Detecting Duplicates in Geoinformatics: from Intervals and Fuzzy Numbers to General Multi-D Uncertainty

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1. Outline

- *Fact:* geospatial databases often contain duplicate records.
- it What are duplicates: two or more close records representing the same measurement result.
- *Problem:* how to detect and delete duplicates.
- *Test case:* measurements of anomalies in the Earth's gravity field that we have compiled.
- *Previously analyzed case:* closeness of two points (x_1, y_1) and (x_2, y_2) is described as closeness of both coordinates.
- *What was known:* $O(n \cdot \log(n))$ duplication deletion algorithm for this case.
- *New result:* we extend this algorithm to the case when closeness is described by an arbitrary metric.

2. Geospatial Databases: General Description

- *Fact:* researchers and practitioners have collected a large amount of geospatial data.
- *Examples:* at different geographical points (x, y), geophysicists measure values d of:
  - the gravity fields,
  - the magnetic fields,
  - elevation,
  - reflectivity of electromagnetic energy for a broad range of wavelengths (visible, infrared, and radar).
- *How this data is stored:* corresponding records (x_i, y_i, d_i) are stored in a large geospatial database.
- *How this data is used:* dased on these measurements, geophysicists generate maps and images and derive geophysical models that fit these measurements.

3. Gravity Measurements: Case Study

- *Typical geophysical data* (e.g., remote sending images):
  - mainly reflect the conditions of the Earth's *surface*;
  - cover a reasonably *local* area.
- *Gravity measurements:*
  - gravitation comes from the whole Earth, including *deep* zones;
  - gravity measurements cover *broad* areas.
- *Conclusion:* gravity measurements are one of the most important sources of information about subsurface structure and physical conditions.

4. Duplicates: Where They Come From

- *Fact:* the existing geospatial databases contain many duplicate points.
- *Reason:*
  - databases are rarely formed completely "from scratch";
  - they are usually are built by combining measurements from previous databases;
  - some measurements are represented in several of the combined databases.
- *Conclusion:* after combining databases, we get duplicate records.

5. Why duplicates Are a Problem

- *Main reason:* duplicate values can corrupt the results of statistical data processing and analysis.
- *Example:*
  - when we see several measurement results confirming each other,
  - we may get an erroneous impression that this measurement result is more reliable than it actually is.
- *Conclusion:* detecting and eliminating duplicates is an important part of assuring and improving the quality of geospatial data.

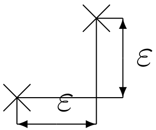
6. Duplicates and Related Uncertainty

- *Ideal case:* measurement results are simply stored in their original form.
- *In this case:* duplicates are identical records, easy to detect and to delete.
- *In reality:* databases use different formats and units.
- *Example:* the latitude can be stored in degrees (as 32.1345) or in degrees, minutes, and seconds.
- *As a result:* when a record (x_i, y_i, d_i) is placed in a database, it is transformed into this database's format.
- *Fact:* transformations are approximate.
- *Result:* records representing the same measurement in different formats get transformed into values which correspond to close but not identical points"

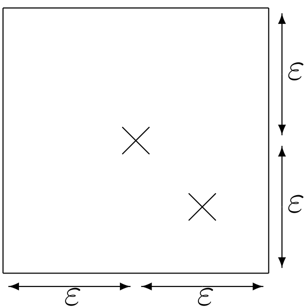
$$(x_i, y_i) \neq (x_j, y_j).$$

7. Duplicates Corresponding to Interval Uncertainty

Geophysicists produce a threshold $\varepsilon > 0$ such that ε-closed points (x_i, y_i) and (x_j, y_j) are duplicates.



In other words, if a new point (x_j, y_j) is within a 2D *interval* $[x_i - \varepsilon, x_i + \varepsilon] \times [y_i - \varepsilon, y_i + \varepsilon]$ centered at one of the existing points (x_i, y_i), then this new point is a duplicate:



8. Duplicates Are Not Easy to Detect and Delete

- *Problem:* detect and delete duplicates.
- *How this is done now:* "by hand", by a professional geophysicist looking at the raw measurement results (and at the preliminary results of processing these raw data).
- *Limitations:* time-consuming.
- *Natural idea:* use a computer to compare every record with every other record.
- *Analysis:* this idea requires $\frac{n(n-1)}{2} \sim \frac{n^2}{2}$ comparisons.
- *Limitation:* this is impossible for large databases, with $n \approx 10^6$ records.
- *Conclusion:* faster algorithms are needed.

9. From Interval to Fuzzy Uncertainty

- *Typical situation:* geophysicists provide several possible threshold values $\varepsilon_1 < \varepsilon_2 < \ldots < \varepsilon_m$ that correspond to decreasing levels of their certainty:
  - if two measurements are ε_1-close, we are 100% certain that they are duplicates;
  - if two measurements are ε_2-close, then with some degree of certainty, we can claim them to be duplicates, etc.
- *Objectives:*
  - eliminate *certain* duplicates, and
  - mark *possible* duplicates (about which we are not 100% certain) with the corresponding degree of certainty.
- *Reduction to interval case:* we need to solve the interval problem for several different values of ε_i.

10. What We Did in Our Previous Work

- *Previously analyzed case:* ε-closeness of two points (x_i, y_i) and (x_j, y_j) is described as ε-closeness of both coordinates.
- *Geometric reformulation:* the set of all points which are ε-close to a given point is a box.
- *Result of the analysis:* there exists efficient $O(n \cdot \log(n))$ algorithms for detecting and deleting outliers.
- *More general situation:* when ε-closeness is described by an arbitrary metric: e.g., Euclidean metric

$$d((x_i, y_i), (x_j, y_j)) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

  or l^p-metric

$$d((x_i, y_i), (x_j, y_j)) = \sqrt[p]{|x_i - x_j|^p + |y_i - y_j|^p}.$$

- *What we do now:* extend the existing algorithms to this more general metric situation.

11. Formalization of the Problem

- By a *metric*, we mean a triple (S, c, C), where
  - $S \subseteq R^m$ is a convex set that contains 0, and
  - $c > 0$ and $C > 0$ are numbers

  such that:
  - S is *symmetric* (i.e., for every point r, we have $r \in S$ if and only if $-r \in S$) and
  - $[-c, c] \times \ldots \times [-c, c] \subseteq S \subseteq [-C, C] \times \ldots \times [-C, C]$.
- We say that points r and r' are ε-*close* if $\dfrac{r - r'}{\varepsilon} \in S$.
- *Comment:* the property of c means that S contains all points close to 0.
- *Example of interval uncertainty:* S is a cube:

$$S = [-1, 1] \times \ldots \times [-1, 1].$$

12. New Algorithm: General Description

- *Stage 1:* for each record, compute the indices

$$p_i = \lfloor x_i/(C \cdot \varepsilon) \rfloor, \ldots, q_i = \lfloor y_i/(C \cdot \varepsilon) \rfloor.$$

- *Stage 2:*
  - Sort the records in lexicographic order $\leq$ by their index vector $\vec{p}_i = (p_i, \ldots, q_i)$.
  - If several records have the same index vector, check whether some are duplicates of one another, and delete the duplicates.
  - As a result, we get an index-lexicographically ordered list of records: $r_{(1)} \leq \ldots \leq r_{(n_0)}$ $(n_0 \leq n)$.

- *Stage 3:* For i from 1 to n_0, we compare the record $r_{(i)}$ with all its $\leq$-following "immediate neighbors" $r_{(j)}$:

$$|p_{(i)} - p_{(j)}| \leq 1, \ldots, |q_{(i)} - q_{(j)}| \leq 1.$$

If $r_{(j)}$ is a duplicate to $r_{(i)}$, we delete $r_{(j)}$.

13. Possibility of Parallelization

- *Problem:* for large n, an $O(n \cdot \log(n))$ algorithm still requires too much time.
- *Possible solution:* if we have several processors that can work in parallel, we can speed up computations.
- *Example:* we have $n^2/2$ processors.
- *Simple result:* by assigning each pair (r_i, r_j) to a different processor, we can detect and delete all duplicates in one step.
- *Other parallelization results:*
  - If we have at least n processors, then we can delete duplicates in time $O(\log(n))$.
  - If we have $p < n$ processors, then we can delete duplicates in time $O\left(\left(\frac{n}{p}+1\right)\cdot\log(n)\right)$.

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