Enhancing Disaster Response with Architectonic Capabilities by Leveraging Machine and Human Intelligence Interplay

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Disaster response presents the current situation, creates a summary of known information on the disaster, and sets the path for recovery and reconstruction. During the last ten years, various disciplines have investigated disaster response in a two-fold manner. First, researchers published several studies using state of the art technologies for disaster response. Second, humanitarian organizations produced numerous protocols on how to respond to natural disasters. The former suggests questioning: If we have developed a considerable amount of studies to respond to a natural disaster, how to cross-validate its results with NGOs' protocols to enhance the involvement of specific disciplines in disaster response?
To address the above question, the research proposes an experiment that considers both: knowledge produced in the form of 8364 abstracts of academic writing on the field of Disaster Response and 1930 humanitarian organizations' mission statements indexed online. The experiment uses Artificial Intelligence in the form of Neural Network to perform the task of word embedding –Word2Vec– and an unsupervised machine learning algorithm for clustering –Self Organizing Maps. Finally, it employs Human Intelligence for the selection of information and decision making. The result is a mockup that will suggest actions and tools that are relevant to a specific scenario forecasting the involvement of architects in Disaster Response.

Keywords: Artificial Intelligence, Disaster Response, Big Data, Word2Vec, Self-Organizing Maps, Architecture.

1. Introduction

After a natural disaster event, disaster response is essential as its assessments present the current situation and a summary of information to guide the rescue forces and other immediate relief efforts or community to the site (UNDACU, 2018). Nowadays, many scholars publish investigations on disaster response focusing on implementation of artificial intelligence to process big data; e.g., AIDR a platform to classify crisis-related communications (Imran et al., 2014), a model that learns damage assessment and proposes applications (Zhang et al. 2019), an automated method to retrieve information for humanitarian crises (Shamoug et al, 2018),or an interphase to have rapid decision making during humanitarian health crises (Fernandez-Luque & Imran, 2018). In parallel, we witness an increasing global presence of humanitarian organizations, humanitarian protocols, and humanitarian declarations -more than 4.000 organizations active in this matter. Some examples from the large ones are the World Food Program (WFP), Cooperative for Assistance and Relief Everywhere (CARE), International Federation of Red Cross and Red Crescent Societies (IFRC), and Action Against Hunger (AAH) (Bünzli et al., 2019). However, their knowledge and produced protocols are not commonly used and cross-connected in an actual disaster event because usually, the produced information is not available in the right format, not extensively dispersed, not easily accessible by users, or has inadequate information management (Meier, 2015).

Moreover, from the produced knowledge on disaster response, few studies undertake the involvement of architects in all its assessments. Commonly architects have been involved in the context of temporary housing (Sanderson, 2015; Ban, 2019; Nolte, 2104). However, in 2017 the American Institute of Architects (AIA) released a handbook describing the role of the architect in disaster assessments. According to AIA, architects should be included in all disaster assessments considering architects as actors that provide a holistic approach to community resilience. Additionally, architects are trained to incorporate different interdependent systems that are valuable during disaster management, especially in the tasks of building safety assessments, temporary housing, and policy recommendations. Table 01 presents a cross-connection of the United Nations disaster assessment with the role of the architect proposed by the AIA, emphasizing the focus on disaster response and its corresponding assessments.

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Table 1. The role of the architect for each disaster assessment.

Assessments	Descriptions
Prevention	Vulnerability assessments Building performance analysis
Mitigation	Building code and land use updates Incentives retrofit program Design innovation Renovation Retrofits
Preparedness	Business continuity Disaster scenario planning Training
Response	**Rapid building safety assessments** **Temporary housing** **Policy recommendations**
Recovery	Detailed building assessment Repair, rebuilt, relocate transitional housing Community and land use planning
Reconstruction	Zonification studies Building logistics Architectural projects

Source: Sample typeset by UNDACU Field Handbook and "AIA Disaster Assistance Handbook."

1.2. Contribution

The majority of scientific knowledge and humanitarian organization mission statements are published as text, which are challenging to analyze by either traditional statistical analysis or modern machine learning methods. Therefore, novel studies strengthen their efforts to create or improve methods to analyze this type of data (Tshitoyan et al., 2019). The present research proposes a method to analyze written knowledge from two narratives concerning disaster response; to subsequently cluster, filter, and prioritizes its information regarding a specific interest. The outcome is a selection of specific literature in academic writing and humanitarian organizations that have similar approaches to the specific interest (a description of a natural disaster by the news). In order to achieve the former, the research presents a pipeline that aims to support informed decision making for disaster response. The pipeline starts by collecting data (Web scraping and APIs) — then process its modality by encoding its representation to numerical vectors (Word2Vec). The pipeline continues with an algorithm to cluster (Self Organizing Maps SOM) the texts based on their similar pattern in their numerical vectors. Ending, when a numerical vector encapsulating a specific interest (encoded query) finds its similar information from the already clustered literature (Fig 01.). This research integrates AI with the abilities of architects, as data collectors and decision-makers to improve the quality of disaster response as it allows significantly to facilitate a) information accessibility, b) fast and direct assessment, and c) logistics decisions.

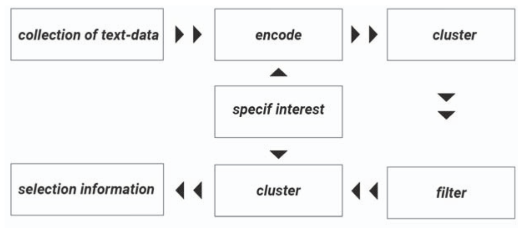

Fig. 1. Pipeline proposed for the present research.

The research is structured as follows. Section 2 describes the methodology applied: Data Collection, Data Processing and Encoding, Data Representation and Clustering, and Information Prioritization and Selection. In each subsection, a short overview of the relevant work regarding each method is described. Section 3 discusses the experimental findings. The last section summarizes the work and indicates the issues encountered in the methodology as well as describes future investigations.

2. Methodology

2.1 Data Collection

As outlined in the introduction, the AIA defined three tasks in disaster response were the abilities of architects can successfully be applied: building safety assessments, temporary housing, and policy recommendations. The tasks mentioned above will serve as keywords to crawl academic writing and humanitarian organizations' mission statement to define a specific framework directed towards architectural responses.

2.1.1 *Academic literature*

To collect academic writing from the field of disaster response, the pipeline follows the approach of Tshitoyan et al. (2019); their research avoids full texts as they contain negative relationships, and its writing style includes complex sentences that will require different encoding methods than the ones proposed in this research. The authors as well propose to work with abstracts since they communicate information concisely and straightforwardly, avoiding unnecessary words.

9000 abstracts from the field of disaster response were collected, using Elsevier's Scopus and Science Direct application programming interfaces (APIs) (https://dev.elsevier.com/) with the following combination of keywords: Building Safety Assessments, Housing and Disaster Response and Policy Recommendations and Disaster Response.

As suggested by Tsitoyana et al. (2019), abstracts that contained in their titles the following keywords: "Foreword", "Prelude", "Commentary", "Workshop", "Conference", "Symposium", "Comment", "Retract", "Correction", "Erratum" and "Memorial" where removed. Concluding a total of 8364 abstracts on disaster response. In Fig. 2, a world-cloud of the collected abstracts is shown, where the main concepts are represented, and an overview of the general intention is graspable.

Fig. 2. World Cloud of 8364 abstracts from the field of Disaster Response

2.1.2 *Humanitarian Organizations*

Humanitarian Organizations have continuously expanded over the past decades. Worldwide more than 125 million people rely on humanitarian aid —double the number of 10 years ago (Bünzli et al., 2019). Commonly, such organizations communicate with their stakeholders via platforms online, sharing their mission statements, aims, and goals. Therefore, data of humanitarian organizations –mission statements and web address– were collected from two web sources:

Wikipedia: 749 texts were collected using Wikipedia API under the Category "Humanitarian aid organizations. The collected texts were already translated into English.

ReliefWeb: 1154 links of Humanitarian Organizations were collected from ReliefWeb (https://reliefweb.int) a specialized digital service of the UN Office for the Coordination of Humanitarian Affairs (OCHA), under the tag "Organizations". By parsing the source text of each retrieved link and search for tags: "about", "about us", "we are", "who we are", "what we do", the description of each organization and mission statements was found.

After joining both datasets (Wikipedia and ReliefWeb), an overlapping of 87 organizations was found, and a resulting 1930 mission statements were recorded. Fig. 3 shows the word cloud of the dataset.

Fig. 3. World Cloud of 1930 mission statements from humanitarian organizations.

2.2. Data Processing and Encoding

To pre-process the text-data, three operations were implemented: first, selection of lower-casing and de-accenting; second, removing stop words; and third, selection of words that are part of a speech (nouns, pronouns, adjectives, verbs, adverbs, prepositions, conjunctions, and interjections).

To encode the text-data to numerical vectors the research uses algorithms for word embedding (a Natural Language Processing) a technique that assigns high-dimensional vectors (embeddings) to words in a text corpus, preserving their syntactic and semantic. Tshitoyan et al. (2019) demonstrated that scientific knowledge could efficiently be encoded as information-dense word embeddings without human labeling or supervision. The algorithm used to transform the text into word embeddings is a Neural Network call Word2Vec (Mikolov et al., 2013a, 2013b) with the method of continuous-bag-of-words (CBOW). The former learns the embedding through maximizing the ability of each word to be predicted from its set of context words using vector similarity. The output of Word2Vec is a 50-dimensional numerical vector for each word from the text corpus.

To continue with the experiment, the pre-processed text (both academic writing and humanitarian organizations) was fed as training data to a Word2Vec algorithm in order to use the knowledge acquired from the previous training to create a domain-specific model Word2VecDR (this is call transfer learning). After the Word2VecDR was trained, it was able to encode all texts from the dataset into a numerical representation -every word of the text was assigned 50 numerical vectors. The texts ranged from 15 to 5668 words, having an average of 824 words per text. Therefore, if an abstract contained 100 words, the resulting vector form Word2VecDR is a list of 100 sub-lists with 50 elements each.

Mikolov et al. (2013a) observed that simple algebraic operations on word embeddings, e.g., vector "King" - vector "Man" + vector "Woman", results in a vector that is closest to the vector "Queen" concluding that the resulting vector is content-related. Furthermore, researchers have also applied statistical operations such as mean or average value on a list of word embeddings, having successful results capturing the content of the text; examples of the former can be found in (Li et al., 2017 & Socher et al., 2014). However, when calculating the mean value or adding each word vector, the resulting vector will be an abstraction (reduced) of its content, hence, losing information. To encapsulate as much information as possible from the list of numerical vectors, the present research proposed to use Higher-Order Statics (HOS). In HOS, mean (X) and standard deviations (s) are related to the first and the second order moments –one could calculate up to n order moments. Skewness (ski) can be calculated from the third-order moments of the data distribution, which measures the direction of the tail in comparison to the normal distribution, where Y is the Median.

$$sk_i = \frac{(X - Y)}{s} \tag{1}$$

If the resulting number is positive, the data is skewed to the left, leaving the tail pointing to the right side of the distribution. If the resulting number is negative, the tail is on the left side of the distribution. Kurtosis (ki) is the fourth-order moment, which measures how heavy the tails of a distribution are (DeCarlo, 1997), where N is the sample size.

$$k_i = \frac{\sum_{i=1}^{N} \frac{(X_i - X)}{N}}{s^4} \tag{2}$$

By applying the fourth moments of HOS to the data, each text is represented by a numerical vector of 200 dimensions or four sub-lists of 50 dimensions for each HOS moment (mean, standard deviation, skewness, and kurtosis). Two advantages of encoding data with HOS are; first, in comparison to the embedding vectors in deep auto-encoders, the resulting vectors of HOS are meaningful and directly interpretable (Saldana, 2019). Second, by using HOS, the computational time for clustering the text-data reduces exponentially since the length of the numerical vector is decreased. Additionally, by using the fourth moments of HOS, each resulting numerical vector encapsulates more information than when using only one statistical value (first or second moment).

2.3. Data Representation and Clustering

Clustering and representation technics assist to adequately explore the collection of data and identify clusters of similar information that share similar properties (Hu & Liu, 2012). For example, to cluster text, the following algorithms have been used: Support Vector Machine (SVM) (Ragini et al., 2018), k-means (Rytsarev et al. 2018), Principal Component Analysis (PCA) (Mir & Zaheer) and Kohonen Self-Organizing Map (SOM) (Pohl et al., 2012). A full review of different clustering algorithms can be found in (Lin et al., 2008). As shown in the work of Pohl et al. (2012), the unsupervised ML algorithm SOM (Khonen, 1982) has proven to have excellent performance when clustering text data and reducing its dimensionality.

Additionally, as presented in the work of Moosavi (2015) *"SOM acts as a nonlinear data transformation in which data from a high-dimensional space are transformed into a low-dimensional space (usually a space of two or three dimensions), while the topology of the original high dimensional space is preserved. SOM has the advantage of delivering two-dimensional maps that visualizes data clusters that reflect the topology of the original high-dimensional space".* SOM is a generic algorithm that can be used for different purposes, having an excellent (85%) performance if it is compared with algorithms that are specific for that purpose. (Khonen, 1982)

The numerical vectors representing the text from humanitarian organizations were fed as inputs into a SOM grid of 20x20. The algorithm started with an initial distribution of random weights, and over one million epochs eventually settled into a map of stable zones or clusters. The output layer of the SOM can be visualized as a smooth changing spectrum were each SOM-node has its coordinates and an associated n-dimensional vector or Best Matching Unit (BMU). For visualization purposes, a color assigned to the weight value (n-dimensional vector) of each BMU and a list of keywords are displayed together. The keywords are the most common terms used in the texts that are clustered in each SOM-node. The size of the word represents the number of occasions the word appeared in the group of text. Fig. 4 shows the consistency in clustering, such as similar keywords, are positioned close to each other.

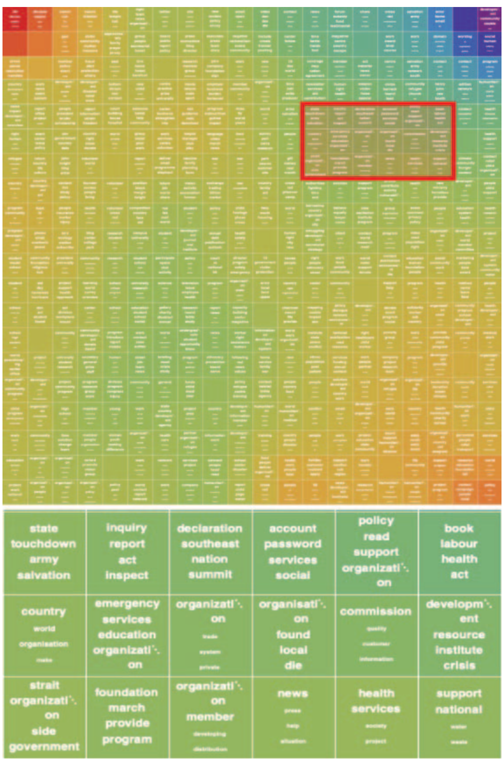

Fig. 4. On the top, a SOM grid of 20x20 of data from the humanitarian organization data, and on the bottom, a zoom of SOM-nodes showing the consistency of the clustering.

An additional step in the pipeline is proposed to filter the number of humanitarian organizations, based on similar interests shared with academic writing. When a new dataset is fed as input to a trained SOM, each data point measures its Euclidean distance to each BMU, the closes the distance, the better the data point fits that node. Therefore, it is possible to feed to the trained SOM the encoded academic writing and find the nodes that get activated based on the similarity in their numerical vector. Fig. 5 shows the activated SOM-nodes of humanitarian organizations that shared a common interest with academic writing.

After collecting all the activated cells, 1081 humanitarian organizations out of the original list of 1930 were filtered. Some of the selected humanitarian organizations are: The International NGO Safety Organization, Nansen International Office for Refugees, Peoplesafe, Rise Against Hunger, SeedChange, and Association of Assistance Solidarity Supportiveness of Refugees and Asylum Seekers.

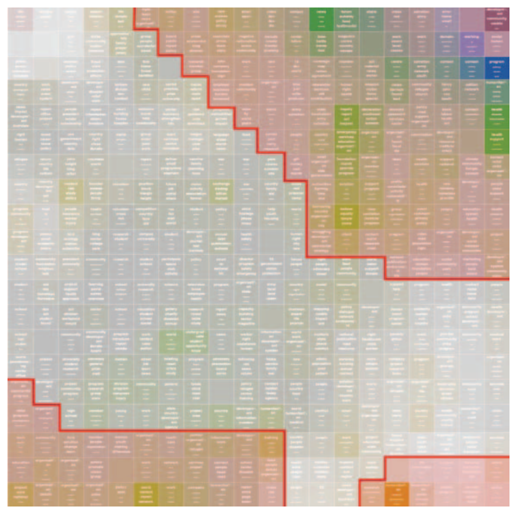

Fig. 5. On the back, a SOM of 20x20 of humanitarian organizations (grey) the cells with color are the ones sharing a similar interest with the academic writing in disaster response. The intensity of the color represents the quantity of matching texts (more intensity more texts).

2.4. Information, prioritization and selection

The filtered dataset of humanitarian organizations (1082) was joined with the dataset of Academic writing (8364), creating a new dataset of 9446 texts. The aforementioned texts were fed as input in a SOM grid of 10x10 that after a million iterations, settled into a map of clustered texts. As described in the contribution, the paper addressed the intention of joining two discourses regarding disaster response. The trained SOM grid of 10x10 (Fig. 6) achieves the objectives as it encapsulates both discourses in an organized manner that serves as a ground for prioritization and selection of information depending on a specific interest.

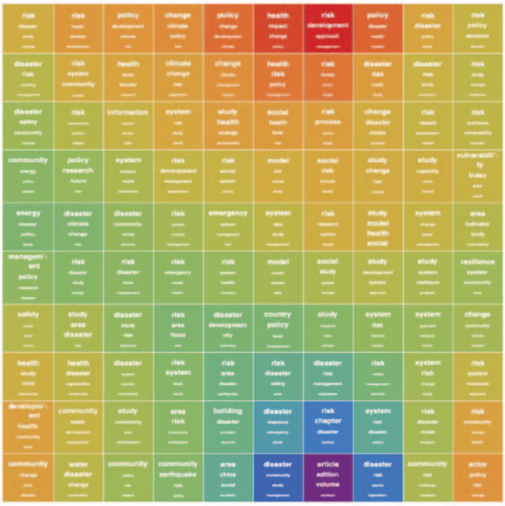

Fig. 6. SOM of 10x10 trained with joined data from filtered humanitarian organizations (1082) and academic writing form the field of disaster response (8364).

After a natural disaster, the first source of information comes from the news; therefore, it is substantial to correlate them with the already clustered of literature (SOM Fig. 6). For experimental purposes, the specific interest (query) was extracted from a news feed describing the 2016 Earthquake of magnitude 7.8 in Ecuadorian coast:

"A magnitude 7.8 earthquake rocked Ecuador's coast April 16, 2016 — killing almost 700 people and leveling homes, schools, and infrastructure. More than 6,000 people were severely injured. The quake's epicenter was offshore about 17 miles from the town of Muisne in Manabí province and 100 miles northwest of Quito, the capital. After the quake, more than 700,000 people needed assistance. An estimated 35,000 houses were destroyed or badly damaged, leaving more than 100,000 people in need of shelter. Water, sanitation, and healthcare facilities were also destroyed." (WorldVision, 2016)

The query was pre-processed and fed into the trained Word2Vec model to extract its words embeddings. The output of the Word2Vec model was encoded with HOS (see section 2.2. Data Processing) having a final vector of 200 dimensions. The query-vector was then fed into the trained SOM of 10x10 (Fig. 6), finding the closest Euclidean distance to a BMU. Fig. 7 displays the closest BMU concerning the query-vector, having as keywords: community, earthquake, risk, safety.

Fig. 7. On grey color, the trained SOM of 10x10 (Fig. 6) on green color the BMU that had the closest Euclidean distance to the query-vector.

3. Results

As explained in the introduction, this research has a specific focus on post-disaster assessments, especially in disaster response, where information should be concise and arrive on time for decision making. The case study selected from 2016 is one of the different scenarios investigated in the research. In Fig. 8, four organizations and four studies were selected from the cluster of texts belonging to the BMU assigned to the query. By analyzing the selected information, a correlation with the specific interest is recognized. Likewise, by comparing the keywords extracted from the query (earthquake, people, severely, assistance, shelter, healthcare, facility) and the ones assigned to the BMU (community, earthquake, risk, safety), an overlapping of the terms shows the consistency in clustering. However, the complete list of the text included organizations and studies from different disciplines that shared the same keywords. Therefore, the final selection, in this case, done by an architect, assures the success of the experiment (by selecting the information relevant for architecture).

Tools

The role of post-disaster public policy responses in housing recovery of tenants
www.sciencedirect.com/science/article/pii/S0197397513000489

Anticipated behavioral response patterns to an earthquake: The role of personal and household characteristics, risk perception, previous experience and preparedness
www.sciencedirect.com/science/article/pii/S2212420918300244

Seismic response of shield tunnel subjected to spatially varying earthquake ground motions
https://www.sciencedirect.com/science/article/pii/S0886779817311306

Remittance and earthquake preparedness
https://www.sciencedirect.com/science/article/pii/S2212420915301898

Organizations

CASA People Helping People
www.casa-india.org/pages/index.php/who-we-are

Centre for Social Justice
www.centreforsocialjustice.org.uk

Partners of the Americas
www.partners.net

United Nations High Commissioner for Refugees UNHCR
www.unhcr.org

Fig. 8. A list of organizations and tools from the cluster text that belongs to the BMU closest to the query vector.

4. Discussion

The present research described a methodology that jointed two discourses from the field of disaster response to provide a ground for selection and prioritization of information regarding a specific interest. By using AI in the form of two algorithms (word2Vec and SOM) together with the ability of an architect to have a qualitative selection, a final result of studies in academic writing and humanitarian organizations relevant for the specific query was achieved.

When working with a data-driven approach is often question whether the accuracy of the results can be thrust. However, to avoid the latter, the research proposed a methodology that involves an interplay of both human and artificial intelligence were accuracy is overpass by a series of filters that are user-dependent, securing the specificity of the final result.

Two limitations were identified during the experiment; first, several lists of humanitarian organizations that are indexed on the web poorly overlap among each other. To settle into a reliable source, one has to navigate the plenty of options and filter many to get a representative number. However, the final selection is considered an abstraction or a subsample of reality. Second, several approaches from different disciplines share similar keywords, e.g., academic writing from the field of health with the field of building safety assessments. Both extremely necessary; however, their approaches are entirely different. Therefore, even if AI predicts similarities among them, the human has to be present to make the final decision and selection.

In 2019 the Mckinsey Global Institute released a paper "Notes From the AI Frontier: Applying AI for Social Good." (Mackinsey Global Institute, 2019) They suggest that:

"AI is not a silver bullet or cure-all, the technology's powerful capabilities could be harnessed moreover, added to the mix of approaches to address some of the biggest challenges of our age, from hunger and disease to climate change and disaster relief."

However, there is a lack of research on how to integrate the use of AI into the work-flow of large-scale disaster response, especially in countries with scarce resources. Therefore, for future work, we plan to apply the proposed methodology to a case study of ongoing disaster to validate the speed and relevance of the results. Additionally, we propose to add a new discourse from social media that will bring new focus from stakeholders in disaster response. Furthermore, we will experiment with different ways of encoding text data into numerical vectors; for example, instead of using word embedding, use the meaning of words throughout time and compare the results from the present research with the later. To conclude, AI is a problem-solving tool, attuned to a specific set of problems; therefore, in the scenario of natural disasters, this type of intelligence can be beneficial, since many problems gather a massive amount of data that requires substantial computational power, and commonly few people are available to process these data. Therefore, by joining the strengths of human cognition with the strengths of AI computation, this research illustrates a method to have a fast and informed disaster response.

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