Geocomputation

Point Pattern Analysis

UCL

Module outline

W1	Reproducible Spatial Analysis	Core Spatial Analysis
W2	Spatial Queries and Geometric Operations	
W3	Point Pattern Analysis	
W4	Spatial Autocorrelation	
W5	Spatial Models	
W6	Raster Data Analysis	Applied Spatial Analysis
W7	Geodemographic Classification	
W8	Accessibility Analysis	
W9	Beyond the Choropleth	Data Visualisation
W10	Complex Visualisations	

This week

- Focus analysis directly on point events rather than aggregating to administrative geography.
- Three main ways to describe or characterise point processes:
  - Descriptive statistics.
  - Distance-based methods: e.g. average nearest neighbour, Ripley's K.
  - Density-based methods: e.g. DBSCAN, kernel density estimation.
- Some practical examples.

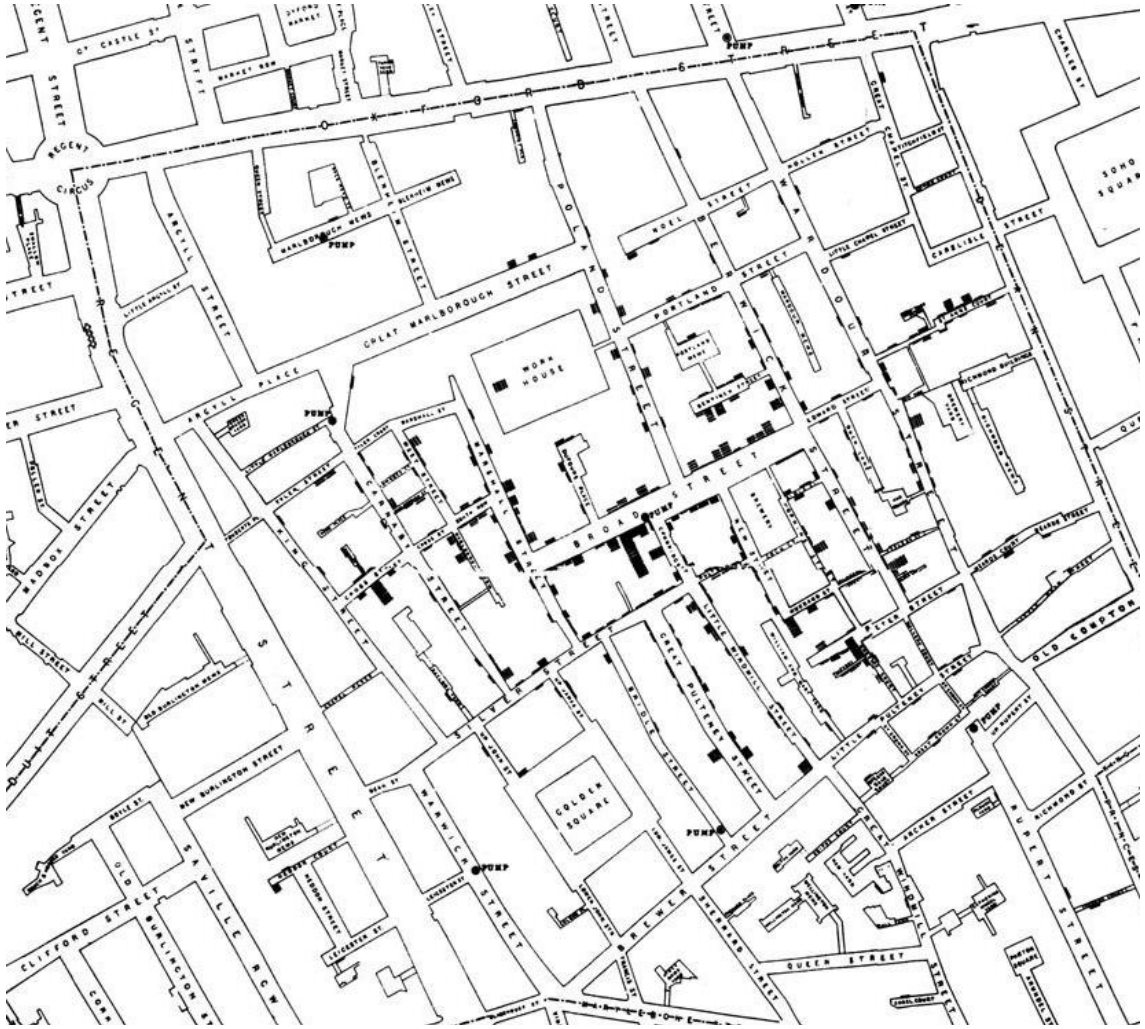
Before we start

- Go to www.menti.com
- Use code: 4309 6301

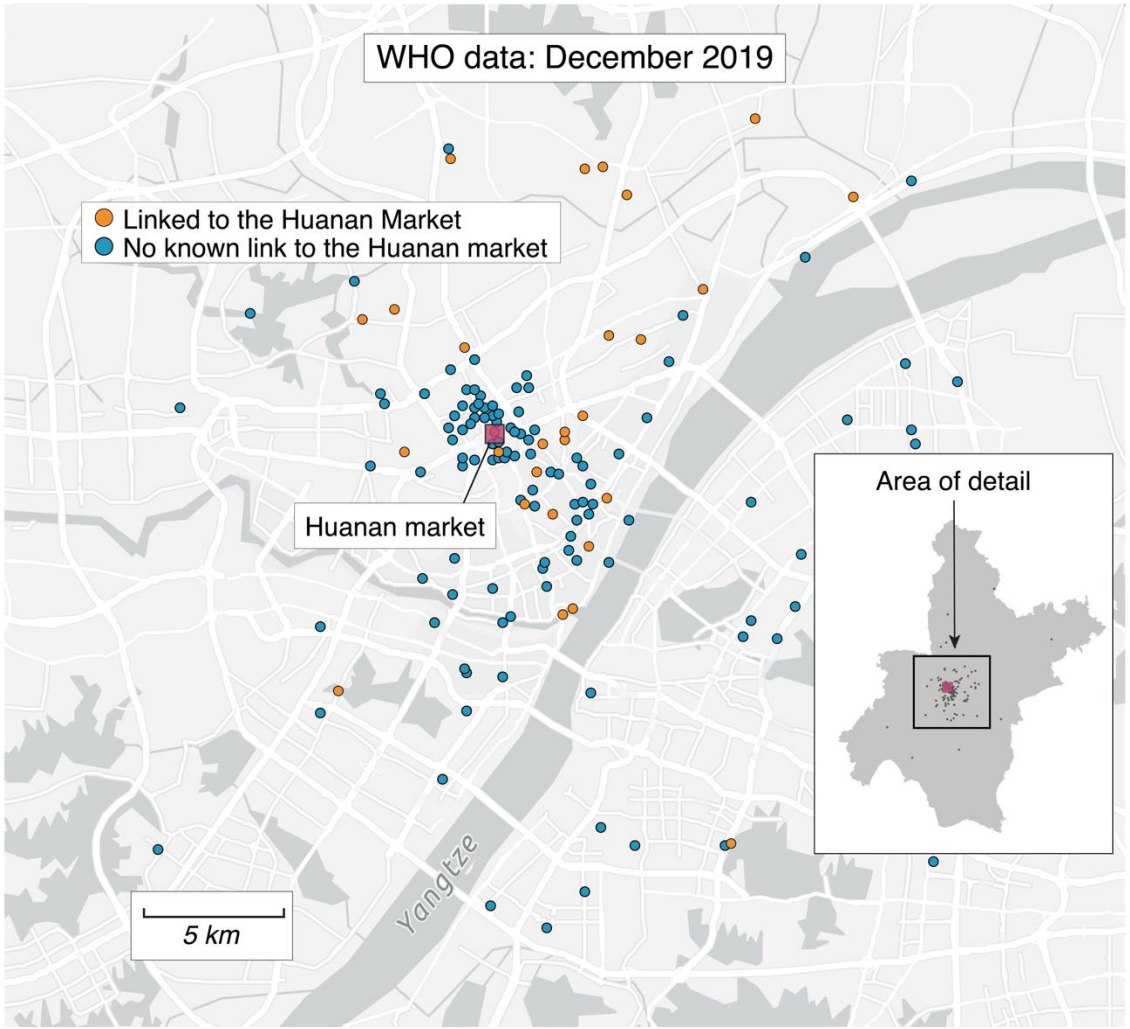
Why do we want to analyse points?

- Points represent the location of individuals, features, or events, providing a spatial reference for analysis.
- Spatial patterns within the distribution of these points can reveal underlying relationships and trends.
- Analysing points allows us to study the occurrence of phenomena or events in relation to similar attribute values (non-spatial information).

Spatial analysis



Spatial analysis



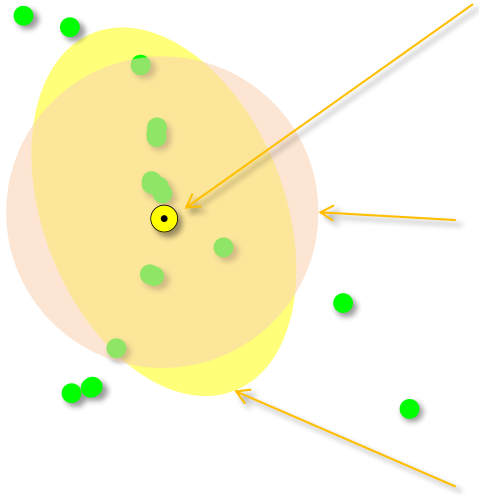
Worobey *et al*. 2022

How do we analyse points?

- Descriptive statistics.
- Density-based methods.
- Distance-based methods.

Descriptive statistics

Descriptive statistics



Mean center
computed average X and Y coordinate values.

$$\bar{s} = \left(\frac{\sum_{i=1}^{n} x_i}{n}, \frac{\sum_{i=1}^{n} y_i}{n} \right)$$

Standard distance
measure of the variance between the average distance of the features to the mean center.

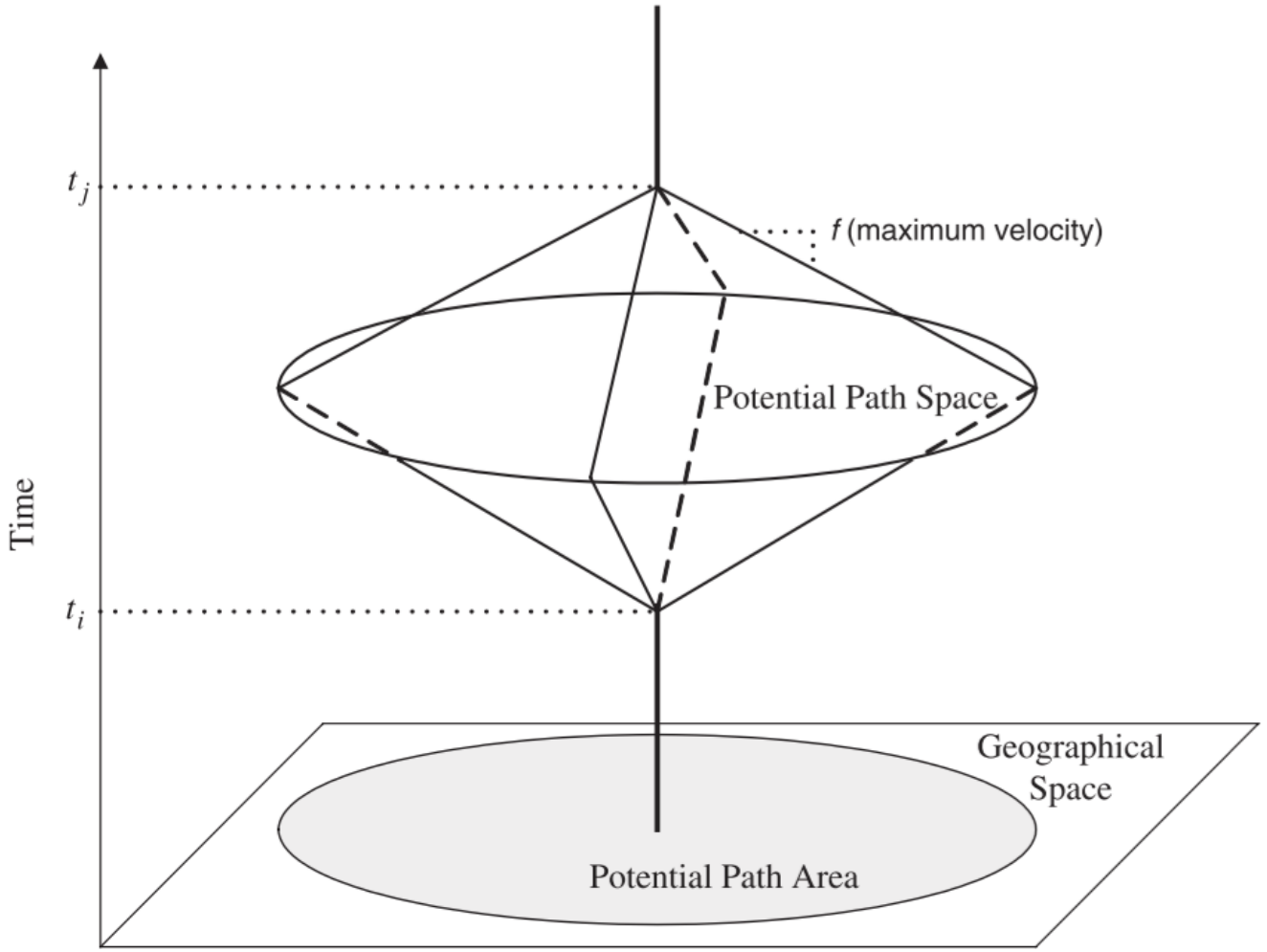
$$d = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \mu_x)^2 + (y_i - \mu_y)^2}{n}}$$

Standard deviational ellipse
separate standard distances for each axis.

$$d_x = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \mu_x)^2}{n}}$$

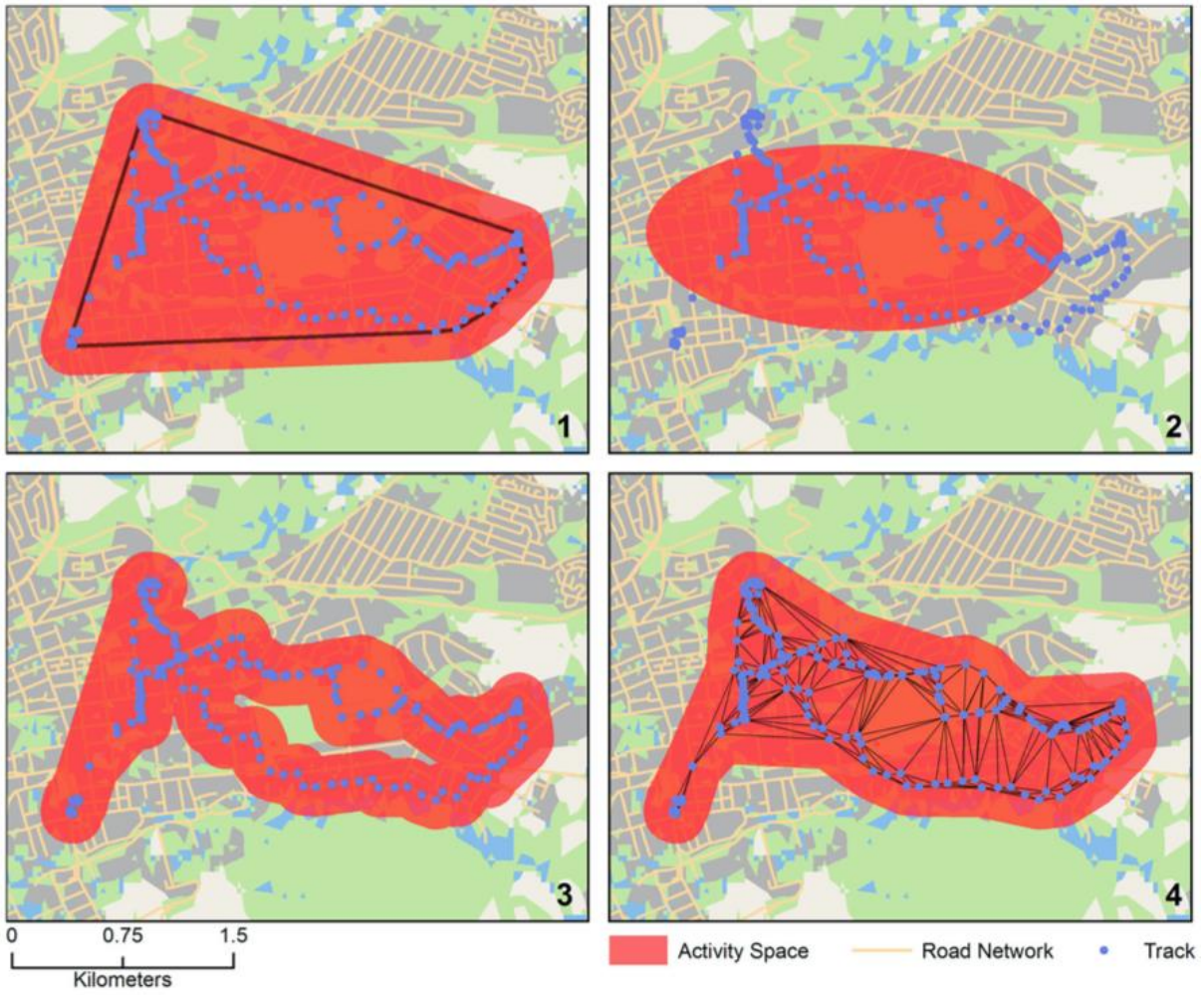
$$d_y = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \mu_y)^2}{n}}$$

Descriptive statistics



Worobey *et al*. 2022

Descriptive statistics



Distance-based measures

Distance-based measures

- Using distance as a summary measure to summarise a point process.
- Measure of spread of the distribution.

Average Nearest Neighbour

- ANN measures the distance between each feature and its nearest neighbour, then averages all these nearest-neighbour distances.
- If the average distance is smaller than the average for a hypothetical random distribution, the features are considered clustered. If the average distance is larger, the features are considered dispersed.

Ripley’s K

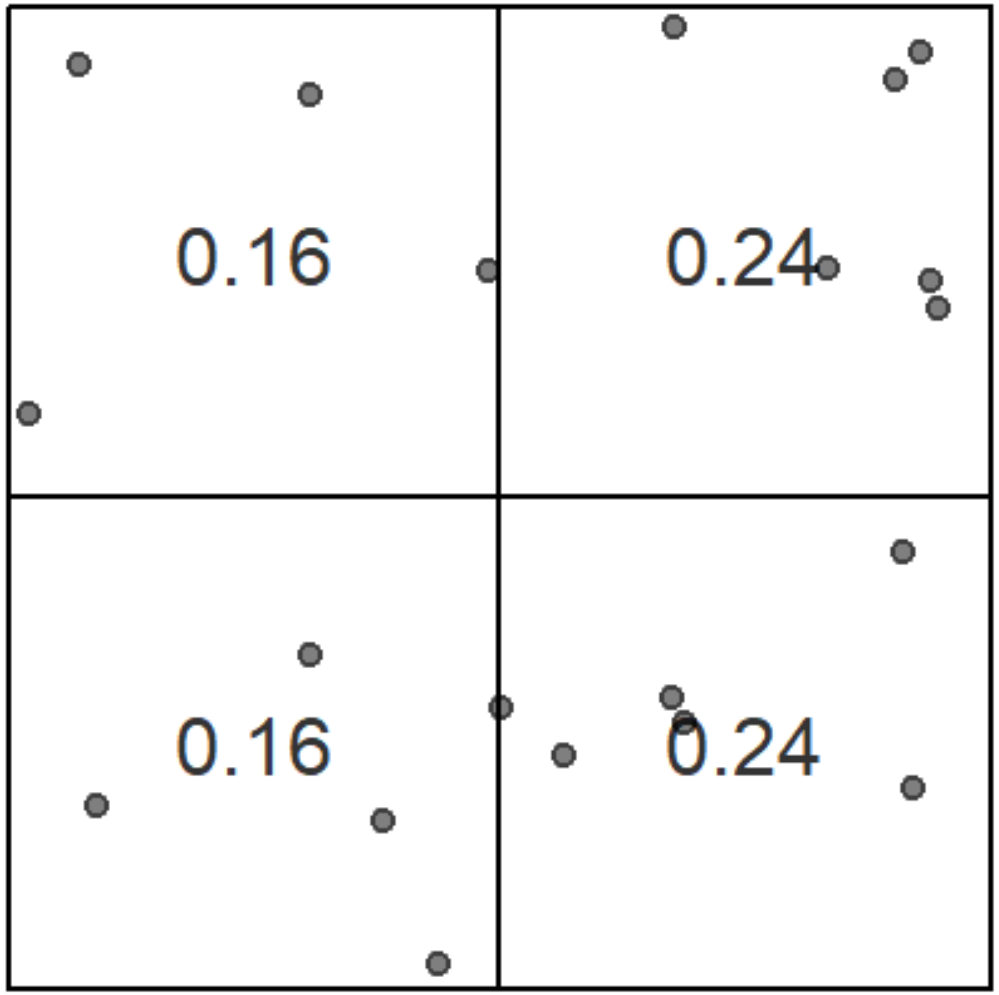
- Ripley’s K counts the number of observations within a user defined set of distances and compares this to a hypothetical (random) pattern of observations.
- Ripley’s K function is generally calculated at multiple distances allowing you to see how point pattern distributions can change with scale. For example, at near distances, the points could cluster, while at farther distances, points could be dispersed.
- Distance-based measure of dispersion across scales.

Density-based measures

Density-based measures

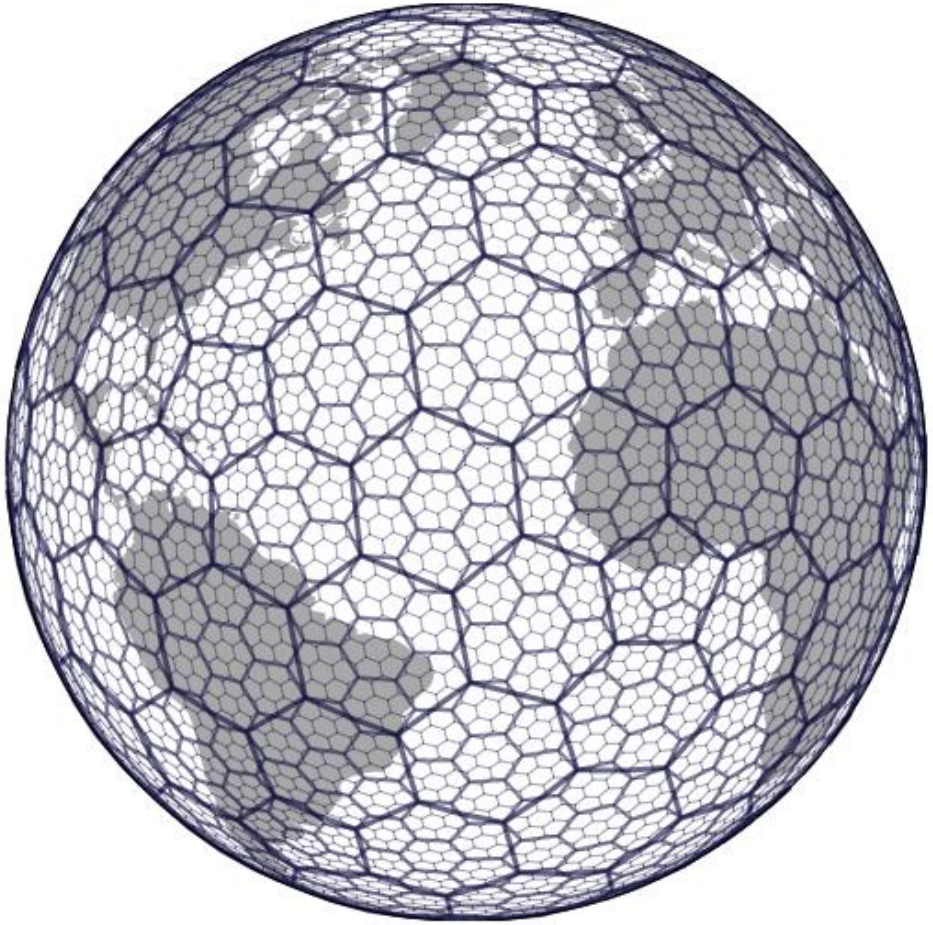
- Measure of the intensity of a point process.
- Density-Based Spatial Clustering of Applications with Noise (DBSCAN) to find high-density clusters and distinguish noise points.
- Kernel Density Estimation (KDE) smooths point data to estimate the density of points across a given area.

Density-based measures



Gimond, M. 2020. *Geodesic geometry*. [online] https://mgimond.github.io/Spatial/index.html

Density-based measures

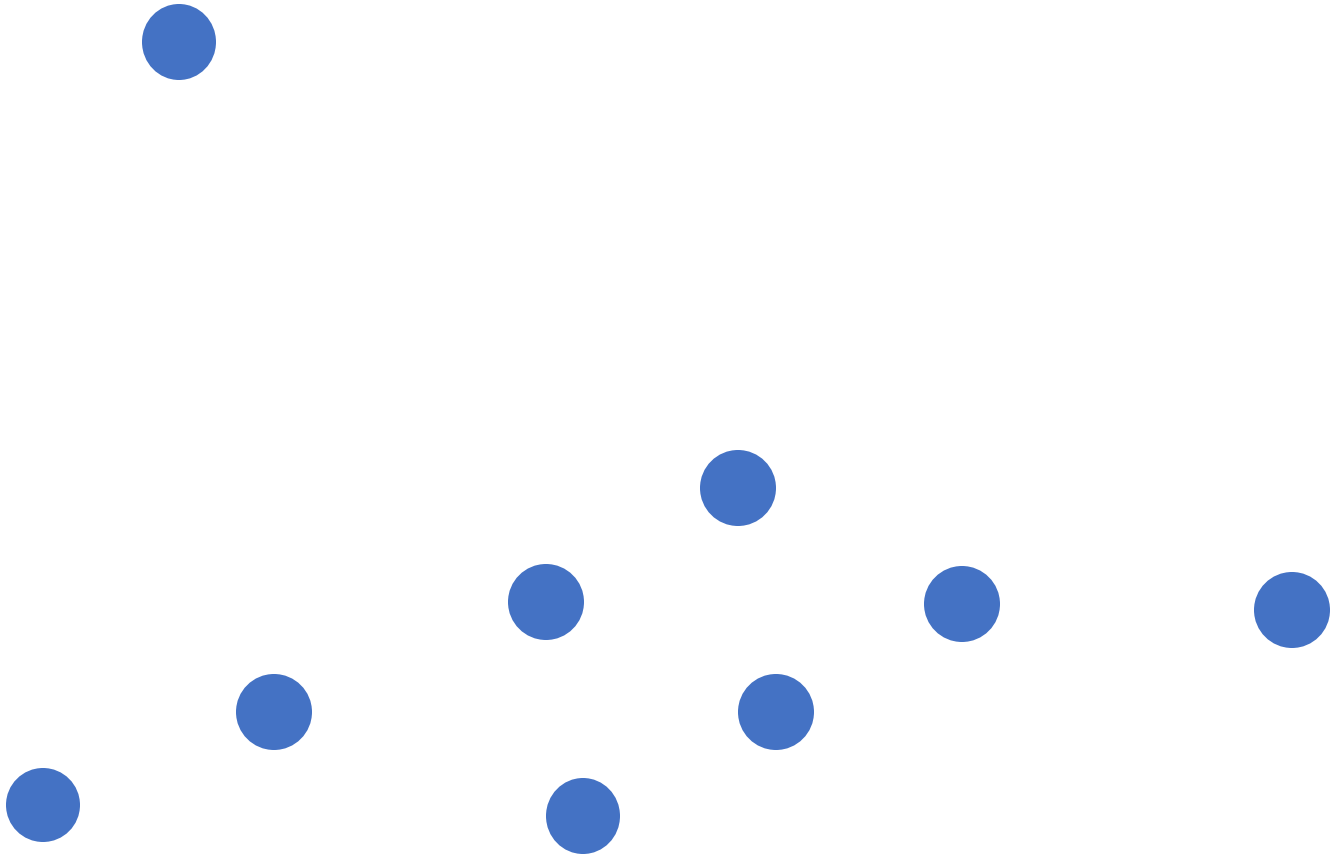


Uber. 2018. *H3: Uber's Hexagonal Hierarchical Spatial Index*. [online] https://eng.uber.com/h3/

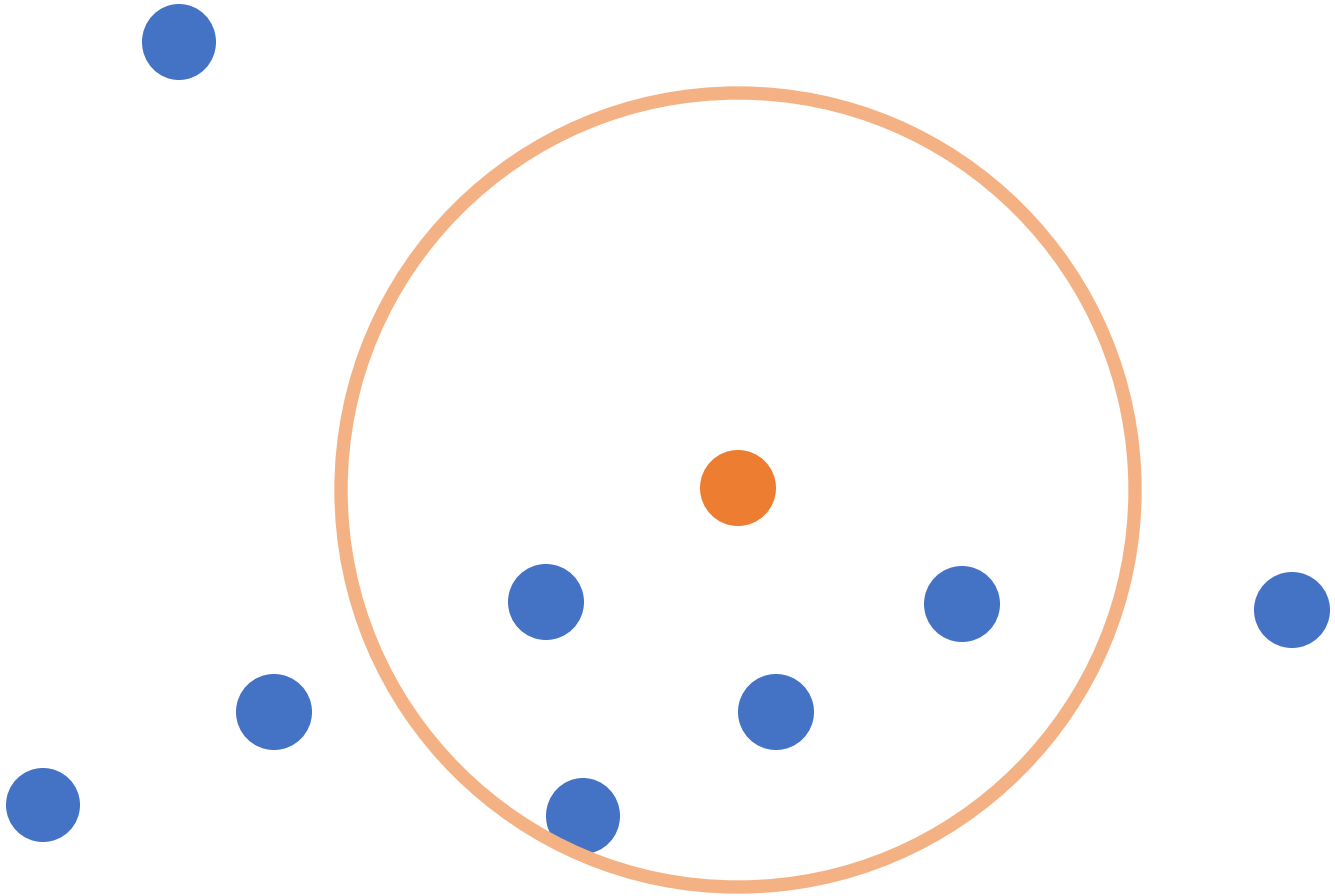
DBSCAN

- Density-Based Spatial Clustering of Applications with Noise (DBSCAN).
- Functionally, DBSCAN detects clusters of points and noise by evaluating density.
- It relies on two key parameters: `minpts` (the minimum number of points required to form a cluster) and `epsilon` (the maximum distance, or search radius, between points to be considered part of the same cluster).
- Points within a cluster must have at least `minpts` points within a radius of `epsilon` to be assigned to that cluster; points that do not meet this condition are classified as noise.

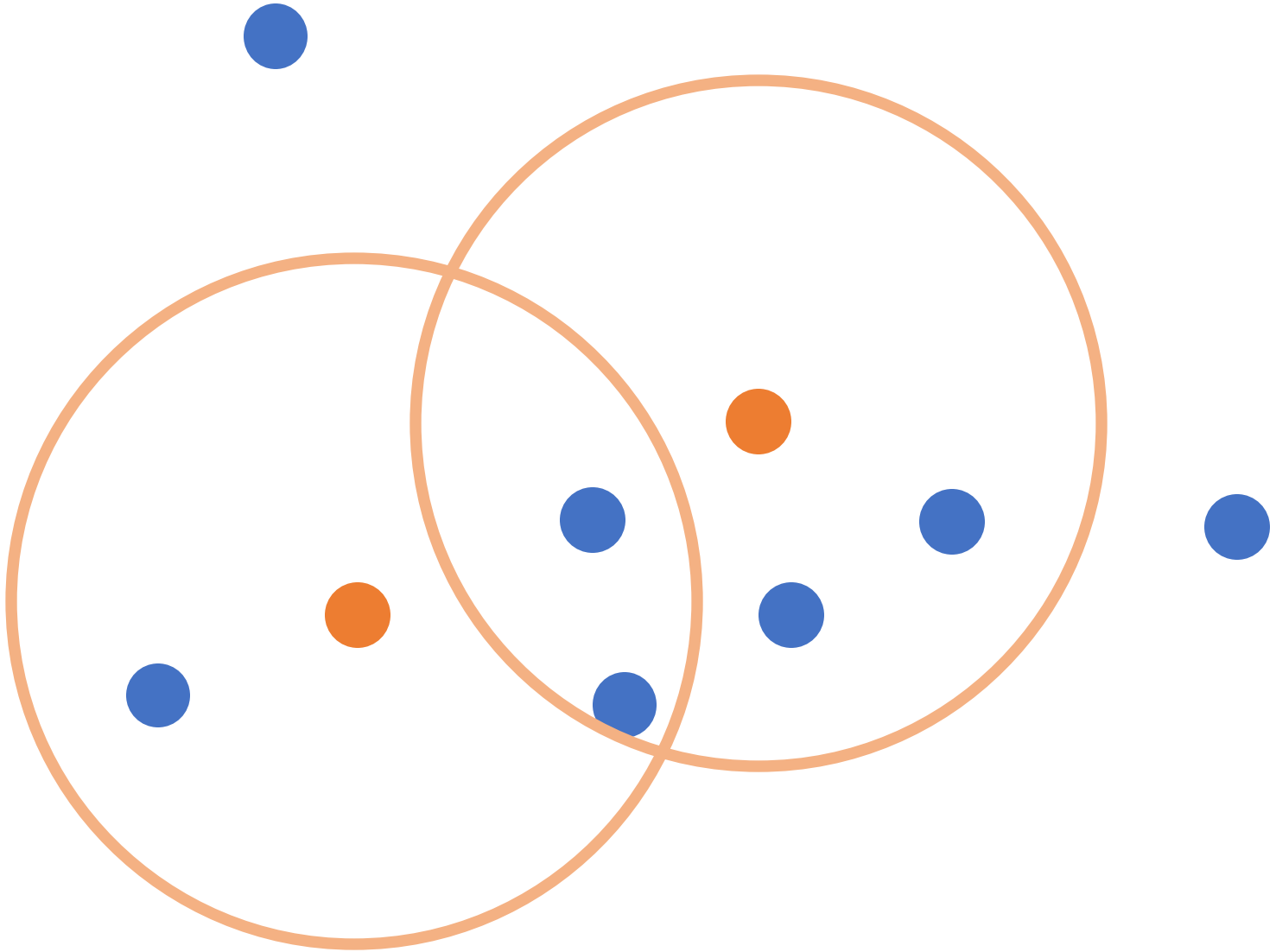
DBSCAN



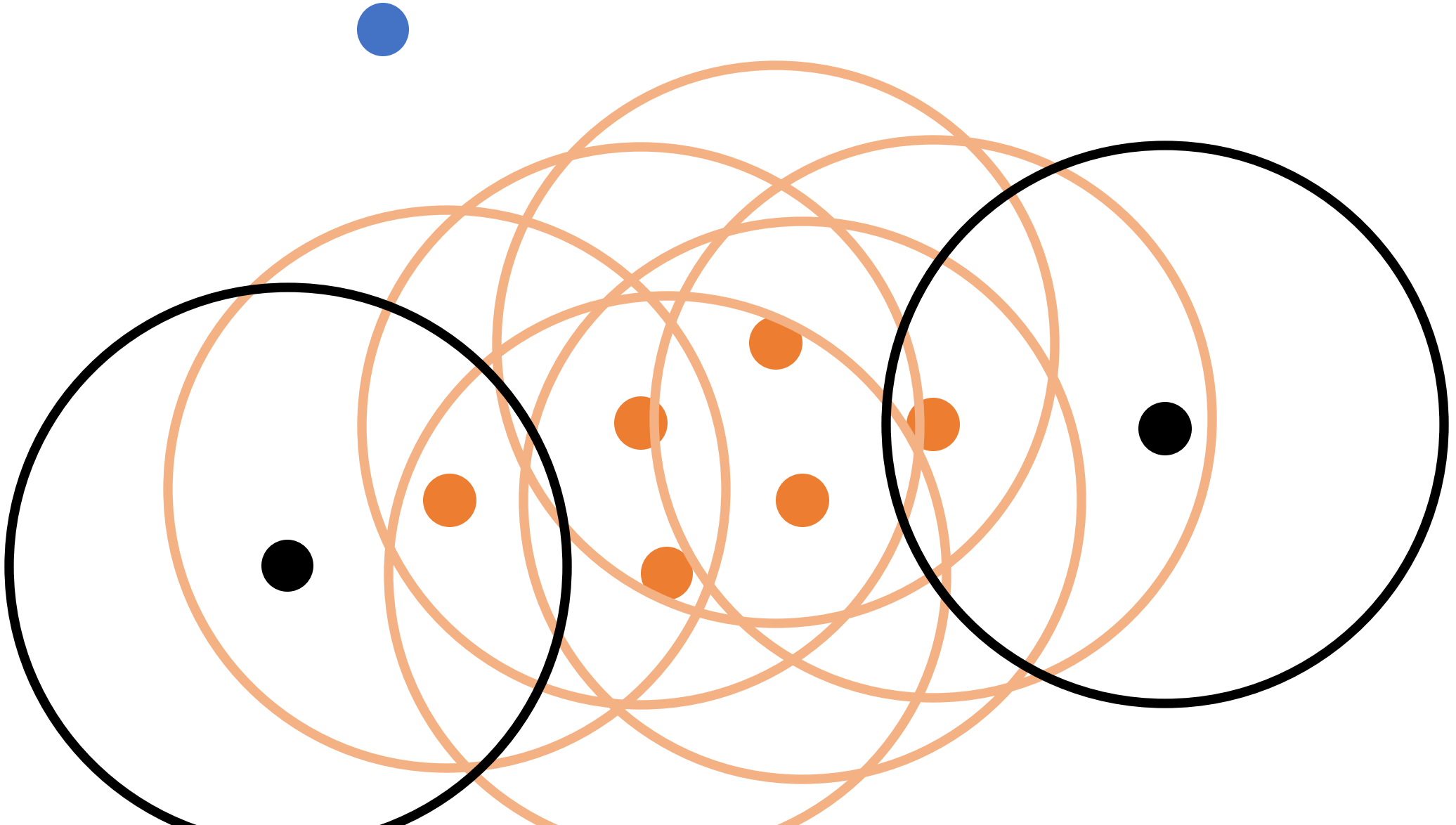
DBSCAN



DBSCAN



DBSCAN



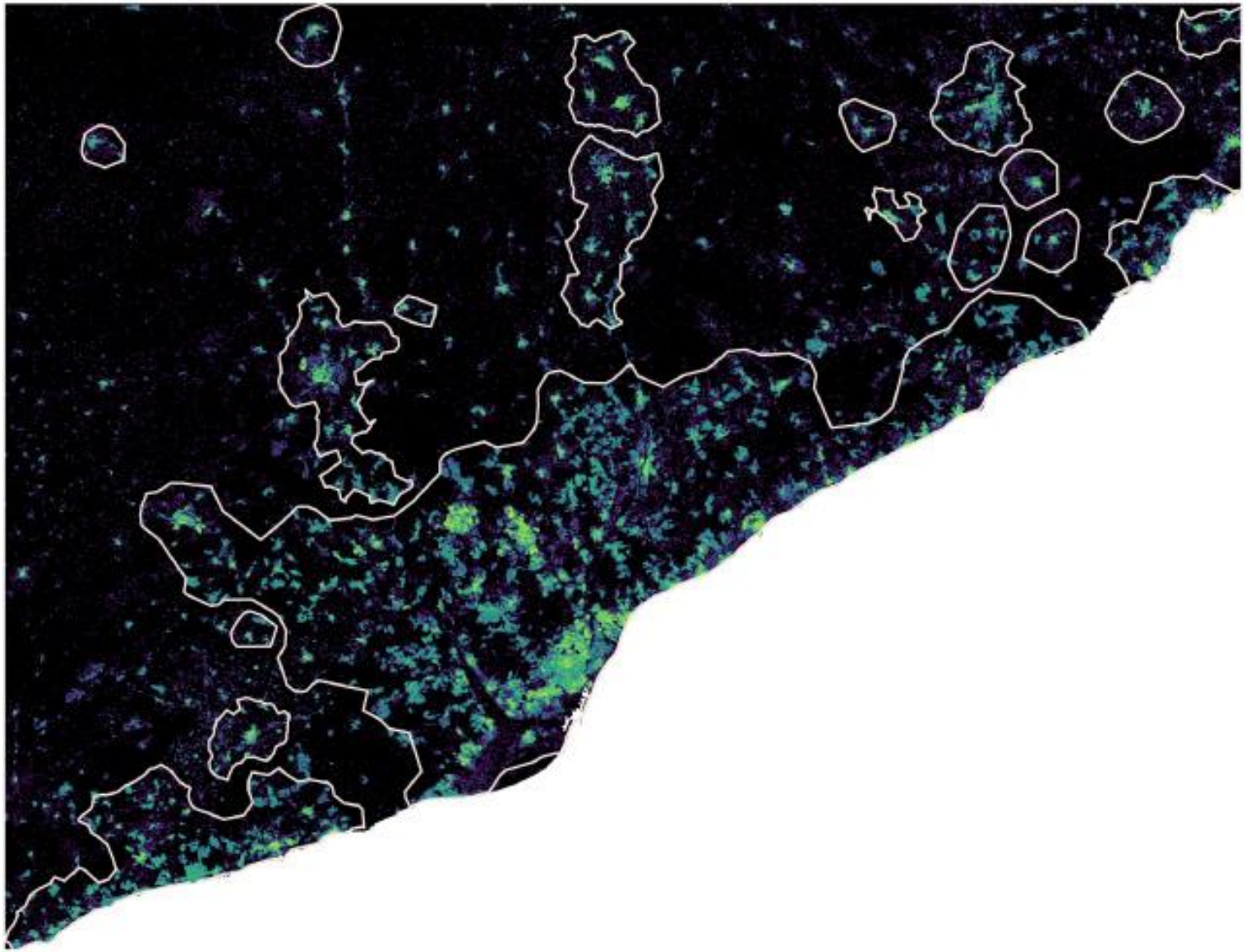
DBSCAN

DBSCAN

- Does not require specifying the number of clusters beforehand.
- Capable of identifying non-linearly separable clusters, including arbitrarily shaped clusters.
- Results are highly dependent on the choice of distance measure.
- Struggles with datasets containing clusters of varying densities, as a single set of parameters may not accommodate all situations effectively.

DBSCAN

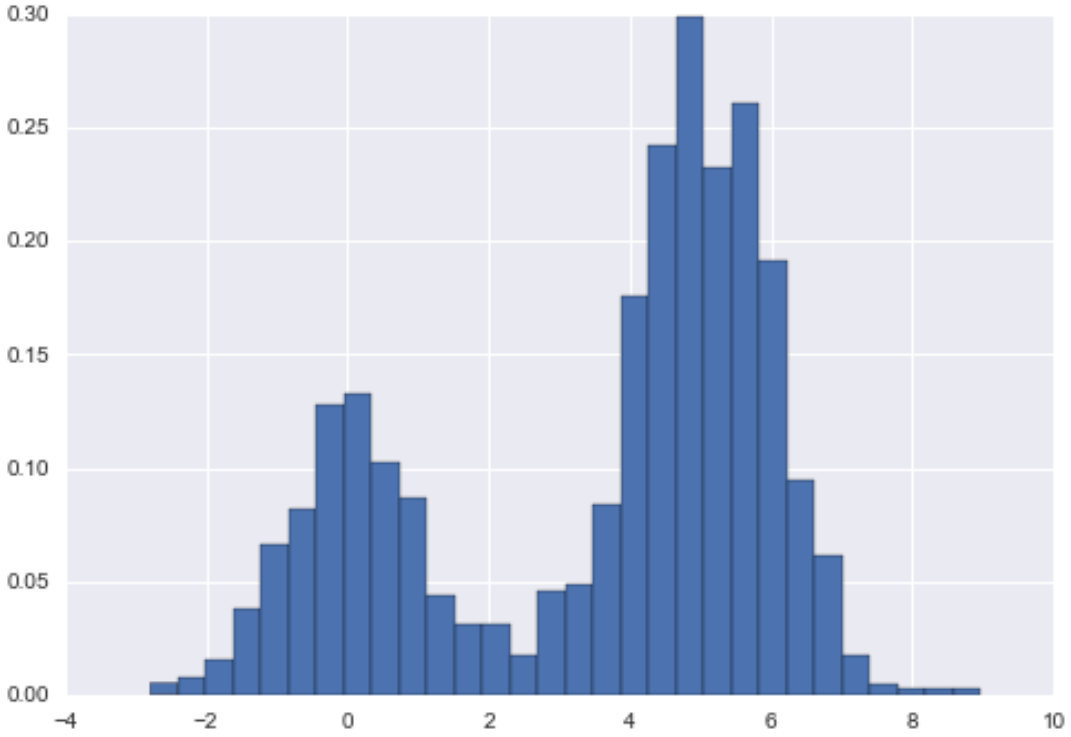
Arribas-Bel *et al*. 2021. Building(s and) cities: Delineating urban areas with a machine learning algorithm. *Journal of Urban Economics* 125: 103217



Kernel density estimation

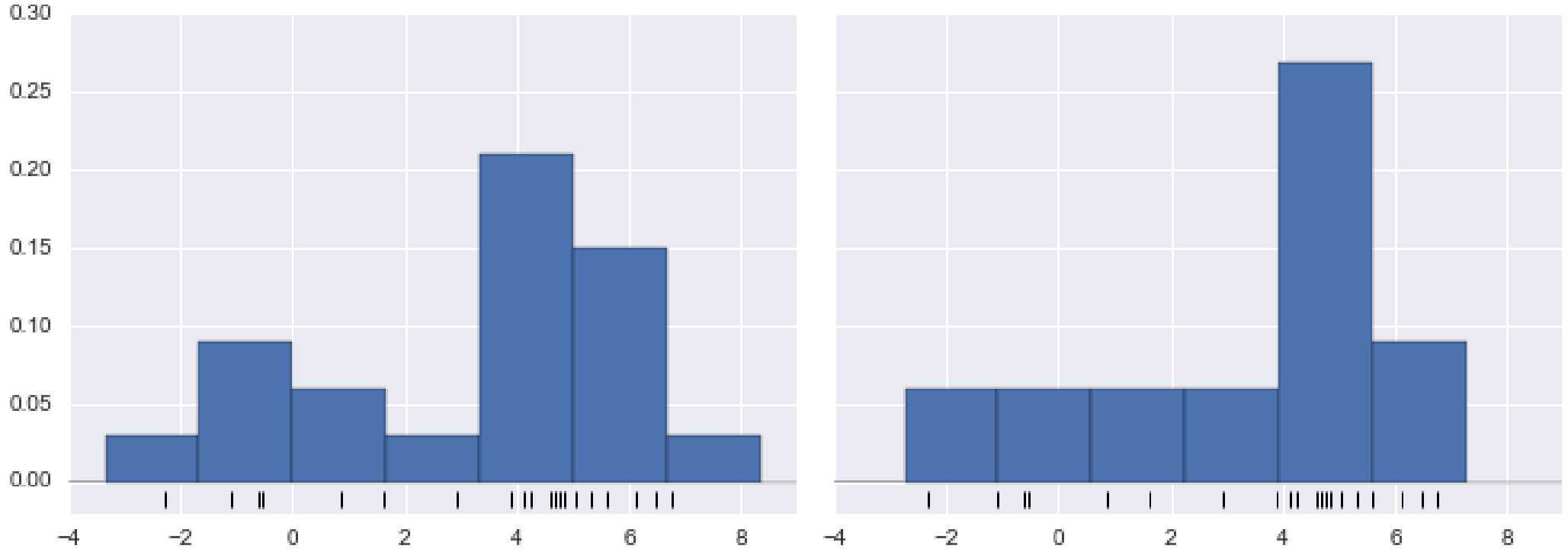
- Heatmap: Kernel density estimation (KDE) is a non-parametric way to estimate the probability density function of a random variable.
- It uses local information defined by windows (called kernels) to estimate densities of specified features at given locations.
- In essence it is a smoothing function where a continuous curve is created, based on a finite data sample.

Kernel density estimation



VanderPlas, J. 2016. *Python data science handbook: essential tools for working with data*. O'Reilly Media, Inc.

Kernel density estimation



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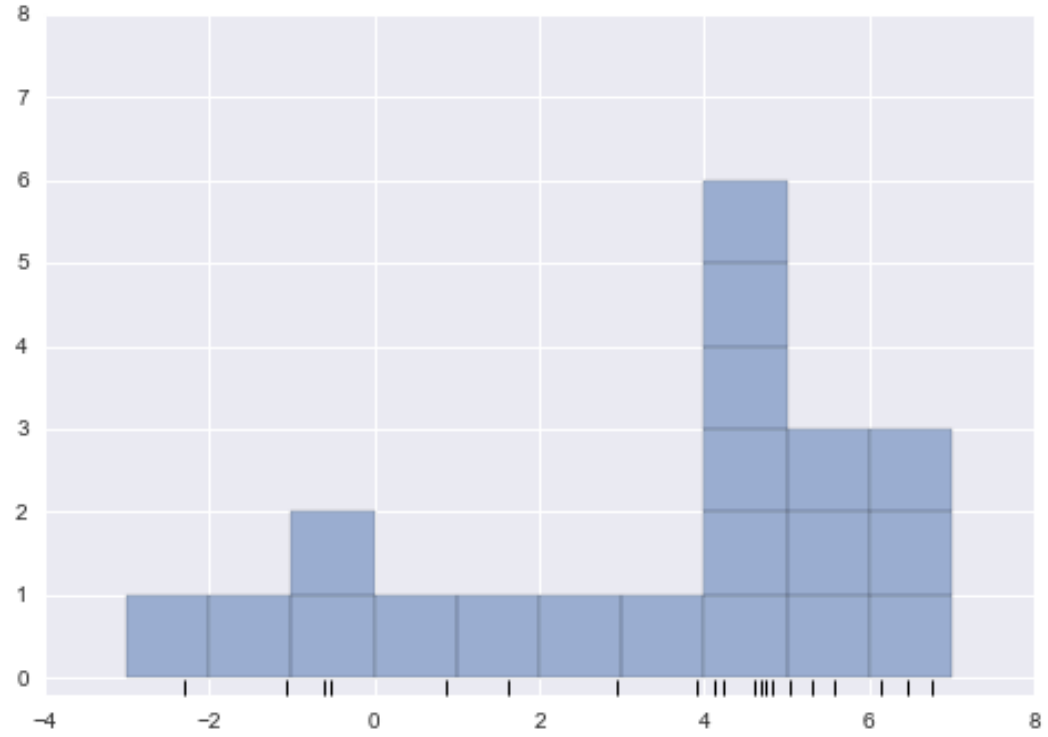

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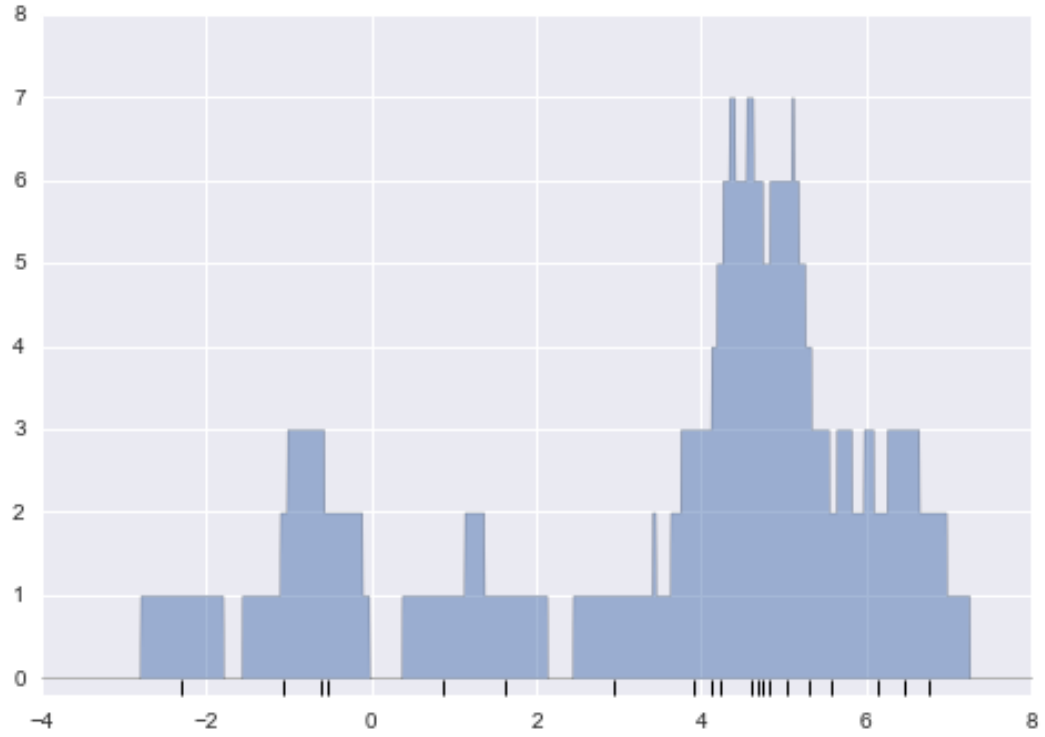
Kernel density estimation



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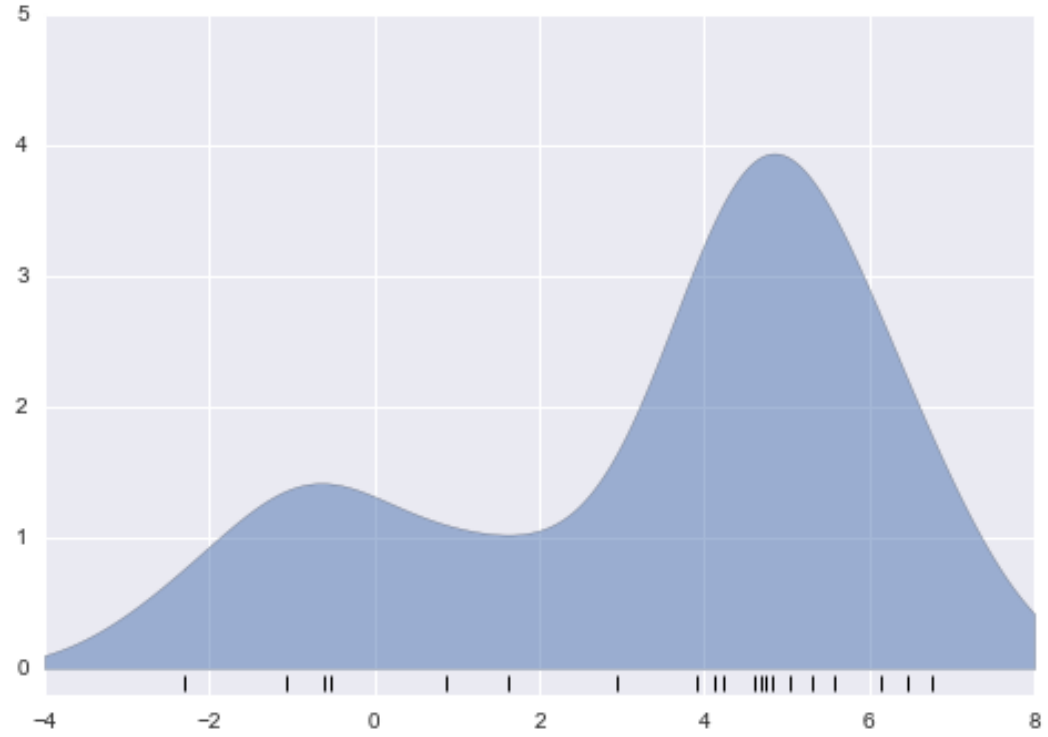

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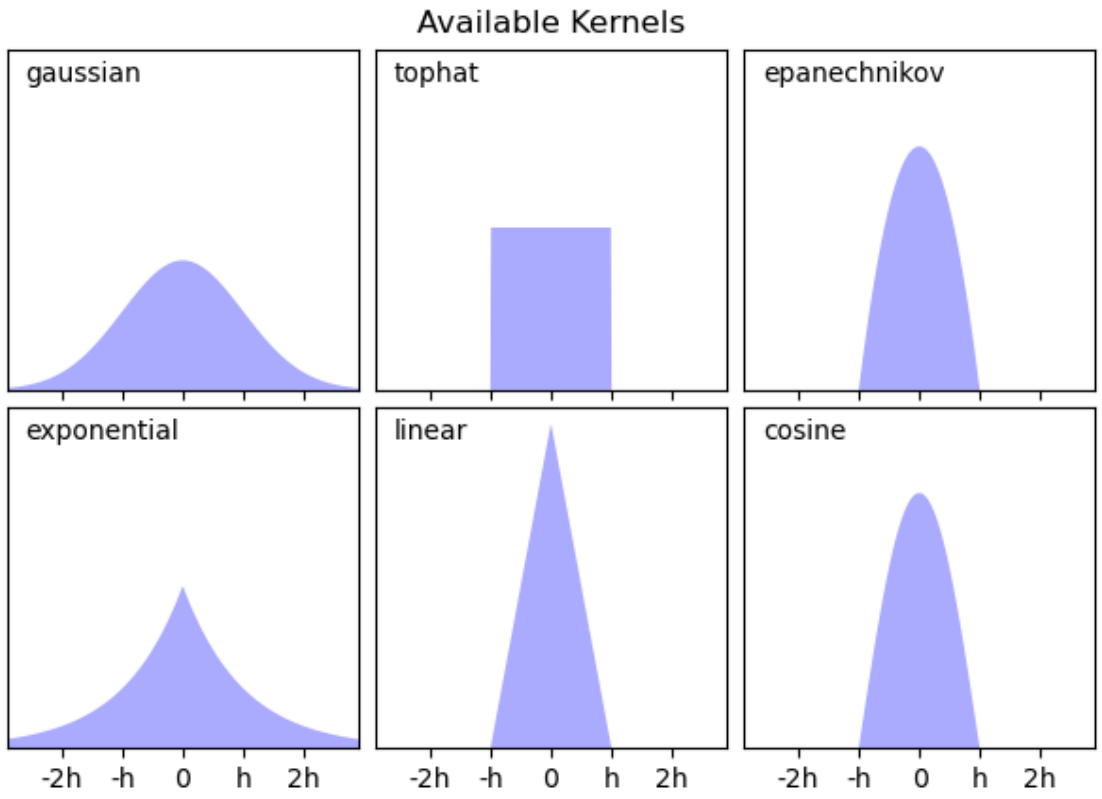
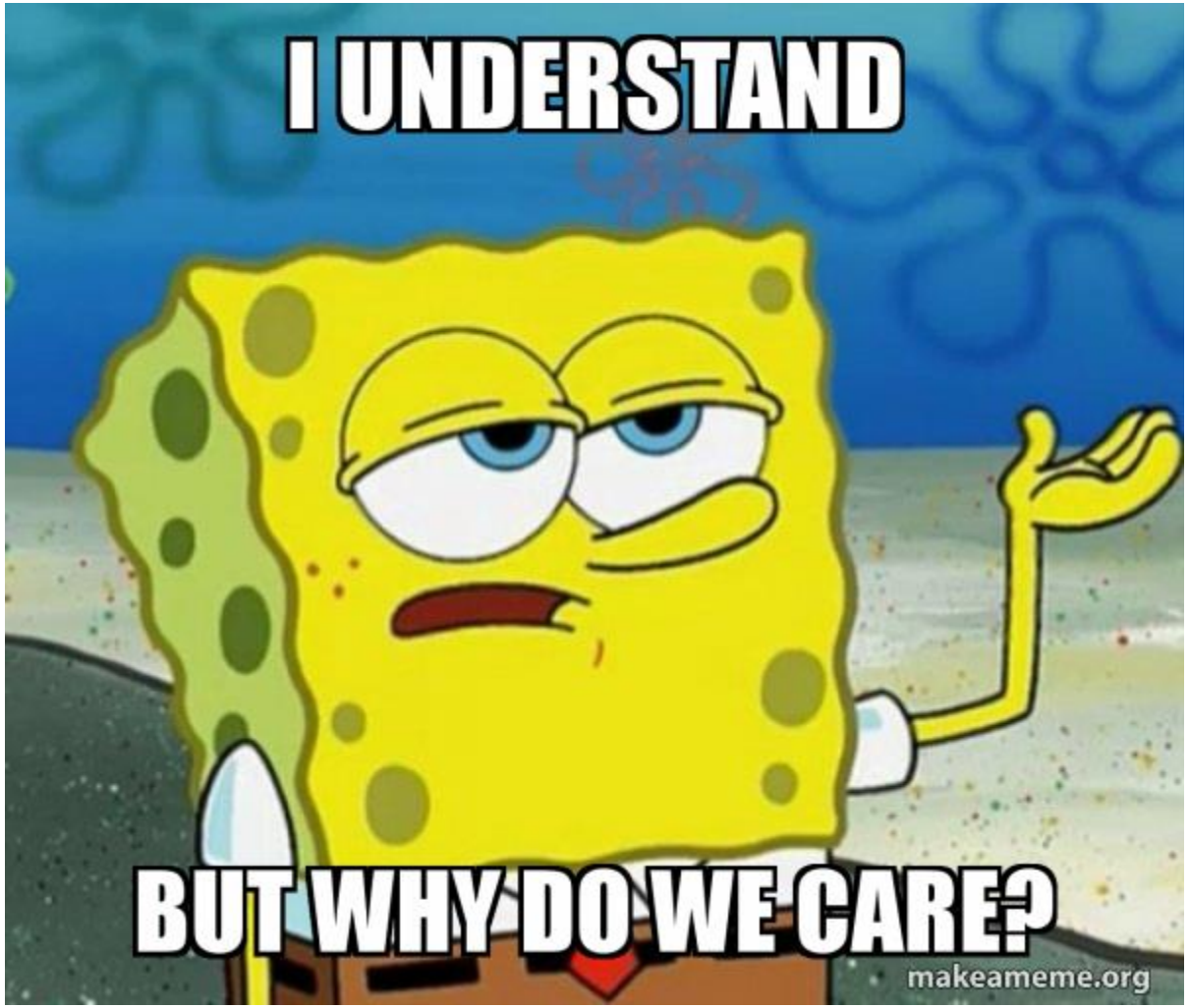


Scikit-learn. 2020. *Density estimation*. [online] https://scikit-learn.org/stable/modules/density.html

Kernel density estimation



Practical examples

Two examples

Point pattern analysis ‘in action’ in some actual research:

- Not all point data sets can be fully analysed with summary measures, e.g. analysis of GPS trajectory data (‘trajectory data’).
- Some problems do not per se look like a ‘point pattern analysis’ problem, but actually can be conceived as such, e.g. surname profiling.

Trajectory data

Van Dijk, J. T. 2018. Identifying activity-travel points from GPS-data with multiple moving windows. *Computers, Environment and Urban System* 70: 84-101

Trajectory data

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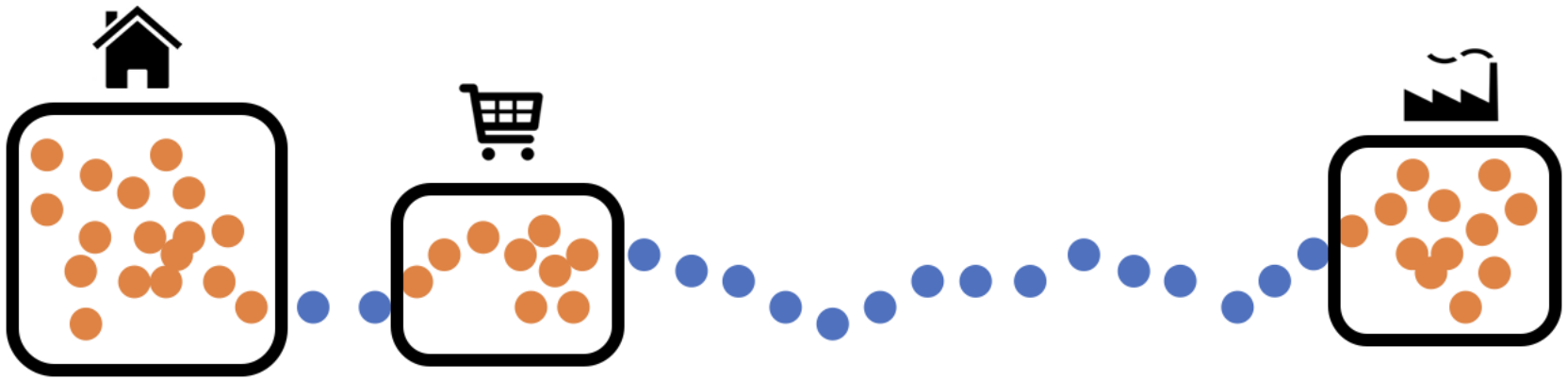

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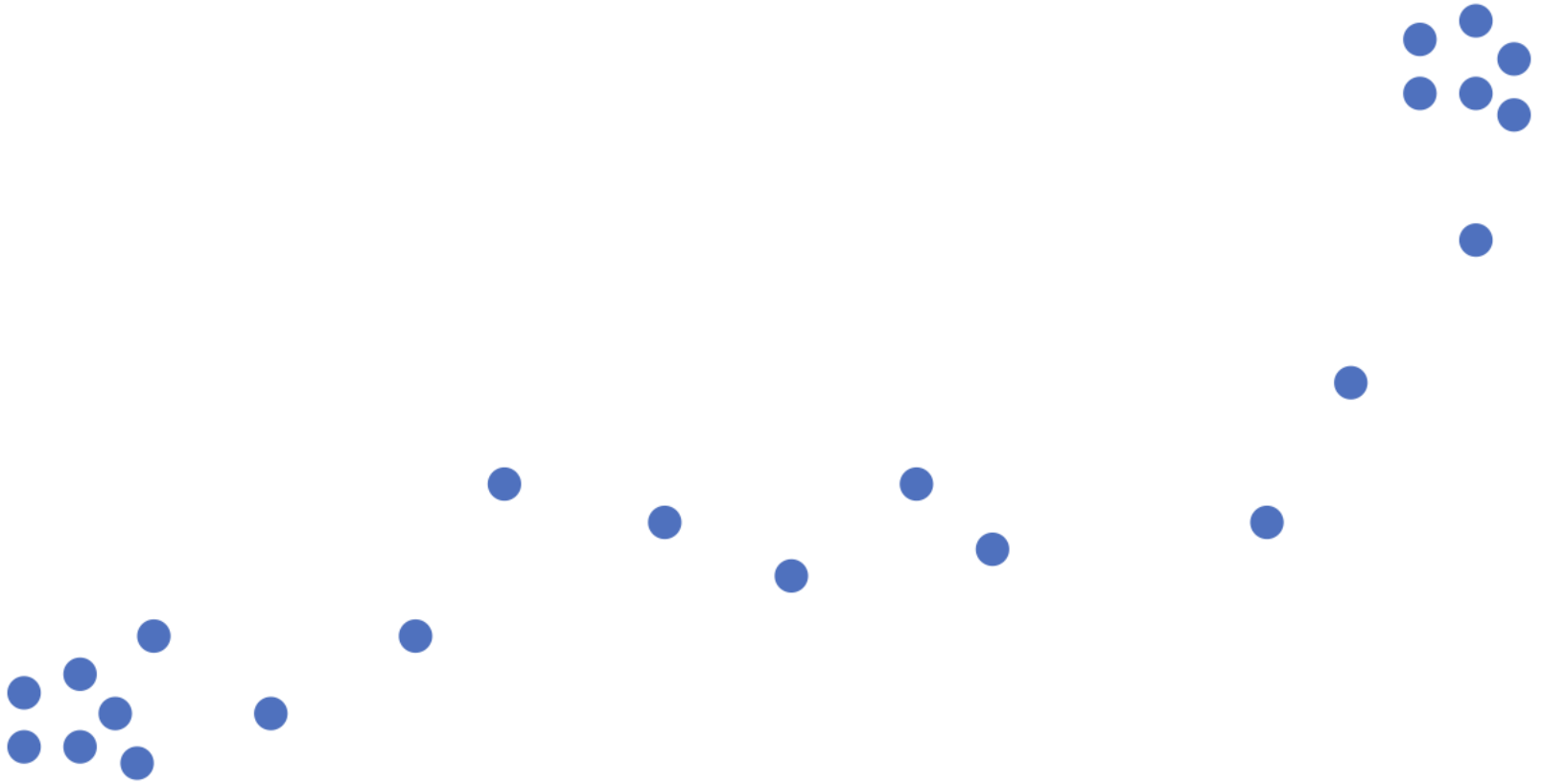

Van Dijk, J. T. & T. de Jong. 2017. Post-processing GPS tracks in reconstructing travelled routes in a GIS-environment: Network subset selection and attribute adjustment. *Annals of GIS* 23(3): 203-217

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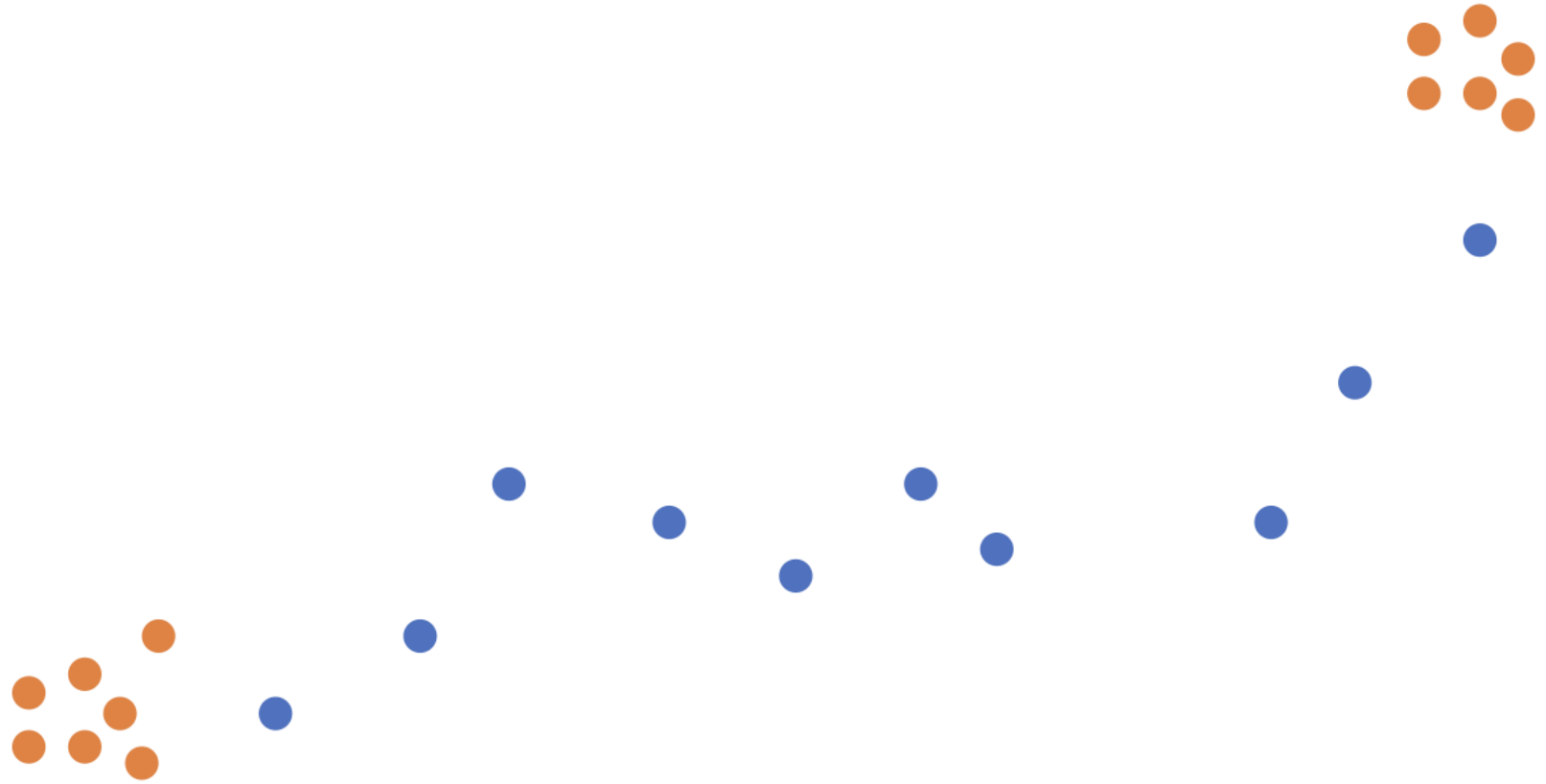

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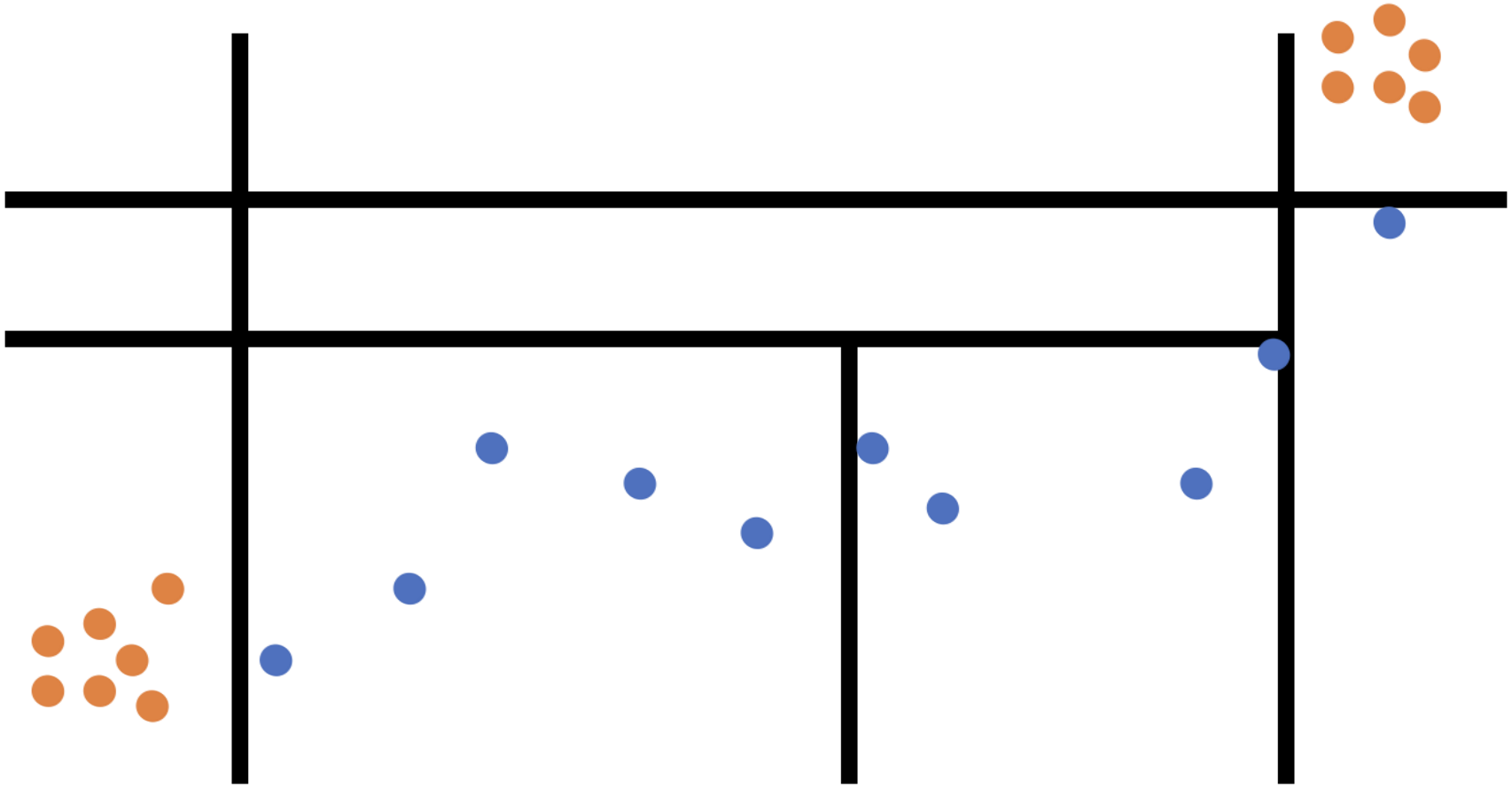

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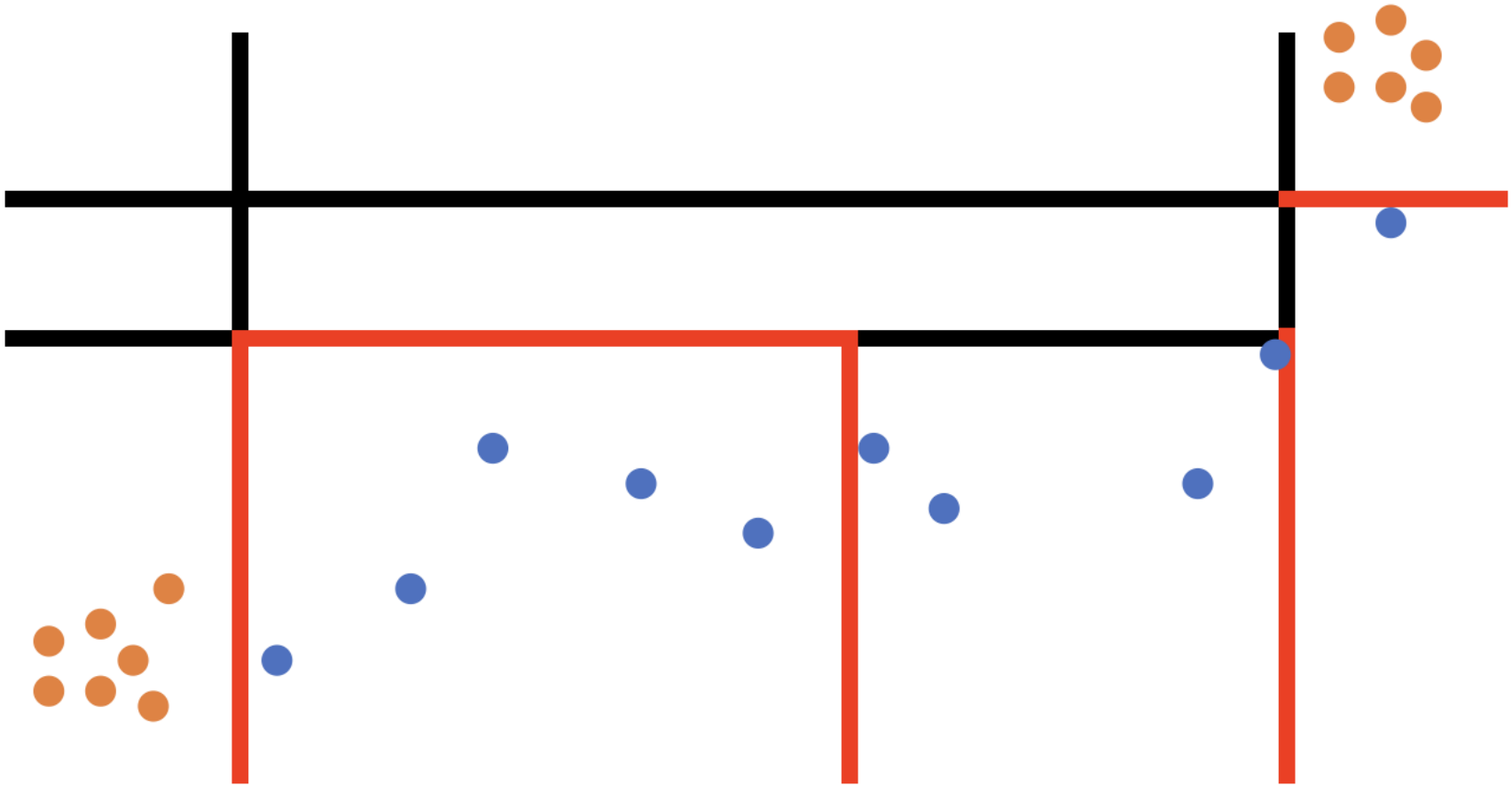

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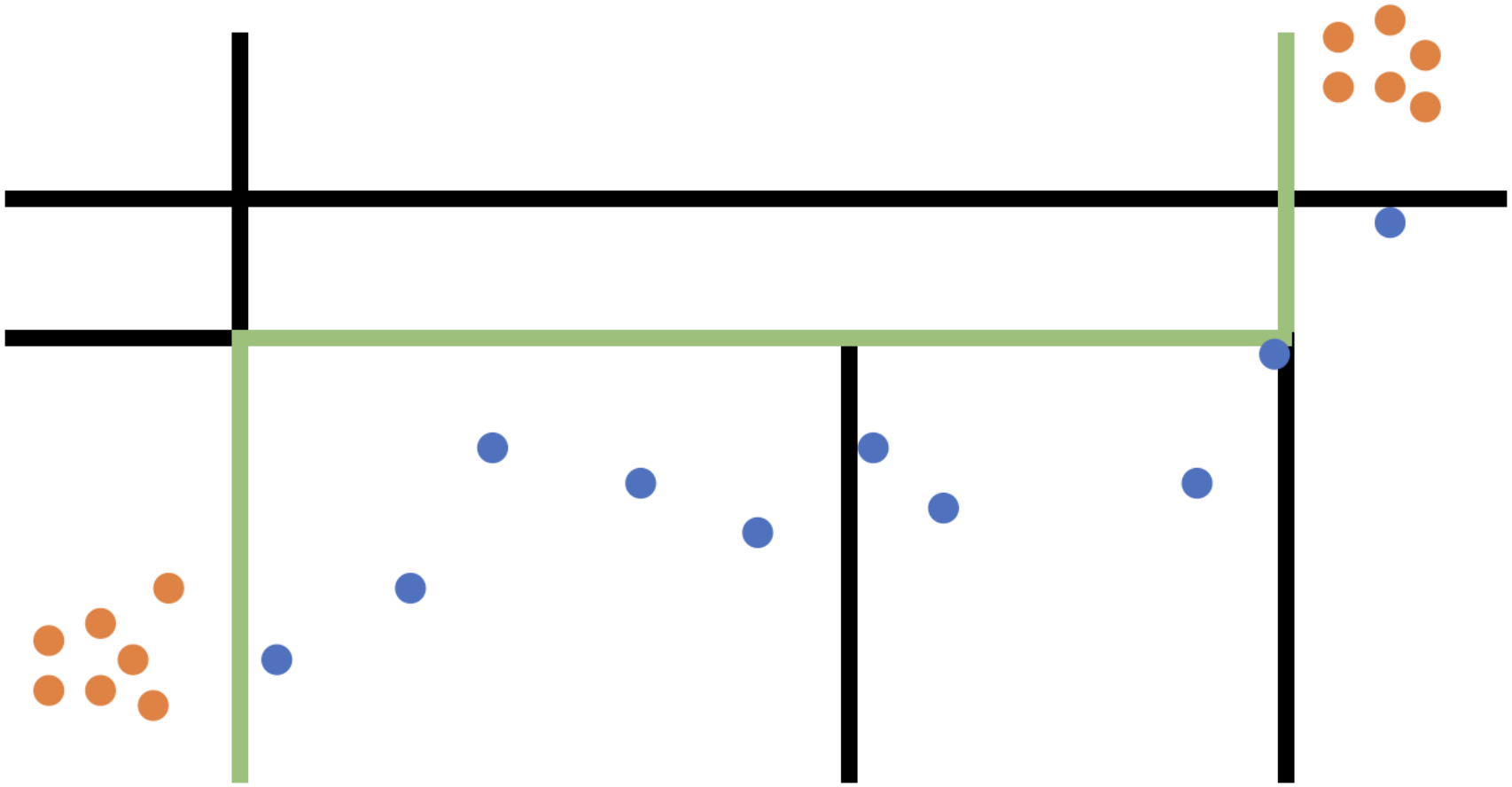

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Surname profiling

- Personal names contain socio-demographic information.
- But also: many surnames contain spatial information at a variety of scales relating to the origins of many of their bearers.
- Data: Historic Census of Population 1851-1911, Consumer Registers 1997– 2016.
- Total of 1.2 million surnames with locations (Historic Parishes, unit postcodes and geo-coded addresses for several years of data).

“Van Dijk”

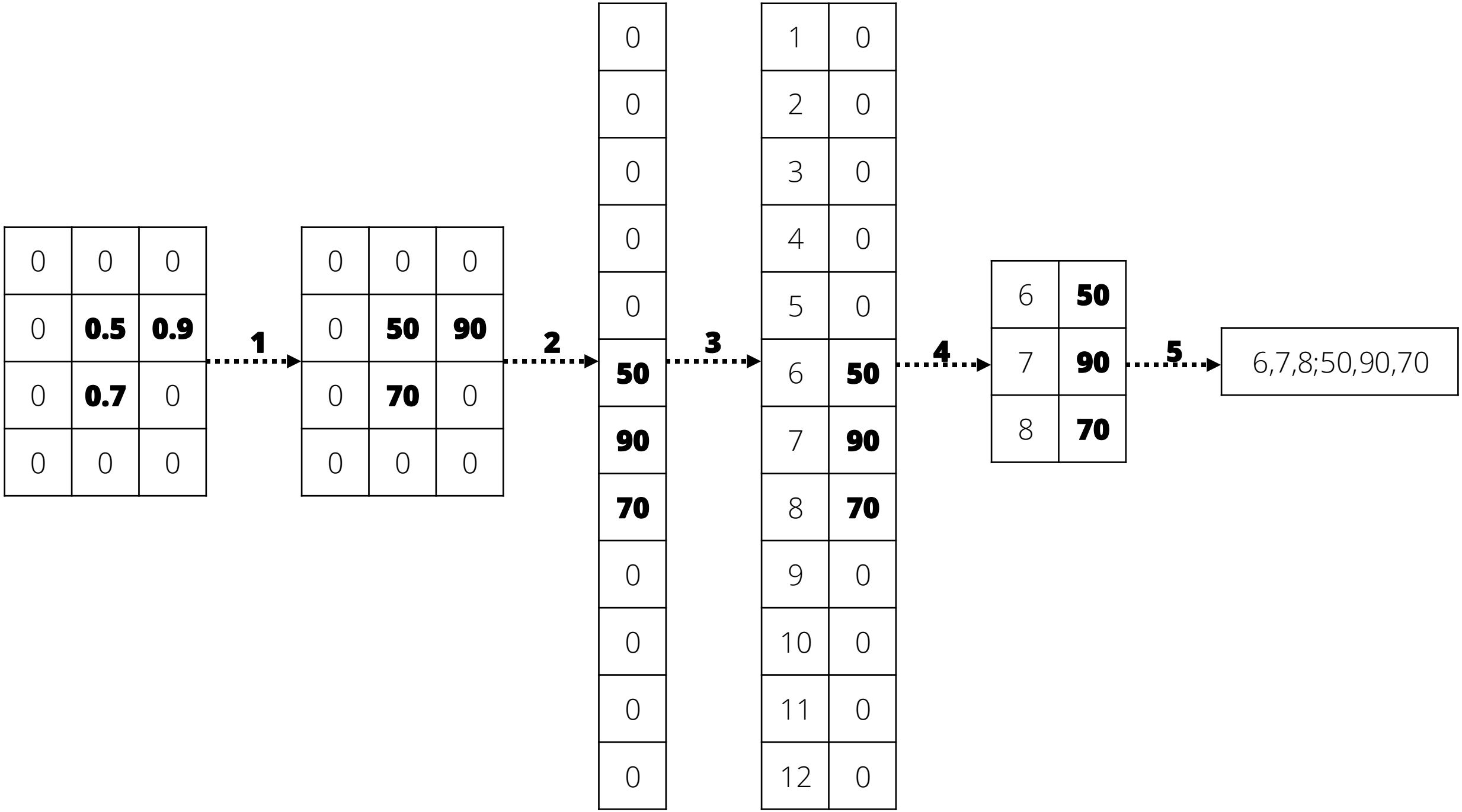
“Lansley”

“Rossall”

Surname profiling

Combination on various point pattern analysis techniques:

- kernel densities to map the surname concentrations of names found in Great Britain executed over a 1000m x 1000m grid.
- deconstruction of grids as sparse matrices to optimise storage and database retrieval (storing 1.2 million KDEs is challenging), followed by DBSCAN to create contours of highest relative density (vectorisation).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12 0
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6 50
7 90
8 70
5
6,7,8;50,90,70

1

50	**90**	20	0	10	10
80	10	0	20	**40**	**50**
30	0	10	**40**	**60**	**80**
0	0	20	**50**	**70**	**50**
0	0	30	**50**	**90**	30

2

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		50	**90**	

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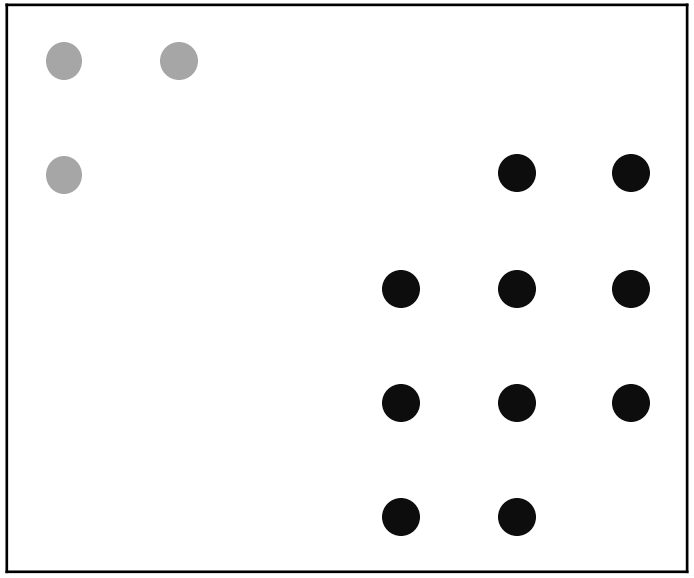

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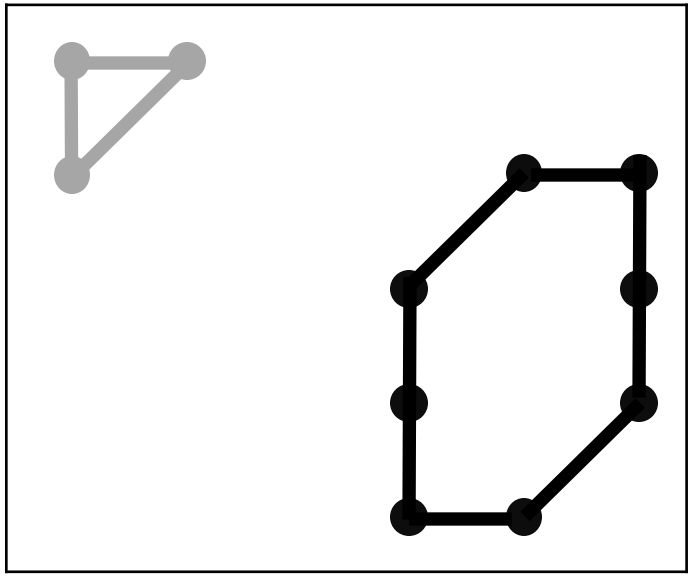
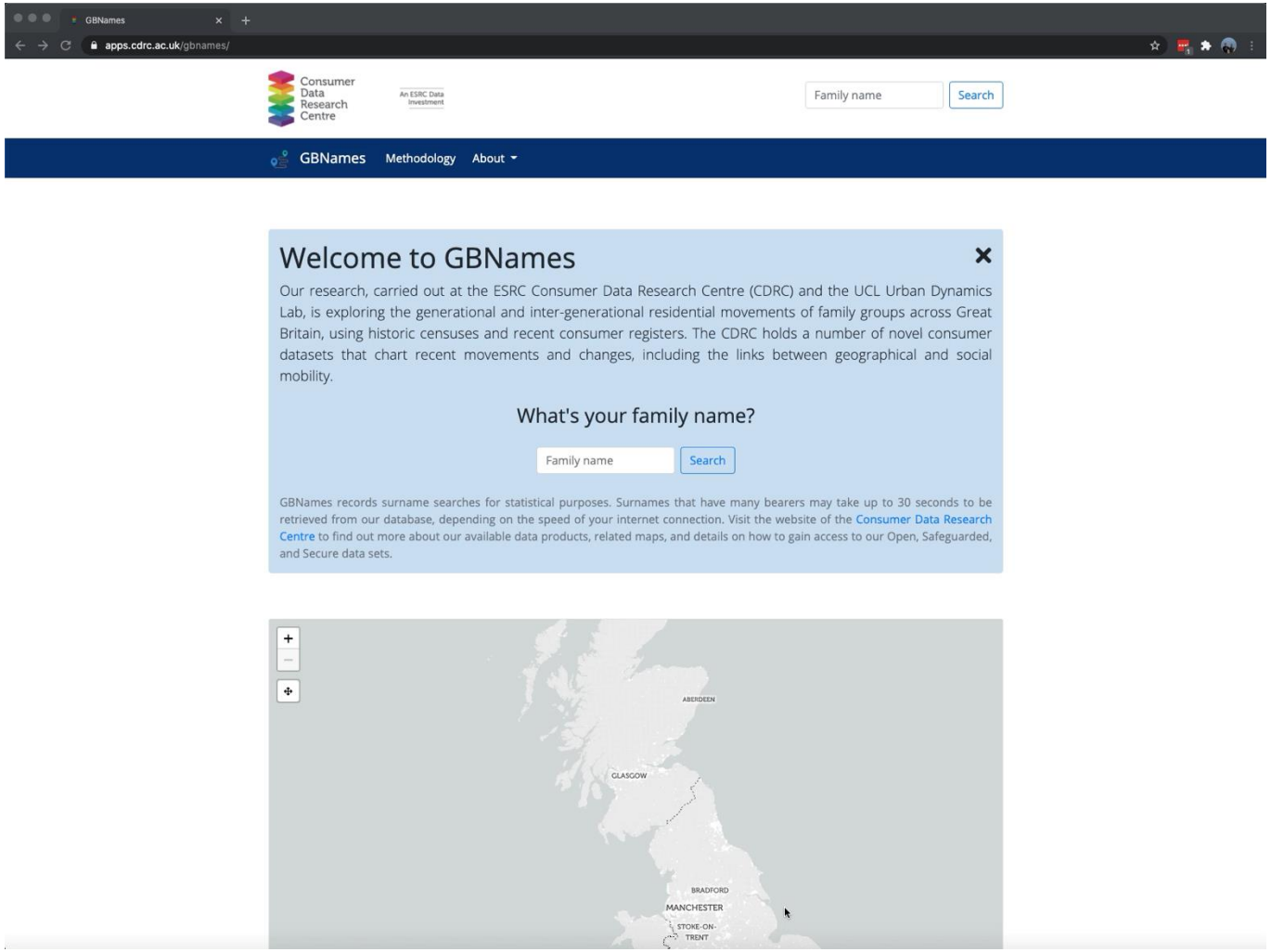


Surname profiling

Why does the DBSCAN work?

- Because the 1000 ×1000 m grid resolution never changes, we know that two adjacent grid centre points are always within a distance of approximately 1415 metres and we can thus use a distance constrained neighbourhood search.
- It is fast.

Surname profiling



Van Dijk, J. T. & P. A. Longley. 2020. Interactive display of surname distributions in historic and contemporary Great Britain. *Journal of Maps* 16(1): 68-76

Conclusion

- Focused on point pattern analysis instead of relying on aggregation to administrative geographies, exploring various techniques.
- Chosen approach depends on the specific research question, such as characterising a point process or identifying clusters.
- Not all data may present themselves as clear candidates for these types of analyses.

Questions

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