Multilingual Entity, Relation, Event and Human Value Extraction

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Abstract

This paper demonstrates a state-of-the-art end-to-end multilingual (English, Russian, and Ukrainian) knowledge extraction system that can perform entity discovery and linking, relation extraction, event extraction, and coreference. It extracts and aggregates knowledge elements across multiple languages and documents as well as provides visualizations of the results along three dimensions: temporal (as displayed in an event timeline), spatial (as displayed in an event heatmap), and relational (as displayed in entity-relation networks). For our system to further support users' analyses of causal sequences of events in complex situations, we also integrate a wide range of human moral value measures, independently derived from region-based survey, into the event heatmap. This system is publicly available as a docker container and a live demo,[1,2] with a video demonstrating the system [3].

1 Introduction

Knowledge extraction aims to convert unstructured texts into structured entities, relations and events. Recently, we have developed a state-of-the-art multilingual knowledge extraction system for three languages including English, Russian, and Ukrainian (Zhang et al., 2018). However, individual extraction components lack the ability to aggregate knowledge from multiple languages and documents. For example, complementary salient information about the *Ukraine crisis* may be extracted from English, Ukrainian, and Russian news documents. We develop a novel framework, as illustrated in Figure 1, to aggregate knowledge elements from multiple documents in multiple languages and visualize these knowledge elements in three interfaces (temporal, spatial, and entity-relation networks) which support effective multi-dimensional search and filtering. The system is publicly available as a series of docker containers and it can be easily run via a single script. We also provide a live demo of the system that efficiently extracts knowledge elements from user input text.

The system improves the ease and speed with which users may discover inter-connections among knowledge elements from multiple languages and documents, so users can isolate subsets of activity that warrant further attention. The complementary dimensions of the three visualization interfaces provide distinct yet comprehensive views of the entities, relations, and events as well as, most notably, their implicit connections.

For example, in the *Ukraine crisis*, a *Transport-Person* event in an *airport* in *Kramatorsk* is part of the *Attack* event in *Sloviansk*. A causal relation between these two events may be discovered both in the event heat-map interface, where the former event in *Kramatorsk* is located near the latter event in *Sloviansk*, and in the event timeline interface, where these two events both occur in *April 2014*. Furthermore, the entity-relation network interface enables users to retrieve and relate entities of interest while reasoning about such events. The interface displays each retrieved entity with its one-hop relations to other entities, which then allows the user to retrieve one-hop relations for any of those entities, thereby traversing the network and discovering information. We see this in traversing the network following the *Leadership* relation from *Donbass People's militia* to *Pro-Russian separatists* and then the *Sponsorship* relation from *Pro-Russian separatists* to *Russia*, suggesting the *Donbass People's militia* is sponsored by *Russia*.

Other types of implicit knowledge that are not readily discovered by traditional methods of knowledge extraction, such as human values, play

[1] System: http://nlp.cs.rpi.edu/demo/aida_pipeline-master.zip

[2] Demo: http://nlp.cs.rpi.edu/software/

[3] Video: https://youtu.be/cQPHaxGLn8k

Proceedings of NAACL-HLT 2019: Demonstrations, pages 110–115
Minneapolis, Minnesota, June 2 - June 7, 2019.

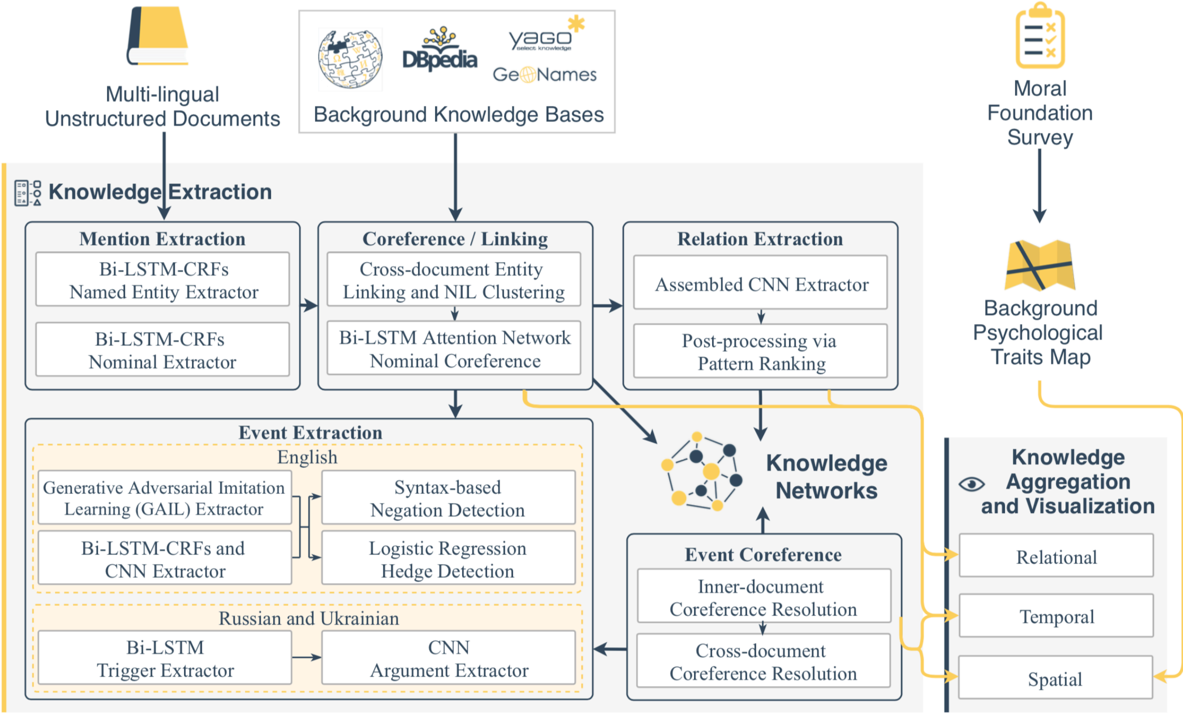

Figure 1: System overview.

a major role in social functioning and motivation (Rai and Fiske, 2011; Haidt, 2012; Graham et al., 2013; Schwartz, 2017). Numerous studies suggest that human values are often central motivating factors for protests, conflicts, and violence (Ginges and Atran, 2009; Fiske et al., 2014; Mooijman and Van Dijk, 2015; Skitka et al., 2017). Therefore, we integrate region-specific estimates of dominant psychological characteristics into the spatial event heat-map, which provides an additional layer of information that can be used to understand geo-spatial event patterns.

Entity	Person, Organization, Geopolitical Entity, Facility, Location, Weapon, Vehicle
Relation	Physical, Part-Whole, Personal-Social, Measurement, Organization-Affiliation, General-Affiliation
Event	Life, Movement, Business, Conflict, Contact, Manufacture, Personnel, Justice, Transaction, Government, Inspection, Existence

Table 1: Main types of knowledge elements

2 Multilingual Knowledge Extraction

The overall architecture of our multilingual knowledge extraction system is illustrated in Figure 1. The system performs entity discovery and linking (Pan et al., 2017; Lin et al., 2018), time expression extraction and normalization (Manning et al., 2014), relation extraction (Shi et al., 2018), event extraction (Zhang et al., 2017, 2019), and event coreference (Zhang et al., 2015). The system supports the extraction of 7 entity types, 23 relations, and 47 event types, as defined in the DARPA AIDA ontology.[4] Table 1 shows the main types.

For Russian and Ukrainian text input, we did not adopt the alternative approach of translating the source documents into English and then applying English knowledge extraction system due to the low-quality of state-of-the-art machine translation and word alignment for these two languages.

Once within-document knowledge elements for each language are extracted, the system performs cross-lingual entity linking to Wikipedia, cross-document entity clustering for unlinkable mentions, and cross-document event coreference resolution for cross-lingual information fusion. Further details of each component are described in (Zhang et al., 2018). Currently, each main component in the system outperforms the best reported results in the literature, as shown in Table 2.

[4] https://www.darpa.mil/program/active-interpretation-of-disparate-alternatives

Components	Ours	State-of-the-art
Name Tagging	91.8%	91.4% (Liu et al., 2018)
Relation Extraction	66.4%	65.2% (Fu et al., 2017)
Event Trigger Labeling	72.9%	69.6% (Sha et al., 2018)
Event Argument Labeling	59.0%	57.2% (Sha et al., 2018)

Table 2: F1 score comparisons of our approach vs. state-of-the-art for English knowledge extraction.

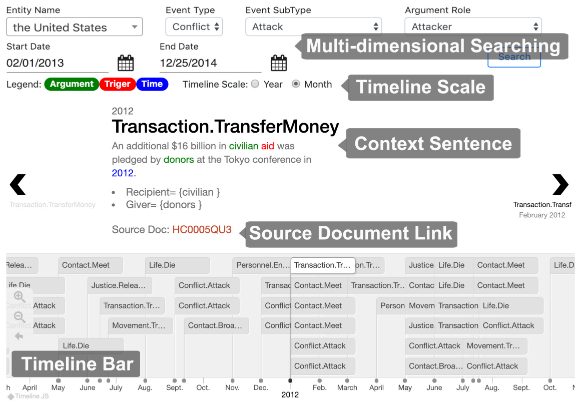

Figure 2: Example of the event timeline interface.

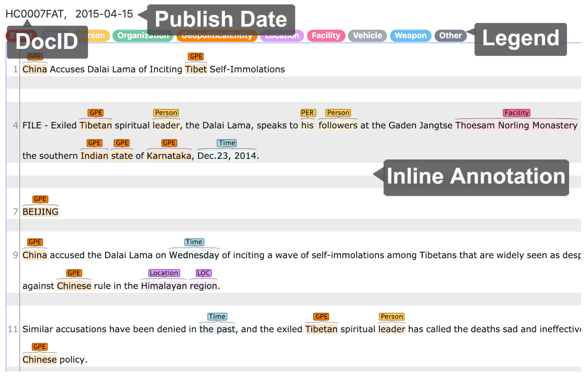

Figure 3: Example source document with inline annotation retrieved from the link in the event timeline interface.

3 Knowledge Aggregation and Visualization

To demonstrate the capabilities of our aforementioned system, we process 10,984 documents about the Ukraine-Russia conflict scenario from the DARPA AIDA program, including 7,415 in English, 2,307 in Russian, and 929 in Ukrainian.

We organize the extracted events in our interfaces, as described below, along the temporal and spatial dimensions in order to assist users both in gaining a comprehensive view of the evolving situations in this scenario and in detecting shared patterns of occurrence and possible connections among events of interest over time and space.

3.1 Event Timeline

We extract and normalize time arguments to construct an event timeline in Figure 2 using TimelineJS for visualization.[5] There are three zones in the web-enabled timeline interface. By clicking on an event in the timeline (*i.e.*, the gray area at the bottom of the screen), the pertinent context sentence for that event is displayed in the middle of the screen with the trigger and arguments highlighted in color, along with a link to the sentence's source document (Figure 3). Clicking on the source document link retrieves the document with full inline annotations and its publication date, to support inference of the absolute date(s) from relative time expressions in the text (*e.g.*, "*two days ago*"). Additionally, at the top of the interface, users may search and filter with multiple criteria (*entity name*, *event type*, *event subtype*, *argument role*, and *time period*) to narrow down the results to a particular query of interest.

[5]https://timeline.knightlab.com/

3.2 Event and Human Value Heatmap

We link event locations to the GeoNames database (Vatant and Wick, 2012) via the entity linking component and visualize involved events on a world map using Mapbox for visualization, as Figure 4 illustrates.[6] Each event is displayed as a dot or, when zooming in, an icon on the map. The color of a dot indicates the language of the source sentence, while the icon denotes the event type. Users can apply filters to the map to view the events of a certain type or language.

In addition to events, we also integrate regional estimates of human values into the heatmap. Specifically, the system encodes the geographic variations of 10 distinct dimensions of the human values in Table 3. These values are proposed in the Schwartz Basic Theory of Human Values (Schwartz, 2012) as a culturally universal taxonomy of human values.

The human values estimates are derived from the European Social Survey (ESS) (Round, 5, 6,

[6]https://www.mapbox.com/

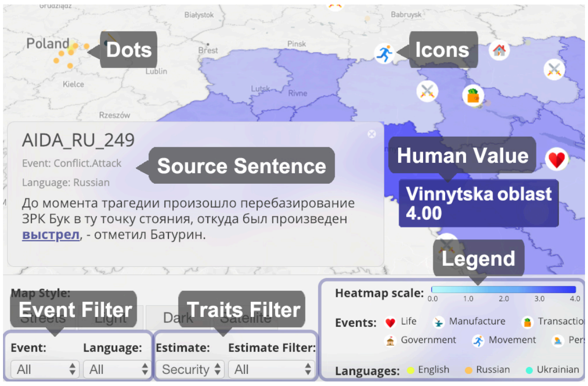

Figure 4: Example event heatmap with events and human values by region.

Human Values	Achievement, Benevolence, Conformity, Hedonism, Power, Security, Self-direction, Simulation, Tradition, Universalism
Age Filter	15-29, 30-44, 45-59, 60+
Gender Filter	Female, Male

Table 3: Human values. In the heatmap, the estimates for these values are displayed by region.

7), a nationally representative survey administered throughout the European Union. While the ESS data is sufficient for directly estimating *national* human values, it cannot be used to directly derive Oblast-level estimates because it is not representative at the Oblast-level.[7] To resolve this issue, we employ a state-of-the-art approach to survey adjustment and small-area estimation called Multilevel Regression and Synthetic Post-stratification with Spatial Smoothing (MrsP-SM) (Park et al., 2004; Selb and Munzert, 2011; Leemann and Wasserfallen, 2017; Hoover and Dehghani, 2018). This involves a model-based approach to post-stratification in which a hierarchical regression model is used to model person-level responses to a survey item as a function of demographic characteristics, region-level factors, and geographic indicators. Then, the model is used to generate predictions for each combination of demographic variables and geographic region. Finally, the predictions are weighted by the demographic population proportions within each region, yielding a set of regularized regional estimates that are adjusted for representativeness. To obtain regional human values estimates in the event heatmap, we estimate MrsP-SM models for each of the 10 Schwartz Human Values domains.

Human values have close ties to the intentions underlying events. A *Demonstration* event may result in violence, property destruction and involvement of extremist groups. The values of *Benevolence*, *Hedonism*, and *Conformity* among authority figures may impact their response to a protest. Additionally, people in areas where *Conflict* events are common may have higher values for *Security* and lower values for *Achievement*.

3.3 Entity-relation Networks

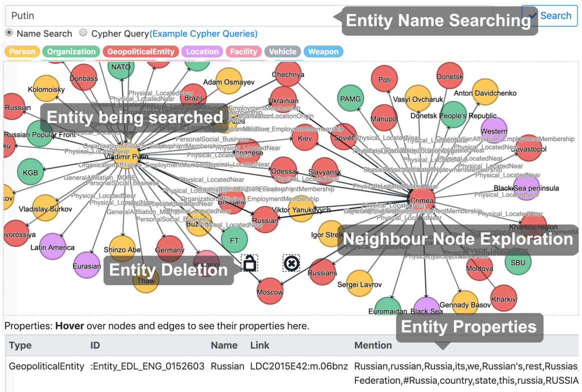

Figure 5: Entity-relation network.

A critical task for users gaining an understanding of complex scenarios is to explore implicit entity relations beyond the scope of traditional inline document annotation. Our interface provides interactive knowledge graph exploration, using Neo4j[8] (Figure 5), where entities can be searched by name and a sub-graph for each entity with its one-hop neighbors and their relations is returned, with entity properties displayed at the bottom of the interface. Users may either explore each retrieved neighbour by double clicking on it for its subgraph, or reduce their search graph by deleting entities no longer of interest. Thus, users can construct a multi-hop entity-relation graph, discovering variable length paths between entities. Each entity is labeled with its canonical name mention, while the entities without name mentions are removed from the network.

4 Conclusions and Future Work

In this paper, we demonstrate a comprehensive multi-lingual knowledge extraction, aggregation

[7]Our regional unit of analysis is the Oblast, of which there are 24 in Ukraine.

[8]https://neo4j.com/

and visualization system which can effectively discover and synthesize knowledge elements from multiple data sources, and present them to users in multiple dimensions. In the future, we plan to conduct utility experiments with users to compare and evaluate the quality and speed of generating summary reports with and without using our interfaces.

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