

# Ward Typology for Community Resilience in England

Maria Fleitas and Simon Rudkin

Department of Social Statistics  
The University of Manchester

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# Motivation

Provide policymakers and emergency practitioners with a granular, community resilience based typology of English wards, that acknowledges the heterogeneity of communities:

- By using readily available census, NHS, and opendata sources
- Becoming an instrument to deliver targeted and efficient interventions.

# Background

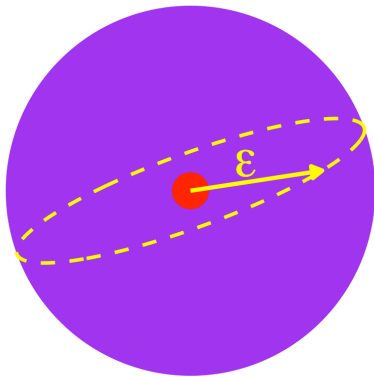
## Community Resilience:

- Community resilience is the ability to mitigate hazards, contain disaster effects, and recover to a stronger state, minimising social disruption and future risks, where a system can recover to a higher state than the pre-disaster state. (Masco, Z. O. Kammouh and Cimellaro 2022)

## Topological Data Analysis (TDA):

- Topological Data Analysis Ball Mapper (TDABM)* (Dotko 2019) is a TDA algorithm that transforms high-dimensional datasets into an interpretable two-dimensional graph, capturing and visualizing the underlying structure of the data. Making complex, high-dimensional structures intuitively interpretable.

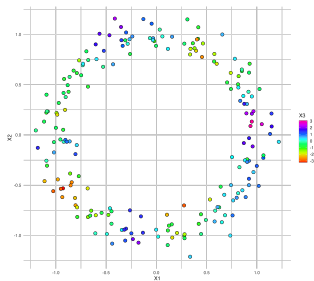
## How does the Ball Mapper. Dotko, P. (2019) work?



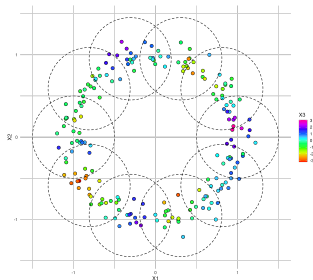
$\epsilon$  ball

- TDABM "covers" data with "balls" of fixed radius  $\epsilon$  and creates a 2D representation of the topology of the data
- Smaller values of  $\epsilon$  produce more granular clusters; larger values generalize more, offering flexibility in exploring.

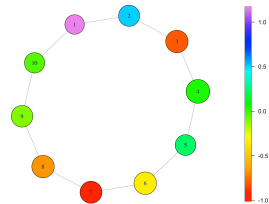
# Topological Data Analysis: Ball Mapper



(1) A scatterplot of data points in 2D just for illustration, but in practice can have many more dimensions. Each dot is colored by an outcome variable



(2) Points have been chosen so that every data point lies within distance  $\epsilon$  of at least one center. Around each chosen center, a ball of radius  $\epsilon$  is drawn.



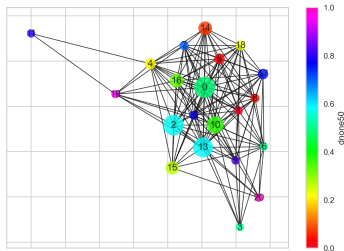
(3) Each node represents one of the balls. An edge is drawn between two nodes if their corresponding balls have at least one data point in common. Each node itself is colored by the average of the outcome variable.

# Data

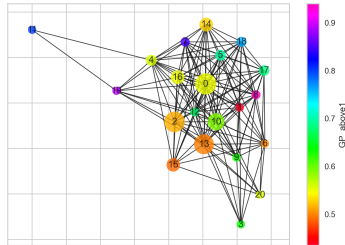
PEOPLES Component	Origin
Demographics: Density, Composition	Census 2021 (TS004, TS006, TS007, TS008, TS021)
Socioeconomic: Education, Income, Deprivation	Census 2021 (TS011, TS054, TS062, TS066, TS067)
Infrastructure: Education, Healthcare, Transport	Schools registry, NHS datasets, ONS airport shape-files

\*Selected PEOPLES framework variables

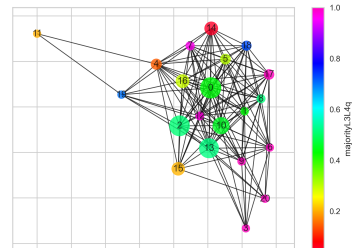
# Analysis of the communities



(a) 50% showing no levels of deprivation



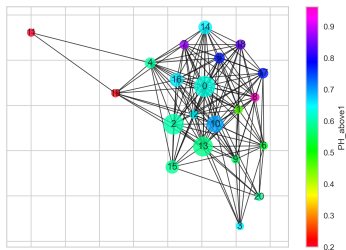
(b) Has at least 1 GP



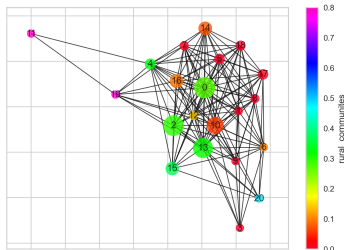
(c) Highly educated communities



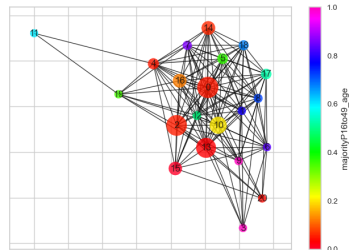
# Topological Data Analysis: Ball Mapper



(d) Has at least 1 Pharmacy

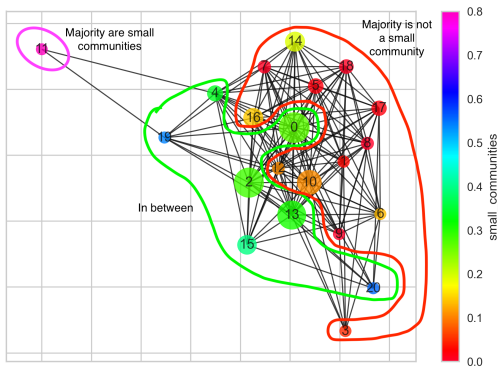


(e) Is a rural community



(f) Age bewteen 16 and 49

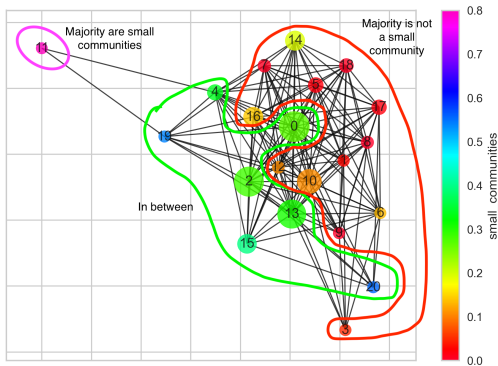
# Topological Data Analysis: Ball Mapper



## High Performing Communities

- **Cluster 3 and 9:** Predominantly urban wards in cities and large towns. Strong outcomes likely due to concentrated infrastructure and services.
- **Cluster 7 and 17:** High-performing residential neighborhoods within cities. These areas are suburban in character but well-connected to urban infrastructure.

# Topological Data Analysis: Ball Mapper

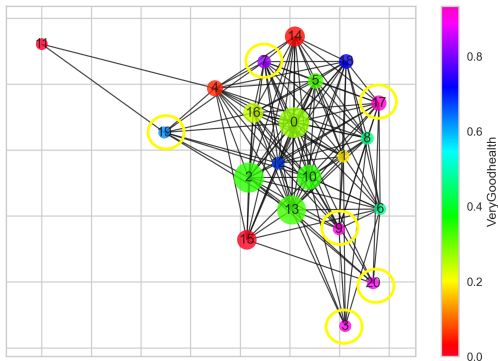


Is a small community

## High Performing Communities

- **Cluster 20:** Found on the periphery of cities like *London*, *Manchester*, and *Birmingham*. These wards combine rural quality of life with urban proximity, making them desirable and top-performing.
- **Cluster 19:** Small, semi-rural communities benefiting from nearby urban centers.

# Topological Data Analysis: Ball Mapper



## Very Good Health as an outcome variable

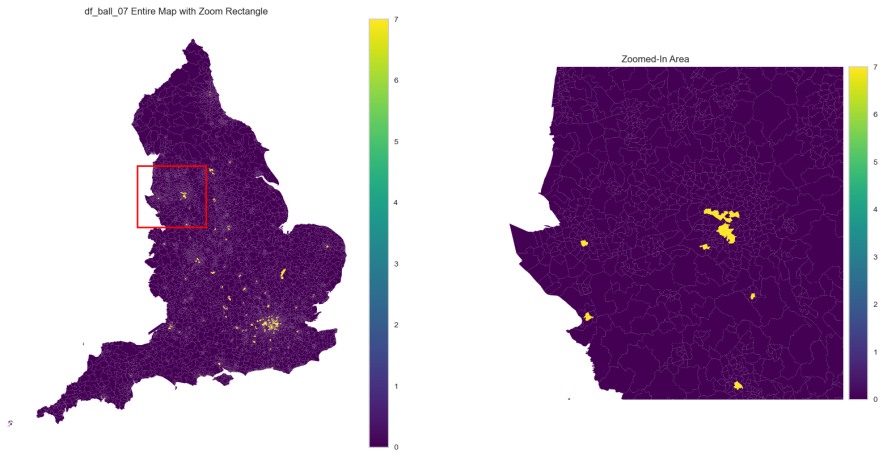
- All High Performing clusters also have a high percentage of participation of Very Good Health

Health can be used as an outcome to monitor resilience. Shin (2021)

# Ball Mapper: Membership Analysis

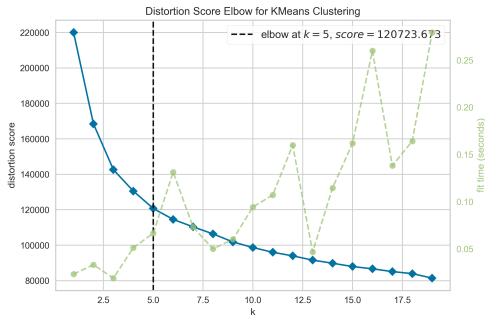
- Ball membership information is retained, allowing analysis of the regions identified
- Names of the member regions can be used to link practitioner insight
- Summary statistics tables can be computed for the ball members
- Mapping of ball membership highlights geographic distribution

# Topological Data Analysis: Ball Mapper



Map of England and zoomin area of Liverpool and Manchester, Ball 7

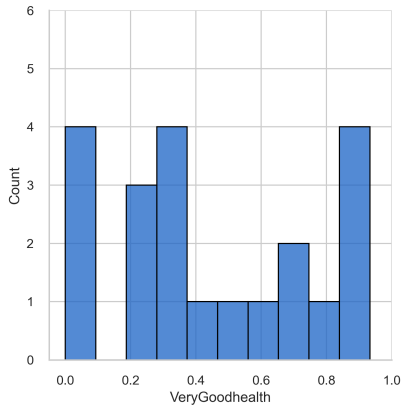
# k-means Comparison



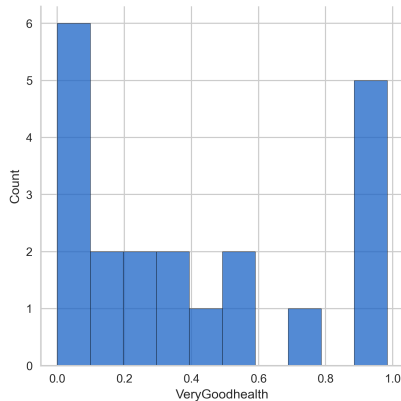
Elbow method

- **Cluster Count:** The elbow method suggests  $k = 5$  as the optimal number of clusters. K-means clustering quality depends heavily on the choice of  $k$ .
- **Separation and Detail:** K-means is sensitive to local density, K-means groups tend to concentrate around high-density values, underrepresenting lower-density regions.

# k-means Comparison



TDABM



k-means

Note: The distribution graph of Very Good Health across clusters formed by TDABM vs. k-means with  $k = 21$ . TDABM shows a more even distribution.



# Conclusion

## Conclusion

- This research developed a ward-level typology for community resilience in England using the Topological Data Analysis Ball Mapper (TDABM) algorithm.
- This approach aids policy making for disaster planning by highlighting structural connections often hidden in traditional clustering.
- Limitations include restricted data availability at the ward level and the subjective choice of TDABM's  $\epsilon$  parameter.

Thank you for listening !

maria.fleitasdelgado@manchester.ac.uk