Active Learning Approach to Record Linking in Large Geodatasets

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November 2020

AUTOCARTO 2020
Virtual Meeting
Introduction

Integration of diverse datasets
• Very common task in geodata domain
• Technical issues
  – file formats
  – data transfer
  – projections
  – etc.
• Most technical issues have been solved

Present challenges
• Variety
  – Semantic diversity: Pols, historic maps, OSM, traditional map products
• Volume
  – Dozens millions of features in a dataset is a new norm
• Automation is needed to make data integration feasible
Problem Statement

• Detect records that refer to the same real-world entity
  – Also this is known as conflation, data matching, record linking, entity resolution or alignment

• Goals of matching
  – Creation of a new datasets that incorporates original data in part or as a whole
  – Cross-verification of the datasets
  – Filling the gaps
  – Updating with newly acquired records
  – Establishing sameness or other types of relations among the features
Earlier Work

• Conflation outside of geodata domain
  – problem formulated as early as 1960s
  – Medical records
  – Census data
  – Bibliographies, product catalogues, inventories, ...

• Geodata conflation: the term used since ca. 1985 at AutoCarto
  – Early work: geometric alignment of features
  – Present interest: VGI
    • NGA Hootenanny: https://github.com/ngageoint/hootenanny
  – Methods
    • Machine Learning – reduce hardcoded matching rules
Record Linking Workflow

- **Preprocessing**
  - conversion to common format or API

- **Pairwise similarity**

- **Classification of pairs**
  - matches
  - possible matches
  - none-matches

- **Evaluated for correctness**
  - some matches may be reconsidered
Challenges Matching Medical and Census Records

• An entity having multiple records in different or in the same datasets
• Records often entered lack a common identifier or identifiers are wrong
  – e.g., SSN should never be trusted
• Matching is achieved by
  – comparing salient attributes
  – discounting data entry errors
  – controlling spelling variations
  – handling missing values
  – detecting special circumstances like change of name or gender.
Semantics of Matching Geographic Features

- Locational information
- Generalization and scale
- Geographic categories
- Temporality: updates and change
- Relations among the objects
- Geophysical fields

What does it mean to be the same in the geographic space?
Locational Information

• Reduces number of potential matches
  – Safe to assume that nearby or overlapping features are at least related or the same real-world object

• Positional accuracy
  – multiple match candidates may fall within error bounds
  – significant problem in VGI
  – lack of attribute-level matching significantly reduces confidence
  – mixing up with neighbors
Geographic Categories and Feature Definitions

• Assumption: matched records should describe real-world objects of the same feature class
  – No such problem in medical and census records

• Same category objects occupying the same space
  – Administrative unit vs. municipality with the same name

• Compatibility of feature definitions
  – Convenience store and a gas station

• Problem of the subcategory “other”
Generalization

• Matching across scales
• Link multiple records with different geometric representations
• Different positional accuracy at different scales
Temporality

• Very large range of temporal intervals
• Emerging, disappearing and changing objects vs. dataset updates
• Changing category
  – A province becomes an independent country
  – Lighthouse vs. museum
  – Restaurant replaced with barbershop
• Changing location
  – Settlement moved due to dam construction
  – Building physically moved
  – Islands merge
Object Relations

• Examples
  – Bridge and its pillars
  – Rock and a group of rocks
  – Museum and a restaurant
  – An arena and a gate
  – Building and main entrance

• Relations cannot be always expressed in the database schema
Case Study: Digital Nautical Chart by NGA

- Public domain data
  - [https://dnc.nga.mil/](https://dnc.nga.mil/)
- More than 4 million features
- 4 scale levels
  - features at different scales are not linked to each other
- Significant temporal span of the data collection events
- Expectation of highly reliable results
Approach

• Goal: highly automated process
  – close to 100% reliability required

• Recommender system with active machine learning learning
  – Each match must be approved by an analyst
  – Analyst feedback is fed back to ML to improve further recommendation

• Steps
  – Preprocessing: all feature loaded into a single table
  – Classification based on minimal distance and a feature class
    • Matches: within predefine accuracy with exact attribute match
    • None-matches: if distance exceeds predefined threshold
    • The rest are possible matches
  – Possible matches are handled by the recommender system
Recommender System

- **Recommender Systems** are tools that support user decision making by suggesting items that they are interested in.

- **Active Learning (AL)** incorporates a user’s response to its recommendations and re-trains the model to improve recommendations over time.

- **Goal** is to provide initially useful and continuously improved recommendations.

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**Target**
Harbor, Cell tower A, point feature, 300ft, 100Watt

**General**
None

**Approach**
- 🎁 90% Cell tower, point feature, 300ft, NA
- ☹️ 63% Cell tower (north beach), point feature, 200ft, 2003 Design
- ☹️ 23% Cell, point feature, 200ft, Gray

**Coastal**
- ☹️ 63% Cell tower (north beach), point feature, 200ft, 2003 Design
- ☹️ 18% Tower, polygon, 200ft, Gray

- 🎁 Reciprocating best match
- ☹️ Pairs better with another entity
- 🎁 Matched
- 🎁 Unmatched
Similarity Vector

\[ S_{i,j} = [d_1, d_2, \ldots, a_1, a_2, \ldots] \]

- **Geographic proximity**
  - minimal Euclidean distance
  - Hausdorff and Fréchet distances
  - percentage of the buffered overlap

- **Attribute similarity**
  - physical measurements: normalized difference
  - categorical values: exact match/not
  - entity names: Levenshtein distance
  - sets of attributes: Jaccard coefficient
Similarity Score

\[
\text{Score} = \begin{bmatrix} d_1, d_2, \ldots, a_1, a_2, \ldots \end{bmatrix} \cdot \begin{bmatrix} w_{d1}^0 \\ w_{d2}^0 \\ \vdots \\ w_{a1}^0 \\ w_{a2}^0 \\ \vdots \end{bmatrix}
\]

- Weights are adjusted after each recommendation using Hierarchical Bayesian Logistic Regression.
Summary

- Summary of the challenges for feature matching in diverse geodatasets
- Outline for a recommender-based active learning record matching system
- Potential improvements: adding more dimensions to the similarity vector
  - Neighbourhood measures
  - Text similarity between description categories
Questions?
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