Geotagging Non-Spatial Concepts

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MOTIVATION

A user wants to identify points of interest (POI) on the map that match his query ...

Results

Query 1: Find *locations* that are **responsible for pollution**

Query 2: Find *locations* that are **related to crime**

Query 3: Find *locations* that are **associated with health**

Non-Spatial Concepts

Question:
How to find locations on the map that are
***related* to** non-spatial concepts?

KEY OBSERVATIONS

- Using the ***semantic information*** associated with concepts for identifying relations between spatial and non-spatial concepts

- Probing the ***textual co-occurrences*** of spatial and non-spatial concepts for identifying relations between spatial and non-spatial concepts

- Generalizing the relatedness based on the ***concepts type*** instead of relatedness between two specific concepts
  - **Example**:
    - **Query:** Find locations related to **Research** in the **United States**
    - **Expected Output:** Display all locations of type '**School**', '**University**' within **United States**

CHALLENGES

- How to ***represent co-occurrences*** of spatial and non-spatial concepts within the same textual resource
- How to ***infer the types*** of spatial concepts that are semantically related to the non-spatial query concept
- How to ***evaluate*** given that there is no known dataset for type-relatedness between spatial and non-spatial concepts

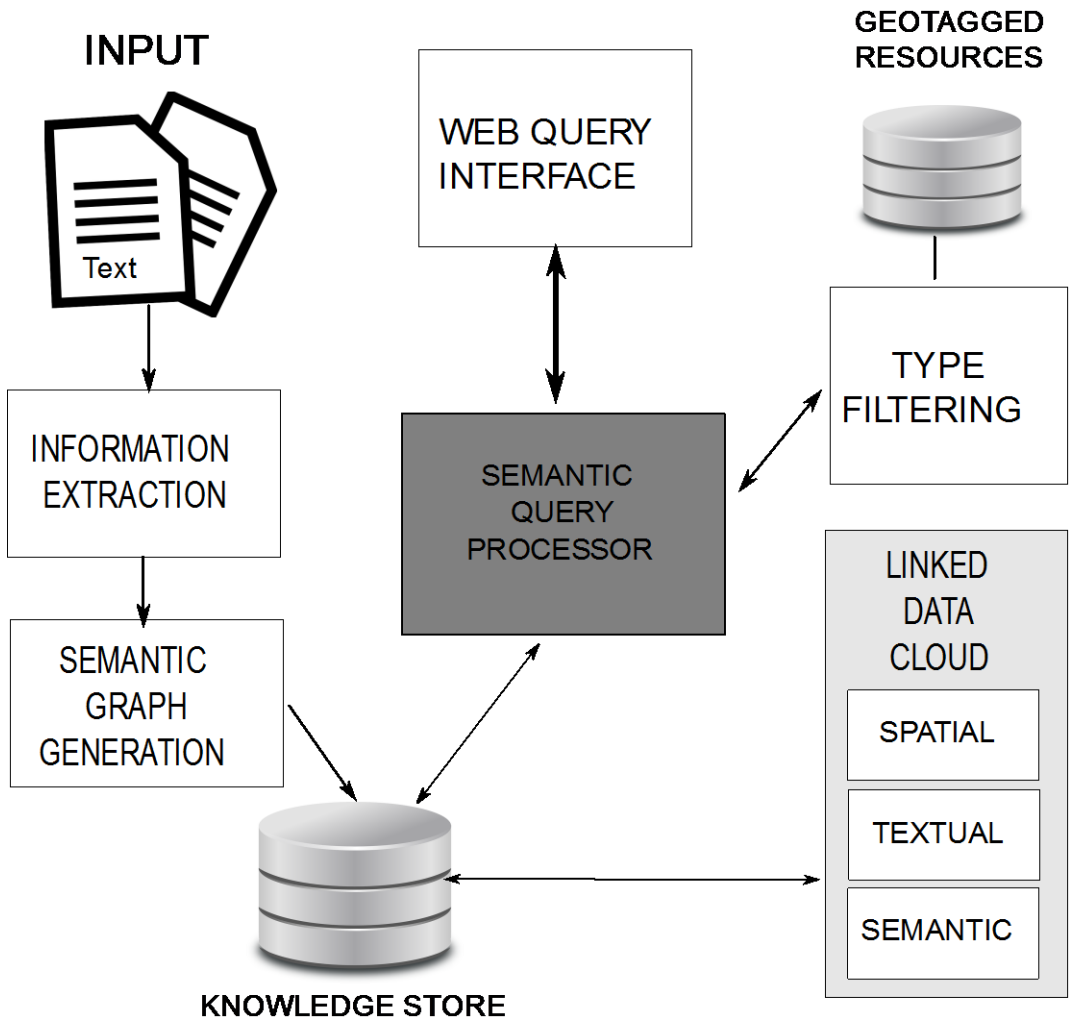
CONTRIBUTION

- We propose **CGTag**, a system for ***geotagging*** a non-spatial concept query with spatial concepts based on ***type relatedness***
- We propose a ***semantic query-processing algorithm*** that utilizes several Linked-Data-based filtering strategies
- We propose ***an evaluation method*** for type relatedness in addition to a baseline to determine the correctness of the results

REPRESENTING CO-OCCURRENCES

- **Hypothesis**
  - "***All concepts mentioned in the same textual resource are implicitly related to each other***"
  - **Example**: A single text document can have (Pollution – Factory – Industry – Waste)
- A clique can be used to represent the concepts co-occurrences
  - Vertex → Concept
  - Edge → Weighted Relation
- Using Cliques
  - To indicate a ***single*** (initially) co-occurrence between the concepts and each other

ARCHITECTURE



COMPONENTS

- **Information Extraction**
  - Identification, disambiguation, entity linking
  - Example: <dbpedia.org/resource/Barack_Obama>**Obama**</>
- **Graph Construction**
  - Construct a **local graph** (document level)
  - A clique is used to represent a single (initially) co-occurrence of a concept with other concepts in the same document
- **Knowledge Store**
  - Online Mode: Answer user queries
  - Offline Mode: Store the result of the local graph construction to a **global graph**

COMPONENTS

- **Semantic Query Processor (SQP)**
  - Infer the types of spatial concepts in the global graph that are most related to the non-spatial concept query
  - ***Parameters***
    - **Input**: the non-spatial concept query
    - **Output**: a location of interest
  - ***Filtering steps***
    - **Co-occurrence threshold** – Co-occurrence frequency/weight
    - **Linked Data properties** – Ontology Type, Spatial Information
      - ***Example***: ***Type:Building*** - Superclass of (Hotel, Restaurant, Shopping Mall, Castle, HistoricBuilding)
    - **Similarity Filtering** - Pairwise document similarity between the textual resources of the concepts (TF-IDF as a representation)

COMPONENTS

- **Type Filtering of Non-Spatial Concepts**
  - Determine the spatial concepts that have a type that matches the types deduced by the semantic query processor
  - If a location is specified in the query, then the location acts as a filtering criteria for the spatial concepts
  - **Example**: Semantic Query Processor proposes: "Art"
    - Spatial linking module attempts to match the type "Art" against the types of geo-tagged resources.
    - If location is specified such as "NYC" then the linking is restricted to "NYC" only

EXPERIMENTAL SETUP

- **CGTag** is evaluated based on two overlapping factors:
  - **Query processing filtering efficiency**
    - Each filtering criteria is evaluated separately and then in combination with each other
    - The number of remaining concepts are observed after each filter has been applied
  - **The accuracy of the type relatedness**
    - Presented 9 evaluators with 30 arbitrarily selected non-spatial concept queries.
    - Given a non-spatial concept, the objective is to understand what would be the expected types of spatial concepts in the result.
      - **Example**: Fishing is more related to ‘Island’ and ‘City’ types than ‘School’ and ‘University’

EXPERIMENTAL SETUP

- **Collections and Datasets**
  - **Wikipedia**: 178K articles
  - **DBPedia**: Rich medium for interlinking the concepts mentioned in Wikipedia with other collection
  - **Linkedgeodata**: Spatial Information + Interlinking dataset
    - An interlinking dataset indicates what a resource in one dataset corresponds to in another dataset
      - **Example**: Obama (DBPedia) → Obama (Wikipedia)
- **Baseline**
  - The co-occurrence threshold is used as the baseline
- **Concept Extraction**
  - DBPedia Spotlight – Provides identification, disambiguation and entity linking

EXPERIMENTAL SETUP

- **Queries**

Query	Airport	City	Island	Mountain	School	Stadium	University
Research	0	0	0	0	1	0	1
Fishing	0	1	1	0	0	0	0
Broadcasting	1	1	0	0	0	1	1

Use Case:

- **Online Phase:** Find locations related to **Science** in the **United States**
- **Semantic Query Processor Output:** School, University
- **Type Filter Output:** Show all locations of type '**School**', '**University**' within **United States**

EXPERIMENTAL SETUP

- Interlinking Dataset
  - We use the criteria as the target ‘Type’ for the queries

Criteria	USA	GERMANY	UK
Airport	3128	27	109
City	8469	7409	4521
Island	92	0	45
Mountain	887	76	587
School	2026	7	154
Stadium	55	6	8
University	70	4	25

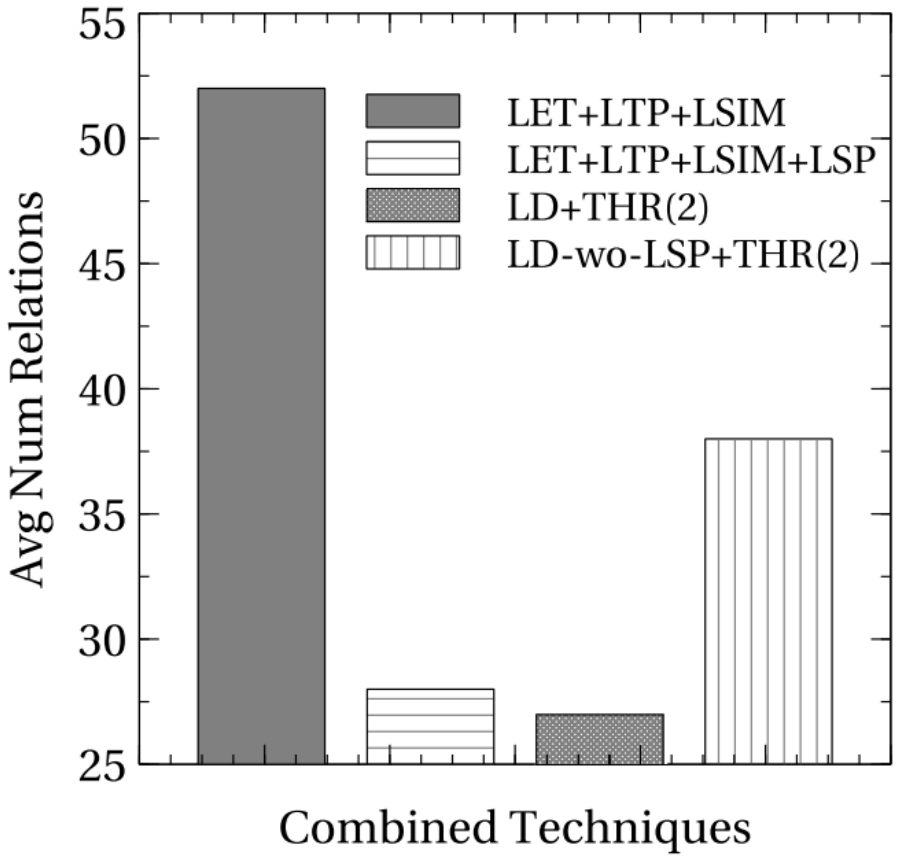
RESULTS

- Type Relatedness Evaluation
  - All linked data filters in addition to the co-occurrence similarity provide the highest accuracy across 3 datasets

Technique	USA	UK	Germany
Linked Data without Similarity	0.43	0.43	0.42
Linked Data with Similarity	0.69	0.7	0.78
Co-occurrence Threshold (3)	0.78	0.68	0.06
Linked Data without Similarity + Threshold (3)	0.53	0.53	0.52
Linked Data with Similarity + Threshold (3)	0.72	0.73	0.76

RESULTS

- **Query processing filtering efficiency**
  - **Evaluated**:
    - LET: Linked Data Type Expansion
    - LTP: Linked Data Type Pruning
    - LSIM: Similarity Pruning
    - LSP: Spatial Pruning
    - THR(2): Co-occurrence filtering with weight 2
    - Linked Data (all) filters
  - **Result**:
    - Linked Data filtering (all) + co-occurrence achieves the highest filtering efficiency while still maintaining a good accuracy



CONCLUSION

- Presented **CGTag**, a system for discovering type relatedness between spatial and non-spatial concepts
- Demonstrates how co-occurrences can be used as a means for discovering implicit relationships between non-spatial and spatial concepts
- Presented a query-processing algorithm that identifies the spatial types related to a query-specified non-spatial concept
- The type-relatedness accuracy averages at 73%

Thank you