

Introduction & Motivation

In the United States, floods are the second deadliest of all-weatherrelated hazards with approximately 98 deaths per year [2]. Planning for flooding events is critical to mitigate their impacts on society. When it comes to handling information about disasters, planning and responding agencies needs to collaborate together. However, it is hard for different groups to share information because they use different systems for managing large amounts of data and information. This makes it complicated to organize and share information in a way that everyone can understand it. Also, it is harder to coordinate effectively, which can slow down response efforts.

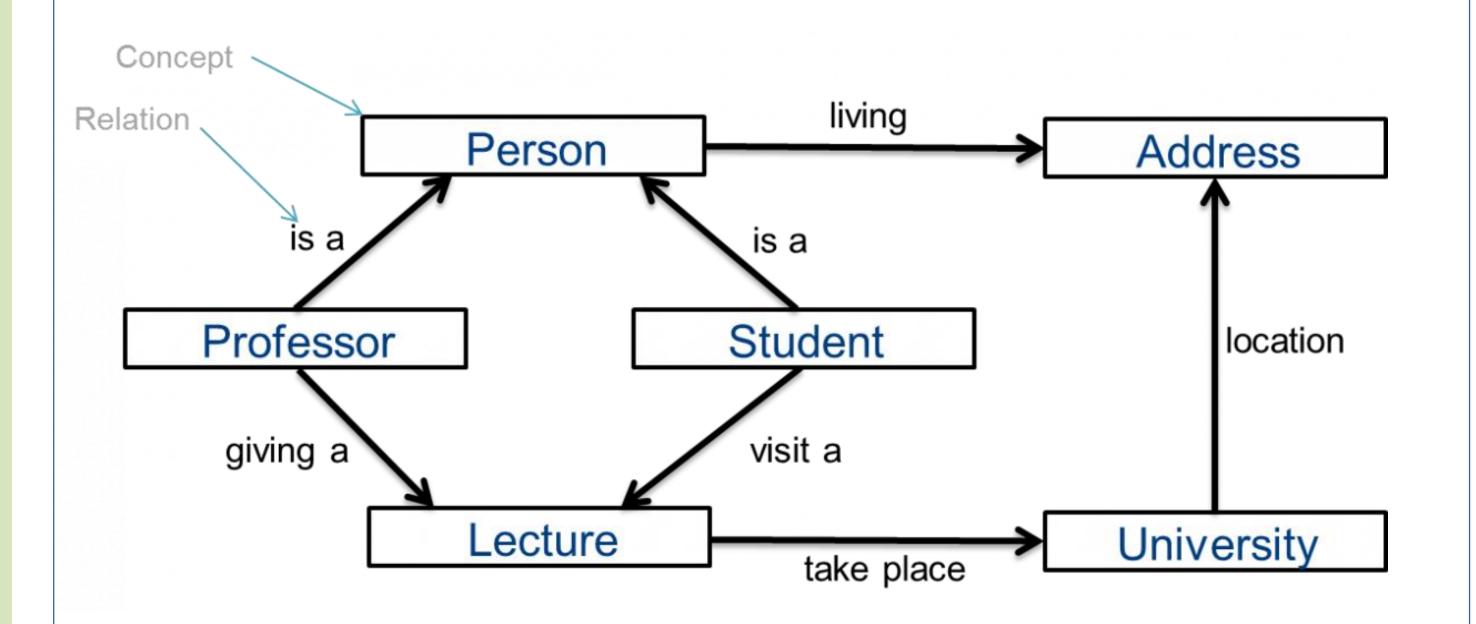


Figure 1. Example of an Ontology [3]

Ontologies present a domain of knowledge, which contains concepts and relationships between the concepts [5]. Ontologies can be used to organize unstructured data, such as text data into a formal conceptualization of a particular domain [1]. However, the process of creating hazard ontologies requires domain expert and it is a time and effort-intensive process.

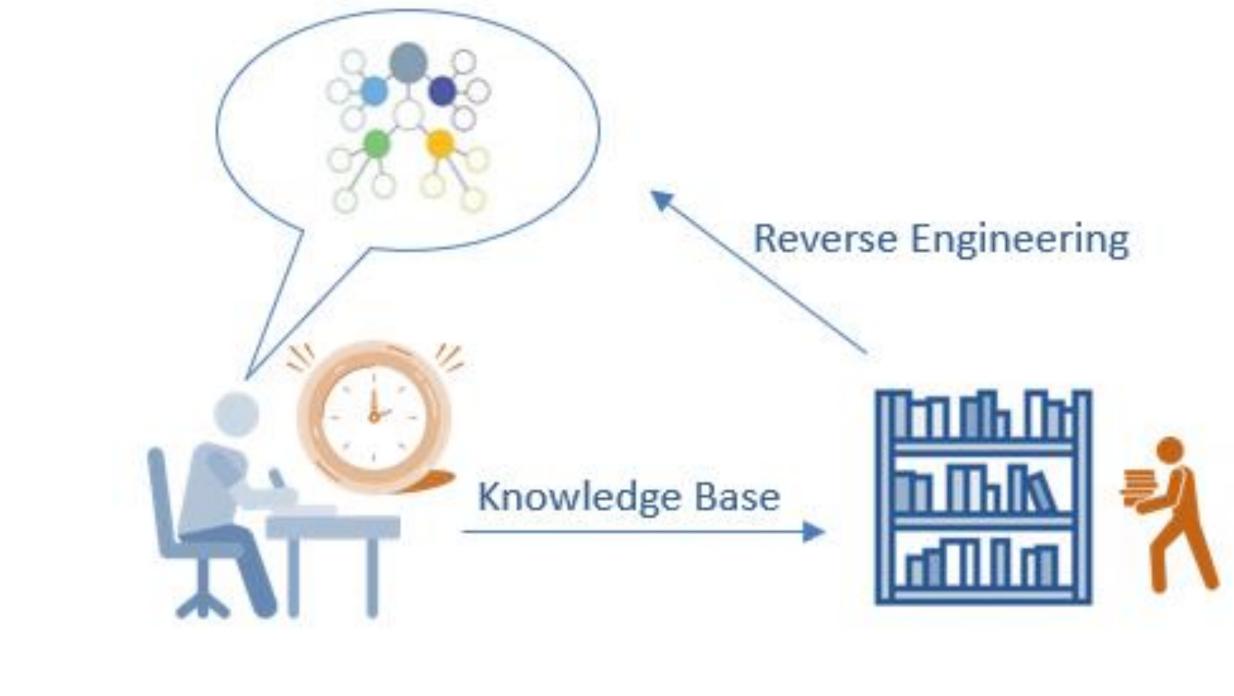


Figure 2. Research Problem

Contact

Sundos Al Subhi salsubhi1@student.gsu.edu College of Arts and Sciences Department of Computer Science Disaster Informatics & Computational Epidemiology

Ontology Learning System (OLS)

Sundos Al Subhi, Dr. Chetan Tiwari, and Dr. Armin R. Mikler Department of Computer Science, Georgia State University

Research Objective

Research objective focuses on applying ontology learning techniques to automate the development of hazard-specific ontologies from knowledge bases of disaster-related information (e.g., scholarly articles).

Dataset & Methods

Dataset: Academic papers, technical reports, and authoritative web resources (e.g., Federal Emergency Management Agency (FEMA)).

Methods:

Ontology learning has been used to automate the construction of ontologies through the development of automated techniques to extract terms, synonyms, concepts, taxonomies, etc. from different data sources [6].

An Ontology Learning System (OLS) is a large and complex framework that encompasses various steps including data processing and information extraction. The steps within the (OLS) are the following:

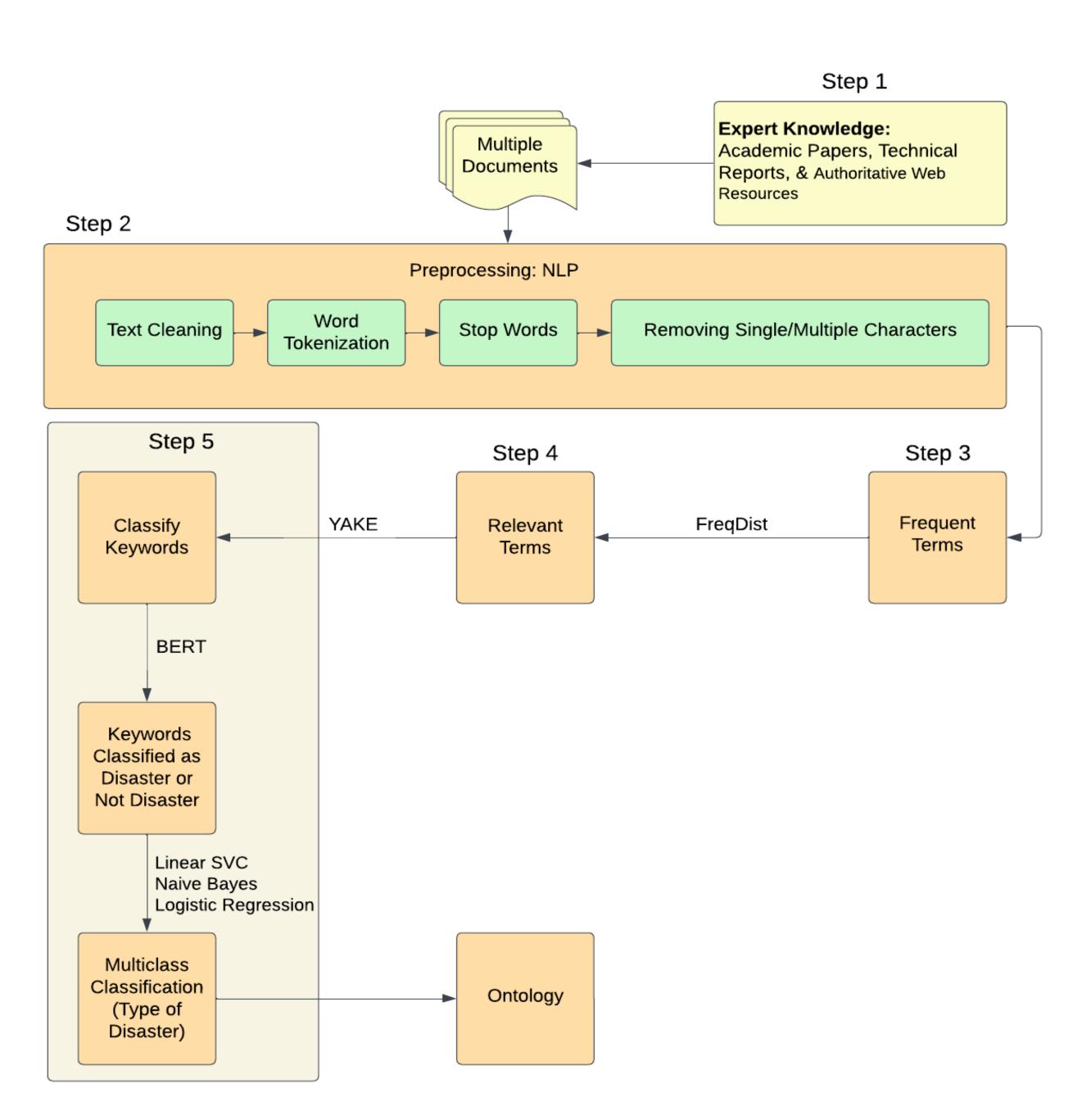


Figure 3. Overview of Ontology Learning System (OLS)

References

[1] Grigoris Antoniou and Frank van Harmelen. 2008. A Semantic Web Primer, 2nd Edition (Cooperative Information Systems). The MIT Press. [2] CDC. Precipitation extremes: Heavy rainfall, flooding, and droughts | CDC [online]. 2020. [3] COCOP. Knowledge management in COCOP [online]. 2024.

[4] Alon Halevy. 2005. Why your data won't mix: New tools and techniques can help ease the pain of reconciling schemas. Queue, 3(8):50–58. [5] Ontotext. What are ontologies? [online]. 2024.

[6] Gerhard Wohlgenannt and Filip Minic. 2016. Using word2vec to build a simple ontology learning system. In International Workshop on the Semantic Web.

The FEMA technical report results (Figure 4-a) display a frequency table with "water," "flooding," and "flood" as the top three terms. In Figure 4-b, the green squares highlight keywords aligning with ontology categories from manual flood ontology created based on the literature. Blue squares suggest keywords for potential additional categories not in the ontology. Figure 4-c outcomes classify terms like "Flash Floods Flooding" and "Ice Jam Flooding" as "Disaster," and "Type Ground Failure" as "Not a disaster," achieving 89% accuracy, precision, and recall in disaster classification.

requency	Word
98	water
72	flooding
42	flood
42	floods
37	storm
33	types
33	areas
28	ice
25	drainage
24	floodplains

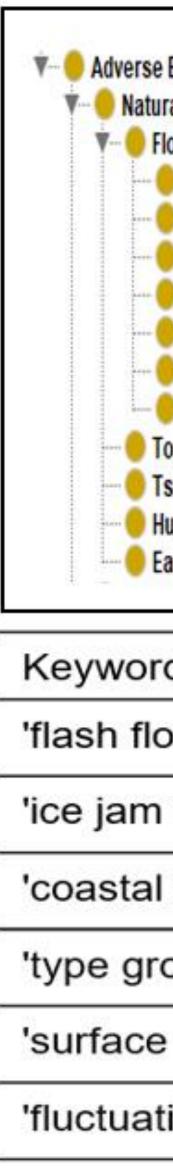


Figure 4. The FEMA Technical Report Results

A multiclass classification approach was tested for categorizing disasterrelated keywords, with preliminary results showing Naive Bayes at 90%, Logistic Regression at 97%, and Linear SVC at 98.4% accuracy for identifying specific types of disasters (e.g., flood or hurricane).

The results of the system have the following limitations: (1) Limited by small datasets (one technical report and a compilation of six articles). (2) Variations in ontology structures hinder validation using a common standard [4]. (3) Findings lack validation by an expert (4) System can identify keywords and concepts but not their semantic relationships.

Results

ds	Output	Classification		
Iced Jam Flood Small Stream Flood Groundwater Flooding Tornado Tsunami Hurricane Earthquake	('floodplains alluvial fans', 3.11417161221946e-05) (coastal flooding erosion', 3.648479221092843e-05) ('photograph flash flood', 3.695314880894683e-05) ('type ground failure', 3.7733917083988624e-05) ('floods flash flood', 4.125730064189592e-05) ('floods flash flood', 4.125730064189592e-05) ('drainage ground failures', 4.299975105647028e-05) (flooding alluvial fans', 4.433579502312275e-05) ('fluctuating lake levels', 4.460553654429235e-05) b			
e Events (Hazards) Iral Destructive Events Flood Flood (Other) Flash Flood Urban Flood Coastal Flood	types floods floodplains', floods floodplains alluvia types riverine flooding', flash floods flooding', 2. ice jam flooding', 1.48932 surface water runoff', 3.0	1', 2.121374293802364e-05) 2.2613420225548734e-05) 4042162026122948e-05) 56948491574e-05) 85928690018591e-05)		

ds	Output	Classification	
oods flooding'	0.95		
flooding'	0.89	Disaster	
I flooding erosion'	0.87		
ound failure'	0.09	Net	
e water runoff'	0.18	Not Disaster	
ting lake levels'	0.33	с	

Limitations