HR-VEAW: A Human Rights Violation Exploration, Analytics, and Warning System

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Abstract

The availability of information from social media, such as tweets, and human rights monitors, such as Amnesty International, Human Rights Watch, and the US State Department has led to new opportunities to measure repression and human rights protections in higher resolution. In this paper, we present HR-VEAW, a Human Rights Violation Exploration, Analytics, and Warning system, to support understanding of social conflict dynamics and human rights violations/protections with quantitative data. After briefly discussing HR-VEAW's data acquisition and analysis components, we demonstrate how it visualizes rich spatio-temporal and conceptual information, enabling the examination of changes in patterns of violation and protection in aggregate over time, or across both space and time. This way HR-VEAW helps to explain social instability and conflicts and to guide decision-making, theorizing, and predictions.

Keywords

data warehousing, data visualization, data exploration, data analytics

1. Introduction

Through a qualitative understanding of conflict dynamics, human rights violations and protections, and ethnic politics and relations, policy analysts and conflict researchers build mental models of the underlying grievances and alliances that structure war and peace. Currently, there is no system that directly allowed policy makers and researchers to both inform their visions of these grievances and policies with systematic, quantitative data, as well as share the resulting maps of the spatial and conceptual patterns that guide decision-making, theorizing, and predictions. The most sophisticated, interactive visualizations (e.g., [1, 2]) provide event-views that count events, but outside of the context of specific grievances.

In this paper, we present a first *Human Rights Violation Exploration, Analytics, and Warning* system (HR-VEAW) that allows users to visualize rich spatial and conceptual information that is relevant to both the escalation of instability, as well as to how negotiators might wind down tensions, and with whom. We process textual data from human rights reports and other social media that communicates both historical and contemporaneous information on who is alleged to have violated or protected a broad array of rights and behaviors for specific groups. This enables us to not only look at changes in patterns of violations and protections in aggregate over time or across both space and time, but fundamentally explore which groups are being targeted or privileged by the government and other actors and on what specific dimensions. For example, it helps to explain why in Ethiopia, the Tigrayan Peoples Liberation Front (TPLF) lost influence due to their broad repression as well as provides clues for why the Oromo Liberation Army (OLA) and TPLF are now cooperating against the government and when that cooperation might end [3].

HR-VEAW implements a scalable information processing pipe-line combining traditional database technologies with data streaming, NLP and sentiment-aspect representations, data visualization, and interpretable ML. In this demo paper, after briefly discussing HR-VEAW's data acquisition and analysis components (§ 2), we demonstrate how it visualizes rich spatio-temporal and conceptual information, helping users to explain social instability and conflicts and to guide decision-making, theorizing, and predictions (§ 3).

2. HR-VEAW System Overview

Figure 1 illustrates an overview of the data flow of the HR-VEAW system, consisting of two phases. The first phase is *Data Acquisition*, in which data from different sources are transformed by the ETL process and stored into a data warehouse. The second phase is *Data Analysis*, in which data visualization and interpretation are used

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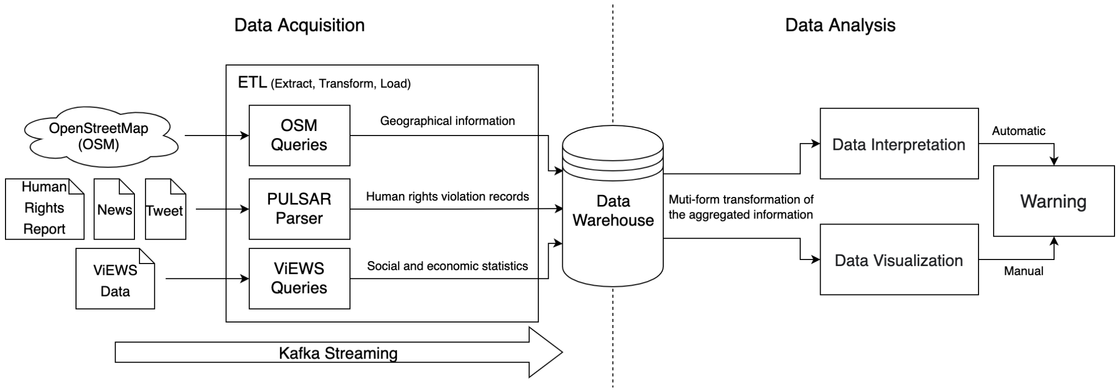


Figure 1: Overview of the HR-VEAW system

to explore the data and to discover patterns of social instability for early warnings.

2.1. Data Acquisition

This phase consists of a variety of ETL (Extract, Transform, Load) processes for different data sources. Human rights reports, news, and tweets, etc. will go through the human rights text parser PULSAR [4]. PULSAR uses rule-based and machine learning-based models to predict and extract structured information such as region, time, victim and human rights aspect from the documents. Social and economic statistics on country and subcountry levels are extracted from the ViEWS project [5] by specialized filtering and aggregation queries. Geographic information such as region names, administrative hierarchies, and region boundaries are retrieved from the online geographic database OpenStreetMap (OSM) [6]. All extracted and transformed data are then stored in a data warehouse (discussed in § 3.1).

The whole data acquisition phase is structured along the producer/consumer paradigm and topic channels, powered by Apache Kafka [7]. There are two major advantages of using Kafka in HR-VEAW. First, Kafka can process high throughput data streams from different sources and can be easily integrated with the ETL process as an event driven message bus. Second, while the data warehouse only stores the structured data after the ETL process, Kafka can persist data/messages during the whole data acquisition phase, so that messages are never lost and can be retrieved at a later time as needed.

2.2. Data Analysis

In this phase, different types of data from the data warehouse could be generated at different aggregation levels and forms suitable for the data interpretation and data visualization modules.

The data interpretation module aims to find the logical relationship between different features in the data. One way to accomplish it is to booleanise some of the aggregated information from the data warehouse to get the corresponding binary indicators. These binary indicators can serve as learning features in machine learning methods, such as the Tsetlin Machine [8], to conduct logical interpretable learning to discover relationship, pattern, and rules between observables and target indicators in the data.

The data visualization module is designed to help the data analyst explore and understand the data. It allows the user to visualize human right conditions across different dimensions such as region, time, victim and human rights aspect. The interactive visualization can help the user discover interesting patterns in the data, such as inequalities across dimensions and specific grievances concerning specific subsections of certain dimensions. Such specific grievance, for instance, could be *Integrity* rights violation against *Oromo* people in Ethiopia.

The final module of HR-VEAW provides early warning of future conflicts based on the data analysis results from the data interpretation and data visualization modules.

3. Data Visualization in HR-VEAW

This section provides implementation details of the data warehouse that drives the data visualization in HR-VEAW, describes the data visualization GUI and services, and presents an example of data visualization use case.

3.1. Data Warehousing

The data warehouse serves as the connection point between data acquisition and data analysis. It is designed to have a star schema which includes a fact table and four dimension tables. The four dimension tables are `REGION`, TIME, VICTIM and ASPECT. The hierarchy (i.e., ontology) information for regions, victims and human rights aspects is from OSM, WordNet [9] and the U.S. State Department, respectively. Each dimension table has a primary key and multiple attributes representing multiple levels in the dimension. For example, for a record in the REGION table, the primary key is the OSM ID for that region, and the other attributes are the OSM IDs of that region's ancestor regions in the administrative hierarchy.

The fact table is called VALENCE. Valence is an output value of PULSAR for each human rights record, representing the polarity of the record. A negative valance represents human rights violation and a positive valence represents human rights protection. The VALENCE table has five attributes: one dimension ID for each dimension and a valence value. If a human rights record contains more than one value in one dimension, then each value will generate one record in VALENCE. For example, if a human rights record involves two regions, then each region will generate a separate valence record.

In addition to the five tables above, the data warehouse has one more basic table and one more view. The table is named BOUNDARY, and contains geographic boundary coordinates for the regions in the REGION table. BOUNDARY has a foreign key referencing the primary key in REGION and thus it has a many-to-one relation to REGION. The view is tentatively called `valence_dimensions`. It is generated by joining VALENCE with all dimension tables so that the group-by attributes that can be requested by the data analysis modules, namely all levels in all dimensions, are present in the view.

3.2. Data Visualization

The main purpose of the data visualization module is to help data analysts discover interesting patterns in human rights situations. These patterns could include difference, similarity and correlation in valence values between regions, time ranges, social groups, and human rights aspects, which are very helpful in understanding and analyzing human rights situations.

The data visualization front-end is shown in Figure 2. The GUI has three sections: a filter section, a visualization section, and a recommendation section.

The filter section contains hierarchical filters that allow the user to select attribute values in different levels of different dimensions. The levels and values in the filters represent their counterparts in the corresponding dimension tables. By allowing the user to select values at different levels, this filter design enables cross-level display and comparison of the data.

The visualization section displays the aggregate values (i.e., sum of valence) for the filtered data subset. Specifically, for each selected region, a 3D visualization will be generated displaying the valence sums in each cell with valid data across time, victim and human rights aspect. The more opaque a cell is, the more negative the valence sum (i.e., more severe the human rights problem). Using opacity as the human rights severity indicator can capture different problem patterns at the same time. For example, an area in the 3D visualization will be dark when either there is a couple of highly severe cells or there are many intermediately severe cells in the area. Cells without data will be left transparent.

The user can pan, tilt, rotate and zoom the visualization with simple mouse movements. Further, there is a legend displaying valence ranges for different opacity levels. An info box is also present to display the cell information (i.e., the corresponding attribute values and the valence sum) when a cell is clicked.

The clicking of a cell will also trigger the rendering of 1D and 2D plots which are displayed beside the 3D plot. These plots correspond to 1D and 2D data cube slices that contain the cell. For example, the first 2D plot in Figure 2 (3rd plot from top) displays the temporal valence change across different aspects for the clicked region and victim. This feature helps the user to acquire clear and precise readings of data subspaces.

The recommendation section is designed to help user discover interesting patterns more easily. HR-VEAW dynamically generates recommendation listings for the filtered data subset based on different ranking criteria. Examples of two ranking criteria are: *valence sum* and *change point*. The ranking scores are calculated for each valence value time series (i.e., the column of cells perpendicular to the map surface in the 3D visualization) that has a specific combination of region, victim and aspect values.

The valence sum criterion calculates the sum of the valence values in each time series and its ranking score is based on Equation 1:

$$s_{(r,v,a)} = \sum_{i=1}^{n} t^{i}_{(r,v,a)} \tag{1}$$

where (r, v, a) is a specific combination of region, victim and aspect values and $t^{i}_{(r,v,a)}$ are the time series values for that combination.

The change point criterion calculates the maximum of absolute changes between adjacent cells in each time series and its ranking score is based on Equation 2:

$$s_{(r,v,a)} = \max_{1 \leq i < n} (|t^{i+1}_{(r,v,a)} - t^{i}_{(r,v,a)}|) \tag{2}$$

where $max(\cdot)$ is the maximum operator and $|\cdot|$ is the absolute value operator.

Each recommendation criterion will provide a listing of the top 10 entries. By clicking an entry, the corresponding time column will be highlighted in the 3D visualization.

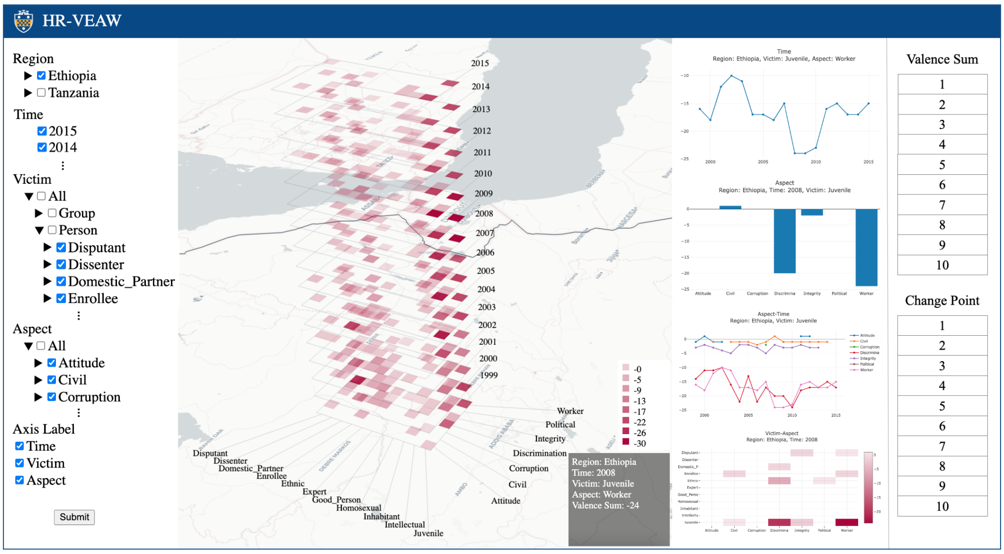


Figure 2: Data visualization GUI

3.3. Example Use Case

An example data visualization use case is illustrated in Figure 3, in which the analyst tries to identify specific grievances that may have caused instability events in the history of Ethiopia.

Instability events are mainly reflected by human rights violations in the sub-aspect *Force* under the the aspect of *Integrity*, which contains primarily armed conflicts between the government and the ethnic groups. Therefore, the analyst first chooses to visualize that sub-aspect across all victims in Ethiopia as shown in Figure 3a.

They realize that there was a large increase in *force events* (i.e., human rights violation events under the Force sub-aspect) in year 2009 and want to find out if this pattern is universal across the country or specific to certain sub-regions. So they select all sub-regions in the filter section to see the time columns across the sub-regions. Then they check the top-1 recommendation from the valence sum criterion, and find out that the Somali region contributed greatly to the aforementioned force event increase, as shown in Figure 3b.

So the data analyst focuses into the Somali region and selects all aspects as well as all sub-aspects under the Integrity aspect. Then they check the top-1 recommendation from the change point criterion, and find out that civil events (i.e., human rights violation events under the *Civil* aspect) also had a large increase around year 2009 in the Somali region with a slightly earlier start, as shown in Figure 3c. This indicates that the increase of the civil events could be the cause to the increase of the force events in the following years. And if this is the case, then dealing with the grievances reflected by those civil events could potentially prevent the increase of the instability events in the following years.

To conclude, through data visualization and exploration with the help of HR-VEAW, the analyst was able to form a hypothesis that the increase of civil events before year 2009 in the Somali region could be the cause to the increase of force events in 2009 and after in the same region, which could guide their further investigation.

4. Demonstration Scenario

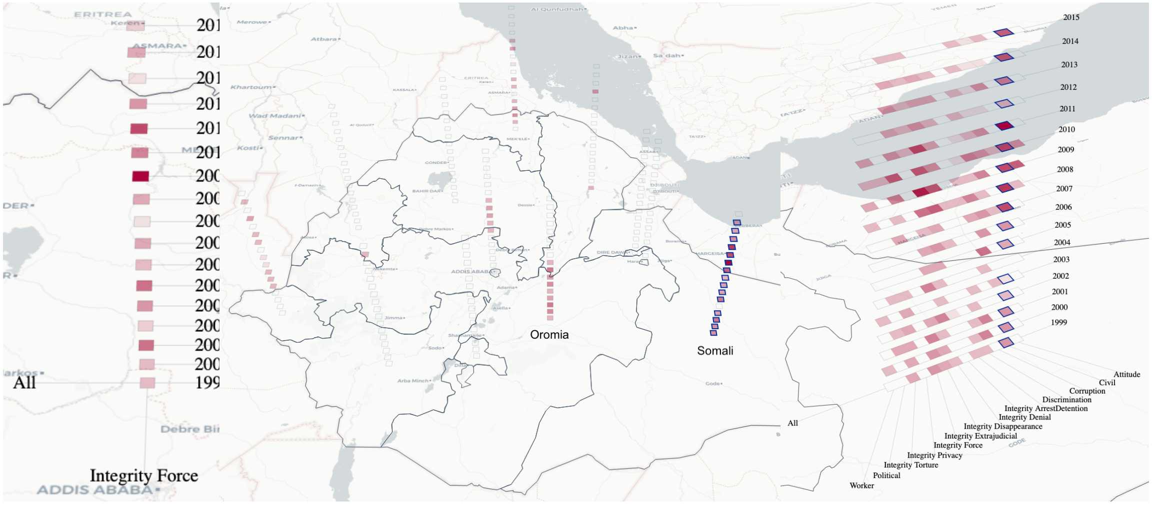
The following demonstration introduces the key concepts and visualization abstraction of HR-VEAW to the attendees. They will comprehend the performance of our propositions during their interactions with our user-friendly interface.

4.1. Demo Artifact

The demo artifact is a web application prototype representing the data visualization module of HR-VEAW. The software stack of the web app consists of Flask, MySQL, JavaScript and HTML. The web app will be served on a dedicated HR-VEAW server, which can be publicly accessed during the demo.

4.2. Demo Plan

Equipment: The conference attendees will have the opportunity to interact with the web app through any web browser on a standard laptop or a tablet.



(a) (b) (c)

Figure 3: (a) The force events saw a large increase in year 2009 in Ethiopia; (b) The Somali region contributed greatly to the force event increase; (c) The civil events also saw a large increase around 2009 in the Somali region with a slightly earlier start.

Datasets: We will pre-load data from U.S. State Department human rights reports, which will primarily cover countries in Africa, where human rights condition is relatively worse.

Scenario 1: The first scenario asks the user to discover difference, similarity or correlation between events in different human rights violation aspects for a specific region. One example result from such discovery could be the use case discussed in Section 3.3, in which correlation between force events and civil events are discovered for the Somali region.

Scenario 2: The second scenario asks the user to discover difference, similarity or correlation between events in different regions for a specific human rights violation aspect. For example, if we look back to Figure 3b, we may realize that with the increase of force events in the Somali region around year 2009, the force events in the neighboring Oromia region was actually decreasing during the same period, which may indicate a negative correlation between the two.

Scenario 3: The attendees will have the opportunity to interact freely with HR-VEAW to conduct any other data exploration tasks such as comparing human rights conditions across time ranges, social groups, etc.

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