

Semantic Concept Discovery Over Event Data

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Preparing a *comprehensive, accurate, and unbiased* report on a given topic or question is a challenging task. The first step is often a daunting discovery task that requires searching through an overwhelming number of information sources without introducing bias from the analyst’s current knowledge or limitations of the information sources. A common requirement for many analysis reports is a deep understanding of various kinds of historical and ongoing *events* that are reported in the media. To enable better analysis based on events, there exist several *event databases* containing structured representations of events extracted from news articles. Examples include GDELT [4], ICEWS [1], and EventRegistry [3]. These event databases have been successfully used to perform various kinds of analysis tasks, e.g., forecasting societal events [6]. However, there has been little work on the discovery aspect of the analysis, that results in a gap between the information requirements and the available data, and potentially a biased view of the available information.

In this presentation, we describe a framework for concept discovery over event databases using semantic technologies. Unlike existing concept discovery solutions that perform discovery over text documents and in isolation from the remaining data analysis tasks [5, 8], our goal is providing a unified solution that allows deep understanding of the same data that will be used to perform other analysis tasks (e.g., hypothesis generation [7] or building models for forecasting [2]). Figure 1 shows the architecture of our system. The system takes in as input a set of event databases and RDF knowledge bases and provides as output a set of APIs that provide a unified retrieval mechanism over input data and knowledge bases, and an interface to a number of concept discovery algorithms. Figure 2 shows different portions of our system’s UI that is built using our concept discovery framework APIs. The analyst can enter a natural language question or a set of concepts, and retrieve collections of relevant concepts identified and ranked using different concept discovery algorithms. A key aspect of our framework is the use of semantic technologies. In particular:

- A unified view over multiple event databases and a background RDF knowledge base is achieved through semantic link discovery and annotation.
- Natural language or keyword query understanding is performed through mapping of input terms to the concepts in the background knowledge base.
- Concept discovery and ranking is performed through neural network based semantic term embeddings.

We will present the results of our detailed evaluation of our proposed concept discovery techniques. We prepared a ground truth from reports on specific topics written by human experts, including reports from the Human Rights Watch or-

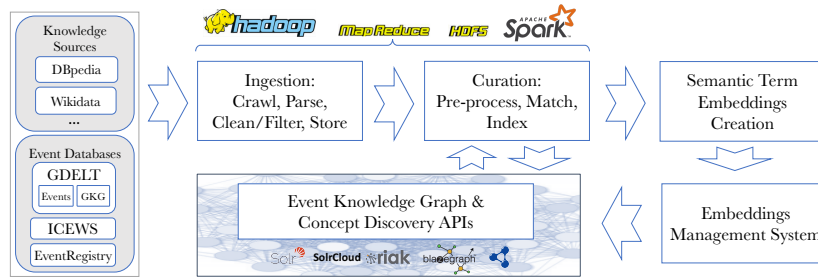


Fig. 1: System Architecture

Question Analysis Deep Analysis - GKG-Based

What would be the consequences of violent Protest in Caracas, Venezuela? Go!

Example Questions:

- What would be the consequences of protests in Caracas, Venezuela?
- How have Nicolas Maduro's policies impacted food shortages in Venezuela?
- What is the situation with the Houthis rebellion in Yemen?
- Did Russian propaganda and cyber-attacks impact the US 2016 election?
- What have been the consequences of the murder of Jo Cox in the UK?

Global Context

Caracas | Protest | Venezuela

DeepSim Analysis
 Powered by GDELT
 DeepSim Context: Location: Venezuela | Location: Caracas | Theme: PROTEST

Key People	Organizations	Themes
Jesús Torrealba Henrique Capriles Nicolas Maduro Eyanir Chinae David Smilde Julio Borges Freddy Guayana Delcy Rodríguez Nicholas Maduro Lilian Tintori Vladimir Padrino Corina Pons Tibisay Lucena	Venezuela Supreme Court United Socialist Party Of Venezuela National Electoral Council Venezuelan National Assembly Central University Of Venezuela Maduro United Socialist Party Of Venezuela Venezuela National Electoral Council Venezuelan Supreme Court National Assembly Henry Ramos Allup Venezuelan National Guard Venezuela National Assembly Venezuela Congress Venezuelan Embassy	Tax Ethnicity Venezuelan Tax Ethnicity Venezuelans Tax Political Party Unity Alliance Tax Econ Free-trade agreements Mercosur Tax Ethnicity Colombians Tax Political Party Democratic Action Party Tax Worldlanguages Bogota Tax Ethnicity Colombian Tax Terror Group Revolutionary Armed Forces Tax Weapons Tear Gas Tax Worldlanguages Amazonas Tax Ethnicity Uruguayan Tax Terror Group National Liberation Army

Currently indexing:
GDELT with **128,946,346 Events** extracted from **157,082,264 News Articles**, with **436,961,965 Mentions**.
EventRegistry with **2,889,497 Events** extracted from **33,549,078 News Articles**.
ICEWS with **14,841,179 Events**.

Fig. 2: Views from the Question Analysis UI

gation, and Wikipedia pages on people and events. The ground truth queries included hand-built test queries on various topics, and an automatically generated set of queries based on the title of the reports. Given only these query terms, we measure the ability of different algorithms to find the concepts mentioned in the original reports. Our study finds that combining our neural network based semantic term embeddings over structured data with an index-based method can significantly outperform either method alone.

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