INSTITUTE FOR EMPLOYMENT RESEARCH
The Research Institute of the Federal Employment Agency

AN OVERVIEW OF DATA PROTECTION STRATEGIES FOR INDIVIDUAL-LEVEL GEOCODED DATA

UNECE Expert meeting on Statistical Data Confidentiality

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BACKGROUND

- More and more geo-referenced data are being collected
  - Important for various research areas (e.g., to assess neighborhood effects, mobility patterns)
  - Highly identifying, availability for research is limited
  - IAB project on geo-referenced data → how to anonymize these data?
- Three main strategies for confidentiality protection
  - Aggregation
  - Geographic Masking
  - Synthetic data

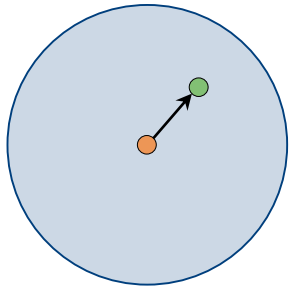
AGGREGATION

- Aggregation within pre-defined areas
  - Administrative areas
  - (Standardized) Grid cells
    - ⊕ External data can easily be linked
    - ⊖ Loss of spatial information
      Choice of aggregation level can bias results

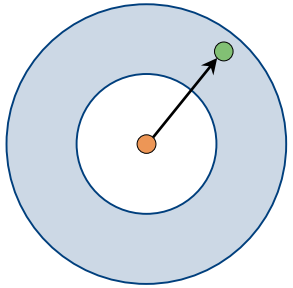
- Flexible aggregation
  - Population-adjusted grid cells
  - Microaggregation
    - ⊕ More efficient trade-off between confidentiality protection and utility
    - ⊖ Cannot easily be linkend to external data
      Harder to interprete

GEOGRAPHIC MASKING

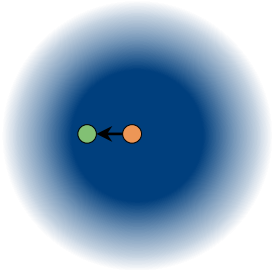
- Deterministic masking approaches
- Random perturbation
  - Original locations are randomly displaced
  - Different methods to draw maximum or minimum displacement distance
  - Possibility to adapt for population density



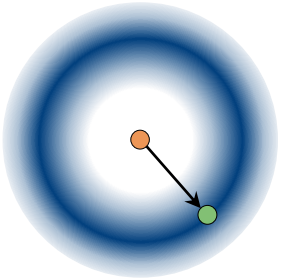
Displacement within a circle



Donut masking



Gaussian masking



Bimodal gaussian masking

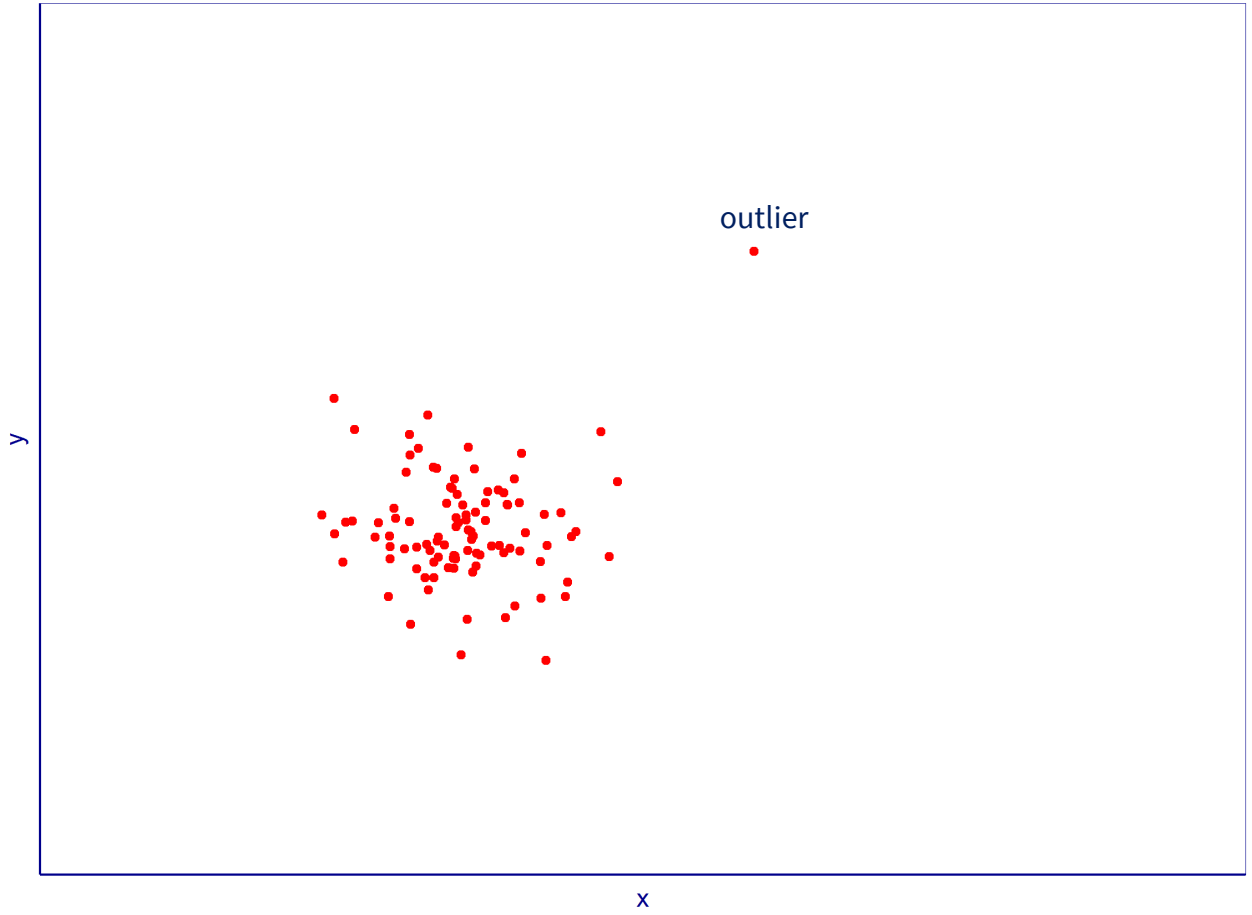
GEOGRAPHIC MASKING

- Deterministic masking approaches
- Random perturbation
  - Original locations are randomly displaced
  - Different methods to draw maximum or minimum displacement distance
  - Possibility to adapt for population density

⊕ Widely used, straightforward method
Point-locations as output

⊖ No guaranteed level of privacy protection, especially in rural areas or areas with heterogenous population density

GEOGRAPHIC MASKING SOMETIMES OFFERS LITTLE PROTECTION



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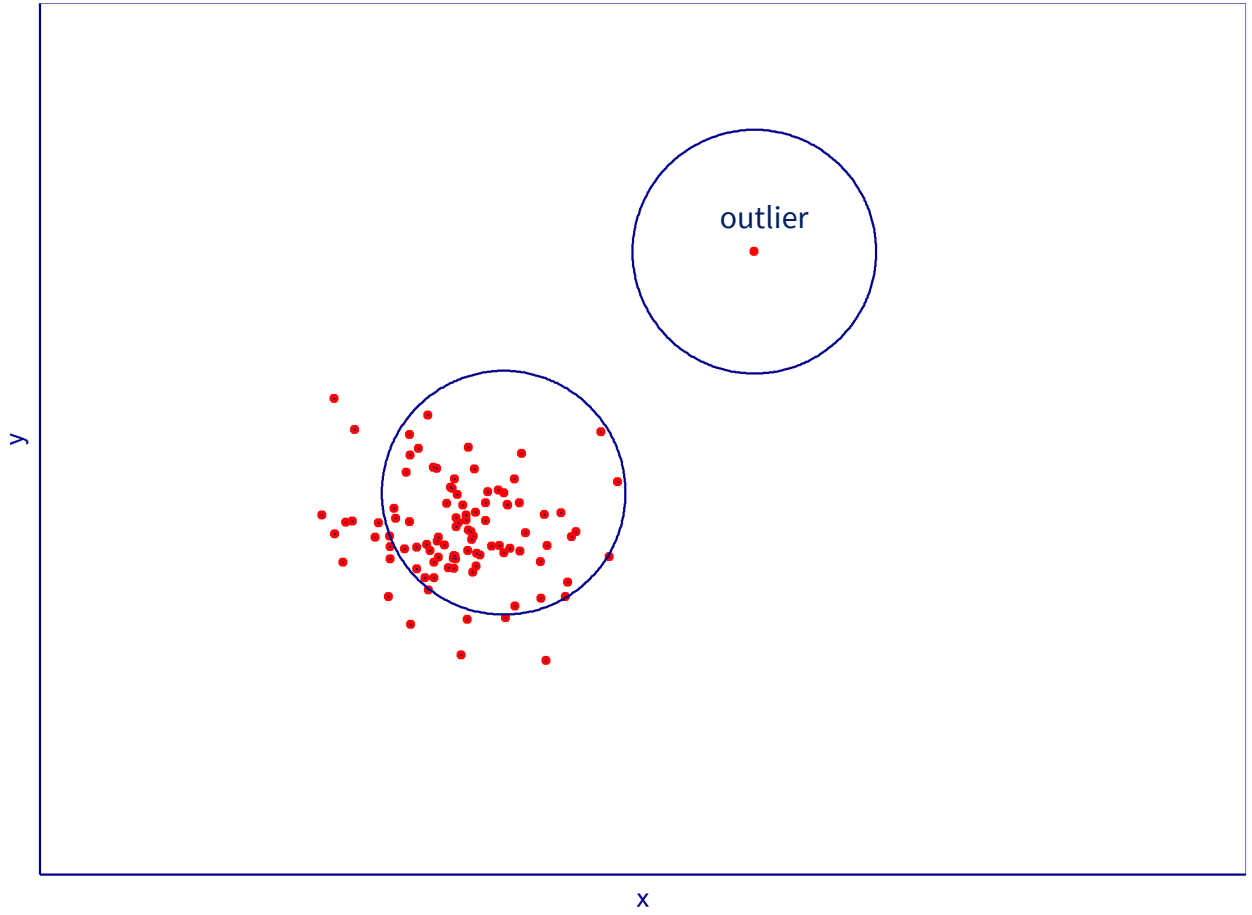

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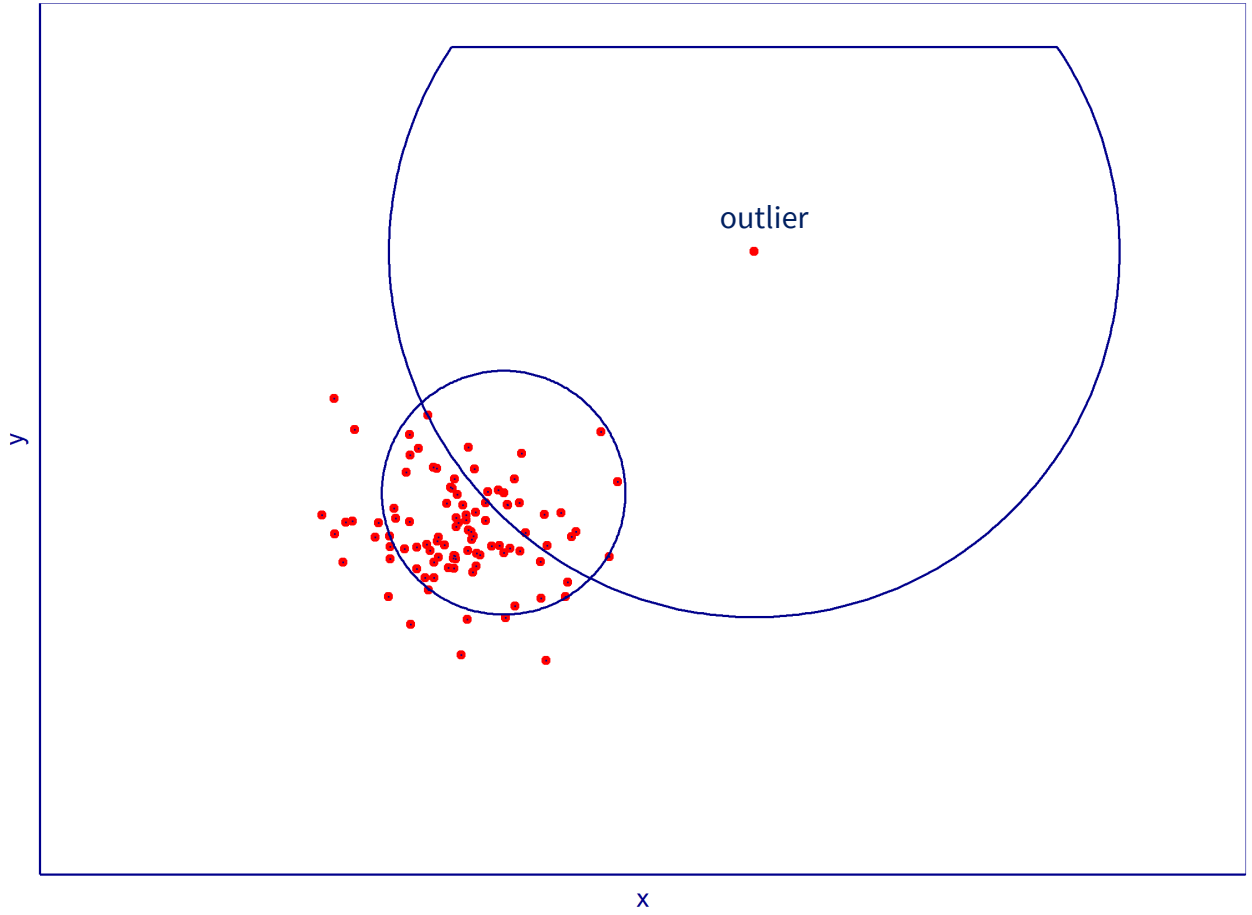

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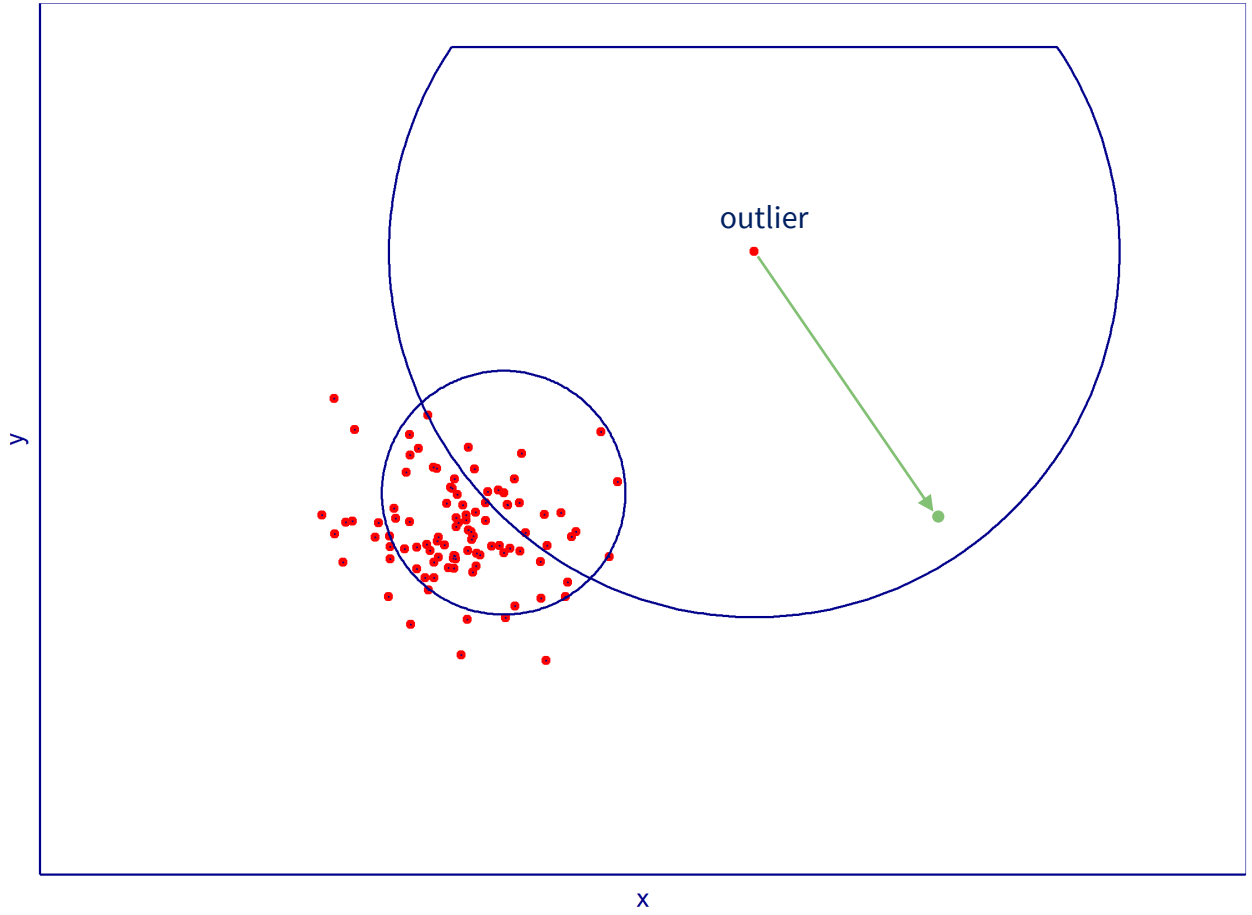


GEOGRAPHIC MASKING

- Location swapping (Zhang et al., 2017)
  - Original location is swapped with another location within a circle or donut
- Adaptive Areal Masking (Kounadi & Leitner, 2016)
  - random perturbation within pre-defined areas with at least k location points
  - Guarantees a certain level of anonymity
  - High alteration of locations

SYNTHETIC DATA

Synthesizing of non-geographic variables

- Account for spatial structure to synthesize non-geographic variables
- Data release
  - Detail level of geographic information
  - Separate release of 2 data sets (Koebe et al. 2023)

Synthesizing of geographic information

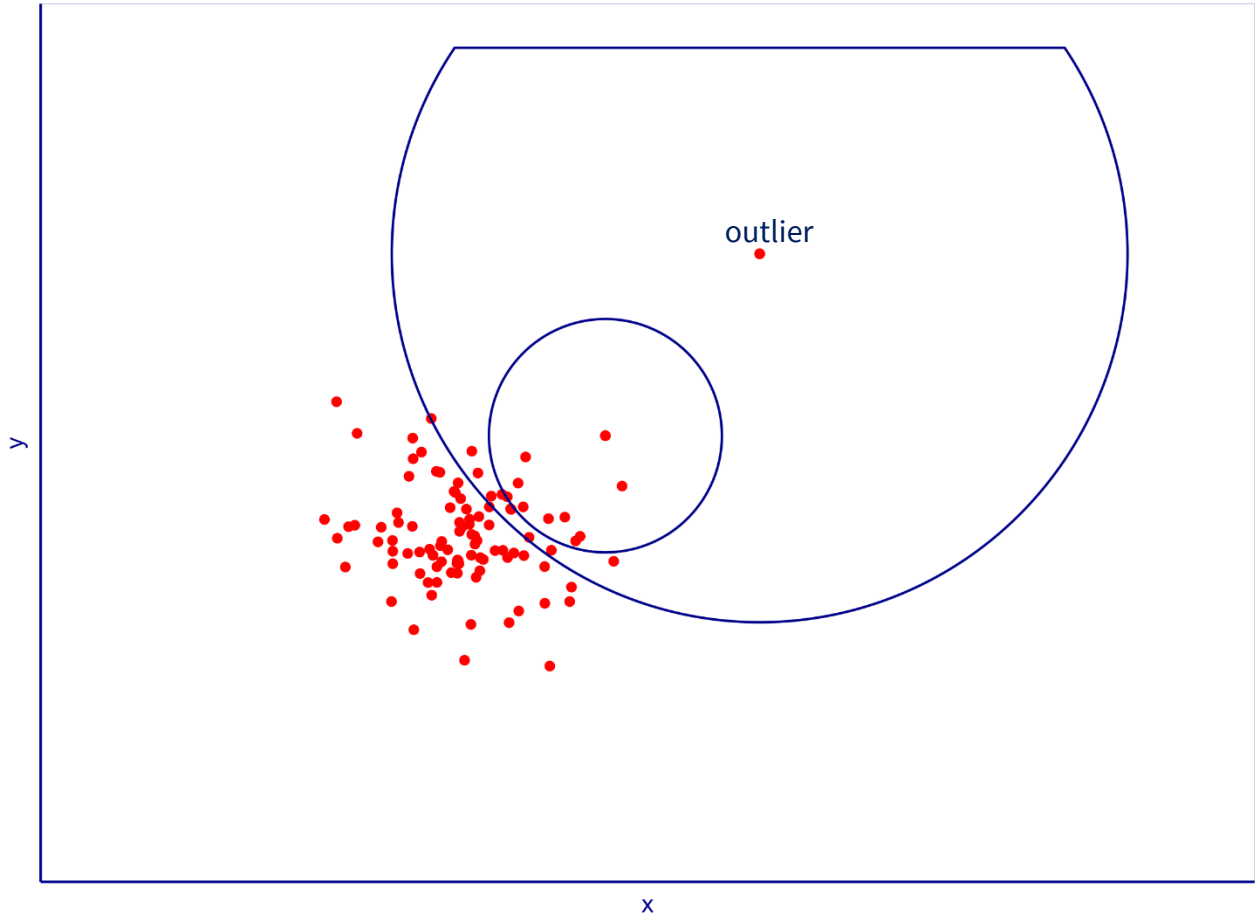
- Aggregated data (Quick, 2021; 2022; Paiva et al., 2014)
- Exact geographic coordninates (Wang & Reiter, 2012; Drechsler and Hu, 2021)
- Fully synthetic data (e.g., Quick et al., 2015)

RISK AND UTILITY ASSESSMENT

RISK ASSESSMENT

- K-anonymity
  - Definition: a record must be indistinguishable from at least $k - 1$ other records
  - Spatial k-anonymity for masking methods: measure the number of locations within a radius equal to the displacement distance
    (1) number of locations around the **original** point
    (2) number of locations around the **masked** location
  - Problems with this measurement
- Alternatives
  - Record linkage attacks (Drechsler and Hu, 2021; Quick et al. 2015)
  - Assessment of overfitting regarding spatial outliers (Quick et al. 2018)

SPATIAL K-ANONYMITY EXAMPLE



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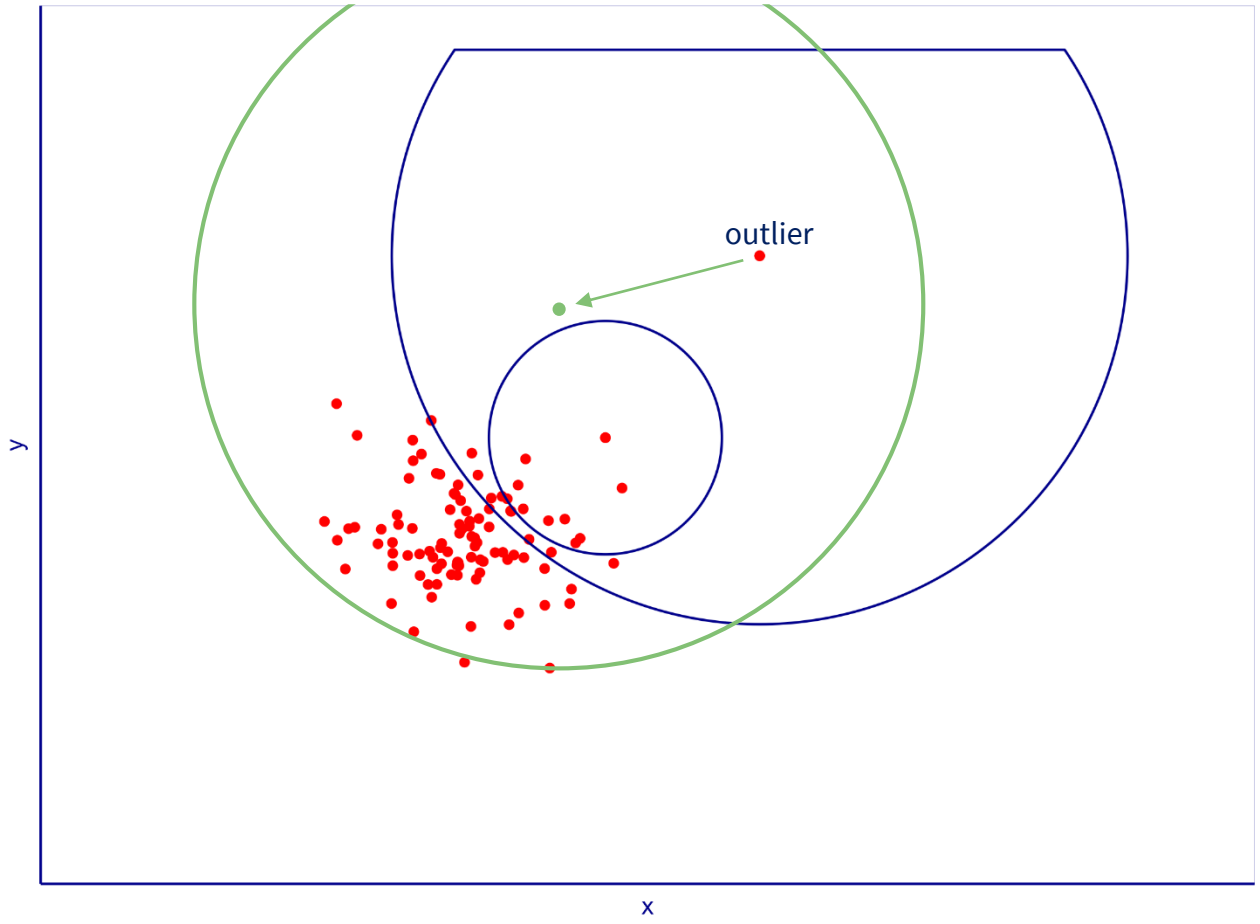


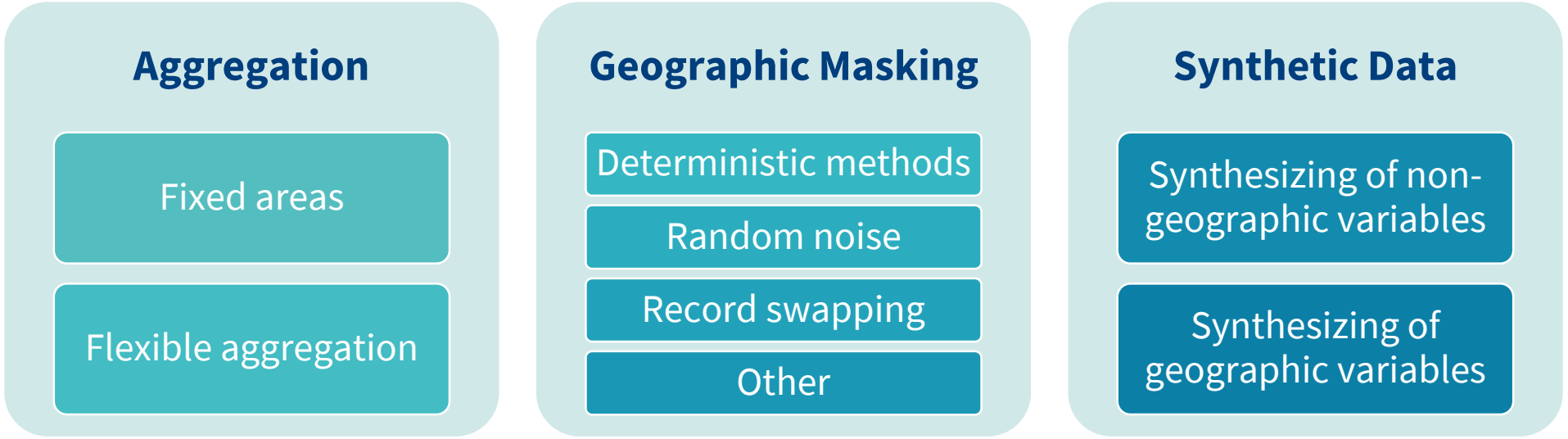
UTILITY ASSESSMENT

Comparison of original and anonymized data

1. Point locations and density measures
   - Distances between original and masked locations
   - Heatmaps using Kernel density estimation
2. Clustering
3. Spatial autocorrelation
4. Applied results

CONCLUSION

- Three main strands of confidentiality protecting strategies



- Some common masking techniques do not provide adequate confidentiality protection
- Common risk measures should be carefully evaluated

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