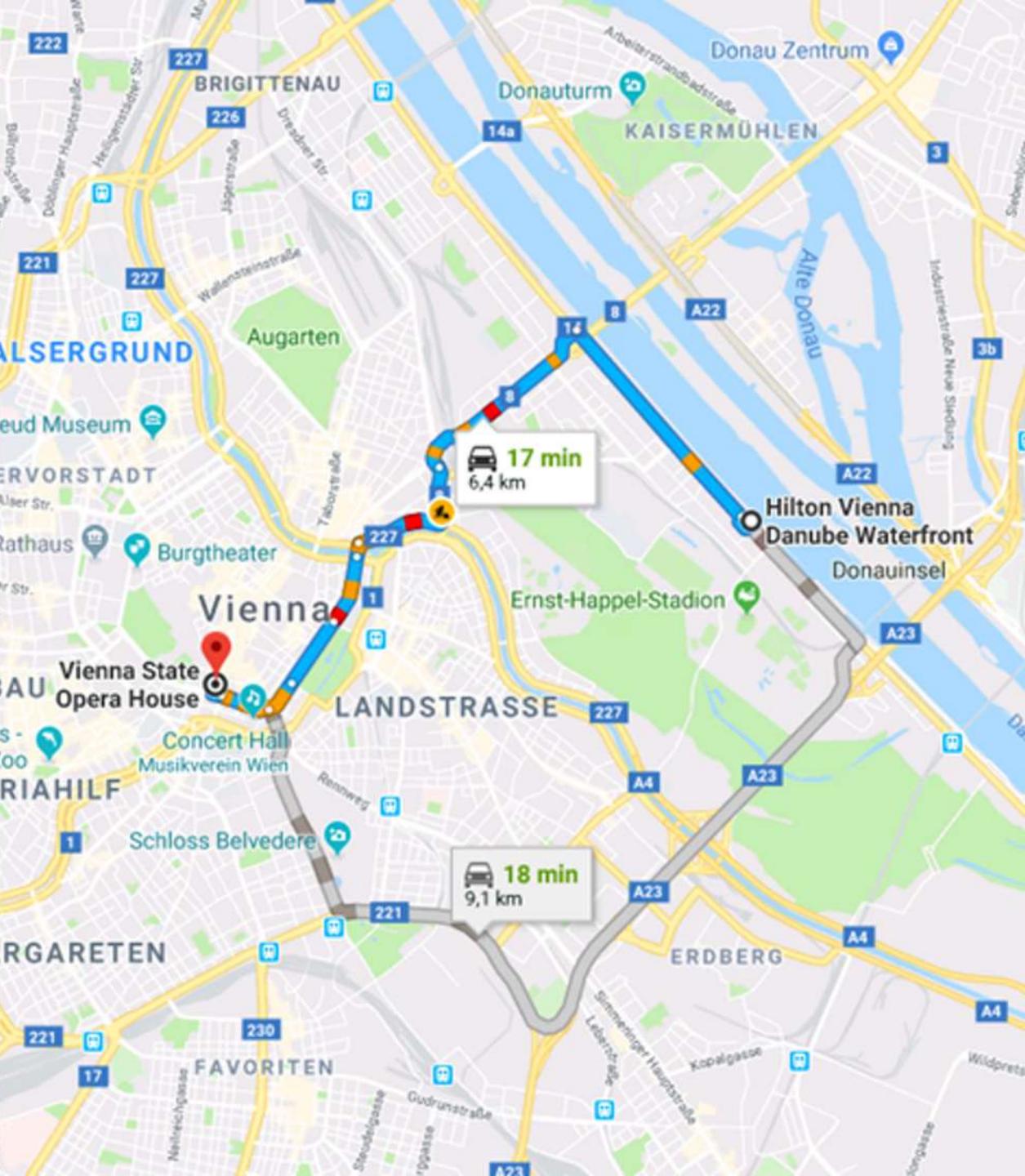
Took 50 sec. Last updated by anonymous at April 03 2018, 10:29:22 AM.

Travel time distributions for each year

```
df: org.apache.spark.sql.Dataset[org.apache.spark.sql.Row] = [tripId: int, departure: timestamp ... 3 more f
```



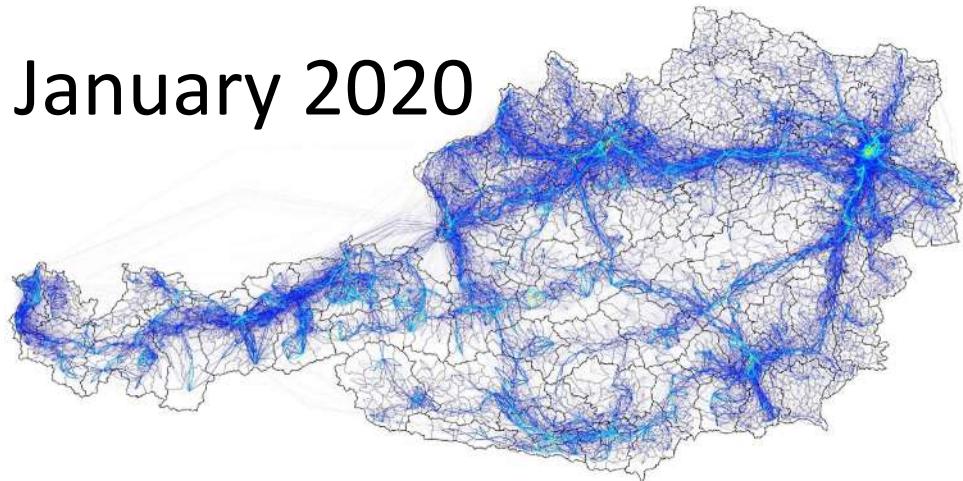
Took 26 sec. Last updated by anonymous at April 03 2018, 10:29:40 AM.



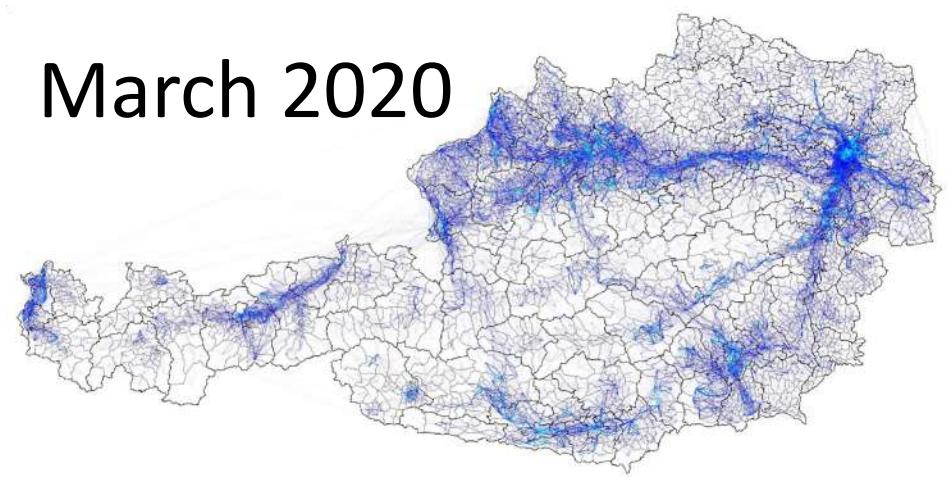
COVID-19 mobility insights

Powered by large scale geospatial algorithms

January 2020

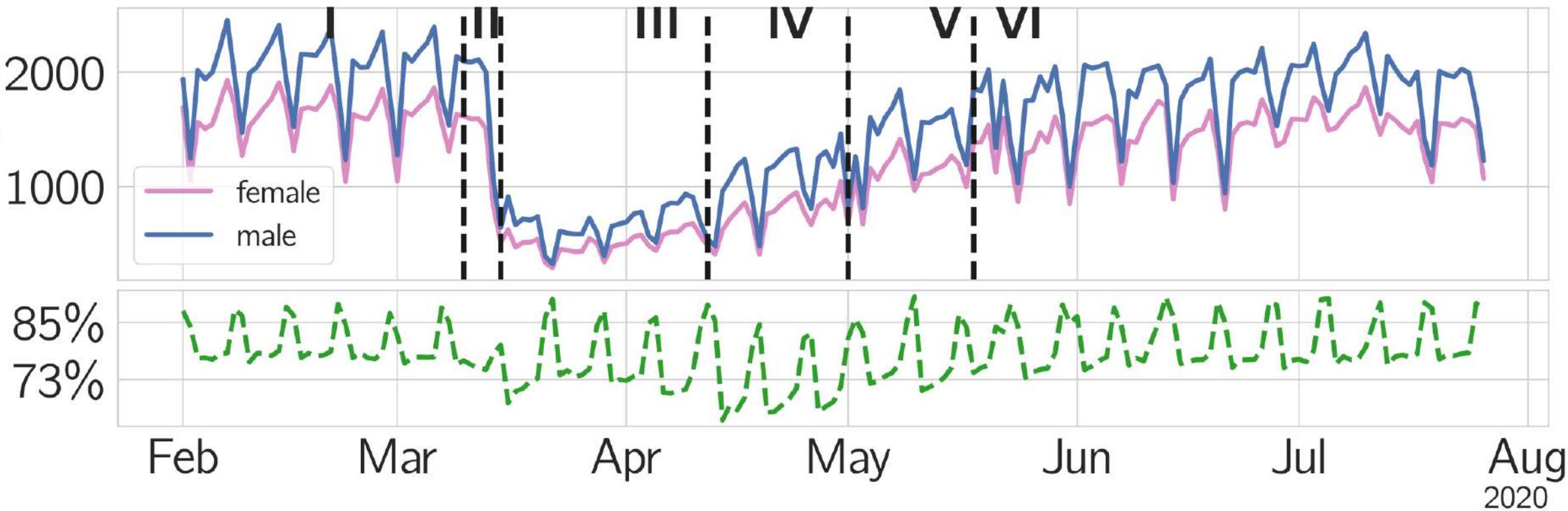


March 2020

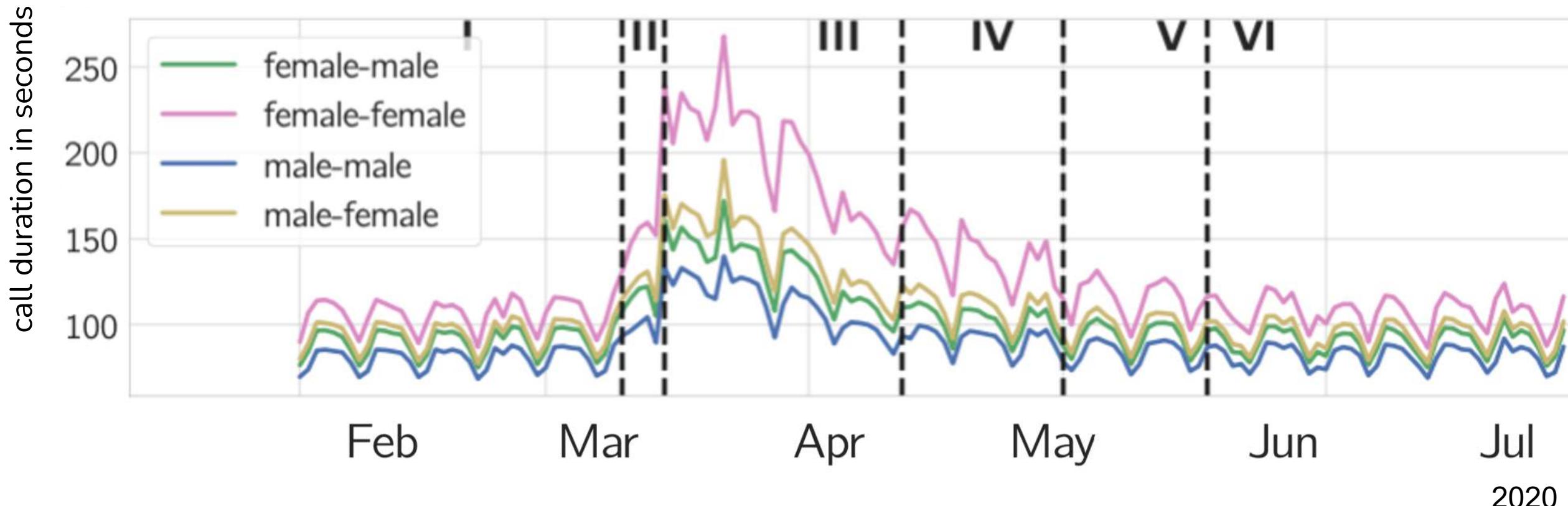


Gendered mobility

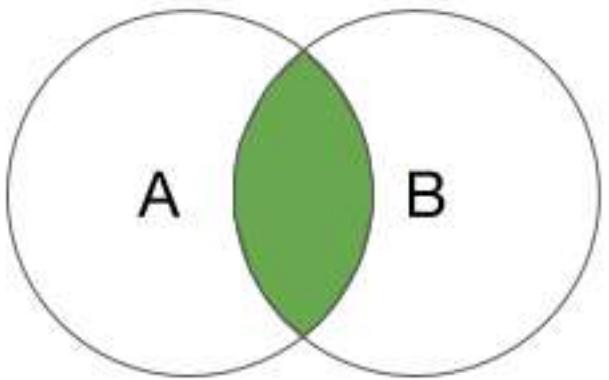
ratio & gendered Radius of Gyration



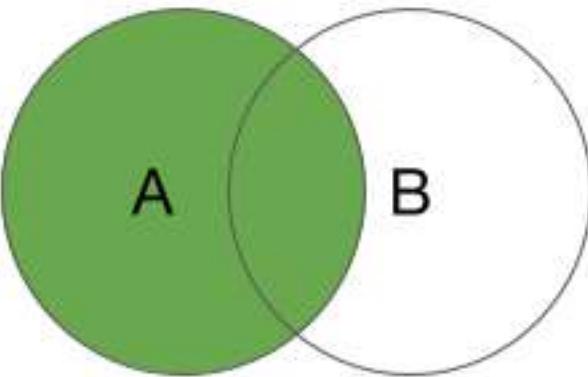
Gendered interactions



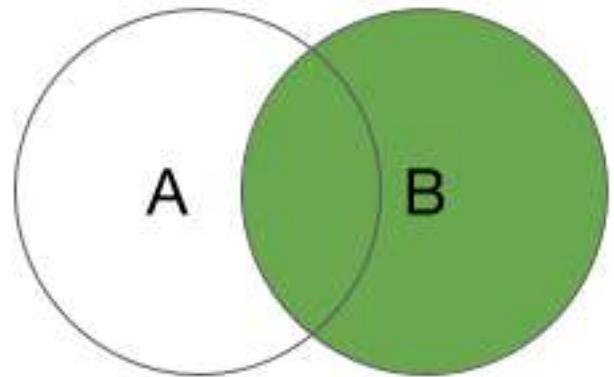
Spatial analytics



INNER JOIN

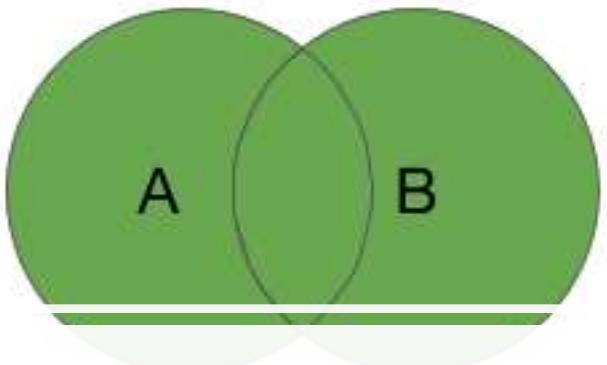


LEFT OUTER JOIN

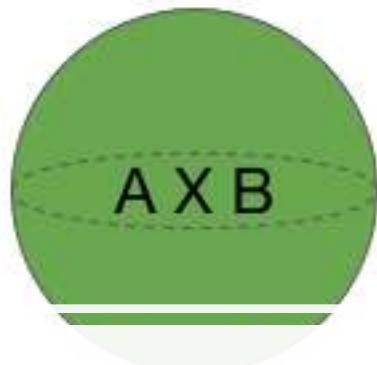


RIGHT OUTER
JOIN

JOIN variants (traditional data)

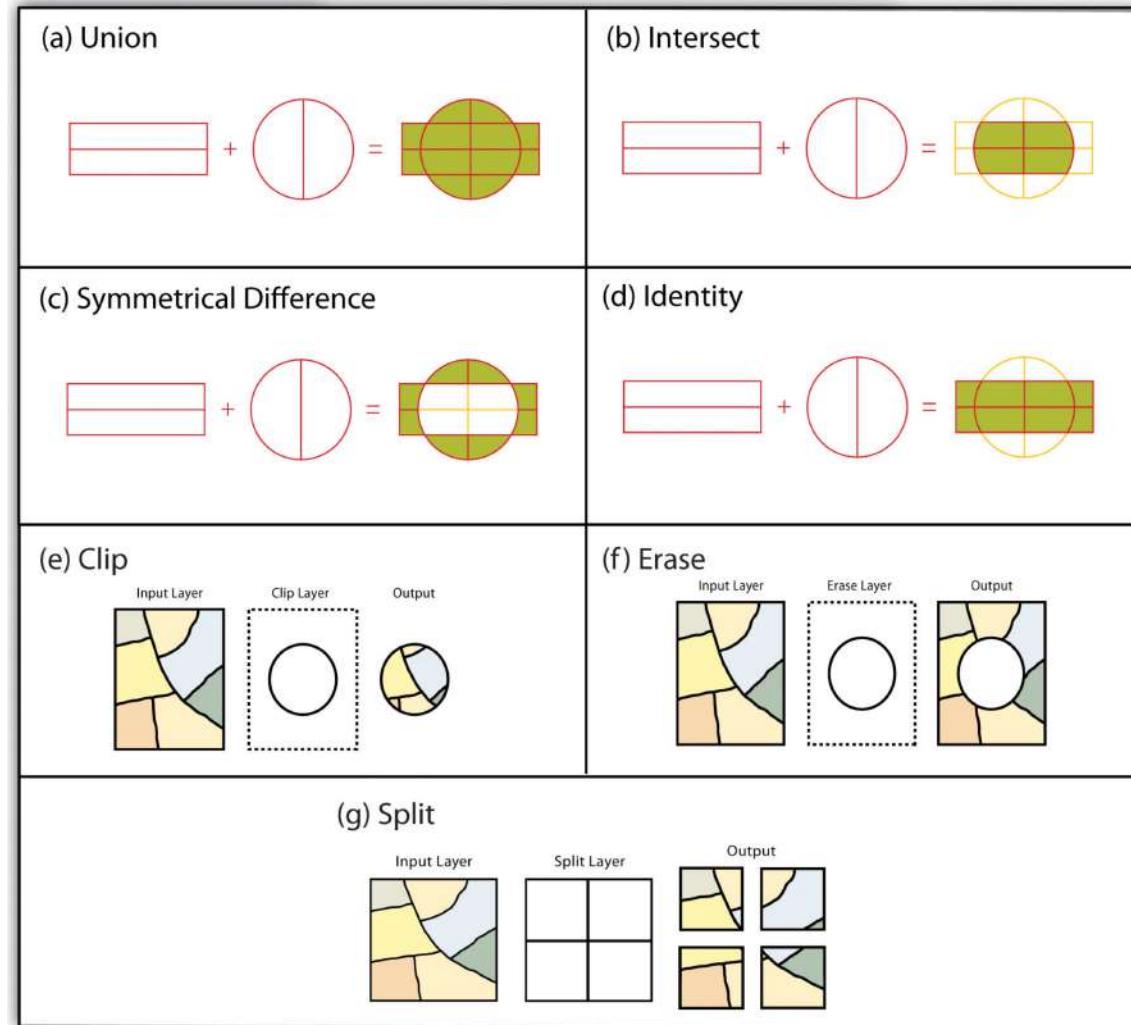


FULL OUTER
JOIN



CARTESIAN
(CROSS) JOIN

Spatial operations

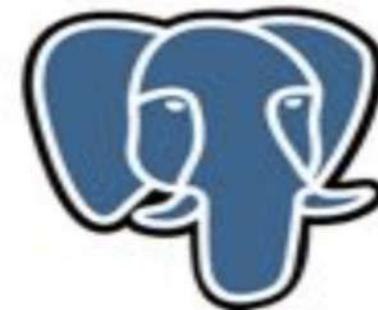


You know, like...

ORACLE®

is to

PostgreSQL



as

ORACLE®

S P A T I A L

is to

PostGIS



Geospatial SQL

```
SELECT superhero.name
```

```
FROM city, superhero
```

```
WHERE ST_Contains(city.geom, superhero.geom)
```

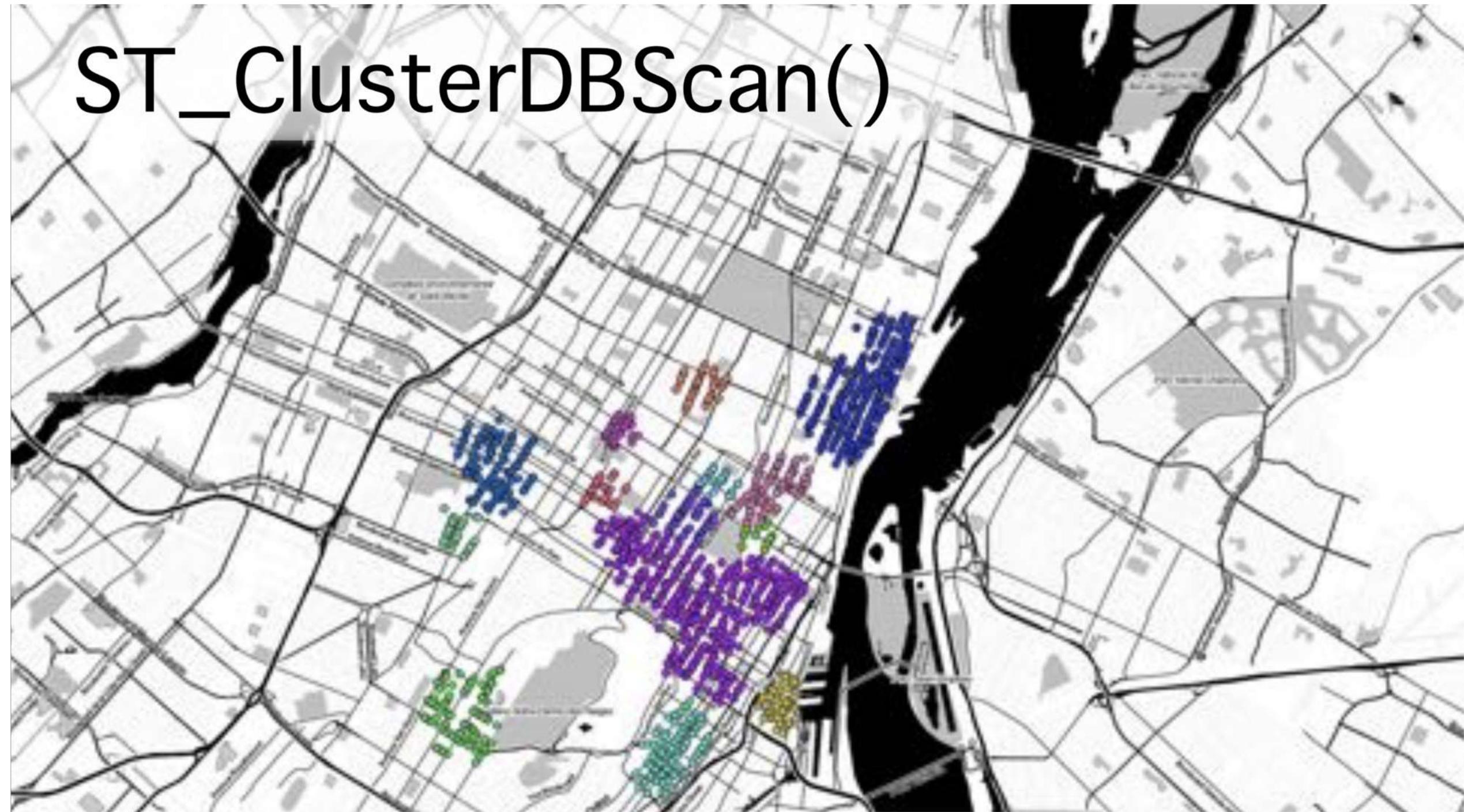
```
AND city.name = 'Gotham';
```

http://workshops.boundlessgeo.com/postgis-intro/spatial_relationships.html

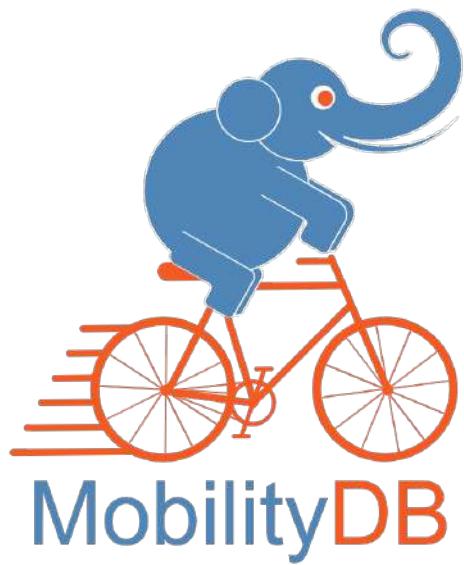
speeding up queries in a database

- create an (scalar) index
- But geospatial data is multi dimensional. Prevent complete cross product by filtering te data first:
 - geo hash
 - space filling curves (Hilbert Kurve, ...)
 - R-tree
 - Quad-tree
 - KD-tree
 - RB-tree

ST_ClusterDBScan()



Postgres spatial addons

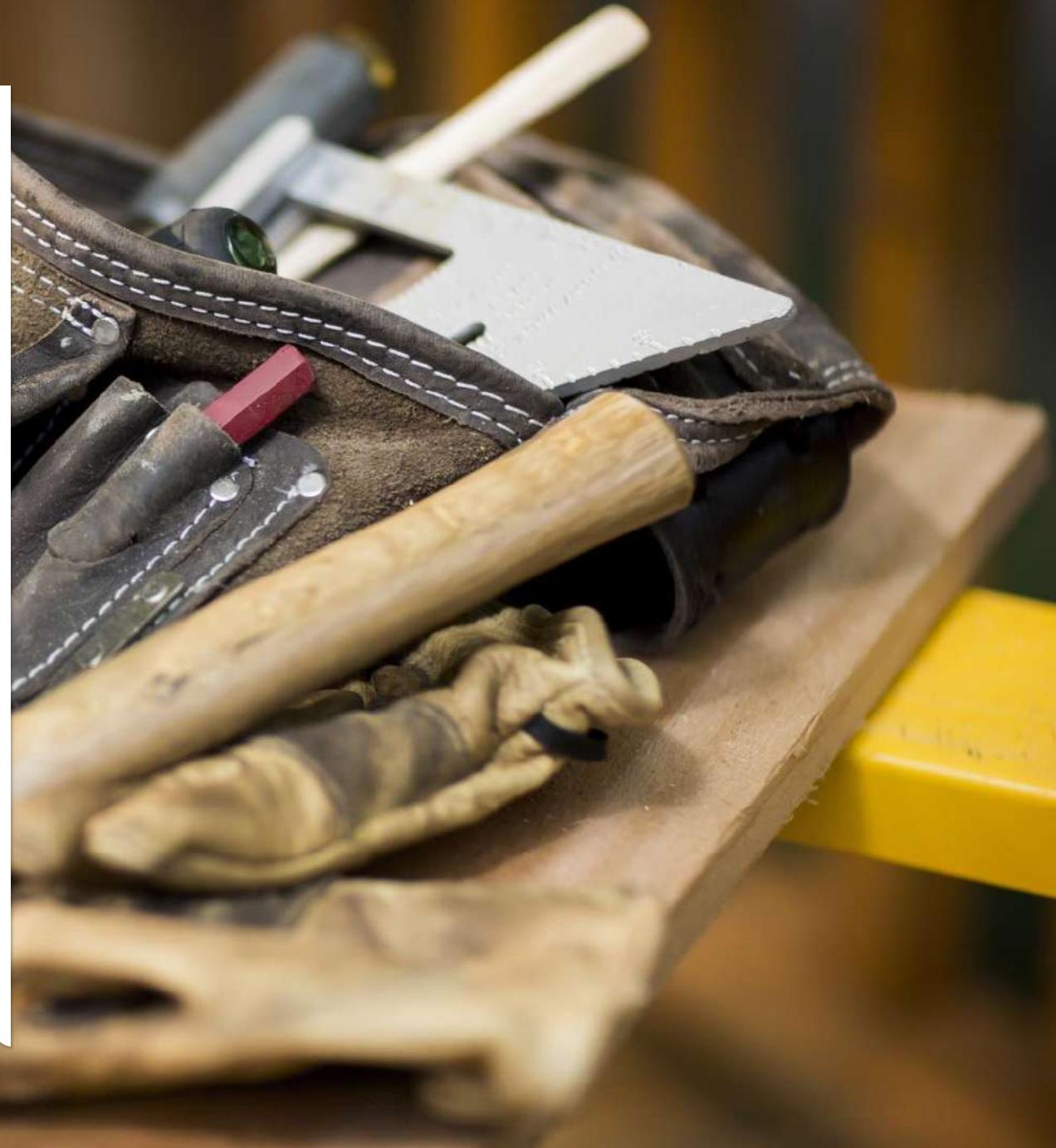


pgRouting Project

pgRouting extends the [PostGIS](#) / [PostgreSQL](#) geospatial database to provide geospatial routing functionality.

Some tools

- python
 - [geopandas](#)
 - [pysal](#)
 - [xarray](#)
- R
 - [rspatial](#)
 - [SP](#)
- Notebooks:
 - [jupyter](#)
 - [rmarkdown](#)



Spatial Visualization

- **QGIS**
- ArcGIS
- **MapBox**
- Carto
- WMF/ WPS Services via geoserver
- [kepler.gl](#)





Common analytical tasks

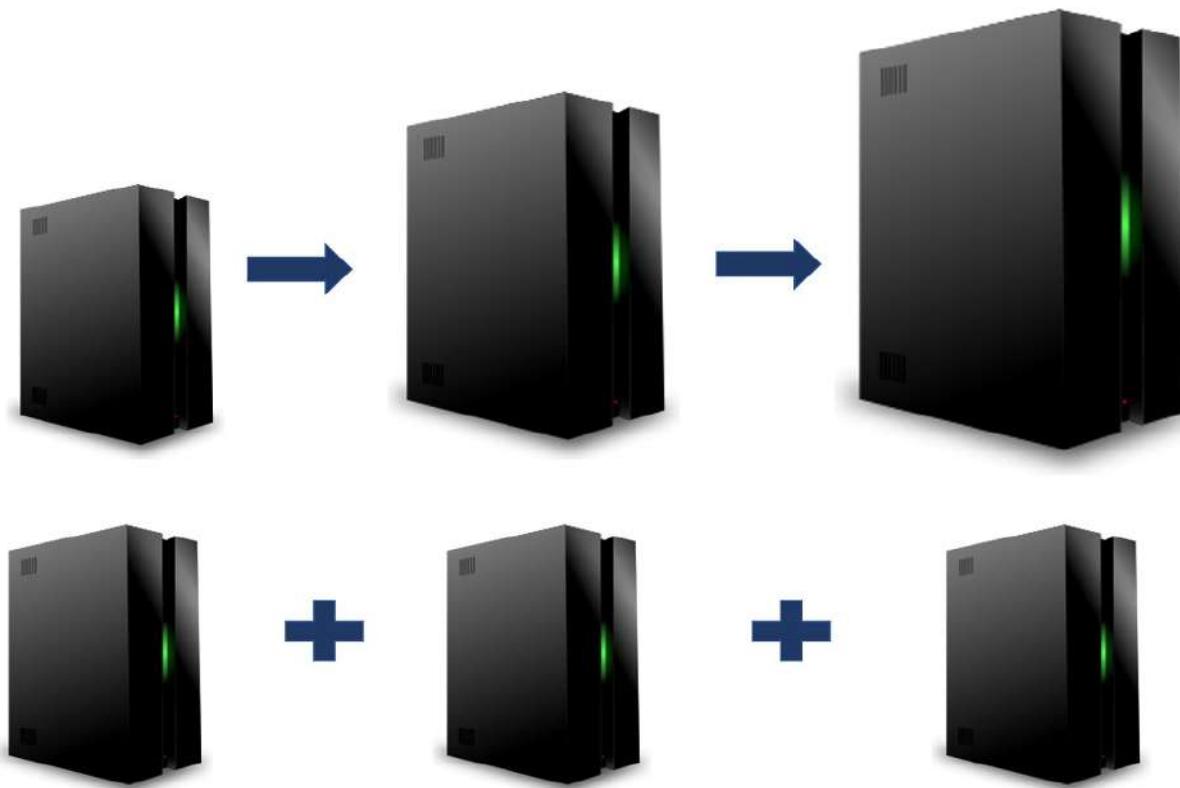
- Clustering
- Watershed analytics
- Interpolation (kriging)
- Pattern detection
- Geospatial Forecasting

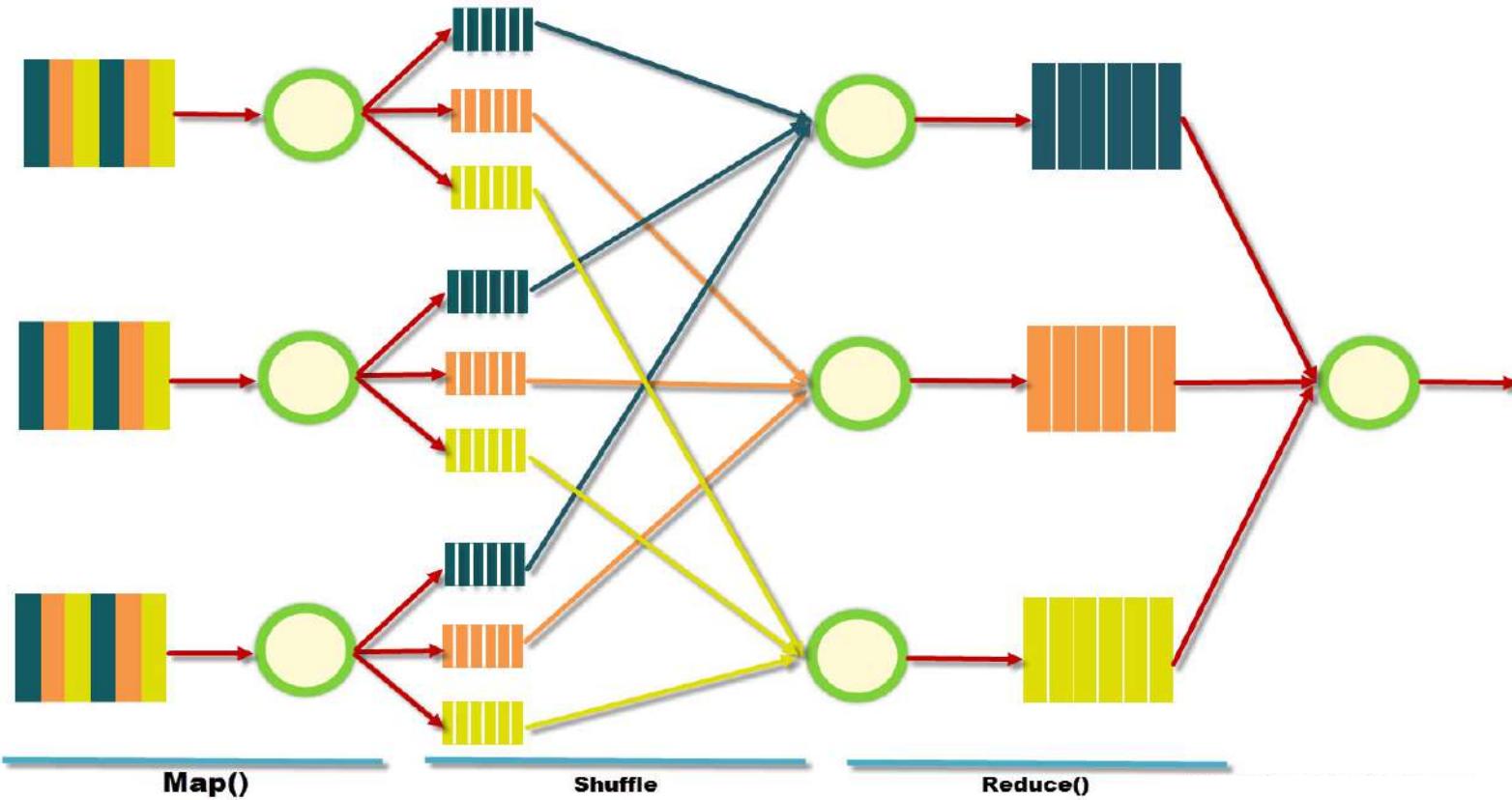
Scaling spatial data processing

LIMITATIONS OF CLASSICAL RDBMS

scalability
scale up only

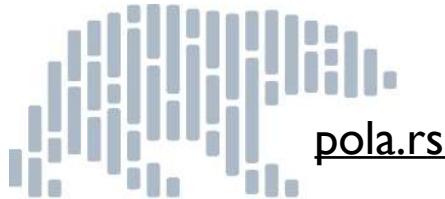
Scale Up





MAP-REDUCE PARADIGM

<http://blog.sqlauthority.com>



Making it faster

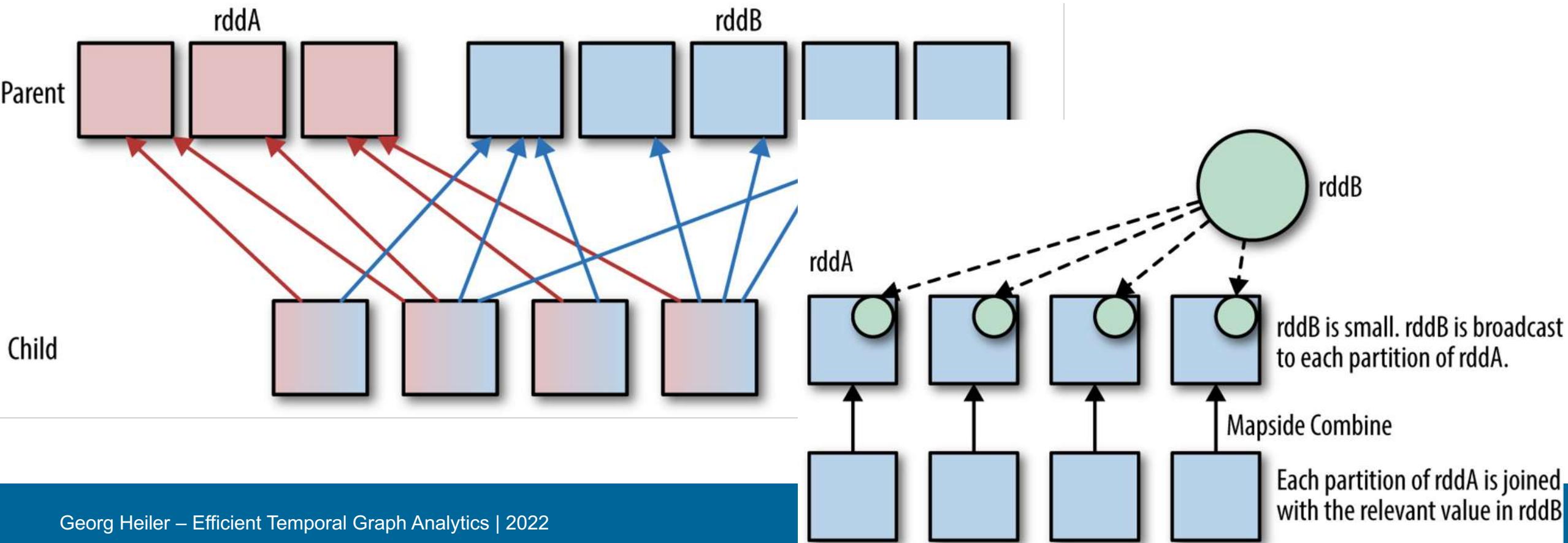
(medium sized data)

- From simple single node without concurrency (pandas)
- To LLVM native code (Ray, Modin)
- DuckDB
- Executed on multiple processes or a couple of machines (Dask, Modin)
- GPU acceleration using cuDf (RAPIDS)
- 100s of nodes Spark

Problem of large data & parallel processing

- PostGIS analytical operations only recently started to be parallelized
 - <http://s3.cleverelephant.ca/2017-cdb-postgis.pdf>, <http://blog.cleverelephant.ca/2017/10/parallel-postgis-2.html>
 - [Fromt version 12 on http://blog.cleverelephant.ca/2019/05/parallel-postgis-4.html](http://blog.cleverelephant.ca/2019/05/parallel-postgis-4.html)
- ArcGIS only recently added parallel processing <https://www.esri.com/arcgis-blog/products/arcgis-pro/analytics/parallel-geoprocessing-in-arcgis-pro/>
- Naive spatial join collapses easily due to full cross product
- Larger and faster spatial data needs more efficient and scalable processing
- Scaling data means partitioning – how to efficiently partition spatial data?
 - Hotspotting?
 - Borders?
- Cloud DWH (BigQuery & Snowflake) as of 2024 already support geospatial functionality
- sedona.apache.org for Spark available

Broadcast (spatial) join explained



scaling out processing

- Python: dask & geopandas <https://r-shekhar.github.io/posts/spatial-joins-geopandas-dask.html>
- DuckDB spatial extension <https://duckdb.org/2023/04/28/spatial.html>
- Hadoop is a cheap general purpose compute infrastructure
- full solutions:
 - [geomesa](#) (well supported)
 - [geowave](#)
 - [rasterframes](#)
- only distributed geospatial SQL, varying degree of optimizations (indices, spatial partitioning)
 - [Apache Sedona](#) (spark)
 - [harsha2010/magellan](#) (spark)
- Most are based on [JTS \(java topology suite\)](#) in some way
- Most offer a SQL based interface similar to postGIS
- <https://github.com/rapidsai/cuspatial>



Geostatistics

Spatial autocorrelation / Moran's I

spatial dependence: Phenomena that are close to one another in space are more likely to have similar characteristics than those that are farther apart

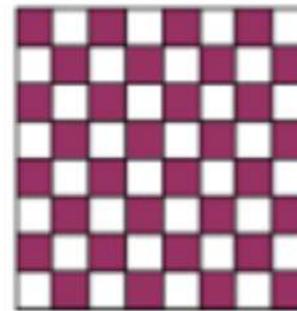
Global Moran's I is a measure of the overall clustering of the spatial data. It is defined as

$$I = \frac{N}{W} \frac{\sum_{i=1}^N \sum_{j=1}^N w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^N (x_i - \bar{x})^2}$$

where

- N is the number of spatial units indexed by i and j ;
- x is the variable of interest;
- \bar{x} is the mean of x ;
- w_{ij} are the elements of a matrix of spatial weights with zeroes on the diagonal (i.e., $w_{ii} = 0$);
- and W is the sum of all w_{ij} (i.e. $W = \sum_{i=1}^N \sum_{j=1}^N w_{ij}$).

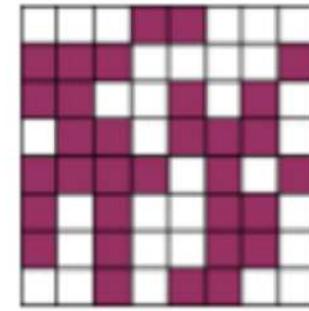
negative spatial autocorrelation



Close in space

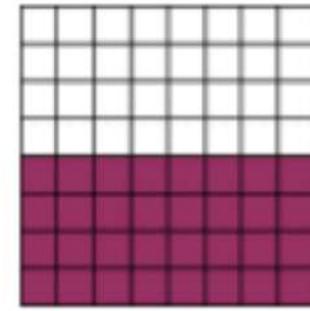
Dissimilar in attributes

zero spatial autocorrelation



Attributes independent of location

positive spatial autocorrelation

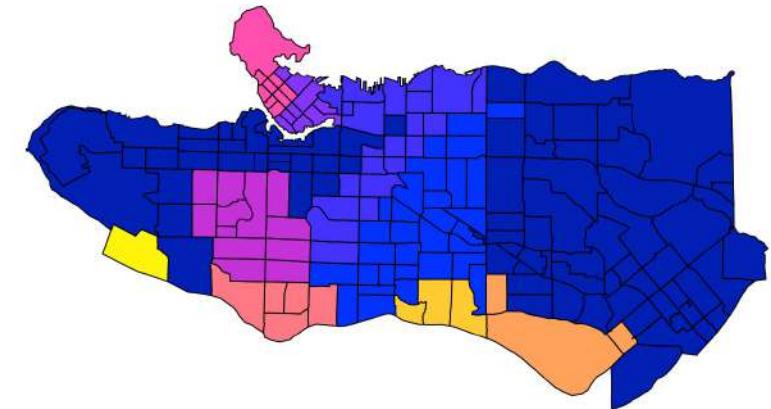
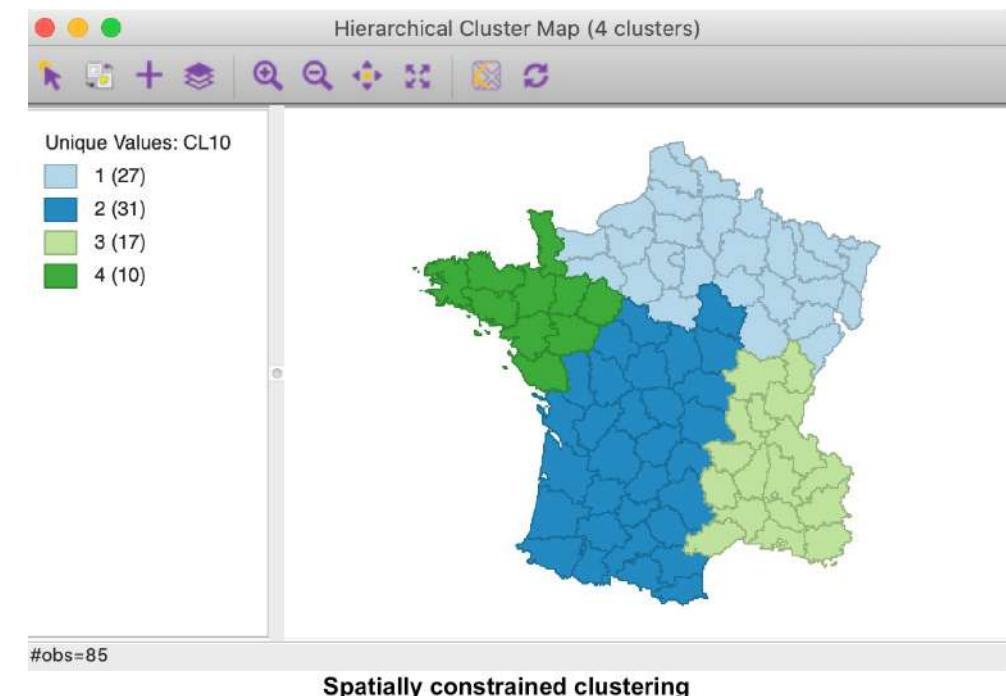


Close in space

Similar in attributes

Spatial clustering

- Geolocation
- Attributes
- Common methods (with spatial extensions)
 - Hierarchical
 - Kmeans
- SKATER

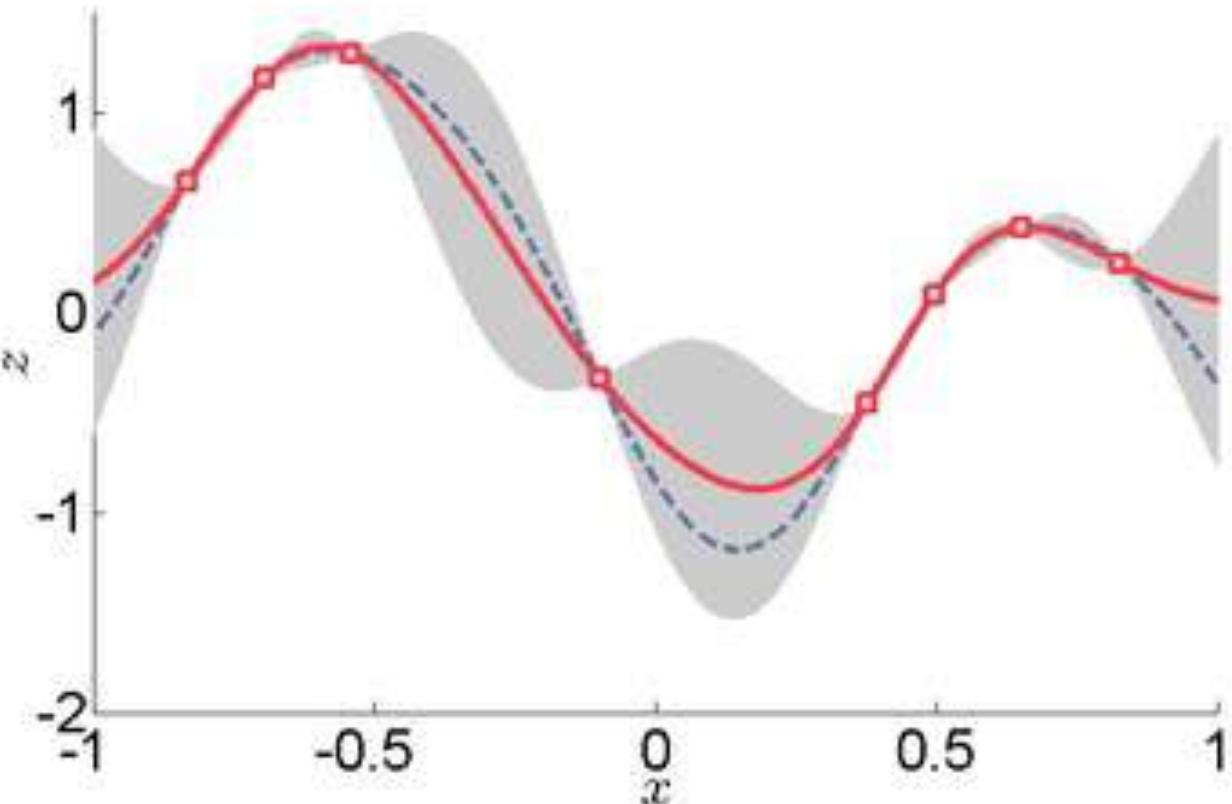


https://geodacenter.github.io/workbook/9a_spatial1/lab9a.htm

<https://www.dshkol.com/post/spatially-constrained-clustering-and-regionalization/>

Kriging

- Spatial interpolation
- Gaussian process regression
- Alternative [Integrated Nested Laplace Approximation](#)



Getis-Ord GI*

- Z-score measuring spatial clustering
- Looking at each feature within the context of neighboring features
- Statistically significant hot spot must have a high value and be surrounded by other features with high values as well

H3 hexagon can make calculation
Of similar statistics much more efficient

The Getis-Ord local statistic is given as:

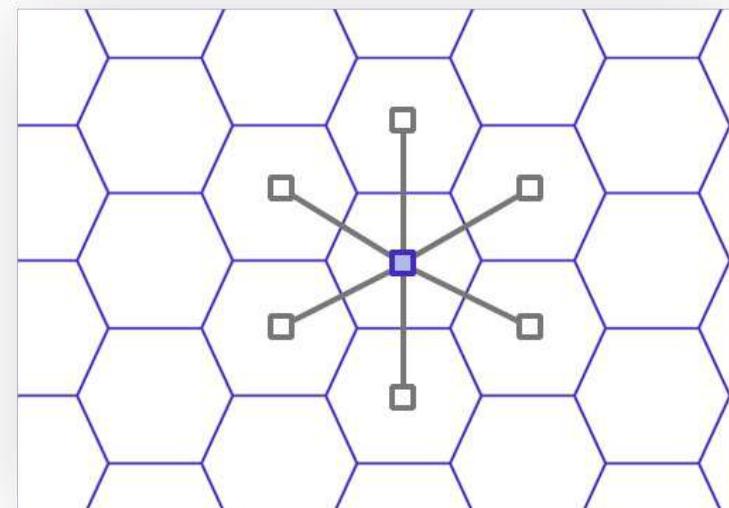
$$G_i^* = \frac{\sum_{j=1}^n w_{i,j}x_j - \bar{X} \sum_{j=1}^n w_{i,j}}{S \sqrt{\left[n \sum_{j=1}^n w_{i,j}^2 - \left(\sum_{j=1}^n w_{i,j} \right)^2 \right] / (n-1)}} \quad (1)$$

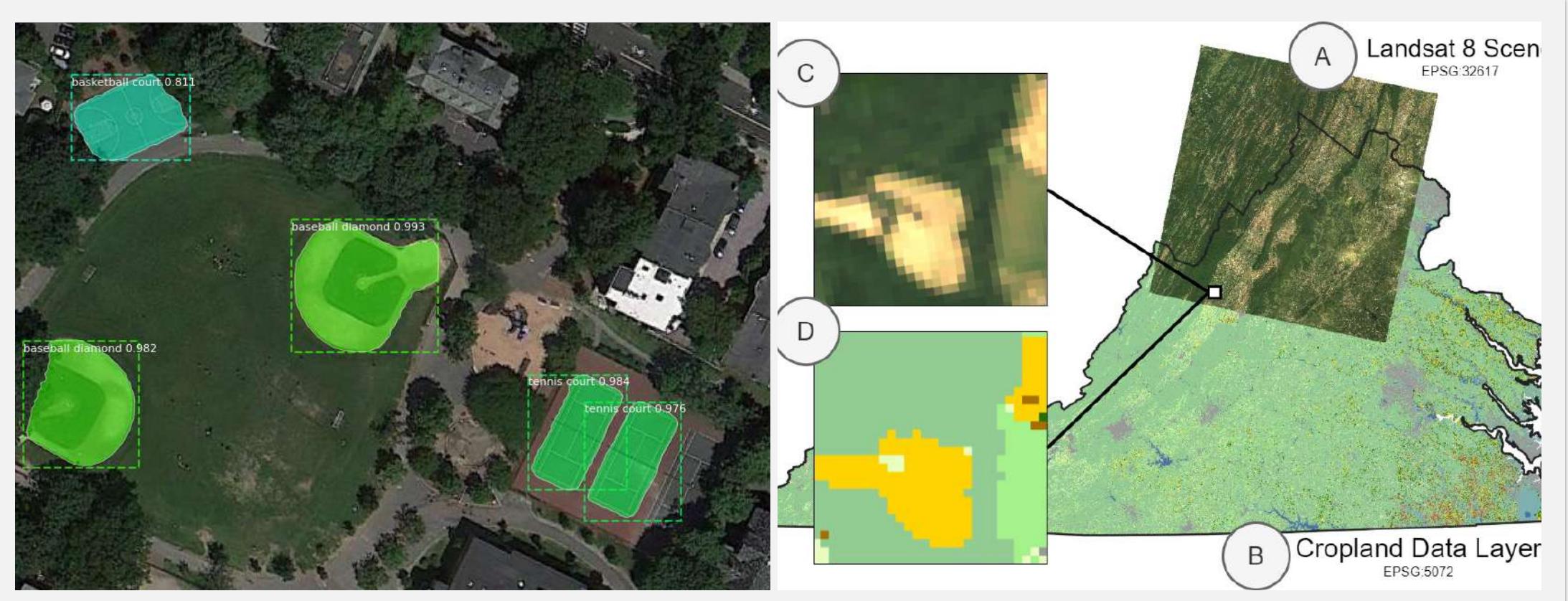
where x_j is the attribute value for feature j , $w_{i,j}$ is the spatial weight between feature i and j , n is equal to the total number of features and:

$$\bar{X} = \frac{\sum_{j=1}^n x_j}{n} \quad (2)$$

$$S = \sqrt{\frac{\sum_{j=1}^n x_j^2}{n} - (\bar{X})^2} \quad (3)$$

The G_i^* statistic is a z-score so no further calculations are required.





Machine learning

<https://github.com/microsoft/torchgeo>

<https://www.microsoft.com/en-us/research/project/geospatial-machine-learning/>

GEOSPATIAL STATISTICS

An Introduction
Georg Heiler UII 2023

Great examples to learn from

- <https://github.com/r-shekhar/NYC-transport>, <https://towardsdatascience.com/geospatial-operations-at-scale-with-dask-and-geopandas-4d92d00eb7e8>
- <https://github.com/gboeing/urban-data-science>
- <https://github.com/geoHeil/spatial-heatmaps>
- <https://automating-gis-processes.github.io/2016/index.html>
- <https://www.kaggle.com/headsortails/be-my-guest-recruit-restaurant-eda>
- cythonized geopandas <http://matthewrocklin.com/blog/work/2017/09/21/accelerating-geopandas-1>
- <https://geocompr.robinlovelace.net>
- <https://cran.r-project.org/web/views/Spatial.html>
- <https://cran.r-project.org/web/views/SpatioTemporal.html>

Links & references

- <https://de.slideshare.net/ChristophKrner/large-scale-geo-processing-on-hadoop>
- <http://blog.cleverelephant.ca/2017/10/parallel-postgis-2.html>
- <http://blog.cleverelephant.ca/2017/12/postgis-scaling.html>
- <http://s3.cleverelephant.ca/2018-postgis-for-managers.pdf>
- https://docs.google.com/presentation/d/14lf1TsVO4Wq7ykgHjIiXYksvzWBW5XvuxJh2CrtraHc/edit#slide=id.g392f8bb753_0_561
- <http://shop.oreilly.com/product/0636920032175.do>
- <http://www.highstat.com/index.php/beginner-s-guide-to-regression-models-with-spatial-and-temporal-correlation>
- <https://geostat-course.org>
- <https://github.com/andrewzm/FRK>
- <https://www.esri.com/arcgis-blog/products/arcgis-pro/analytics/new-clustering-tools-in-arcgis-pro-2-1-more-machine-learning-at-your-fingertips/?rmedium=redirect&rsource=blogs.esri.com%2Fesri%2Farcgis%2F2018%2F01%2F22%2Fpro-2-1-new-clustering-tools>
- <http://xarray.pydata.org/en/stable/> , <https://ncar.github.io/PySpark4Climate/sparkxarray/overview/>
- https://www.paradigm4.com/try_scidb/
- <https://github.com/r-spatial/spdep/>
- <http://geonode.org>
- <https://carto.com/blog/inside/postgres-parallel/>
- <https://anitagraser.com>
- <https://www.wiley.com/en-us/Statistics+for+Spatio+Temporal+Data-p-9780471692744>
- <https://medium.com/@christoph.k.rieke/essential-geospatial-python-libraries-5d82fcc38731> <https://github.com/sacridini/Awesome-Geospatial>
- <https://cloudnativegeo.org/>

Links to tutorials

- <https://pythongis.org/>
- <https://sustainability-gis.readthedocs.io/en/latest/lessons/L1/intro-to-python-geostack.html>
- <https://www.whiteboxgeo.com/>
- <https://courses.spatialthoughts.com/python-foundation.html>
- [https://geographicdata.science/book/notebooks/03 spatial data.html](https://geographicdata.science/book/notebooks/03_spatial_data.html)
- <https://geocompx.org/post/2023/ogh23/>
- <https://movingpandas.org>