Extracting and Organizing Disaster-related Philippine Community Responses for Aiding Nationwide Risk Reduction Planning and Response

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Abstract

Philippines is one of the most disaster-prone countries in the world. Typhoons and floods are normally experienced in the country, for which in every experience, spike of data in all mediums are evident. Given this, it granted researchers the opportunity to analyze and study these data. Attempting to amend the current situation of the country in terms of handling disasters, disaster risk reduction strategies were directly taken from local communities by an online participatory platform, *Malasakit*, in light of the specific needs of the people. Gathering their insights provided numerous ideas on how to prevent and mitigate disasters experienced by the country, however these ideas come in an unstructured form. This research aims to convert unstructured data to structured form by extracting those disaster-related community responses in Filipino, organize the extracted information, and generate a report for decision makers to address. Provided, it collated insights listing items to "what do people want or need in their community". It was implemented through Part-of-Speech-based Information Extraction (IE) and Clustering techniques. As support, Part-of-Speech Tagger, Word Embeddings, Ranking and Report Generator modules were used.

Keywords: Information Extraction, Clustering, Word Embeddings, Lexical Analysis, Community Responses, Disaster Risk Reduction Strategies

Contents

List of Figures

List of Tables

Chapter 1

Introduction

In this chapter, an overview of the study is presented – stating the research problem, related works, proposed solution, research objectives, scope of the study, and the work's significance.

1.1 Overview of the Current State of Technology

Disasters are one of the primary reasons for disrupting the world's social and economic status. It comes in many forms, natural and man-made, such as flood, earthquake, fire, and radiation. From 2006 to 2015, the average occurrence of natural disasters is at 376.4, resulting in 69,827 deaths at the average and about US$ 137.6 billion worth of damages. Around the world, China, USA, India, Indonesia, and Philippines are the most disaster-prone countries – where Philippines average on 18.1 counts of natural disasters annually (Guha-Sapir, Hoyois, Wallemacq, & Below, 2017).

In these occurrences, efforts have been given by numerous people and organizations to provide support for the experienced losses. There are those that provided relief programs, money and goods, and some were inspired to help and address the problem through research, even using technology for practical use. In fact, these types of situations produce a large amount of data across different sources that are usable in contributing knowledge about disasters.

One work, called *FILIET* (Regalado, Kalaw, Lu, Dela Cruz, & Garcia, 2015), took opportunity in acquiring tweets to classify and extract disaster-related contents. Since *FILIET's* data came from an online platform, finding out relevant

information was the priority than looking for solutions that could help in disaster prevention and mitigation. As a result, the presented information, that is details about experienced disasters such as casualty, damages, and donations, was only stored in an ontology.

A more direct approach was conducted by *Malasakit* (B. M. Nonnecke et al., 2017), an online participatory tool. It collects responses from local communities with ideas and solutions on how to make the country better handle disasters, which may contain suggestions involving prevention or mitigation. Existing works analyzed the responses through classification (De La Cruz, Oco, & Roxas, 2017) and modeling (Gorro et al., 2017) techniques, providing a general representation and understanding of the responses given. Even though hints to what people want or need for their communities were presented, more can still be exploited by capturing specific points in the responses that can directly help disaster risk reduction. Doing so would present a large number of ideas that would need certain methods for arranging. Nevertheless, when these ideas are brought up, they can be further used by not only researchers, but also organizations that handles disasters in the country.

Hence, this research attempts to fill what is missing from *Malasakit* and its related works: the extraction of key insights or actionable points in community responses regarding disaster prevention or mitigation, the organization of these thoughts, and a medium that can connect local communities with respective decision makers.

In the first place, *Malasakit* responses are unstructured. This poses an opportunity to perform *Information Extraction (IE)*, a method focused on automatically extracting and providing structure to a given unstructured text (Jurafsky & Martin, 2018). A structured information has many usefulness, particularly to disseminate information to an intended target, may it be people or technology (a different program). In relation to *FILIET*, this study adopts the idea of using Part-of-Speech for Information Extraction. It is then supplemented by introducing a grouping and ranking technique that organizes the extracted ideas. Furthermore, information dissemination in a form of a list report was made as medium to relay and communicate the ideas with corresponding decision makers.

1.2 Research Objectives

1.2.1 General Objective

The objective of this research is to extract and organize disaster-related community responses and generate a report for decision makers to address.

1.2.2 Specific Objectives

This research specifically aims to:

- Extract key insights or actionable points in community responses;
- Organize similar ideas from extracted text;
- Generate report from structured information; and
- Evaluate system's performance and report's contents.

1.3 Scope and Limitations of the Research

A Part-of-Speech (POS)-based Information Extraction (IE) system was developed to identify and filter suggested details from a disaster domain data. In particular, these are keywords or phrases that contain ideas or actions to an object or place that can prevent or mitigate disasters in the Philippines.

Data extracted were from Philippine local community responses collected by *Malasakit* (B. M. Nonnecke et al., 2017), an online survey tool gathering insights on how their Barangay 'neighborhood' can help them prepare for disasters (more details at Chapter 4). 934 responses in text form were used in this study, focusing on responses in Filipino language, with consideration to those in English. These responses undergone preprocessing to format the data, fix typographical errors and expand shortcut texts. Additionally, a gold standard was produced containing the expected information to be extracted per response.

Post-extraction, related information was grouped by the affixed response category in *Malasakit's* data to give a general view of the information, while similar concepts were collated through clustering to reduce duplicates. Techniques investigated in this study are n-grams, Sørensen-Dice coefficient, and word embeddings. Aside from grouping, ranking of the information was part of the organization task. Beforehand, *Malasakit's* categories were sorted based on urgency, with highest priority on those representing concrete actions that can be addressed by decision makers. Provided with this, there are two ways that can be used for information ranking, these are through frequency counts of the extracted entries and the priority arrangement of the categories.

The system includes a report generation module that produces a formal collection of information. The report was generated through a template-based technique. It is in a list format, emphasizing the solutions or actions that decision makers can act on. In detail, there would be fields pointing to an extracted information's frequency count, priority level, response category, and the solution's details like "proposed action" and "target".

Standard metrics were reviewed to find appropriate evaluation for the IE product and research's application in the real world. The metric/s serve as performance basis for future related works. In addition to that, the generated report was assessed based on its usefulness of information and format.

1.4 Significance of the Research

This research contributes to Philippines' disaster risk reduction planning and management by extracting and presenting key insights provided by the Filipino community. In light with that, the information extracted extended the capabilities of *Malasakit* (B. M. Nonnecke et al., 2017) which can make use of the product of this research to advise corresponding decision makers such as organizations and government agencies about the primary needs of people in their local areas.

Furthermore, the product of this research can act as a platform for collecting and relaying solutions about disasters, a component usable not only to decision makers but also to other current and future researches and applications. In the same way, the study can be used as an inspiration to conduct research that tackle disaster-related problems and provide an effective, concrete solution by connecting citizens with decision makers; especially on researches that involves dissemination as solution for a particular problem. Adding to this, functionalities presented can be used to develop or supplement various applications related to the field.

1.5 Research Methodology

This chapter enumerates the activities that led to the completion of the research. Included activities consists of Research Design, Literature Review, Data Acquisition, Insights Processing, Experimentation, Evaluation and Analysis, Consultation, and Documentation.

1.5.1 Research Design

The motivation, problem, and purpose of the research was defined in this stage. It includes formulating an idea of the solution, setting the steps necessary to address the problem, identifying resources needed, the scope and limitations in doing research, and the significance of solving the problem and producing the solution (refer to Chapter 1).

1.5.2 Literature Review

Existing works on Disaster, Information Extraction and Clustering were surveyed to expand the proponent's knowledge in the given fields (refer to Chapters 2 and 3). Various approaches in several domains and how they were evaluated was examined, finding the closest literatures for this study. Ideas from these related literatures was applied, took into account but was not limited to the involved components, data or resources, metrics, and underlying research gaps.

1.5.3 Data Acquisition

Data gathered came from *Malasakit's* Local Community Responses (B. M. Nonnecke et al., 2017). It captured insights given by people to improve their Barangay or community (more information available at Chapter 4). This data ensured the absence of personal identifiable information as it only includes those for extracting insights, including actual community responses or comments and annotations done by *Malasakit* pertaining to the category of user comments. The responses have been preprocessed and if needed can be corrected further of misspellings, shortcut texts and spacing. Along this data, a gold standard was made by the proponent for evaluating the extraction process. The expected (or correct) set of insights to be extracted per response was listed accordingly.

1.5.4 Insights Processing

The architectural design (see Chapter 4) shows the processing of disaster-related insights. It is expressed by the unstructured responses going through four main software modules implemented, namely information extraction, information clustering, information ranking, and report generation modules. In addition to this, a preprocessing module was developed for applying input text correction or standardization, and language identification. Moreover, this design is also supplemented by including other resources utilized by the software such as tagger and word embeddings models, and a view of the report (see Figure 4.4 and Figure 4.3) which contains suggestion entries. The format provided in the report is not fixed, other possibilities in presenting and accessing the information was considered. Additional tasks included in this activity debugged and integrated these components to form a holistic software.

1.5.5 Experimentation

Having *Malasakit's* community data and developed software that processes insights, there were experimentations on both the utilized data and software components. In terms of data, there was a test on another dataset in another domain. The assumption is that since the solution processes texts, it should be able to handle inputs regardless of the domain. On the other hand, software components involved adjustments in configurations which can be through the usage of different clustering approaches, various word embeddings models, preprocessing tools, and lexicalization of entries.

1.5.6 Evaluation and Analysis

Evaluation came in two parts: system and report evaluation. In system evaluation, the Information Extraction's performance was measured through standard, quantitative metric/s such as Precision, Recall, and F-Measure. Whereas, for the organized information a qualitative analysis was done by the proponent to bring out the characteristics (positive and negative) and coverage of the approaches and collated information. For the generated report, selected decision makers or *Malasakit* members evaluated it based on the usefulness and presentation of the information. The assessment can be then used to improve the output and accessibility of the developed program. Generally, both parts have corresponding analyses that highlights their contents, capabilities, issues and limitations.

1.5.7 Consultation

Experts in Disaster, Research, and Computer Science fields were continuously consulted to facilitate better contents in the software, report, and document. Considering their inputs, changes were reflected in the document. The desired frequency for consultation was achieved, at least once a month with either of the experts.

1.5.8 Documentation

Throughout the research, constant documentation was done, which reflected the products of every research stages. It was written formally, covering from the tackled problem to the implemented solution, with affixed analyses and evaluations in this research.

Chapter 2

Review of Related Literature

Philippines has experienced countless disasters in the past years. These occurrences resulted into an outburst of data all over different mediums. Under this chapter are several works from researchers who were able to make use of disaster data and Information Extraction techniques, discussing their problems, solutions, sources of data, and architectures.

2.1 Information Extraction

Information Extraction (IE) is a subarea of Natural Language Processing, where it turns unstructured texts into structured texts (Jurafsky & Martin, 2018). A basic overview of the process starts with an unstructured text that will be processed by analyzing and finding features to extract information. Then, given enough features, intended information are extracted and placed on a structured formatting. Normally, components used consists of a Named-Entity Recognition (NER), Relation Extraction, Temporal Expression, Event Extraction, and Template Filling (Jurafsky & Martin, 2018). Although there are times that components could be lesser or greater than this generic architecture, that depends mainly on the problem being dealt with (how simple or complex it is). There are several ways to develop these components, implementations include rule-based, machine learning, ontology-based, or hybrid (mixed) approaches.

In this section, several IE implementations are reviewed. In these works, different approaches and architectures for solving a particular problem or domain are supplied – featuring an IE for disaster and more from other domains such as medicine, media, and business.

2.1.1 FILIET: An Information Extraction System for Filipino Disaster-Related Tweets

The research done by Regalado et al. (2015) is about *FILIET*, a Filipino Information Extraction tool for disaster-related tweets. Their main goal is to capture the most relevant disaster-related information from twitter and make use of these information to help in disaster relief efforts.

FILIET processed around 2,000 tweets about Typhoon Mario and Ruby, that were manually tagged into five categories: Caution and Advise (CA), Casualty and Damage (CD), Call for Help (CH), Donation (D), and Others (O). FILIET is composed of six modules, namely crawler, preprocessing, feature extraction, category classifier, rule inductor, and ontology population module.

The crawler module functions as an automated tweet collector. Twitter's Stream API and Twitter4J was used to collect tweets and was preprocessed using a shortcut text normalizer (NormAPI), tokenizer (ArkNLP), Part-of-Speech tagger (POS Lookup), and Filipino Named-entity Recognition (SOMIDIA gazetteer).

Under feature extraction, presence (binary feature indicating presence of hashtags, URLs, and retweets), tweet length, and word features (unique words without stop words, accented characters, and links) were extracted from tweets.

The process is followed by the classifier module, for which tweets with extracted features were labeled with the five categories through k-Nearest Neighbor, Random Forest, and J48 algorithms using Weka.

Provided with the labels, handcrafted pattern-based, POS-marked rules were applied to extract information like typhoon signals, suspension of classes, casualties, damages, and items donated.

Finally, the extracted information was stored into a retrievable ontology using Protegé and OWL API, that functions as a connector for information that are related with each other.

Experimenting on FILIET extracted multiple information such as CA's location and advice/caution, CD's location, object destroyed, object details and victim's name, CH's location and victim's name, and D's location, donated items and item details. Results for the experimentations garnered multiple values found on Table 2.1, with absolute F-Measure scores on Mario dataset's D-Resource, D-Detail, and D-Victim extracted information, and Ruby's CD-Victim, D-Detail, and D-Victim extracted information. Generalizing FILIET's IE performance, the authors indicated a 0.4 F-measure score.

Table 2.1: Results in Extracting Information from Mario and Ruby Datasets

Categories	**MARIO**			**RUBY**		
	Precision	**Recall**	**F-Measure**	**Precision**	**Recall**	**F-Measure**
CA-Advice	0.5593	0.3388	0.4219	0.6332	0.3010	0.4080
CA-Location	0.6762	0.3352	0.4482	0.8216	0.4454	0.5777
CD-Object	0.4737	0.1125	0.1818	0.5693	0.3790	0.4550
CD-Detail	0	0	0	0.7531	0.1317	0.2247
CD-Victim	1	0.9825	0.9912	1	1	1
CD-Location	0.4700	0.0803	0.1372	0.6274	0.5142	0.5652
D-Resource	1	1	1	0.9688	0.8267	0.8921
D-Detail	1	1	1	1	1	1
D-Victim	1	1	1	1	1	1
D-Location	1	0.2602	0.4130	1	0.2778	0.4348

Provided with the scores, there are parts in this work that can be improved, namely improvement on the preprocessing modules, categories used, and extraction rules. For preprocessing modules, state-of-the-art or improved models for Filipino POS and Named-entity Recognition can be utilized. It is also stated in the recommendations that FILIET has room to implement a Lemmatizer module for better detection and handling of words.

Regarding the categories used, there can be experimentations into increasing and decreasing its scope (adding and reducing categories), to fit the contents in the tweets. In extraction rules, POS markers can be extended into capturing more patterns and also by adding specific set of rules for special and/or common cases. Additionally, an automated, adaptive approach can be implemented to ease in developing the said rules.

FILIET is certainly one of the concrete examples that uses technology to analyze disaster-related texts. However, it focused more on finding relevant information than its second goal, to make use of the extracted information. Granted, it missed the part wherein information is used by people, could be through the act of relaying the information to respective bodies or organizations such as the Barangay, Fire Stations, and more, or simply through visualizing its findings.

Not only that, information extracted consists of casualty, damages, and donations, which are details about a disaster. It may be better to couple the information with a set of solutions in order to assist disaster handling. Examples could be pointing out locations with high casualties to find ways in lessening them, finding areas with high damages to secure and fix, and organize donations from twitter users. Exceedingly important, is to find ways on how to prevent and mitigate disasters.

2.1.2 Other IE Applications

Reviewing other literature showed that there are notable IE applications distinguishable by their purpose and usage of IE, data processed, methodology, and extracted information. Below are works arranged by different types of approaches used, specifically rule-based, ontology-based, machine learning, and hybridized approach. A comparative summary is provided at Table 2.2, with added details regarding each work's data, technologies, evaluation metrics, and performance scores.

C. Cheng, Cagampan, and Lim (2016) generalized data points that resulted into a "read less, know more" information by extracting the 5Ws (*who*, *what*, *when*, *where*, *why*) from Filipino news articles. Their approach made use of grammar rules or markers and sentiment analysis. The rules used were the following:

- for *who*, a *pantukoy* (article) was used as a marker to determine people (e.g., the word/s following *si*, *sina*, *ni*, and *nila*);
- for *what*, phrases in gold standard was used;
- for *when*, names of months, days, and time formats were used;
- for *where*, adverb of place, *pang-abay sa lugar* or *panlunan* (e.g., word/s following *kina*, *nasa*, *mula sa*, and *tungo sa*) were used; and
- for *why*, conjunctions (cause) or *pangatnig na pananhi* were used (e.g., word/s following *kaya* and *dahil sa*).

These kinds of rules can be effective on a specific domain and is capable of being extended further to better fit other domains and cover a larger variety of examples. Additional action to take in order to capture more information is to narrow down the details (lessening the words to process) before extraction. Solely, the concept of extracting 5Ws present valuable information that more or less provides the whole sense of a text.

Saggion, Funk, Maynard, and Bontcheva's (2007) study aspired to model information about countries, regions, and companies that can be used to determine areas where businesses are ideal to be set up. OWL and PROTON upper ontology was used, where it contains the said information, formatted with their relations, properties, and hierarchies. The General Architecture for Text Engineering (GATE) framework was also applied to develop a large language processing technology containing ANNIE, an IE system. The company intelligence IE takes

up-to-date information such as company name, their activities, employee count, names of board of directors, and more; whilst the country/region intelligence IE extracts details such as country name, official language, currency, exchange rate, foreign debt, unemployment rate, GDP, foreign investments, region area, population, and more.

Having developed an IE system that targets businesses, results are crucial. Even with quantitative basis and capability of pointing out valuable information that can get businesses confident about their decisions, without testing and analysis on user acceptance, it could not be evaluated based on its impact or effectivity in the real world. Hence, in this type of systems, having businesses try and rate the system is as important as developing the product.

Peña and Melgar's (2015) research used Protégé ontology editor and extracted information from discussion forums. The subject of the forum containing comments from students are about course offerings. Their idea is to help improve institutions by providing information to which courses students are more interested in. With attention to data coming from people, complications may incur and affect how the system processes, for which requires a more considerate processing or handling of texts. That is why, as their study dealt with informal language, heavy text standardization was applied: filtering out offensive language, special characters, and irrelevant texts, while misspelled words were corrected and words in general are reverted to their root words (lemma). Cleaned and standardized, the information extracted includes courses, teachers, materials, comments, and words that refer to a subject.

Developing an IE to collect insights from and for students is a step towards making one for a larger population. In this study, the purpose was to listen to students and find out which courses are more interesting; modifying this purpose a little bit, an IE system can be used to gather insights in largely engaging topics such as politics and disasters – answering "what do people think or want?".

Culotta, Bekkerman, and McCallum (2004) aimed to connect people through email and webpage contents by generating a large social network and contact information using Conditional Random Fields (CRF) IE and Graph-partitioning clustering. From personal emails and with the help of the Web, 25 fields were successfully extracted such as First Name, Middle Name, Last Name, Nick Name, Suffix, Job Title, Company Name, Address Line, Country, Mobile Phone, and many more – forming an address book. The address books are then connected to others that forms a social network, for which clustering makes sure, through thresholds, that connections are under the right groupings.

Approaching Web data as a supplement into providing and verifying more related information is evident in this work. Local and Web data were bridged together that boosted the extraction and clustering process. This gives an idea to make use of the Web as a large database of information.

The next set of works combined rule-based, ontology-based, and/or machine learning approaches to form a hybrid IE. The combination can be through the IE as a whole or mixed under its components and also the distribution can be balanced or weighing more on a particular approach.

Livelo, Ver, Chua, Yao, and Cheng's (2017) work introduced machine learning to C. Cheng et al.'s (2016) linguistic rules IE, that is intended to speed up processing and understanding of unstructured news data. Processing of the system starts with parsing and transferring news articles into a word table – with word tokens, Part-of-Speech (POS) tags, and Named-entity tags field. Possible 5W candidates were then gathered through a rule-based approach, making use of the information provided by the word table. Filtering the candidates, machine learning (*who*, *when*, *where*), rule-based weighing (*what*), and hybrid (*why*) feature extraction were performed, retaining the most suitable candidate with respect to the Ws.

In their hybrid IE implementation, they took into account other criteria and made use of machine learning to automate the decision process. The machine learning component looked into the candidate string, number of words, sentence for which the candidate belongs, numeric position of the candidate, distance of the candidate from the beginning of the sentence, frequency count, 10 word-neighbors (before and after), and POS tags of word-neighbors to find the most suitable information to be extracted. In this way, the combined approaches efforts considered a wider range of information, covering whole sentences. Despite having the ability to extract lots of information, their main issue lies in determining which is the right one to represent the whole article. Having said that, there has to be considerations outside quantitative metrics as to which information are or can be accepted (even if it is over- or under-extracted) to satisfy the goal.

Ali et al.'s (2017) IE is another that used OWL ontology, but instead was used on social robots or "an interface to convey information and to provide recommendations" in service to persons with disability. Particularly, multiple ontologies (i.e., domain, hotel, medical, city and transport) were merged for extraction and was added with a Support Vector Machines (LIBSVM) classifier for filtering out irrelevant information to form a hybrid IE. The social robot accepts three types of query related to medical drugs (specifically diabetes), hotel accommodations, and city information, then extracts precise information such as name, link, information, and polarity from the Web.

The main issue in this work is with regards to processing large data. There are ways to lessen the load such as retrieving only the top related searches from the Web or introduce a better equipped machine learning algorithm like Artificial Neural Networks to potentially produce more precise and wider scope of information. Other than that, applying hybrid IE for social robots accommodated the extraction of large data through machine learning and extraction of detailed information through ontologies.

Maternal Medical Information Extraction (MaMIE) System by Borra, Santos, Gonzales, and Reyes (2013) extracted English maternal health records to lessen the details of such records whilst maintaining vital information. Records were taken from De La Salle University Medical Center (DLSUMC), Dasmarinas, Cavite, Philippines and was processed through seven modules namely, Text Zoner, Sentence Splitter, POS Tagger, Named-Entity Recognizer (NER), Preparser (POS groups), Semantic Interpreter, and Template Generator. Its hybridized approach consists of a statistical NER, while the remaining are rule-based. Resulting extracted information consists of the general information, obstetrical history, family history, past medical history, social and personal history, vital signs, and clinical discussion section of a patients records, which are all stored in a database.

Based on their work, one important point in extracting medical information is aside from only using generic terminologies, their IE has to be custom fitted to include medical (e.g., diseases, medicines, and procedures) and local (e.g., locations, names, and organizations) terminologies to capture integral parts of the text. Simplistically and generally, the domain knowledge must be prioritized to better handle the texts.

Table 2.2: Comparative Summary of Information Extraction Applications

Related Literature	**Resource/s**	**Techniques**	**Evaluation Scores**
FILIET: An Information Extraction System for Filipino Disaster-Related Tweets (Regalado et al., 2015)	2,000 tweets	Twitter's Stream API, Twitter4J (Crawler), Protégé and Owl API (Ontology), Weka Classifier: k-Nearest Neighbor, Random Forest and J48 [IE] NormAPI (Normalizer), ArkNLP (Tokenizer), Part-of-Speech tagger (POS Lookup), and SOMIDIA Gazetteer (Filipino NER)	Multiple Values (per category), but is represented by 40% F-measure
Organizing News Articles and Editorials through Information Extraction and Sentiment Analysis (C. Cheng et al., 2016)	800 Filipino News Articles	Grammar Rules Information Extraction and Sentiment Analysis: Bag-of-words, TF-IDF weighting, Naïve Bayes, and Support Vector Machines	[IE] Kappa Statistics - What: 5.49%, Who: 24.65%, Where: 56.51%, Why: 6.82%, and When: 68.71%; and Correctness - What: 5.88%, Who: 6.06%, Where: 19.51%, Why: 50%, and When: 84.39% [Tested with Hybrid IE of Livelo et al.] Complete Matches - What: 0.00%, Who: 6.06%, Where: 19.51%, Why: 50%, and When: 84.39%

Table 2.2 continued from previous page

Related Literature	Resource/s	Techniques	Evaluation Scores
Extracting Social Networks and Contact Information from Email and the Web (Culotta et al., 2004)	1441 Total Email Messages from Two Recipients	Conditional Random Fields (CRF) Information Extraction and Graph-partitioning Clustering	[IE] Accuracy (Token): 94.50%, F-score: 80.76%, Precision: 85.73%, and Recall: 76.33%
Maternal Medical Information Extraction (MaMIE) System (Borra et al., 2013)	12 Maternal Records	Text Zoner, Sentence Splitter, POS Tagger, LingPipe Named-Entity Recognizer (NER), Pre-parser, Semantic Interpreter, and Template Generator	[IE] Precision: 87.39%, Recall: 86.74%, and F-measure: 87.06% [POS tagger] Accuracy: 82% [NER] Accuracy: 70.58%
Ontology-based information extraction for business intelligence (Saggion et al., 2007)	MUSING Document Repository, Company Web Pages, Financial News (Yahoo! Finance), World Bank, Monetary Fund, BBC, Wikipedia, and CIA World Fact Book	OWL, PROTON, GATE Framework, ANNIE, Named Entity Recognition (JAPE), OCAT	[Company Intelligence IE] Precision: 85.6%, Recall: 93.6%, and F-score: 84% [Country/Region Intelligence IE] Precision: 94%, Recall: 67%, and F-score: 81%
Ontology-based Information Extraction from Spanish Forum (Peña & Melgar, 2015)	Spanish Discussion Forum	Protégé, Freeling, Lucene, and Jena API	Precision: 76%, Recall: 75%, and F-score: 75%

Table 2.2 continued from previous page

Related Literature	Resource/s	Techniques	Evaluation Scores
A Hybrid Agent for Automatically Determining and Extracting the 5Ws of Filipino News Articles (Livelo et al., 2017)	250 Filipino News Articles	[Hybrid IE] Rule-based and Machine Learning (J48, Naïve Bayes and Support Vector Machines), TPOST, and Stanford NER	[IE] Accuracy – What: 89.20%, Who: 63.33%, Where: 59.25%, Why: 50%, and When: 71.38%; F-Measure – What: 94.29%, Who: 77.29%, Where: 45.13%, Why: 50%, and When: 71.38%; and Kappa Statistics – What: 74.40%, Who: 59.35%, Where: 71.00%, Why: 70.40%, and When: 61.25% [Tested with Rule-based IE of C. Cheng et al.] Complete Matches – What: 28%, Who: 43.84%, Where: 56.4593%, Why: 11%, and When: 59.1743%
Merged Ontology and SVM-Based Information Extraction and Recommendation System for Social Robots (Ali et al., 2017)	4902 Training Sentences and 2737 Test Sentences	Merged Ontology, SVM (LIBSVM), WordNet, GATE, GSE, Protégé, OWL, DL, SPARQL, Pellet, FACT++, and Hermit	Precision: 95%, Recall: 77%, and Accuracy (F-measure): 85%

2.2 Other Disaster Data Analysis

In this section, ways to analyze and mine disaster texts are presented. Specifically discussing text classification (or categorization), topic modeling, and word embeddings.

2.2.1 Classification

In the study of De La Cruz et al. (2017), a multi-class classifier has been developed as a module for an e-participation toolkit (B. M. Nonnecke et al., 2017). It classified community responses related to disaster preparedness and contributes to the field by adding disaster-relevant data for classifiers. There are 10 categories for classification namely, Local Government Units (LGU) accountability, Education and training, Communication, Solidarity, Early warning, Flood control, Personal preparedness, Equipment and supplies, Relief, and Infrastructure.

There were 263 responses used for this study. Each response was cleaned through regular expressions and manually categorized. These responses acted as the classifier's training data, whilst 500 untagged responses were used for testing. Additional pre-processing for the data includes the computation of Term Frequency - Inverse Document Frequency (TF-IDF) weights, a text weighing system with respect to a terminology's relevance over the whole document.

Using the training data, a Support Vector Machine classifier model was created. The classifier labeled the untagged responses and was evaluated through 10-fold cross validation and a social scientist. With 10-folds, the average accuracy of the classifier was 93.30%. However, from the verification of the social scientist, only 63.8% was deemed to be correctly classified due to the following reasons: the classifier's TF-IDF bias - words that frequently appear in a given category will automatically be labeled under that category (potentially the inability to make use of verbs), untagged responses contain misspellings, and ambiguous/broad categories.

De La Cruz et al.'s work acts as an organizer that provides automatic annotation to community responses or data. A research gap on this matter pertains to the limited and outdated categories it can use as label, for which this classifier may need to be updated. Despite this, the stated 10 categories in this paper may be used as basis for importance or urgency; since they are the ones initially established, they must be the most important categories at the moment.

2.2.2 Topic and Language Modeling

Gorro et al.'s (2017) work involves the use of word embeddings (word2vec) and bi-term topic modeling for qualitative analysis. Data analyzed consists 976 disaster risk reduction responses taken from Philippine barangay communities and their main goal is to find out the people's narratives regarding disasters and discover clues as to topics with importance. The data undergone preprocessing, removing data noise such as special characters, numbers, and unnecessary words.

Through bi-term topic modeling, a process of finding, learning and using two terms that are occurring frequently in a particular order to determine similar topics, they produced 10 topics labeled through a manual qualitative method called "open coding". Ideas revolving among the 10 topics prioritizes disaster preparedness through warnings, evacuation preparation, infrastructure and solid waste management. Evaluating the model, a word intrusion test was performed by replacing a word in a topic with an irrelevant word and letting human evaluators point out the "intruder word". The test garnered an average score of 55.71%, showing a good connection between words found on the topics.

Extending their work, word2vec was implemented to find out word similarities above 60% threshold and come up with narratives (or concepts). The narratives that were distinguished are "Community preparedness for emergency", "Helping the barangay in clean-up drive", and "Awareness through seminars and information". In evaluating the result, the cosine similarity was computed, resulting in an average of 0.9020; and a word2vec analogy was listed, for instance, 'community' + 'disaster' - 'preparedness' = 'emergency' means a community experiencing a disaster without preparedness (or being prepared) will result into an emergency, or 'community' + 'bagyo' - 'tulong' = 'disaster' meaning a community experiencing 'bagyo' (typhoon) without 'tulong' (help) will result into a disaster.

Analyzing the approaches and results, bi-term topic modeling consists of words with low distinction compared to the other produced models, which means that it can result into closely similar topics such as "Typhoon preparation in a barangay" and "Disaster preparation in every barangay". With this, one recommendation is to provide a generalization function that can merge these ideas into one automatically. Another, playing around the topics by filtering them into distinct ones to produce a variety in topics that may raise other important concerns.

The results on the other hand, can be useful in coming up with generic and specific categories that most responses are under, mainly for organizing or summarizing the data. It can also be used to find key relationships or measure importance in their given subject that are evident in community responses.

Table 2.3: Comparative Summary of Other Disaster Data Analysis

Related Literature	**Resource/s**	**Approaches**	**Evaluation**
A Classifier Module for Analyzing Community Responses on Disaster Preparedness (De La Cruz et al., 2017)	763 Disaster Preparedness Responses	Support Vector Machine Classifier and TF-IDF Weighting	10-fold Cross Validation: 93.30% and Social Scientist: 63.80%
Qualitative Data Analysis of Disaster Risk Reduction Suggestions Assisted by Topic Modeling and Word2vec (Gorro et al., 2017)	976 Disaster Risk Reduction Responses	Bi-term Topic Modeling and Word2Vec (Word Embeddings)	Word Intrusion Test: 55.71% and Cosine Similarity: 90.2%

2.3 Platforms for Sourcing Disaster Data

This section discusses data sources in disaster domain. It includes community data, online data, and historical data. These collections contain textual and numerical data that can be used for processing and visualizing information.

2.3.1 Malasakit

A cross-platform web survey application called *Malasakit* (B. M. Nonnecke et al., 2017; B. Nonnecke et al., 2018) was developed with a vision of making Philippine communities a part of Disaster Risk Reduction (DRR) planning and response. It was developed using HTML5, Django web framework and SQLite database, with minimal user interface design. In *Malasakit 2.0* (B. Nonnecke et al., 2018), voice recognition was added to accommodate participants with visual impairment.

It has two parts, quantitative and qualitative feedback gathering that pertains to DRR which are available in numerous languages/dialects. Quantitative feedbacks taken are about the participant's demographics (personal assessment) and his/her agreement with presented issues and DRR strategies. An example for this is the statement, "I have suffered the consequence of a typhoon or flood", for which the participant has the choice to enter a number from 0 (strongly disagree) to 9 (strongly agree).

On the other hand, qualitative feedbacks consist of an open-ended question, "How could your Barangay help you better prepare for a disaster" for *Malasakit 1.0* and "How can your barangay better help vulnerable groups such as elderly, women, children, and persons with disabilities during typhoon or flood?" for *Malasakit 2.0*. Based on the questions, *Malasakit 1.0* is geared towards DRR strategies, while *Malasakit 2.0* is towards vulnerable groups. Apart from asking these questions, a collaborative evaluation for other participants' answers is included.

Malasakit 1.0 was tested on Philippine local communities around eight locations, namely Caloocan, Cebu, Davao, Iloilo, Legazpi, Malabon, Manila, and San Mateo City. 12 Field tests were conducted, totaling to 998 participants with over 7,157 evaluations, 2,481 collaborative evaluations, and 896 qualitative feedback entries. *Malasakit 2.0* on the other hand, gathered 1,582 evaluations, 950 collaborative evaluations, and 280 qualitative feedback entries from 261 participants around Sampaloc, Manila and Simon of Cyrene (persons with disability organization), Albay, Bicol. After gathering responses from communities, *Malasakit* allows the data to be exported in a comma-separated values file for textual analysis.

Results under quantitative feedbacks show correlations with three pair of ideas: first, having an early warning system would help a barangay in terms of response; second, participants that are highly prepared for disasters have participated in disaster drills and clean-up drives, proper coordination in their family, and ample amount of food and water supplies to withstand a disaster; and last, support within the community entails better disaster response in the barangay.

Under qualitative, collaborative evaluation produced the top-rated suggestions for DRR strategies. Ideas presented in *Malasakit 1.0* were revolving around waste management (cleaning drainages to lessen or prevent floods) and early warning system (alerts and forecasts). In *Malasakit 2.0*, suggestions focus on bringing persons with disabilities to evacuation centers immediately and necessity of having rescue teams in each barangay.

In this work, it is evident that they have already produced an application to collect data and was able to analyze the data, presenting general ideas from local communities that are valuable information specially to improving their handling, mitigation and prevention to disaster-related issues. However, their work did not highlight specific suggestions provided by their respondents and lacks the capability to disseminate information directly to decision makers (the ones who are better equipped to providing the needs of the people). In this case, it now becomes an integral part to act on the insights given. Provided that access, it would be beneficial to connect the people with governing bodies, and be able to handle, extract, organize and analyze the responses automatically.

2.3.2 Twitter

Twitter, a social networking platform, is widely known to be a good source of information. As users call it, *tweets* can be used to post and engage with information related to any topic, may it be from personal messages to news. An added feature enables users to include *hashtags (#)* for grouping and keeping track of threads that pertains to a topic.

Researches took advantage of this platform by gathering information from tweets. Several applications looked into disaster-related contents in the hopes of presenting relevant information that can aid disaster management planning and relief efforts. One existing work, classified typhoon-related tweets to find out information under resource coordination, urgent rescue needed, urgent rescue resolution, damage reporting, missing people, and media storm coverage (Lam, Paner, Macatangay, & Delos Santos, 2014). For this research, they gathered 2,356 tweets. Another, attempted to classify tweets based on disaster experienced by a

user such as flood, earthquake, fire, landslide, and the likes (Beduya & Espinosa, 2014). In this case, they made use of at least 17,000 tweets containing a variety of disaster types.

A different approach was taken by Regalado et al. (2015), which classified relevant and irrelevant disaster tweets and extracted details such as typhoon signals, suspension of classes, casualties, damages, and items donated. Similar to typhoon classification, only 2,000 tweets were used for this study.

Altogether, their works exhibit ease in accessing and collecting twitter data but showed challenges in processing them. Moreover, contents of their research were limited to proving the feasibility of their studies, the development of their application, and discussion of issues and challenges. Distribution of information, however, was not presented.

2.3.3 NOAH

Nationwide Operational Assessment of Hazards (Project NOAH) is a disaster prevention and mitigation program in the Philippines that enables government agencies "to provide a 6 hr lead-time warning to vulnerable communities against impending floods and to use advanced technology to enhance current geo-hazard vulnerability maps" (Lagmay, Racoma, Aracan, Alconis-Ayco, & Saddi, 2017). They developed a Web-based Disaster Geographic Information System (Web-GIS) for information dissemination, which is a good example of visualization tools for disasters. The Web-GIS consists of six visualization components ranging from land to sky technologies that uses state-of-the-art technologies and historical data to collect and generate near-real-time information.

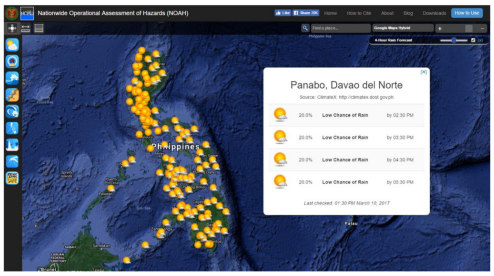


Figure 2.1: Rainfall Probability

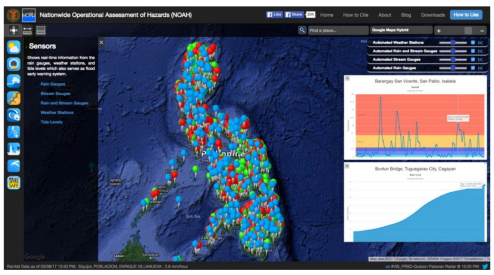


Figure 2.2: Weather and Water-level

First is an estimation of rainfall probability (see Figure 2.1) made for disaster preparedness. It has an accuracy of 82.68% and forecasts are updated every hour up until the next 4 hours. It displays icons that represents 0-20%, 20-30%, 30-40%, 40-60%, and 60-100%.

Second are weather and water-level sensors (see Figure 2.2). It displays color-coded pins such as light blue for light rainfall intensity, blue for moderate, dark blue for heavy, orange for intense, and red for torrential rain. In addition to this, the visualization includes graphs providing rainfall intensity values.

Third, Light Detection and Ranging (LiDAR) and radar-derived topography. These two provide high-resolution topography maps of the Philippines in a 1:5000 and 1:10,000 scale, respectively. Provided the scales, it enables the other components such as the flood and hazard maps to view and identify the danger in a community scale instead of regional.

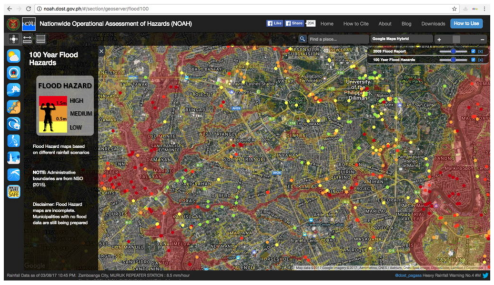


Figure 2.3: Flood Simulation

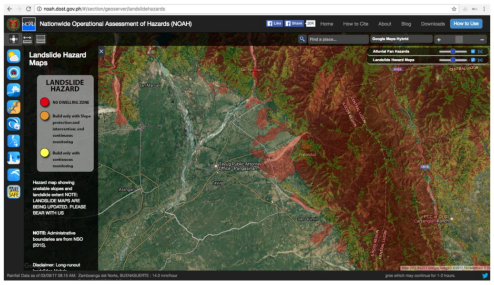


Figure 2.4: Landslide Mapping

Fourth, 1- and 2-dimensional flood simulations and flood events crowd sourcing (see Figure 2.3) for local emergency responses and infrastructure overhaul. Simulations provide flood hazard levels in no flood (green), low (yellow), moderate (orange), and high (red) metrics based on the typical height of a Filipino (167.64 cm), modelled from Manny Pacquiao, a well-known boxer. Data used came from 5- to 100-year rainfall returns, major rivers prone to extreme flooding by the Department of Public Works and Highways (DPWH), and citizen reports.

Next, landslide inventory, simulations and monitoring (see Figure 2.4) for disaster awareness and preparedness. The inventory has 96.07% accuracy, which means its entries mostly contain areas that are prone to landslides. These areas are mapped by placing three colors: red for the most dangerous sites, orange to be most likely susceptible to landslides, and yellow as the least susceptible. Areas without color impose safety and are good for infrastructure.

Last, storm surge simulation and hazard maps (see Figure 2.5) that are classified with advisory levels 1, 2, 3, and 4, measured by 2-, 3-, 4-, and 5-meter storm height. Specifically, it gives details on "... predicted flow depths, velocities, discharge hydrographs, dynamic and static pressure, specific energy, and area of inundation."

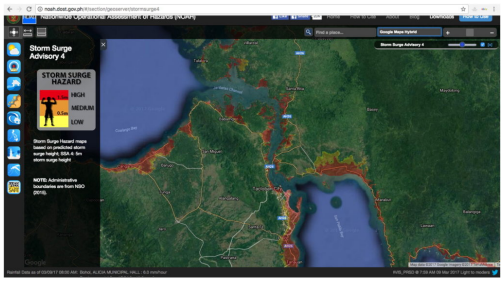


Figure 2.5: Storm Surge Simulation and Hazard Map

Generally, this work presents visualizations that can be useful in wide disaster-related applications. There can still be a lot of changes and improvements to features, interface, accuracy and performance. Since the country experiences a lot of disasters, one idea is to keep on feeding more real data to make better warning and simulations, as accuracy and performance should be the priority.

Table 2.4: Comparative Summary of Disaster Data Platforms

Platforms	Data and Resource/s	Technologies	Related Literature
Malasakit	Malasakit 1.0 Community Responses: 7,157 evaluations, 2,481 collaborative evaluations, and 896 qualitative feedback entries Malasakit 2.0 Community Responses: 1,582 evaluations, 950 collaborative evaluations, and 280 qualitative feedback entries	HTML5, Django Web Framework, SQLite Database and Twilio audio-based interactive voice response	• Malasakit 1.0: A Participatory Online Platform for Crowdsourcing Disaster Risk Reduction Strategies in the Philippines (B. M. Nonnecke et al., 2017) • Malasakit 2.0: A Participatory Online Platform with Feature Phone Integration and Voice Recognition for Crowdsourcing Disaster Risk Reduction Strategies in the Philippines (B. Nonnecke et al., 2018) • A Classifier Module for Analyzing Community Responses on Disaster Preparedness (De La Cruz et al., 2017) • Qualitative Data Analysis of Disaster Risk Reduction Suggestions Assisted by Topic Modeling and Word2vec (Gorro et al., 2017)
Twitter	Disaster Tweets (author collection varies)	Tweet Crawler, Preprocessing Techniques	• Classifying Typhoon Related Tweets (Lam et al., 2014) • Disaster-Related Participant Tweet Identification using SVM (Beduya & Espinosa, 2014) • FILIET: An Information Extraction System for Filipino Disaster-Related Tweets (Regalado et al., 2015)

Table 2.4 continued from previous page

Platforms	Data and Resource/s	Technologies	Related Literature
NOAH	Historical Data: Rainfall, Weather, Water-levels, Storm Surge, Hazard, Flood, Landslide, and Topography Maps	Web-GIS and various data collection technologies (e.g., weather stations, rain gauges, LiDAR, etc.)	• Disseminating Near-real-time Hazards Information and Flood Maps in the Philippines through Web-GIS (Lagmay et al., 2017)

Chapter 3

Theoretical Framework

This chapter discusses theories and concepts related to the study, which consists of topics related to Information Extraction, Clustering, and Filipino Part-of-Speech.

3.1 Information Extraction

Information Extraction (IE) automatically "turns the unstructured information embedded in [natural language] texts into structured data" (Jurafsky & Martin, 2018). It has been widely used by various fields such as Data Science, Media, Finance, Law, and Medicine that makes use of the structured information for analyses and dissemination. Based from Grishman (1997), the IE process has three parts. First, extracting "facts" from a given text; next, integrating facts to produce a larger (or new) facts; and last, transferring these new facts into a certain format. In this section, approaches, tasks and subtasks related to developing IE systems are discussed.

To give an example, input and output of IE using a news article is provided by Jurafsky and Martin (2018):

> Citing high fuel prices, United Airlines said Friday it has increased fares by $6 per round trip on flights to some cities also served by lowercost carriers. American Airlines, a unit of AMR Corp., immediately matched the move, spokesman Tim Wagner said. United, a unit of UAL Corp., said the increase took effect Thursday and applies to most routes where it competes against discount carriers, such as Chicago to Dallas and Denver to San Francisco

information like lead airline, new fare, effective date, and follower airline can be extracted from the article, resulting in 'United Airlines', '$6', 'Thursday', and 'American Airlines', respectively.

3.1.1 Approaches

Stated by Appelt (1999), "there are two basic approaches to the design of IE [Information Extraction] systems, which we label as the *Knowledge Engineering* [Rule-based] Approach and the *Automatic Training* [Machine-learning] Approach." Knowledge engineering revolves around formalizing rules from data (specifically a corpus), whereas automatic training runs an algorithm on an annotated data in order to learn patterns or its set of rules. Alternatively to these two, an ontology, containing concepts and relationships on a particular domain can also be used for IE. In developing IE systems, it is important to note that not all components or sub-tasks has to follow the same paradigm, which even allowed a combination of rule-based, machine learning and/or ontology in a single task to produce an entirely new *hybrid* approach.

Knowledge Engineering (Rule-based)

By their definition, researchers ideal process is pointed towards automatic training since knowledge engineering requires iterative rules modification to have a high-performance IE system. Despite that, knowledge engineering should not be taken lightly as hand crafting rules can tackle problems that would be difficult to automatically process or learn, that is including patterns that have yet to be encountered by the system.

Advantages notable to knowledge engineering suggests ease in implementation and control – one can develop good extraction rules with "right level of generality". At the same time, disadvantages require repetitions in testing and debugging, as well as being limited to the engineer's skills and knowledge in the domain or one's ability and speed in crafting rules. Having pointed out advantages and disadvantages, knowledge engineering is best used when linguistic resources and rule writers (engineers) are available, resources are scarce or expensive, IE specifications has a great chance of changing (especially when frequent), and highest possible IE system performance is needed.

Automatic Training (Machine Learning)

Automation of the process done by knowledge engineering through analysis of data takes away strain on the engineer. In this process, human expertise is not necessarily required, since it focuses on deriving rules within the data. As long as annotators abide on the general knowledge (providing proper annotations like indicating person or organization names), automatically trained IE systems can be developed. Furthermore, in deriving rules, automated training covers all of the data – running through each entry in rule generation. A disadvantage in this approach however, indicates dependency of the system with the data, limiting its knowledge to entries used in training it. Another, automatic training requires acquiring large volumes of data. Considering challenges in annotating, guidelines has to be created to prevent confusions as to person names that can be company names or non-profit organizations that can be confused with companies. It is then important to note the consistency of annotations in the data.

Moreover, mistakes on the data or changes in specifications may require heavy modifications (applied to a lot of entries) and retraining, instead of directly modifying or adding rules. One example is initially having specifications on extracting location names such as countries, cities, and states. If the specification is changed by adding the scope of extracting landforms (i.e., mountains, hills, plateaus, and plains), entries in the data will have to be reannotated to accommodate the change.

Provided with advantages and disadvantages in automatic training, it is best to be used when linguistic resources are unavailable, raw texts are available, training data is large and easily (affordable) acquired, IE specifications are constant or stable, highest possible IE system performance is optional.

3.1.2 Tasks and Subtasks

In general, there are five tasks, components or steps in developing an IE system, namely *named-entity recognition (NER)*, *relation extraction*, *temporal expression*, *event extraction*, and *template filling* (Jurafsky & Martin, 2018). Furthermore, Grishman (1997) added *lexical analysis* before performing the NER process and included processes such as *coreference resolution*.

An IE system can be shaped based on a particular problem by adding or reducing the tasks. There are instances where preprocessors are included; in fact, *FILIET* (Regalado et al., 2015) applied preprocessors to clean disaster-related tweets and only utilized NER and lexical analysis for rules crafting and IE.

Preprocessing

Before undergoing Information Extraction, data must be prepared by reducing noise or dirt in data to prevent loss of performance. There are four preprocessing for texts that can be used, namely *Cleaning*, *Tokenization*, *Sentence Splitting*, and *Standardization/Normalization*.

Cleaning removes unwanted characters or words that are present in the data. For example, data from social media can contain emoticons (expression symbols) or Uniform Resource Locators (URLs) that may hinder machine processing, which the solution is by omitting these characters.

Tokenization simply separates words in the data from punctuations or symbols (normally separated through whitespaces) forming *tokens*. One example using the sentence "Good day, how may I help you?", the tokens would be 'Good', 'day', ',', 'how', 'may', 'I', 'help', 'you', '?'.

Sentence Splitting separates contents in a paragraph into individual sentences to avoid processing large chunk of texts. It is done through regular expressions, using punctuations or end of line (EOL) as markers. There are some instances that instead of sentences, a huge chunk of text is split into paragraphs.

Standardization or *Normalization* transform words into a given, consistent format. An instance of this is reducing a calendar date (e.g., January 1, 2018) into MM/DD/YYYY (i.e., 01/01/2018) format or vice-versa. Another, expands or corrects a shortened variation (e.g., abbreviated, truncated, or phonetically substituted) or typographical error in words (e.g., from gr8 to great), which normally exists in social media and informal domains.

Lexical Analysis

In analyzing lexicons, *Part-of-Speech (POS) Tagging* and *Morphological Analysis* are the main processes for structuring the input data. These processes provide additional details or *features* to words that will help in the overall language analysis, determining the right (or necessary) information to extract.

POS Tagging labels words with their corresponding POS such as Noun, Pronoun, Adjective, Adverb, Determiner, etc. These tags have certain formats for which standards are abbreviated like *Penn Treebank* by Marcus, Marcinkiewicz, and Santorini (1993) for English and *MGNN Tagset* by Nocon and Borra (2016) for Filipino (see Appendix A). A POS tagger can be implemented through rule-based,

machine learning (commonly statistical or sequence models), and hybridized approaches. Primary challenge for any of the approaches is on how to handle lexical ambiguity, that is a word having multiple POS candidates. Regardless, implementing this component and using POS tags as features can surface language patterns that will be helpful in rule creation, learning, or machine process of IE systems.

Morphological Analysis pertains to finding out a word's structure or formation. In this process, root words are discovered and variations (inflected, derived, and compounded words) are explored. Two specific techniques adhere to this idea, namely *Stemming* and *Lemmatization*, which both processes the root word.

Stemming formulates the structure of a word by chopping off characters (features) outside of the root word, specifically the affixes attached to the inflected word. For example, the Filipino term *magtatago* 'will hide', the prefix *mag-* and partial reduplication *ta-*, will be chopped off to get *tago* 'hide' as the root word. Moreover, this process is often visualized through character branches to show the structure of the word and how the root word was extracted. Issues encountered in stemming include over-stemming and under-stemming.

Lemmatization on the other hand, extracts the root word through the use of vocabulary or dictionary. A vocabulary often contains the lemma and its variations or forms. Some may provide additional information such as morphological information or descriptions (e.g., grammatical tense, point-of-view, POS, and more). Issues encountered include being limited to the number of entries present in a vocabulary (out-of-vocabulary), not capturing word features or root word outside the vocabulary.

Differentiating the two through an example, stemming the word 'occupied' may result into the root 'occupi' by removing *-ed* prefix, whilst lemmatizing the word may result into 'occupy' or 'occupied' if it does not exist in the vocabulary. Furthermore, stemming does not require much of morphological analysis as it can reduce affixes in a word without other heuristics; thus, can be faster compared to lemmatization but may need intervention as to fixing broken root words.

Named-entity Recognition (NER)

NERs as defined by Jurafsky and Martin (2018), is the process of detecting and labeling entities in a text, where entities are "... roughly speaking, anything that can be referred to with a proper name". Common entities that are labeled include a person, location, organization, date, and time. For NER, there is a standard format in labeling such as PER for person, ORG for organization, LOC for lo-

cation, etc. A factor needed to take note of is the ambiguity of an entity. Some entities can have multiple labels that has to be considered for accurately providing the right type. NERs can be developed through lists, rules, and supervised machine learning (normally using sequence models). Terminologies related to these techniques include *IOB tagging*, *word shapes*, and *gazetteer*.

IOB Tagging pertains to features that labels a word as inside (I), outside (O), and beginning (B) of an entity. For example, the phrase "United Airlines said Friday it has increased fares..." is labeled as B, I, O, B, O, O, O, and O, where 'United' is the beginning of the entity and any word part of it is an inside like 'Airlines'; as to 'Friday', it is another entity and is labeled as B.

Word Shapes, primarily used for labeling unknown words, are features that corresponds to letter type or case patterns. Formatting for word shapes retain punctuations or symbols, and replaces uppercase letters with 'X' marker, lowercase letters with 'x', and numbers with 'd'. One example, the flight "AirAsia Z2-420" will have the corresponding feature of "XxxXxxx Xd-ddd". Additionally, shortened word shapes can be used as features by reducing consecutive duplicate shapes, turning shapes from the previous example into "XxXx Xd-d".

A *Gazetteer* is a resource used by NERs, containing a list of entities such as person, location (i.e., countries, cities, landmarks, shops, and more), product (e.g., biological, mineral, commercial, and more), and organization (with extensions or abbreviations) names. It can also include dates such as January, February, Sunday, Monday, and the like.

Coreference Resolution

Coreference Resolution or Analysis as stated by Grishman (1997) "... has the task of resolving anaphoric [an expression depending on another expression] references by pronouns [e.g., he, she, it, this, that, etc.] and definite noun phrases." In the sense, coreference resolution finds and links the entity referred to with the corresponding pronouns and noun phrases (applicable also on abbreviated mentions like 'Burger King' and 'BK'). For example, given the sentence "The neighbors love Malcolm, they made a cake for him.", through coreference resolution, the word 'they' should be linked with the neighbors, whereas 'him' should be linked with Malcolm. A more complicated example involves noun phrases; for instance, "The kid fought off the robber at the store." followed by the sentence "The hero deserves his praise.", the kid and hero should be linked with each other.

Relation Extraction

As the term suggests, relation extraction is the process of finding and identifying connection/s (semantic relations) between extracted entities. It can be developed through hand-written patterns, supervised, semi-supervised and unsupervised machine learning. Generally, relations are in binary, meaning two entities are joined together by a single relation.

Illustrated by Jurafsky and Martin (2018) at Figure 3.1 are sample relations to particular entities (in blue), where samples (in orange) of generic ones are *part-of* and *employs* relationship. Furthermore, there are several domains that established relation sets or a list of binary relations such as the Unified Medical Language System (UMLS) which provided relations between substances, organisms, function, structures and many more, and Wikipedia's infoboxes which are structured facts in the form of *category = "value"* (e.g., state = "California" or president = "John L. Hennessy").

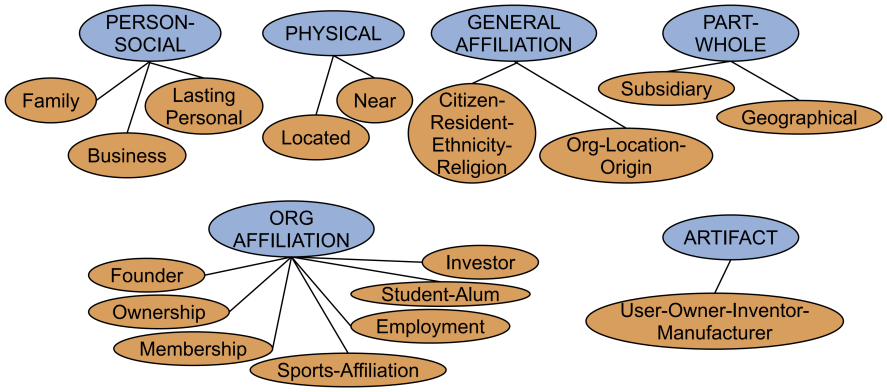


Figure 3.1: Relation Network Samples

A concrete example in applying relation extraction given "American Airlines, a unit of AMR Corp., immediately matched the move, spokesman Tim Wagner said.", indicates entities such as 'American Airlines', 'AMR Corp.', and 'Tim Wagner', that are organization, organization, and person entities, respectively. Using the entities, relations can be found such as: 'American Airlines' is a part of 'AMR Corp.' and 'Tim Wagner' is affiliated with the organization 'American Airlines'. In line with this, the relations can also be interpreted as 'American Airlines' is a unit of 'AMR Corp.' and 'Tim Wagner' works for 'American Airlines'.

In pairing entities with a relation, there are formats that can be followed. One format is a model-based view wherein it contains domain, classes, and relations. The domain (D) is a set of entities that are represented as variables, illustrating the set show D = a, b, c, ...; classes are entities grouped per type like Organization

(Org) = a, b and Person (Pers) = c; and relations are represented in a format like *PartOf* (relation) = ¡a,b¿ (a is a part of b) and OrgAff = ¡b,c¿ (c is affiliated with b). Another format is called *Resource Description Framework (RDF) triple* where entities and relations are formatted through a subject-predicate-object expression. An example for this is the *DBpedia* resource with over 2 Billion RDF triples.

In the light of relational resources, *WordNet* offers a hierarchical representation of relations between words. It has a "... is-a [or Instance-of] or hypernym relation between classes, Giraffe is-a ruminant is-a ungulate is-a mammal is-a vertebrate is-a animal..." (Jurafsky & Martin, 2018). Provided with resource such as WordNet, data for relation extraction can be increased.

Temporal Expression

Temporal Expression extraction pertains to capturing time and date entities. There are three types of temporal expression, namely absolute, relative and duration. *Absolute temporal expressions* refer to time and dates "... that can be mapped directly to calendar dates, times of day, or both" (e.g., 'January 1, 2018' and '12:00PM'), whereas *relative temporal expressions* refer to "... particular times through some other reference point" (e.g., yesterday, next semester, and last quarter) and *duration* "... denote spans of time at varying levels of granularity (seconds, minutes, days, weeks, centuries, etc.)" (Jurafsky & Martin, 2018).

Temporal expressions can be found through *lexical triggers* which are nouns, proper nouns, adjectives, and adverbs pertaining to time and date. Examples for this are the words 'morning', 'January', 'recent', and 'hourly', each with respect to the part-of-speech given. It can be automatically detected or recognized through rule-based approaches, particularly making use of patterns (automata or regular expressions). Another, uses sequence-labeling by implementing the *IOB scheme*, where B indicates the beginning of a temporal expression, I is any word or number that follows it but has to be a part of the temporal expression, and O are words that are not temporal expressions.

As temporal expressions are extracted, these entities have to undergo normalization. Temporal expressions are standardized into a specific point in time (relative are turned into absolute) or duration under a certain format. A format used is ISO 8601 standard for encoding temporal values. For this format, dates are represented through YYYY-MM-DD, weeks are in YYYY-Wnn (n refers to week number), durations in Pnx (n refers to the length and x refers to the unit), clock times in HH:MM:SS, financial quarters in Qn (n refers to quarter number), and many more other representations within the standard.

Going deeper than formatting, normalization enables computation of relative and duration temporal expressions. Through a temporal anchor, a reference point like document date or publish date, can be used to add and subtract days from terms such as tomorrow or yesterday. Calculating dates however are not as simple as it is, since there are ambiguities that may be present. For instance, the phrase "the weekend" can refer to the weekend that passed or the coming weekend.

Event Extraction

An event as defined by Jurafsky and Martin (2018) "... is any expression denoting an event or state that can be assigned to a particular point, or interval, in time." Usually in English, verbs like 'increasing' and noun phrases 'the increase' contain events. However, there are also times that verbs do not indicate one. One instance is "took effect", for which when the event took effect is indicated and not the event exactly. With this in mind, a lot of words and features have to be considered. That is why machine learning has been the primary approach in detecting and modeling, as such process can handle and take into account features like character affixes, nominalization suffix (e.g., *-tion*), part-of-speech, light verbs (e.g., make, take, have, etc.), subject syntactic category, morphological stem, verb root, and WordNet hypernyms.

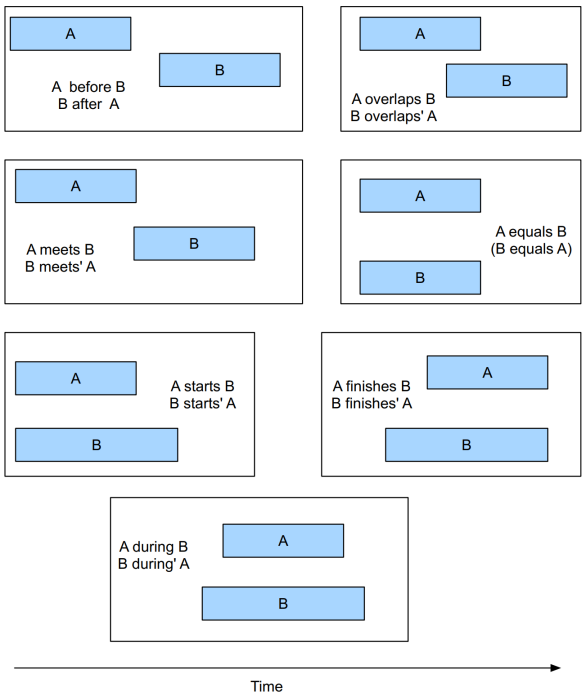


Figure 3.2: Temporal Relations Order

Having events and temporal expressions extracted, the information together can be used to make a timeline of events. For this, events are to be determined whether they are pointing to the same event and their order. It involves the process of using binary relation detection and classification techniques, identifying which temporal relations shown at Figure 3.2 match the events.

Template Filling

In an IE System, visualization of the output is an essential task. It may be done through simple, static labels or through an advanced technique by finding appropriate labels per information. Template filling refers to the task of finding "... documents that invoke particular scripts [templates] and then fill the slots in the associated templates with fillers [information] extracted from the text." (Jurafsky & Martin, 2018).

Basically in this task, the appropriate template has to be selected and how the output is to be presented is formulated, in order to fill in the template with the extracted information under the right labels. Performing advanced template filling mentioned statistical approaches which involves template recognition and role-filler extraction.

3.1.3 Evaluation Metrics

There are various ways in building an Information Extraction (IE) system. Standard metrics are used to measure the overall performance for proper evaluation and comparison – differentiating each IE system from each other. Metrics primarily used are *Accuracy*, *Precision*, *Recall*, *F-Measure*, and *Kappa Statistic*.

Accuracy is the "closeness of agreement between a measured quantity value and a true quantity value of a measurand" (BIPM, IFCC, IUPAC, & ISO, 2012). In this case, the measured value is represented through a given system's output, whilst the true value is an expected output, normally given by respective annotators or experts as the *gold standard*.

Comparing two values for instance, if the result is the same (or above a threshold), the score will increase, whereas having different values (or below the threshold) will not increase nor decrease (unless penalty is applied) the score. Normally, the equation for accuracy counts the number of correct instances divided by the total number of instances (multiplied by a hundred to get the percentage value).

Provided with the system's output and true value (gold standard) in an Information Retrieval setting, **Precision** or **Positive Predictive Value** is computed through the number of relevant documents (correctly) retrieved by the system over the total number of documents retrieved (Hripcsak & Rothschild, 2012). **Recall** or **Sensitivity** on the other hand, are relevant documents that has been retrieved by the system among relevant documents, or relevant documents retrieved over total number of relevant documents. An example formula for the two metrics are:

$$Precision = \frac{|\{relevant\ documents\} \cap \{retrieved\ documents\}|}{|\{retrieved\ documents\}|} \tag{3.1}$$

$$Recall = \frac{|\{relevant\ Documents\} \cap \{retrieved\ documents\}|}{|\{relevant\ documents\}|} \tag{3.2}$$

Precision (Equation 3.1) provides the idea as to the number of documents retrieved by the system which are relevant, but are only limited to it; thus, does not provide if all relevant documents has been retrieved. Recall's (Equation 3.2) idea is also limited, as it represents the relevant documents that has been successfully retrieved but does not represent the rest of the documents retrieved that are irrelevant (Dietrich, Heller, & Yang, 2015).

F-Measure, also known as **F-Score** or **F1 score** (Equation 3.3), is the harmonic mean of Precision and Recall. The 1 in F1 is a value for β, a weight for precision or recall.

$$F = \frac{(1+\beta^2) \times precision \times recall}{(\beta^2 \times precision) + recall}; F1 = \frac{2 \times precision \times recall}{precision + recall} \tag{3.3}$$

Kappa Statistic or **Kappa Coefficient (κ)** measures the agreement between observers or raters, annotating or "...evaluating the same thing" (Viera & Garrett, 2005). It is a measurement for consistency, since multi-observer/raters often provide variations into their assessments. The Kappa statistic ranges between values -1 and 1. A kappa with the value of 1 pertains to an absolute agreement, 0 for agreement by chance, and negative values for agreement less than chance (possibly no agreement).

In calculating the Kappa statistic (Equation 3.4), the formula is represented by "the difference between how much agreement is actually present ('observed' agreement $[p_o]$) compared to how much agreement would be expected to be present by chance alone ('expected' agreement $[p_e]$)" (Viera & Garrett, 2005).

$$\kappa = \frac{p_o - p_e}{1 - p_e} \tag{3.4}$$

A table of agreement is shown at Table 3.1 with given values for a sample calculation for Kappa Statistic. Raters A and B were asked to evaluate which among N (100) lectures were useful or not.

Table 3.1: Table of Agreement between Two Raters

Rater A \B	Yes	No
Yes	(a) 15	(b) 05
No	(c) 10	(d) 70

Values (a) and (d) are the ones that both raters agree on, which are also the values needed for computing the observed agreement:

$$p_o = \frac{a+d}{N} = \frac{15+70}{100} = \frac{85}{100} = 0.85$$

On the contrary, values (c) and (d) are the ones which raters disagreed on and is used for computing the expected agreement by adding the probability of raters answering yes and no:

$$p_e = \left(\frac{a+b}{N} \cdot \frac{a+c}{N}\right) + \left(\frac{c+d}{N} \cdot \frac{b+d}{N}\right) = \left(\frac{20}{100} \cdot \frac{25}{100}\right) + \left(\frac{80}{100} \cdot \frac{75}{100}\right) = 0.65$$

Given the two variables, the Kappa Statistic can be computed:

$$\kappa = \frac{p_o - p_e}{1 - p_e} = \frac{0.85 - 0.65}{1 - 0.65} = 0.57$$

3.2 Clustering

Clustering as defined by Gan, Ma, and Wu (2007), is "a way to create groups of objects, or clusters, in such a way that objects in one cluster are very similar and objects in different clusters are quite distinct." Strongly established, the main criterion for grouping is through similarity or association. Clustering was firstly introduced by Driver and Kroeber (1932) for anthropology, where ethnic groups were compared and clustered based on their cultural similarities. It has then been applied to numerous fields such as pattern recognition, artificial intelligence, information technology, image processing, and many more.

In general, data objects may come in a form of text, numbers, or a combination of the both. Under this section, ways to cluster words are presented. Techniques cover string similarity, as well as, semantic similarity; particularly, n-grams, Sørensen-Dice Coefficient, and word embeddings.

3.2.1 N-grams

Defined by Jurafsky and Martin (2018), "an *n-gram* is a sequence of N [number of] words". In the phrase "all of a sudden...", a 1-gram or *unigram* consists of the sequence with individual words like 'all', 'of', 'a', 'sudden', a 2-gram or *bigram* is a sequence of "all of", "of a", "a sudden", and so on. In some cases, n-grams can be a sequence of characters instead of words.

In the context of language modeling or the process of assigning probabilities to succeeding words, word sequences, and even whole sentences (Jurafsky & Martin, 2018), n-gram models can compute for succeeding word predictions using the conditional probability of a word w given a word history h. It is able to do so by checking the number of times h has been followed by w in the corpus – a collection of text. For example, the same phrase above will produce the equation:

$$P(w|\text{all of a sudden}) = \frac{Count(\text{all of a sudden } w)}{Count(\text{all of a sudden})}$$

.

However in this process, it would be difficult to run through and count instances of a sequence given large data. Imagine computing for the probability of an entire sequence alone, it will require counting the number of times a sequence came up to the corpus divided by the number of words with the same length of the sequence. Having said that, there are other ways to compute probabilities of sequences such as a *Markov* assumption.

The idea for *Markov*, instead of looking at the whole history to compute for the probability, an approximation of the history can be used by only looking at the last few words; particularly, the $N1$ previous neighboring word/s. With the same example and using a bigram, instead of computing for $P(w|\text{all of a sudden})$, it can be reduced and approximated using $P(w|\text{sudden})$. Generalizing this equation with respect to the n-gram, approximating the conditional probability of the next word in a sequence (Equation 3.5) and the whole sequence (using *chain rule of probability*, Equation 3.6) are:

$$P(w_n|w_1^{n-1}) \approx P(w_n|w_{n-N+1}^{n-1}) \tag{3.5}$$

$$P(w_1^n) \approx \prod_{k=1}^{n} P(w_k|w_{k-1}) \tag{3.6}$$

Furthermore, additional tasks done to the approximation is applying smoothing, normalizing the n-gram's probabilities into relative frequency (values between 0 and 1), and using log probabilities instead of raw probabilities for computations.

In the context of clustering, n-grams can be used in both semantic and string similarity. For semantic, n-gram language models can be used to provide a sense to which the words relate to each other by grouping together sequences that are close in terms of usage counts or probability values. In fact, semantic clustering can be done on not just words but also sentences and even in between dialects and languages.

For example, in terms of word order, "all of a sudden I notice three guys standing on the sidewalk" will make more sense than producing the same words in the order "on guys all I of notice sidewalk three a sudden standing the". It means that there is a particular structure in the sentence that can be observed and followed, usable to compare and pinpoint words, phrases, or sentences that can be grouped together. Another example are "Hey, how are you?" and "Hello, how are you?" Assumingly, both should have the same or at least close probability values as it ends with the same phrase. In this case, the two sentences can be under the same cluster, possibly labeled as "greeting", and can be further used to find other sentences related to them.

For string similarity, the concept of using n-grams alone (without the probabilities) is applied, normally adding a similarity or distance measure as criterion for comparing and grouping similar or dissimilar texts. One common process is to dissect two words with their character n-grams and compare each n-grams to compute its similarity to each other.

3.2.2 Sørensen-Dice Coefficient

Sørensen-Dice Coefficient or *Dice's Coefficient* (Dice, 1945) is used to measure orthographic similarity between words. It uses character n-grams to represent the structure of the words and calculates the similarity or distance score by counting the shared or matching n-grams. Specifically, Dice's coefficient is computed by counting the matched n-grams and multiplying it by 2, then dividing the produced value with the combined total number of n-grams present between two words. Formally, the equation for similarity, given two words x and y is:

$$S\phi rensenDice = \frac{2 \times |ngrams(x) \cap ngrams(y)|}{|ngrams(x)| + |ngrams(y)|} \tag{3.7}$$

where *ngrams* is a function containing a set of character n-grams (provided an n) of a text. The similarity score is bounded between zero and one and using 1 Sørensen-Dice can be used to transform the value into a distance score (how far the two words are from each other).

Applying this function on 'compliment' and 'complement' given an n of 2 (or bigram) produces the sets {co, om, mp, pl, li, im, me, en, nt} and {co, om, mp, pl, le, em, me, en, nt}, respectively. Substituting the values to the Equation 3.7 results in 0.778 similarity or 0.222 distance score.

Dice's coefficient can be used in language modeling by using the n-grams and values to discover similarities between words or even in languages. Another application is clustering, wherein words are grouped together based on their orthographic similarities.

3.2.3 Word Embeddings

Word embeddings is a type of language modeling that "embeds" words into a vector space. Through these vectors, the meaning of a word is represented, and similar ones are embedded near each other (e.g., synonyms, tenses, gender-related, and country-capital relationships). Thus, this vector space model can be used to find syntactic and semantic relationships among words.

A visualization of the multi-dimensional vector space projected in 2D space using T-distributed Stochastic Neighbor Embedding (t-SNE) is shown at Figure 3.3 (Jurafsky & Martin, 2018). It exhibits clustered words based on sentiment polarity (i.e., neutral, positive, and negative) and at Table 3.2 shows more kinds of word similarity relationships from Mikolov, Chen, Corrado, and Dean (2013).

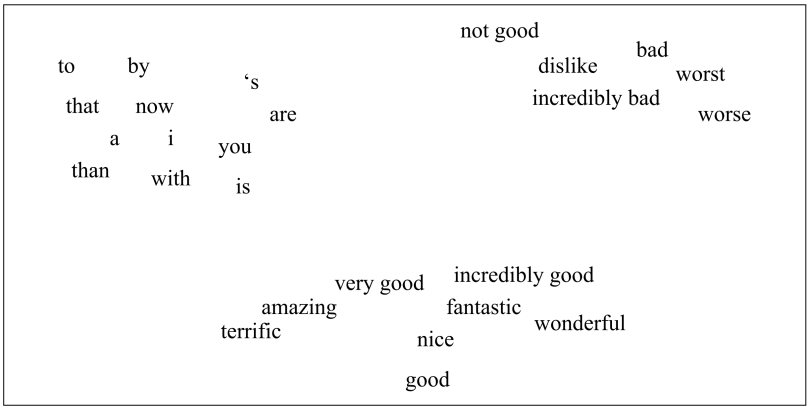


Figure 3.3: Vector Space Visualization Example

Table 3.2: Word Similarity Pair Examples

Relationship	**Example 1**	**Example 2**	**Example 3**
France - Paris	Italy: Rome	Japan: Tokyo	Florida: Tallahassee
big - bigger	small: larger	cold: colder	quick: quicker
Miami - Florida	Baltimore: Maryland	Dallas: Texas	Kona: Hawaii
Einstein - scientist	Messi: midfielder	Mozart: violinist	Picasso: painter
Sarkozy - France	Berlusconi: Italy	Merkel: Germany	Koizumi: Japan
copper - Cu	zinc: Zn	gold: Au	uranium: plutonium
Berlusconi - Silvio	Sarkozy: Nicolas	Putin: Medvedev	Obama: Barack
Microsoft - Windows	Google: Android	IBM: Linux	Apple: iPhone
Microsoft - Ballmer	Google: Yahoo	IBM: McNealy	Apple: Jobs
Japan - sushi	Germany: bratwurst	France: tapas	USA: pizza

Aside from explicit word similarities, another property of word embedding enables word offsets, applying algebraic operations and cosine distance in the vector space. A famous example by Mikolov, Yih, and Zweig (2013) showed gender-related offsetting like *vector*("King") – *vector*("Man") + *vector*("Woman") = vector("Queen"). Another is corresponding to a word's tense, like vector("biggest") – vector("big") + vector("small") = vector("smallest").

A renowned work using word embeddings for word similarity tasks was done and documented by Mikolov, Chen, et al. (2013), under the *Word2Vec* package. They established two log-linear models that captures context similarity in words from a large set of data, namely Continuous Bag-of-Words (CBOW) and Continuous Skip-gram model (architecture found at Figure 3.4). In a nutshell, CBOW's main task "predicts the current word based on the context", whilst Skip-gram "predicts surrounding words given the current word" (Mikolov, Chen, et al., 2013).

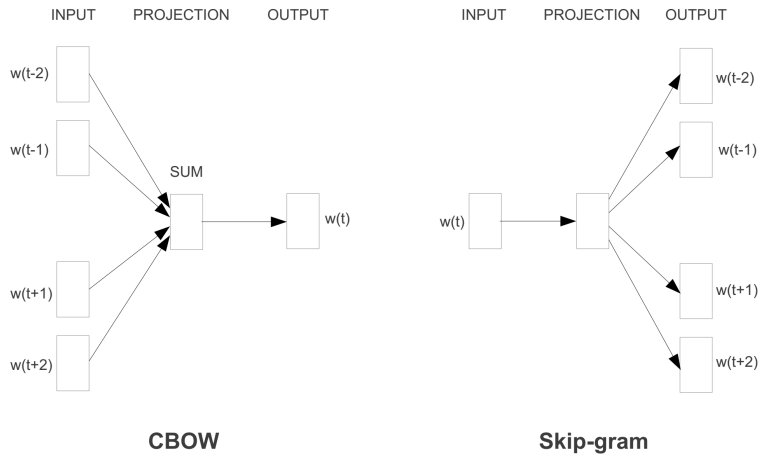


Figure 3.4: CBOW and Skip-gram Architectures

In CBOW's architecture, the hidden layer is omitted. With this, a bag-of-words containing all word vectors are averaged and shared into the projected layer. As shown in its architecture, note that these vectors include history (i.e., $w(t-1)$, $w(t-2)$,...) and future (i.e., $w(t+1)$, $w(t+2)$,...) words which constitutes the context and predicts the middle or current word that is $w(t)$. Oppositely, Skip-gram's architecture, from an input word $w(t)$ through a continuous projection layer, produces words before and after it.

An experiment comparing different models through semantic-syntactic word relationship test, resulted into CBOW and Skip-gram performing better. CBOW achieved better results in terms of syntactic tasks, while Skip-gram is better on semantics tasks. Overall, CBOW and Skip-gram's simpler architecture produced high quality vectors.

Another well-known word embedding model incorporates global corpus statistics in its vectors, called *Global Vectors* or *GloVe* (Pennington, Socher, & Manning, 2014). Instead of just learning from neighboring words, it adds on the global statistics that can capture frequent repetitions or patterns in the data. Specifically, this statistic utilizes ratios of co-occurrence probabilities.

In comparison with Word2Vec, evaluation methods include word analogy, word similarity, and named-entity recognition tasks. In these experiments, GloVe performed better in most of the tasks, even outperforming Word2Vec's CBOW on word similarity utilizing only less than half of the data size.

A straightforward improvement by Mikolov, Grave, Bojanowski, Puhrsch, and Joulin (2017) involves using these existing algorithms to accommodate training large datasets such as Common Crawl (630 Billion words), Wikipedia Meta-pages (9.2 Billion words), and Statmt.org News (4.2 Billion words). With this attempt, their work developed new high-quality pre-trained word and phrase representations. Learning from their implementation and analysis, it is fairly important to note the removal of duplicates in data and addition of position-dependent weights and subword features in the architectures.

Expounding on subword models, one notable work was created by Bojanowski, Grave, Joulin, and Mikolov (2017) called *FastText*. It was made to be fast, efficient, and able to handle languages with rich morphology and unknown words. As an extension of Word2Vec, specifically its skip-gram model, FastText makes use of bag-of-character n-grams for word representations.

In particular, vectors are represented by each character n-grams (ranging from three to six), and words are represented by summing up these vectors. A given example to visualize this represented the word 'where' with n-gram of three:

<wh, whe, her, ere, re>, and the whole sequence <where>.

Notice the special boundary symbols < and > used in the representation. These symbols signify if the character sequence acts as a prefix or suffix to a word. Having said that, the representation of 'her' and whole sequence pertaining to the pronoun <her> are different from each other.

Evaluating FastText, results showed that it outperforms other models in word similarity and analogy tasks. Even in comparison with other subword models, FastText was able to provide better, yet comparable results. In other experiments, it has been discovered that FastText does not rely on large training data, in fact was able to thrive given small datasets.

Provided with these three main developments in word embeddings, Word2Vec, GloVe, and FastText has been available in public as pre-trained word embedding models and representations. These pre-trained models were used as baseline to start researches in several Natural Language Processing tasks and there are also attempts in refining these models.

3.3 Filipino Part-of-Speech (POS)

Part-of-Speech (POS) is a categorization of words based on its grammatical function. *POS Tagging* is the process of labelling words with their corresponding POS, wherein it is guided by a collection of tags, called a *tagset*. At this time of writing, one of Filipino's latest is called *MGNN tagset* by Nocon and Borra (2016) (see Appendix A), a version sourced from C. K. Cheng and Rabo's (2004) tagalog tagset and English's Penn Treebank (Marcus et al., 1993).

MGNN tagset itemizes Filipino POS and their tag counterparts. A short listing of the counterparts with examples are provided on Table 3.3. In this sample, only the main categories are provided. The actual tagset contains subcategories (subcategories count beside the tag name) that concatenates more characters at the end of the main category's tag name. Instances of these concatenations are NNP for proper nouns, NNPA for proper noun abbreviation, PRP for personal pronouns, DTC for common noun determiner, CCP for ligatures (*pang-angkop*), CCU for preposition (*pang-ukol*), VBTS for past tense verb, JJD for describing adjective, RBJ for interjections (*sambitla*), and PMP for period punctuation. In addition to this, MGNN tagset also considers compound tags (combination of tags) and were recorded as seen on Nocon and Borra's (2016) data. An example is the "magandang babae" 'beautiful girl' for which *magandang* is tagged as JJD_CCP, because *maganda* is a describing adjective that ends with *-ng* ligature.

Table 3.3: MGNN Tagset: Main Categories

POS	Tag Name	Examples
Noun (Pangngalan)	NN (4)	tao, Pilipino, Dra., Bb., km, cm
Pronoun (Panghalip)	PR (10)	ako, kami, ito, sino, dito, ganyan
Determiner (Pantukoy)	DT (4)	ang, si, ni, kay, sina,
Lexical Marker	LM (1)	ay
Conjunctions (Pang-ugnay)	CC (6)	maging, pero, kasi, ng, at, -ng
Verb (Pandiwa)	VB (14)	mag-, pwede, mayroon, -um-
Adjective (Pang-uri)	JJ (6)	maganda, pareho, mas, pinaka-,
Adverb (Pang-abay)	RB (15)	kung, dahil sa, huwag, oo, hoy
Cardinal Number (Bilang)	CD (1)	1, una, tatlo, II
Topicless (Walang Paksa)	TS (1)	Umuulan., Alas dos na.
Foreign Words	FW (1)	English, Spanish, Latin
Punctuation (Pananda)	PM (6)	'.', '!', '?', ',', ';', '#', '+', '('
Compound Tags	tag1_..._tagN (161)	pinakamagandang (JJCS_ JJD_CCP), ako'y (PRS_LM)

Provided with a tagset, POS tagging can be automatically done. In Miguel and Roxas' (2007) research, a comparative analysis between different Tagalog POS taggers was done. These taggers followed C. K. Cheng and Rabo's tagset and was implemented in various kinds of approaches namely template-based n-gram POS tagger (TPOST), memory-based POS tagger (MBPOST), supervised probabilistic POS tagger (PTPOST), and rule-based POS tagger (Tag-Alog).

Among these taggers, the highest performing was PTPOST with 78.3%, followed by MBPOST (77%), Tag-Alog (72.5%), and TPOST (70%). Based on the results, PTPOST's lexical and contextual probability values proved to be more effective than the other approaches which used tagging rules, sentence and lexicon collections, and word-tag database.

Revived after almost a decade, a new set of POS taggers were developed, this time for Filipino and follows the MGNN tagset. The goal was to move forward, devise and apply new approaches for POS taggers to update "... data contents, software usability, performance and availability" (Nocon & Borra, 2016).

The new set was started by Nocon and Borra (2016), which introduced the use of Statistical Machine Translation (SMT) for POS tagging (SMTPOST). It was then followed by a Hybridized POS tagger (HPOST) that combined SMT, dictionary-based, regular expression-based approaches (Go, Nocon, & Borra, 2017) and Filipino Stanford POS Tagger (FSPOST) that uses maximum entropy cyclic dependency network (Go & Nocon, 2017).

Comparing the three taggers, FSPOST garnered the highest performance score with 96.15% accuracy which is considered to be the state-of-the-art in Filipino. The other two, although lower than FSPOST, got scores higher than the PTPOST, with 89.11% for SMTPOST and 91.63% for HPOST. Upon analysis, the key to FSPOST's high performance was due to an extensive use of features (e.g., word and tag context, affixes, and word shapes), lexicalization, bidirectional inference, and smoothing.

Chapter 4

Architectural Design

This chapter discusses in detail the design and implementation of the Filipino text analysis tool for disasters. Its overall task is to extract valuable information or insights from a group of text regarding disasters, organize that information, and generate a report out of it. It is packaged as a Python Application Programming Interface (API) or library with a collection of functions that can be usable for building software applications (see Appendix B for list). The discussion mainly includes a description of the tasks involved, content about the resources and components used, and high-level view of the algorithm. Seen at Figure 4.1 is an illustration of the tool's overall design.

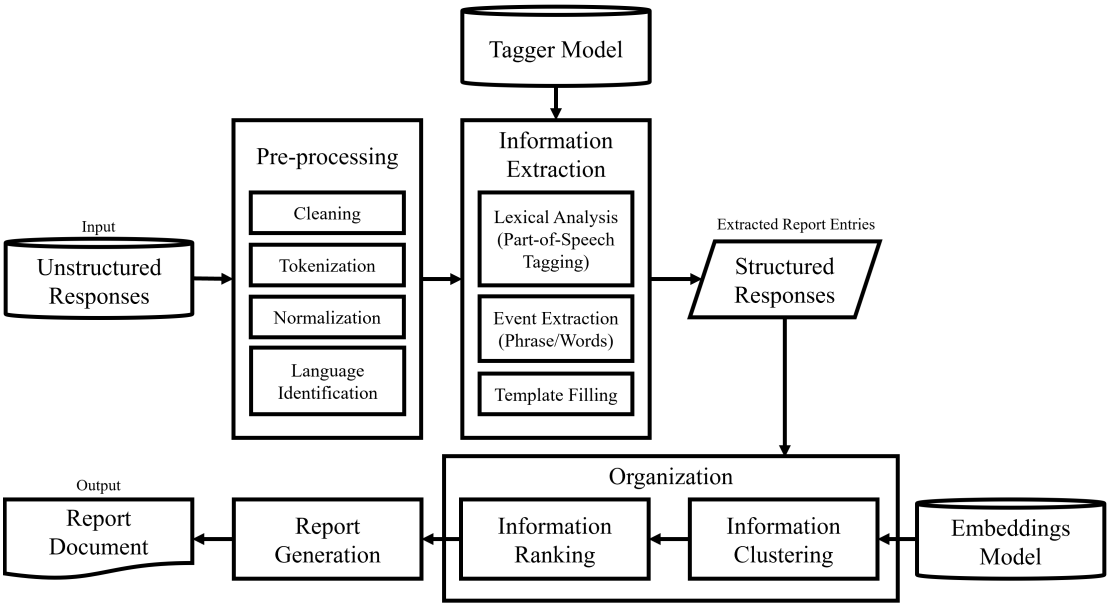


Figure 4.1: Architectural Diagram

4.1 Malasakit Community Responses

Disaster-related community responses gathered by *Malasakit* (B. M. Nonnecke et al., 2017), a cross-platform online participatory tool, were exported into an Excel (.xlsx) file. The purpose of using this data is to give the local community a chance to have a say in disaster-related issues experienced in their barangay and be part of the disaster risk reduction strategies planned by the government for the country.

The file contains a single sheet with a list of qualitative responses. Under the list are 934 instances gathered in Filipino and English, taken from different parts of the Philippines such as Caloocan, Cebu, Davao, Iloilo, Legazpi, Malabon, Manila, and San Mateo City. Each entry is comprised of two features (or columns) namely, *response* and *tag*. The *response* feature contains the ideas and was the main target for extracting and organizing information, while the *tag* (or response category) feature represents a wider, general view of the response given which was used for ranking (see Table 4.1 for sample entries).

Table 4.1: Sample Malasakit Responses

Response	**Tag**
Linisin ang mga baradong kanal 'Clean up the clogged canals'	Infrastructure Maintenance and Management
Magsagawa ng programa, seminar, information drive upang magbigay ng kaalaman sa kuminidad 'Conduct programs, seminars, and information drives to provide knowledge to the community'	Information Campaign and Capacity Building
Magkaroon ng komunikasyon kung saan magkikita sa panahon ng kalamidad. 'Have communication on where to meet during calamities'	Preparedness for Emergency
Provide first aid kits	Disaster Relief
Prepare a place for evacuees	Community-wide Logistic Support for Disaster Response

The *response* feature (qualitative responses) contains the participant's answer to an open-ended question, "How could your Barangay help you better prepare for a disaster". These responses have been preprocessed which removed punctuations like commas and periods, and words are lowercased. In spite the preprocessing, it still contains words that are misspelled (e.g., kawpa, bagy0, maayus, bahaa, esatesa, etc.), shortened (e.g., brgy, LGU, kpag, pwd, magtulong2, etc.), improperly joined (e.g. 'drillsawareness', 2months, etc.), and invalid suggestions (e.g. none, asdf, 3638484, blank, etc.). Some were corrected by running other preprocessing tasks such as tokenization and normalization (word standardization).

Table 4.2: Malasakit Community Responses Codebook 4.7

Category	Definition
Early Warning System	Mentions any form of communication and procedure that notifies community members of a potential hazard either face to face and/or through the means of technology (e.g., SMS, door-to-door, warning system, etc.).
Information Campaign and Capacity Building	Mentions any process of educating the community through orientations, seminars, trainings, simulations, and drills that reduce vulnerabilities and help the community to cope with hazards.
Infrastructure Maintenance and Management	Mentions a procedure to prevent and mitigate disaster hazards (e.g. maintenance of critical infrastructure like canals, river, drainage and other utilities, waste management).
Preparedness for Emergency	Mentions any plans or actions of an individual, family, or community to explicitly prepare prior a for disaster, either tangible or intangible steps.
Community-wide Logistic Support for Disaster Response	Mentions any items, infrastructure, and equipment that will respond to the needs of the community before and during the typhoon.
Disaster Relief	Mentions any act that provides goods, medicine, financial assistance, to the victims of disaster for their rehabilitation.
Local Government Accountability	Mentions specific task that assigns responsibility to the local government unit (barangay council) in their role in policy-making and policy implement -ation, and coordination with different agencies towards disaster risk reduction management.
Filipino values	Mentions any act that shows Filipino cultural values in times of disaster (e.g., pagkakaisa, pagtutulungan, bayanihan spirit, kapitbahayan, volunteerism, etc.).
Others	Mentions any statements not classified under the above categories (e.g., build organization, corrupt -ion, active participation, coordination, etc.).

On the other hand, the *tag* feature contains either one of the following nine *response categories*: Early Warning System, Information Campaign and Capacity Building, Infrastructure Maintenance and Management, Preparedness for Emergency, Community-wide Logistic Support for Disaster Response, Disaster Relief, Local Government Accountability, Filipino Values, and Others. Category descriptions from *Malasakit* (*Codebook Version 4.7 for the Malasakit qualitative responses*, 2017) can be found at Table 4.2.

A gold standard was prepared by the proponent for this dataset, to be used as basis for evaluating the system's result. Under this gold standard are the expected or correct insight extractions that corresponds to a response. There would be two kinds of gold standard: one that forms insight phrases to be extracted and another with word sets containing the proposed action and its target. Given the sentence "paglilinis ng kanal wastong pagtatapon ng basura at kailangan mag ikot ikot ang mga tanod upang bantayan mga gamit ng tao", an example for the gold standard phrases are the following: "paglilinis ng kanal", "pagtatapon ng basura", and "mag ikot ikot ang mga tanod"; and for gold standard word sets: "paglilinis, kanal", "pagtatapon, basura", and "mag ikot ikot, tanod".

As part of the tool, data utility scripts were developed to be able to accept, read data resources like the unstructured responses, and write outputs. After reading, data are saved on a *MalasakitResponse* object that consists of attributes that describes a particular response such as response ID, response text, tag, part-of-speech, insights, and more. Provided with this data structure, it may undergo the major tasks such as data preprocessing, information extraction, information organization, and report generation.

4.2 Preprocessing

Since *Malasakit* responses has already been preprocessed, this module is optional. Nevertheless, the collected data can still be tokenized, cleaned and normalized to fix responses with typographical errors and shortcut texts. Starting with tokenization, it separates words in a sentence to form 'tokens', while cleaning removes unwanted characters for processing such as punctuation.

Under normalization, a process of following a standardized format in texts or converting texts into their original, proper forms, involve two subprocesses. One is by joining unmerged prefixes (e.g., *mag karoon* into *magkaroon* 'have') and the other is through overwriting or correcting typographical and shortcut texts (e.g., *bkt* into *bakit* 'why').

For the first subprocess, an extendable prefix list from Oco and Borra (2011) was used to find and check all unmerged (or isolated) prefixes in the text. Once found, the prefixes are joined with the next word. Based on the previous example, *mag* is joined with *karoon*. Note that in this prefix list, those that can stand alone as a word (e.g., i-, na-, nang-, magsisi-, maki- pang-, papa-, etc.) were removed to prevent inappropriate merging. Whereas for the second subprocess, a *Filipino Normalizer* (Nocon, Kho, & Arroyo, 2018) was utilized to automatically process the text. It covers *textspeak* (shortcuts), *swardspeak* (gay-lingo), *conyo* (upper middle class English-Tagalog colloqualism), and *datkilab* (metathesis or reversed words) styles, built from social media sources. It was implemented using Google's Tensorflow and Statmt's Moses but only utilized the Moses version as it is the one with the best performance.

In addition to these preprocessing tasks, a language identification module was implemented, with the intention of directing the right natural language to the Part-of-Speech tagger. An off-the-shelf tool called *LangID* or *langid.py* (Lui & Baldwin, 2012) was utilized. This tool was made using Numpy's Naïve Bayes classifier and trained on a multi-domain language identification corpus that is comprised of government documents, software documentation, newswire, online encyclopedia and an internet crawled text. It was developed to be able to label 97 languages (follows ISO 639-1 language code in labeling) and perform well across different domains.

Applying *LangID* to the preprocessing tasks, its model was filtered to focus on two languages: English (en) and Tagalog (tl). This way, the model will have fewer choices and was deemed appropriate to consider languages that are only present in the current data. Aside from providing its language, a confidence value is part of *LangID's* output.

4.3 Information Extraction

The responses were automatically extracted with information through Part-of-speech-based approach. In detail, responses are labeled by the *Filipino Stanford Part-of-Speech Tagger (FSPOST)* of Go and Nocon (2017). It was built from Wikipedia data using Maximum Entropy Cyclic Dependency Network, which makes use of features such as word and tag contexts, word affixes, and word shapes to determine the appropriate tag for a word. Specifically, FSPOST makes use of the following features to understand Filipino's morphology:

- *Naacl2003unknowns* – pertains to the use of word shapes and suffixes of a word from NAACL 2003;
- *Wordshapes (-1,1)* – pertains to word shapes of the words before, currently tagged and after;
- *Left5words* – pertains to the two words before, two words after, and two tags before the word to be tagged;
- *Distsim* – or distribution similarity of words, uses the same set of features found in most tagger models of Stanford POS Tagger;
- *Pref6* – takes prefixes with lengths 1 to 6;
- *Inf2* – takes infixes with lengths 1 to 2; and
- *engNNCasFW* – a user-added feature that replaces words in the English dictionary that are tagged as common nouns NNC into foreign words FW.

Training through these features as parameters produces the tagger model, a file distributable and usable to users. Originally, FSPOST was programmed on Java programming language but a Python implementation was done through Natural Language Toolkit or NLTK (Loper & Bird, 2002). This transition still enables the usage of the tagger model without any complications. Furthermore, using NLTK facilitates switching of languages in tagging. Once the language identifier labels a response, NLTK can be used to switch from using NLTK Part-of-Speech Tagger for English or FSPOST-NLTK for Tagalog/Filipino.

Equipped with FSPOST, "events" wherein described as verb phrases or verb-noun words that contain actionable suggestions given by the community are extracted. It is done through a pattern of finding a verb and traversing through words until a noun is found (extends if there is a comma or conjunction *at* 'and' that is followed by another noun). A subprocess of event extraction records only the verbs and nouns in the events, forming word sets. In other words, the whole extraction focuses on capturing the insights regardless of the number of sentences in a response – meaning there are no limits of having a single solution per user entry and at the same time a response may not contain any insights.

With regards to creating patterns on English and Filipino, NLTK uses Penn Treebank which is the basis for MGNN Tagset or the one used by FSPOST. Given that, patterns can be generalized into the first two characters such as NN for nouns, VB for verbs, JJ for adjectives, etc.

After extraction, template filling transforms the unstructured responses into structured texts, acting as entries to the report. It works by having a set of information and plugging them into corresponding fields. Each entry will provide details about a response's suggested action that can be found under the "proposed action" field and target of the action under "target" field. More details are discussed at the report generation module.

4.4 Information Organization

Organizing the information is comprised of two modules namely, Information Clustering and Information Ranking. There are two ways that it can be set up. One is by organizing all entries or the information entirely, clustering similar entries and being ranked based solely on frequency. Another is organizing the information by response categories, clustering similar entries under each category, ranking them by category priority and locally based on frequency.

A sample illustration can be found at Figure 4.2. The left side exhibits entries from 1 to N that are organized by descending frequencies and without being sorted by the categories, while the right side are firstly organized by categories (Information Campaign and Capacity Building is more prioritized than Others) and then are followed by entries 1 to N (again in decreasing frequency) that reside within each categories. The final report that is generated for the tool follow this illustration's template, specifically by default sorts responses per categories first then frequency. More information about the prioritized categories are discussed at the information ranking module section.

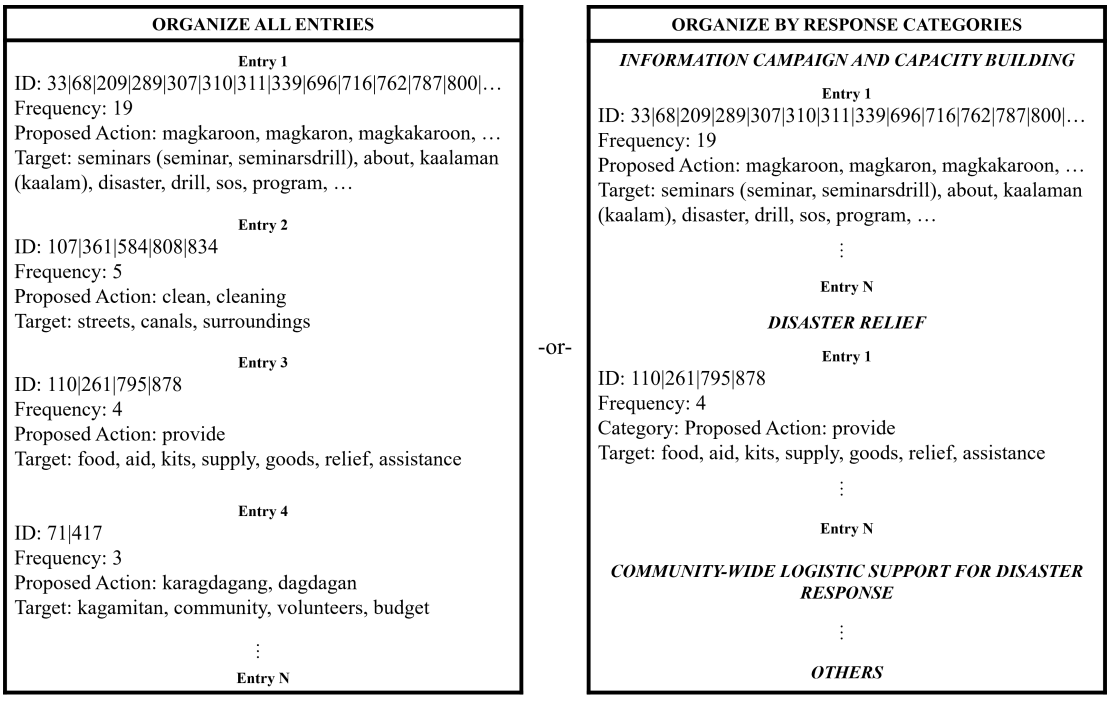


Figure 4.2: Information Organization Options

4.4.1 Information Clustering

Entries with similar contents are collated into a cluster. Those with exact word duplicates are filtered, retaining a single instance. Frequency counts are increased accordingly, and extra information are appended. In order to cluster entries properly, string (Sørensen-Dice Coefficient) and semantic (word embeddings) clustering were implemented, mainly to capture word similarities in the information.

For string similarity, an online available Python library called *Strsim*[1] was used. The collection consists of numerous string similarity and distance measures, one of which is the Sørensen-Dice Coefficient. For word embeddings, pre-trained Tagalog Wikipedia models[2] were used as resources and *Gensim* Library (Řehůřek & Sojka, 2010) for implementing Word2Vec (Mikolov, Yih, & Zweig, 2013) and FastText (Bojanowski et al., 2017).

The process of clustering starts by collecting all of the extracted insights from the structured information. The set of insights are then compared to one another to find words that are similar orthographically or semantically. Specifically, the process compares two types of string pairs. The first one compares the proposed actions or verbs (to join similar actions) and the second compares the targets or nouns (to remove duplicates within the clusters).

Applying a clustering technique on a pair of strings result into a computed number that represents their similarity. This similarity value is checked whether it is lower, higher, or equal to a similarity threshold. A value lower than or equal the threshold means the pair are not similar to each other, thus there would be no clustering involved. On the other hand, a value higher than the threshold means the pair are similar and should be joined into a single cluster, appending their information such as IDs (combined by vertical bar), frequencies, actions, and targets. In cases that a pair is exactly similar, only one instance of the word will remain, but their information is still appended.

Provided with the two types of string pair, their joining conventions are also a bit different from each other. Combining actions are done through commas (e.g., "magkaroon, pagkakaroon, nagkakaroon, magkakaroon" 'have'), while appended target words are through commas and similar target words are through parentheses (e.g., 'signal, supplies (food, equipment, boats), roadway, storage'). At the end of this clustering process, a list of clusters with attached frequency counts can be used for ranking.

[1] `Strsim` codebase: `https://github.com/luozhouyang/python-string-similarity`.

[2] Pre-trained Tagalog Wikipedia Word Embeddings models: `https://github.com/Kyubyong/wordvectors`.

4.4.2 Information Ranking

The clustered information was ranked based on urgency. Since, information organization accommodates two options, ranking the information can use frequency counts in decreasing order, the given response categories as basis for prioritization, or a combination of both. Moreover, the prioritization ranking for categories was arranged beforehand based on its characteristic of being actionable by decision makers which are organizations or government units specific to handling national disasters.

Having said that, those that are not actionable by decision makers was the least priority such as entries under Preparedness for Emergency and Local Government Accountability which pertains to community effort and actions made by oneself, and miscellaneous categories such as those that mentions Filipino values and Others that involve topics outside the provided categories like corruption. Arranging the categories that prioritizes those that can be done before, after, and during disasters will make words tackled (or extracted) be in line with concrete actions to be considered or implemented by decision makers.

The currently applied priority ranking for the Malasakit Codebook 4.7 categories are as follows: Information Campaign and Capacity Building, Disaster Relief, Community-wide Logistic support for disaster response, Infrastructure Maintenance and Management, Early Warning System, Preparedness for emergency, Local government accountability, Filipino values, and Others. It has been stored in a list that can be modified for future changes.

Describing the process, after receiving the clustered information, if all entries were to be organized, the whole list of clusters will be sorted by frequency. Meaning, each of the entries are compared to one another where the highest counts are placed on top of the list. Otherwise, organizing entries by categories searches for and transfers the groups into a new cluster list based on the priority ranking. To elaborate, the group under Information Campaign and Capacity Building will be searched first in the cluster list and once found is transferred into a new list. The same process is done on the next group, Disaster Relief, then followed by the rest of the priority list.

Note that information organization's process on category ranking, clusters and ranks the information per category. So, once a category has been processed, it has already undergone frequency ranking, and once the whole list has been processed, it will then undergo prioritization raking or reordering of the category groups.

4.5 Report Generation

The ranked information was transformed into a report, generated in a list format. The report that is included in this tool was written in a Microsoft Word and Excel file. In this module, its main task is to add details and design the entries on those formats. Formatting the report considered alternatives such as displaying solutions per entry or per category, which can be toggled through the information organization module.

The report generation process follows a template-based approach, as to fill in predefined fields with the appropriate information. Since the goal here is to produce a report that fit the needs of decision makers and *Malasakit* team, the templates were designed to display information that will most likely be useful to them.

The Word document template was designed for reading and marking items. It is in a two-column format, ideally done to compress and reduce the page length of the contents. It consists three main parts: introduction, insights list, and *Malasakit* response list. The introduction is comprised of the report's title, timestamp, and brief introduction to the contents. The insights list is comprised of the ranked information, displaying the categories as heading (if organized by response categories), and lists each entry with the following fields: response ID/s, frequency count, proposed action, and target. The *Malasakit* response list is comprised of a table for reference, showing the response ID and text. Adding to the labels, for every page in this document show a footer with this research's title, proponent's name, and year.

The Excel file template was designed for analysis, disclosing more information related to the responses. It consists four main parts or sheets: response information, word set insights, cluster list, and ranked cluster list. In each row, response information is comprised of the two protected columns: raw response text and response category. It is then followed by language ('tl' or 'en'), normalized response text, part-of-speech (Stanford notation), response ID, and extracted insight phrases. The second sheet contains response IDs with extracted insights in word set format, where one row contains a single word set (proposed action/s followed by target/s). The next sheet contains the list of clustered information, with a cluster number heading and under it are its response IDs, frequency count, proposed action/s and target/s. The last sheet is comprised of the ranked version of the previous sheet.

4.6 Report Document

The final output for this software would be the generated report document which can be relayed to or used by decision makers in handling disasters. It contains the structured and organized key insights provided by the community. There are two reports that will be generated in each run of the tool. One is the official report intended for decision makers in a form of a Word document (.docx). Two is a report beneficial for users, researchers, and developers much like the Malasakit team, by overwriting and adding details to Malasakit's Excel file (.xlsx). Screenshots of the excel and word report are shown at Figure 4.4 and Figure 4.3, respectively, while more can be seen at Appendix C. Giving back to Malasakit, the contents of all reports, the API modules, its input and outputs, are freely accessible.

	A	B	C	D	E	F
1	INFORMATION CAMPAIGN AND CAPACITY BUILDING					
2	Cluster 1					
3	13|46|208|236|243|307|311|598|603|6	19	maging, palaging, laging	kapitbahay, tao, disaster, mamamayan, awa		
4	Cluster 2					
5	26|208|209|339|507|576|649|762|766	18	dapat	barangay, seminar, oras, prepared, kalamida		
6	Cluster 3					
7	33|68|209|307|310|311|339|696|716|7	16	magkaroon, magkakaroon	seminars (seminar, seminarsdrill), about, kaa		
8	Cluster 4					
9	80|121|132|149|156|169|215|222|234	15	be	advantage, possibilities, calamities, barangay		
10	Cluster 5					
11	130|215|245|249|259|266|340|390|794	12	have	assembly, disaster, drill, place, representativ		
12	Cluster 6					
13	207|238|269|289|332|343|344|382|396	12	conducting, magconduct, conduct, pag	seminars (seminar), drills, community, assen		
14	Cluster 7					
15	101|104|169|287|333|343|347|396|583	10	preparing, prepare	typhoon, disaster, seminar, times		
16	Cluster 8					
17	169|222|303|331|343|358|614|627|654	10	help	prepare, families, disasters (disaster), outcor		
18	Cluster 9					
19	26|362|764|813|852|883|903|926	9	may	pangangailangan, seminar, meetings, kalami		
20	Cluster 10					
21	101|104|179|218|337|347|350|386|405	9	inform, informs, informing	consequence, people, neighbor, subordinate		
22	Cluster 11					
23	152|200|216|303|594|627|798|876|927	9	giving, living	disaster, drill, knowledge, seminars, leaflets,		
24	Cluster 12					
25	344|382|390|398|485|700|842|846|860	9	regarding	prevention, disaster (disasters), awareness, p		
26	Cluster 13					

Figure 4.3: Excel Report Screenshot

FILIPINO TEXT ANALYSIS TOOL REPORT

Oct-08-2019 03:46:06

The information below were extracted and organized automatically.

INFORMATION CAMPAIGN AND CAPACITY BUILDING

Entry 1

ID/s: 13|46|208|236|243|307|311|598|603|618|631|651|758|760|766|854|903|925

Frequency: 19

Proposed action: maging, palaging, laging

Target: kapitbahay, tao, disaster, mamamayan, aware, kabarangay, kabaro, kalamidad, darating, pagbeforeafter, during, bagyo, trahedya, gawim, paalala

Entry 2

ID/s: 26|208|209|339|507|576|649|762|766|811|813|836|852|854|885

Frequency: 18

Proposed action: dapat

Target: barangay, seminar, oras, prepared, kalamidad, sakuna, posters, drill, like, for, example, about, paraan, encourage, before, during, and, after, of, the, calamity, my, weekly, roong

Entry 3

ID/s: 33|68|209|307|310|311|339|696|716|762|787|800|847|926|930

Frequency: 16

Proposed action: magkaroon, magkakaroon

Target: seminars (seminar, seminarsdrill), about, kaalaman (kaalam), disaster, drill, sos, program, regarding, and, iinvite, emergency, training, progma, mamamayan, weekly, meeting, orientation

Entry 4

ID/s: 80|121|132|149|156|169|215|222|234|340|585|654|794|831|929

Frequency: 15

Proposed action: be

Target: advantage, possibilities, calamities, barangay, times (time), drills, typhoon, disaster, preparedness (prepare), programs, officials, instructions, orientation, effects, duty

Entry 5

ID/s: 130|215|245|249|259|266|340|390|794|838

Frequency: 12

Proposed action: have

Target: assembly, disaster, drill, place, representative, check, emergency, needs, training (taraining), barangay, officials, seminar, meeting

Entry 6

ID/s: 207|238|269|289|332|343|344|382|396|595|677|855

Frequency: 12

Proposed action: conducting, magconduct, conduct, pagconduct

Target: seminars (seminar), drills, community, assembly, lot, organisasyon, regarding

Entry 7

ID/s: 101|104|169|287|333|343|347|396|583|644

Frequency: 10

Proposed action: preparing, prepare

Target: typhoon, disaster, seminar, times

Entry 8

Figure 4.4: Word Report Screenshot

Chapter 5

Results and Discussion

This chapter contain results and analyses on the different experiments done. Experiments include those with regards to the utilized data or models, and software modules. Specifically, different clustering approaches, various word embeddings models, preprocessing tools, and lexicalization of entries was implemented. In addition, the software was tested on a different domain text. Evaluation was done through quantitative and qualitative analysis, for Information Extraction and organizational tasks, respectively.

5.1 Information Extraction

In evaluating the system, the Information Extraction's performance was measured through system-gold standard match counts (see Table 5.1) and standard, quantitative metrics such as Precision, Recall, Accuracy and F-Measure (see Table 5.2). Moreover, there were two tests, comparing insight phrases to know the performance in extracting insights and comparing word sets (see Table 5.4) to know the performance in extracting action/verbs and target/nouns. Sample format of the two are as follows:

- General format for Insight Phrases: [sentence number, insight 1, insight 2, ..., insight N]
  - [1, magkaisa dapat ang mga tao]
  - [4, paglilinis ng kanal, pagtatapon ng basura, mag ikot ikot ang mga tanod]

- General format for Word Sets: [sentence number, action/verb, target/nouns]
  - [1, magkaisa, tao]
  - [64, pagbibigay, pagkain, tubig]

5.1.1 Insight Phrases

Table 5.1: Insight Phrases System-Gold Standard Match Count Results

Insight Phrases %		
Measure	**Original**	**Normalized**
Complete Match	19.59	18.23
Over-extraction	8.35	8.99
Under-extraction	25.48	24.98
Overlapping-extraction	0.3	0.66
Complete Mismatch	46.27	47.13

Table 5.2: Insight Phrases Standard Metric Results

Insight Phrases %[1]				
Measure	**Original$_{ic}$**	**Original$_{wc}$**	**Normalized$_{ic}$**	**Normalized$_{wc}$**
True Positive	53.73	41.35	52.87	40.24
False Positive	29.69	17.65	29.39	17.46
False Negative	16.59	9.78	17.74	10.6
True Negative	0	31.22	0	31.70
Precision	64.41	70.09	64.27	69.74
Recall	76.41	80.87	74.87	79.15
Accuracy	53.73	72.57	52.87	71.94
F-Measure	69.90	75.09	69.17	74.14

Complete Matches and True Positives (TP) are statistical measures that counts the number of extractions that matches the gold standard (GS) or are considered as actual insights. In addition, there are partial matches that are also considered as insights which are the following: Over-extractions (OE), Under-extractions (UE), and Overlapping-extractions (OVE).

[1]For the metrics, values in parenthesis are based on word counts (wc), while those outside of it are based on insight counts (ic).

OE is a type of partial matches with more words in extractions than GS contents. Sample of OE in the results are instances of GS entries without Auxiliary verbs at the start of the insight such as *dapat*, *kailangan*, and *be* (e.g., *dapat* makiisa ang komunidad / makiisa ang komunidad). Another, OE includes a word or few words after conjunctions 'at' or 'and' which made it longer. Unlike in GS, some ideas are separated into two entries. An example for this is in GS, "linisin ang kanal" and "itapon ang basura" are separate entries, while "linisin ang kanal at itapon ang basura" is a single extraction entry. Adding to the causes of having OE, forcing to search for a noun to end an insight added unnecessary words that could have stopped on an adjective or pronoun. Instances in this case are, "be more aware and let the constituents / be more aware" and "help each other when the time / help each other".

UE are partial matches with less words in extractions than GS contents. With the same cause in ending a noun for an insight, the effect for UE is different. Instead of having more words, UE shows necessary details missing in the insight. The phrase "make the barangay gym" is a sample of UE which should be "make the barangay gym ready for evacuation" to complete the insight. Despite this, there are some instances that UE can stand without the additional detail such as "ayusin ang drainage", "do announcements", and "conducting seminars", which could have been "ayusin ang drainage ng barangay", "do announcements via megaphones", and "conducting seminars for disaster preparedness and occassional drills".

OVE are partial matches that are equal in length or wherein certain words overlaps with the GS. Sample for this is "kaylangan maging aware" and "maging aware sa balita", where they overlap with "maging aware". There are instances that OVE entries only differ in spelling, which a normalizer failed to overwrite while in GS the annotator enforced the correct spelling, or the other way around (e.g., provide first aid *kita* / provide first aid *kits*).

Complete Mismatch are entries that does not match with either the system or GS. Under this measure belong the sum of False Positives (FP) which are extracted insights that are not actual insights or not in the GS, and False Negatives (FN) which are not extracted insights that are actual insights or in the GS.

In FP, majority of the instances counted were deemed to be either unusable or insufficient suggestions (as they were missing details) but were still extracted as it indicates an action/verb and a target/noun. Instances of FP are the following: "mentioned in the survey", "magkaroon ang mga tao [of what?]", and "allow the residents [to?]".

In FN, results were similar to OE. As some instances with multiple ideas and conjunctions such as 'at' were joined by the system; unlike in GS, the entries were separated. In this system extraction, "magkaroon ng komunikasyon at ikutin ng mga council members", only the first insight was counted as a match with the GS counterpart "magkaroon ng komunikasyon", while the second could not be matched with the same extracted entry and is counted as FN. The restriction to match only once was placed so that the automated evaluation would not be prone to partial matches error.

In addition, there are a great number of annotated insights that started with a noun, adjective, or adverb. Examples include "paggamit ng public address system", "announcement of a disaster", "proper information dissemination", and "regularly clean canals". Moreover, there were also insights with typographical errors in the extraction's end that did not match with normalized GS as annotations in it are correctly spelled (e.g., maayos na waste *dsiposal* [disposal]).

True Negatives (TN) are instances wherein the system did not extract as it is not an actual insight or not in the GS. For insight counts, TN is valued zero (0). It is due to the information available (in the insight/phrase level) focusing on those insights that were extracted and which should be extracted by the system, and not those that were not extracted. However, using word counts, the true negative can be computed by the total word count of the corpus. Specifically using the equation,

$$TrueNegative_{wc} = Total_{wc} - (TP_{wc} + FP_{wc} + FN_{wc}),$$

the words that were not extracted by the system and is also not an actual insight can be counted. Provided, statistical measures were computed through insight counts and word counts. For reference, a matrix has been provided in Table 5.3 as an alternative view for representing the TP, FP, FN, and TN statistical measures.

Table 5.3: Confusion Matrix of Information Extraction

	Classified	**Actual**
True Positive (TP)	Insight	Insight
False Positive (FP)	Insight	Not Insight
False Negative (FN)	Not Insight	Insight
True Negative (TN)	Not Insight	Not Insight

Precision is the percentage of extractions that are insights and Recall is the percentage of insights that were extracted. Currently, Precision and Recall of the IE is 64.41 and 76.41, respectively. With word counts, values are higher with 70.09 and 80.87, respectively. To increase the values for these two, FP and FN are aimed to be low in value, while TP should be higher.

The 53.73 (or 72.57 word count) Accuracy is another value that represents the percentage of correct extraction, meaning more than half are considered to match with the GS. The 69.90 (or 75.09 word count) F-Measure score is the harmonic mean of Precision and Recall which can also be interpreted as the overall performance for extracting insight phrases.

A normalized version of the insight phrases was also evaluated. Generally, the original version gained better scores compared to it. The cause of this is mostly on spelling mismatches, specifically over-normalization (e.g., *kits* to *kita* and "ayusin ang mga" to "ayusin ang Metro Rail mga"), annotation normalizations (e.g., *kagamitin / kagamitan* and *pundo / pondo*), and unnormalized typos (e.g., *plansan*, *taraining*, and *alertoat*). Despite this, numerous words in the data were still standardized (e.g., *di* to *hindi*, *san* to *saan*, and *meron* to *mayroon*).

5.1.2 Word Sets

Table 5.4: Word Sets Match Count and Standard Metric Results

Word Sets %		
Measure	**Original**	**Normalized**
Exact Match	18.75	18.22
Partial Match	25.6	26.43
Action Match	8.22	9.32
Target Match	17.47	16.08
Crossover Match	4.02	2.48
No Match for Gold Standard	25.94	27.46
No Match for System	37.86	37.97
True Positive	51	50.2
False Positive	31.09	30.75
False Negative	17.88	19.02
True Negative	0	0
Precision	62.14	62.03
Recall	74.06	72.54
Accuracy	51.03	50.24
F-Measure	67.58	66.88

Exact matches (EM) pertains to matches that has the same action/verb and target/noun with GS. Similar to CM and TP, it is ideal to have higher value for this measure. Partial matches (PM) label pertains to matches that has the same action and almost the same target noun with GS.

Instances of PM mostly differ in a few words, more or less than the actual GS annotations like [magkaroon, early, warning] / [magkaroon, early, warning, system] and [pagbibigay, assistance, goods] / [pagbibigay, humanitarian, assistance, goods]. There are some instances that could have been EM, only to differ in spelling like [improving, *imformation*, dissemenation] / [improving, information, dissemenation].

Under partial matches, action matches (AM) pertains to only the action field matches with GS. Another is target matches (TM) which pertains to only the target field matches with GS. AM and TM are comprised of entries with either insufficient or incorrect action/target, mismatches with GS' typographical corrections (e.g., *pgbaha / pagbaha* and *baranggay / barangay*), and GS' missed corrections (e.g., *paguusap / pag uusap*, *nagpeperform / nagpe perform*, and *pagconduct / pag conduct*). Providing an instance to insufficient or incorrect action/target, examples that exists in the data are like [conducting, lot] / [conducting, seminar, activities, disaster, awareness] and [think, meeting] / [organize, meeting, home, owners]. Similar to OE, TM also includes entries that recorded auxiliary verbs that differed with GS' verbs (e.g., [kailangan, ka-barangay] / [magtulungan, ka-barangay]).

Adding to the partial matches, there are crossover matches (COM) that is when action matches the target field of GS or vice-versa. Examples for this are the pairs: [mabilis, pagbibigay] / [pagbibigay, pagkain, tubig] and [do, train, deaf, emergency, responders] / [train, deaf, emergency, responders], where the action is designated on the first field while the rest indicates the targets/nouns.

No matches for System (NMS) is when an extraction does not match with any of the GS entries. No matches for GS (NMGS) is when a GS entry does not match with any extractions. NMS and NMGS' contents are generally the same with FP and FN. Examples for entries that were not considered as a suggestion by GS are the following: [maiwasan, pagbaha], [pagpapadala, kunting], and [putting, pockets]. For reasons that they contain verbs but were used as a justification to the real suggestion, failed to include a proper target, or unusable to act as a solution. On the other hand, NMGS samples mostly have actions that were tagged with a different Part-of-Speech, which definitely could not be extracted due to the verb to noun pattern rule.

Based on the results, less than 20% are exact matches, while PM has the highest number of correct instances with more than 25%. Represented with a combined value of 74.06%, extracting action and target fields were effective provided with a straightforward Part-of-Speech pattern-based design. Perfectly extracting both fields, however, still needs work.

Overall, word sets' Precision, Recall, Accuracy, and F-Measure metric values exceeded half, garnering 62.14, 74.06, 51.03, and 67.58, respectively. Comparing with its normalized counterpart, PM, AM, and FP values improved, while everything else were lower than the original.

5.2 Information Organization

Quantitative and qualitative analysis were conducted on organized information to bring out the positive and negative characteristics, as well as, the coverage of clustering approaches and collated information. Each of the experiments was clustered through Dice Coefficient (Dice, 1945), Word2Vec (Mikolov, Chen, et al., 2013), and FastText (Bojanowski et al., 2017). Furthermore, Lexicalization was applied as sub-clusters by providing a word that can represent the entire word group. The word group is attached beside the representation enclosed with parentheses.

Experiments were generated, analyzing Malasakit Responses that were organized and ranked with all of the entries, and another grouped by response categories. Extending the test of all entries, a normalized version will also be evaluated. To determine the impact of the 50% default clustering threshold, a value that indicates if words are considered as similar or not, adjustments such as decreasing to 20% and increasing to 80% were made.

In this type of analysis, the following is aimed to be discovered: the set of words that are similar to each other, top community suggestions, response category with highest number of suggestions, effectivity of a normalizer, more appropriate clustering approach or threshold, and many more.

5.2.1 General Statistics

A statistical view has been provided that encompasses quantifiable values in the reports. The tables include the produced runtime and number of pages of the report, as well as, the number of entries and frequency (total responses = 1,392)

a report has. In each table, experiments are abbreviated into the following:

- Organize All Entries (OAE), which is the base of the experiments,
- Normalized (N), the normalized version of the evaluation,
- Threshold (T), which indicates a threshold adjustment from 50 to an attached number beside the abbreviation, and
- Organize by Response Category (ORC), an alternative organizational format.

Table 5.5: Report Production of Experiments

Exp.	**Approach**	**Runtime**	**HH:MM:SS**	**Total pp.**	**Insight pp.**
OAE	Dice	604.42	0:10:04	60	27
	Word2Vec	667.37	0:11:07	60	27
	FastText	937.81	0:15:38	45	12
OAE-N	Dice	551.97	0:09:12	60	27
	Word2Vec	623.75	0:10:24	61	28
	FastText	926.11	0:15:26	45	12
OAE-T20	Dice	622.92	0:10:23	49	16
	Word2Vec	666.10	0:11:06	58	25
	FastText	677.15	0:11:17	38	5
OAE-T80	Dice	614.51	0:10:15	68	35
	Word2Vec	669.66	0:11:10	67	34
	FastText	1999.28	0:33:19	65	32
ORC	Dice	625.57	0:10:26	79	46
	Word2Vec	660.49	0:11:00	71	38
	FastText	1546.92	0:25:47	57	24

Under production of the report (shown at Table 5.5), runtime for the entirety of the program was included (from reading the file up to generating the report, together with the sum of the execution time of each modules/tasks). Majority of the experiments clustered in Dice's coefficient were deemed to be the fastest and lightest (least resources used) per experiments, with an average runtime of 10 minutes and four seconds. Oppositely, the slowest overall are experiments that made use of FastText clustering with an average runtime of 20 minutes and 17 seconds.

The quickest experiment to have been completed was OAE-N using Dice's coefficient. It was completed at nine minutes and 12 seconds and clustered insights

worth 27 pages. Adding 33 pages for the Malasakit Response List as reference for the user, the total number of pages for this experiment is 60. On the other hand, the longest runtime was OAE-T80 using FastText word embeddings clustering. It took more than 30 minutes, in exactly 33 minutes and 19 seconds, and was able to cluster 32 pages worth of insights. Noticeably, OAE-N was faster than the base OAE. It is due to the fact that even though there are more components in OAE-N, post-normalization lessened the total words and may have helped in tagging; as comparing the runtimes, the two experiments extremely differed in tagging time.

Generally, the clustering approach with the least number of insight pages are FastText experiments, which indicates more words joined. As a matter of fact, the lowest number of pages was clustered by FastText with only five pages; given 1,392 total responses, most of them belonged into a cluster. Compared to FastText, Dice's coefficient and Word2Vec clustering have a large gap of insight pages in between experiments. Note that insight pages were provided but does not represent which among the clustering approaches produced the best set of insights.

Table 5.6: Report Composition of Experiments

Exp.	**Approach**	**Entries**	**CEC %**	**CIC %**	**Highest Freq.**
OAE	Dice	363	45.73	85.85	80
	Word2Vec	375	29.87	81.11	257
	FastText	114	57.02	96.48	490
OAE-N	Dice	365	45.48	85.70	82
	Word2Vec	380	28.16	80.39	255
	FastText	112	61.61	96.91	378
OAE-T20	Dice	179	63.13	95.26	127
	Word2Vec	339	25.96	81.97	657
	FastText	6	83.33	99.93	806
OAE-T80	Dice	506	33.00	75.65	79
	Word2Vec	489	30.88	75.72	104
	FastText	455	35.60	78.95	137
ORC	Dice	666	31.38	67.17	26
	Word2Vec	526	27.19	72.49	95
	FastText	295	47.12	88.79	159

Under Table 5.6, the composition of the report, that is the total number of entries, percentage of cluster entry counts (CEC) or number of entries that have actions merged (frequency greater than 1), percentage of cluster insight counts (CIC) or number of responses that have been clustered, and highest frequency count are presented. With regards to highest frequency of those organized per response category, the highest value found among all categories were placed –

with an in-depth version that can be seen at Tables 5.7, 5.8, and 5.9.

For OAE experiments, the clustering approach with the lowest amount of clusters is Word2Vec, with 29.87% CEC and 81.11% CIC. Conversely, FastText produced better results, with 57.02% CEC and 96.48% CIC. Connecting the total entries with cluster percentage, it has been evident that as the total entries shrinks, the higher the cluster percentage values are.

The highest frequency value, however, does not relate into cluster percentage, but depends more on the type of clustering approach used. Aside from the highest amount of cluster percentage, FastText also produced the highest frequency with 490 responses under one cluster. The second, although produced the lowest cluster percentage among the three approaches, is Word2Vec with 257 responses. The last approach clustered at the most 80 responses in one cluster.

The normalization factor in OAE-N shifted a number of texts that should or should not have been merged. Comparing to the base OAE, OAE-N experiments that made use of Dice and Word2Vec increased the values of the total entries and decreased cluster percentages, while its effect on FastText decreased its total entries and increased cluster percentages. The normalizer's effect on an entry's highest frequency increased values for Dice, while decreased values for word embeddings approaches.

Comparing the base OAE and threshold adjustment experiments, the number of entries of OAE-T20 and OAE-T80 significantly decreased and increased the values, respectively. The effect is reversed for highest frequency where in OAE-T20 the values increased, with values more or less doubled, and in OAE-T20 values were decreased by more or less half of the original.

For CEC percentage of OAE-T20, there were lesser clusters made by Word2Vec, whereas the other two approaches gained more. For CIC percentage, all approaches achieved higher values. In fact, under this experiment, FastText achieved the overall highest cluster percentages with 83.33% CEC and clustering almost all of the responses with 99.93% CIC. Conversely, OAE-T80 produced more clusters using Word2Vec, and less on the other two approaches. Moreover, OAE-T80 has lesser CIC values than OAE.

From the given statistics, the gist of the adjustment is when the threshold is reduced, there would be more responses clustered, whereas increasing it would entail a more selective clustering process. Noticeably, there are changes in the quality of entries and clusters inside the report. More information about analysis of the insights produced will be designated on another subsection.

With regards to ORC experiments, entries were spread out which resulted into total entries values that more or less doubled in count. The highest count is 666 for Dice, followed by 526 for Word2Vec and 295 for FastText. In terms of cluster percentages, the approach with the most amount is FastText, followed by Word2Vec and Dice. In terms of highest frequency, the results follow the order of OAE experiments, which evidently showed FastText as being able to produce the highest amount of frequencies compared to the other two approaches.

For ORC experiments, the statistics per category has been provided at Table 5.7 using Dice, Table 5.8 using Word2Vec, and Table 5.9 using FastText. Values provided include the total number of entries, cluster percentages, highest frequency in an entry, and total frequency count of the category.

Counting the total frequency of responses a category has, the top five are as follows: Information Campaign and Capacity Building (393), Early Warning System (259), Preparedness for Emergency (198), Infrastructure Maintenance and Management (169), and Filipino Values (114). The lowest among categories is Disaster Relief with only 34 responses included.

Table 5.7: Report Composition of ORC through Dice's Coefficient Clustering

Category	**Total Entries**	**CEC %**	**CIC %**	**Highest Freq.**	**Total Freq.**
Information Campaign and Capacity Building	152	36.84	75.57	20	393
Disaster Relief	24	16.67	41.18	5	34
Community-wide Logistic Support for Disaster Response	49	30.61	57.50	8	80
Infrastructure Maintenance and Management	84	36.90	68.64	25	169
Early Warning System	109	38.53	74.13	16	259
Preparedness for Emergency	84	28.57	69.70	26	198
Local Government Accountability	57	19.30	41.03	7	78
Filipino Values	54	27.78	65.79	12	114
Others	53	20.75	37.31	4	67

Applying Dice's Coefficient to ORC experiment, the top five categories with the highest number of total entries are ordered from highest to lowest and as follows: Information Campaign and Capacity Building (152), Early Warning System (109), Infrastructure Maintenance and Management / Preparedness for Emer-

gency (84), Local Government Accountability (57), and Filipino Values (54). The lowest count for the total entries is Disaster Relief with 24 entries. Counting the total entries signifies which categories have more variety of suggested actions attached to it.

In terms of highest frequency, it signifies which actions and categories have been highly suggested by the community. It can also be looked at which actions and disaster strategies are more important or urgent to the people. Numerically, the top five categories are as follows: Preparedness for Emergency (26), Infrastructure Maintenance and Management (25), Information Campaign and Capacity Building (20), Early Warning System (16), and Filipino Values (12). Again, the lowest count for this is Disaster Relief with 5 responses under one cluster.

In terms of cluster percentages, CEC signifies how dense or focused the suggestions of people are, particularly to the proposed actions needed in a community, while CIC signifies the amount of suggestions that has been clustered together. Statistics showed that less than half of the categories got CEC values greater than 30%, while more than half got CIC values greater than 65%. The category with highest CEC percentage is under Early Warning System with 38.53%, while the lowest is Disaster Relief with 16.67%. On the other hand, the category with highest CIC percentage is under Information Campaign and Capacity Building with 75.57% and lowest is Others with 37.31%.

Table 5.8: Report Composition of ORC through Word2Vec Clustering

Category	**Total Entries**	**CEC %**	**CIC %**	**Highest Freq.**	**Total Freq.**
Information Campaign and Capacity Building	130	22.31	74.30	95	393
Disaster Relief	16	31.25	67.65	9	34
Community-wide Logistic Support for Disaster Response	33	27.27	70.00	33	80
Infrastructure Maintenance and Management	70	27.14	69.82	33	169
Early Warning System	93	29.03	74.52	48	259
Preparedness for Emergency	63	33.33	78.79	43	198
Local Government Accountability	40	17.50	57.69	18	78
Filipino Values	48	35.42	72.81	20	114
Others	33	27.27	64.18	16	67

Applying Word2Vec, the top five categories with the highest number of total entries are as follows: Information Campaign and Capacity Building (130), Early Warning System (93), Infrastructure Maintenance and Management (70), Preparedness for Emergency (63), and Filipino Values (48). The lowest count for the total entries is Disaster Relief with 16 entries.

In terms of highest frequency, the top five categories are as follows: Information Campaign and Capacity Building (95), Early Warning System (48), Preparedness for Emergency (43), Infrastructure Maintenance and Management / Community-wide Logistic Support for Disaster Response (33), and Filipino Values (20). The lowest count for this is Disaster Relief with 9 responses under one cluster.

The highest in CEC with 35.42% is under Filipino Values. On the other hand, in CIC percentages, the highest is Preparedness for Emergency with 78.79%. The lowest for both CEC and CIC percentage was Local Government Accountability with 17.5% and 57.69%, respectively. Among all categories, the results show that a third got CEC values greater than 30% and five out of nine got CIC values greater than 70%.

Comparing Word2Vec statistics with Dice's coefficient, the total number of entries shifted but the categories with highest and lowest values remained the same. In highest frequency, categories were rearranged as values increased for all categories. Information Campaign and Capacity Building shifted up to first, having one cluster in the hundreds unlike Dice with only 20. Provided, entries were found by Word2Vec to be similar with others, thus was merged accordingly.

In spite the higher frequencies and supported by the values in CEC percentages, Dice was still able to have more clustered entries as compared to Word2Vec, where five out of nine categories have higher CEC percentage. Meanwhile, basing on CIC, Word2Vec was able to join more similar words with eight out of nine categories have higher CIC values than Dice. It is important to note, however, that results between cluster percentages does not entail which approach produced clusters that are better in quality (with regards to word similarity).

Applying FastText, the top five categories with the highest number of total entries are as follows: Information Campaign and Capacity Building (57), Early Warning System (44), Infrastructure Maintenance and Management (39) / Preparedness for Emergency (39), Filipino Values (30), and Others (26). The lowest count for the total entries is Disaster Relief with 14 entries.

In terms of highest frequency, the top five categories are as follows: Information Campaign and Capacity Building (159), Early Warning System (108), Preparedness for Emergency (40), Community-wide Logistics and Support for Disaster Response (40), and Infrastructure Maintenance and Management (36). The lowest count for this is Disaster Relief with 11 responses under one cluster.

Table 5.9: Report Composition of ORC through FastText Clustering

Category	**Total Entries**	**CEC %**	**CIC %**	**Highest Freq.**	**Total Freq.**
Information Campaign and Capacity Building	57	52.63	93.13	159	393
Disaster Relief	14	28.57	70.59	11	34
Community-wide Logistic Support for Disaster Response	21	42.86	85.00	40	80
Infrastructure Maintenance and Management	39	38.46	85.80	36	169
Early Warning System	44	52.27	91.89	108	259
Preparedness for Emergency	39	51.28	90.40	40	198
Local Government Accountability	25	44.00	82.05	27	78
Filipino Values	30	46.67	85.96	25	114
Others	26	50.00	80.60	17	67

In cluster percentages, less than half of the categories got CEC values greater than or equal to 50%; At the same time, CIC values of most categories are above 80%, for which a third are above 90%. The category with highest CEC percentage is under Information Campaign and Capacity Building with 52.63%, and Disaster Relief as lowest with 28.57%. Similar to CEC results, the highest CIC percentage is under Information Campaign and Capacity Building with 93.13% and lowest is Others with 80.6%.

Comparing FastText with Dice's and Word2Vec, total entries were reduced significantly which means more responses have been joined and majority of the frequencies were increased. It is evident since almost all of the cluster percentages and highest frequency values were in favor of FastText. The only instances that were not is CEC percentage of Word2Vec under Disaster Relief and highest frequency under Preparedness for Emergency.

5.2.2 Experiments Clustered by Dice's Coefficient

In the base OAE experiment, the most frequent suggestion clustered ideas that Barangays should be (dapat) active, aware, alert, prepared, and updated. It relates to ideally having communication (komunikasyon), programs (programa), seminars/drills, announcements (anunsiyo), evacuation, and food (pagkain).

Generally, highly used verbs pertains to *procurement* (e.g., magkaroon, pagbibigay, and provide), *dissemination* (e.g., pagiinform and ma-inform), *sanitation* (e.g., maglinis, linisin, and linisan), *preparedness* (e.g., ihanda, maiwasan, and mkaiwas), and *solidarity* (e.g., magtulong, makipagtulongan, and helping).

Procurement mentioned the following items in need for the Barangay: early warning system, medical kits, flashlight, garbage cans (basurahan), shelter, and grocery/supply. Topics for dissemination suggested information about disasters such as typhoons, floods, storms, and the consequences that comes with them. Sanitation points mostly towards cleaning the surroundings (kapaligiran), specifically sewers (kanal/imburnal) and areas near the households (harap/daan).

Mainly to avert or avoid ramifications such as floods (pagbaha), spread of tragedies (trahedya), and getting trapped, community- and self-preparedness by alarms and designating places such as schools (paaralan) for evacuations was suggested. For solidarity, it has been recommended for families (magkakapamilya) and Barangay to continuously help (magtulongan) each other.

Aside from these suggestions, there are other low frequency ideas that can be deemed useful such as putting up leaflets or signages (karatula), utilizing media and officials, enforce laws, teach first aid, and more.

With regards to the approach, clustering words orthographically expectedly joined words not farther than prefixes and suffixes. Even without implementing a normalizer, since shortcuts or typographical errors are not far from the original's form/structure, comparing orthographically was still able to cluster some words together (e.g., mkaiwas, magtulong2, baranggay, and taraining).

As a matter of fact, implementing Lexicalization in all experiments, where one word is designated to represent a cluster (particularly in each of the Target/Noun field), orthographic clustering was successful in joining words related to each other. Instances are tenses and unstandardized variants like seminars [seminar, seminarsdrill], floods [flooding], and basura [basurahan]. In spite this, there are instances with close string distance but are not exactly related. Examples for this are evacuation-elevation and pagkain-pagkalap.

Normalized Evaluation

In OAE-N experiment, A Filipino Colloquialism Translator (Nocon et al., 2018) was implemented as a normalizer. Sample normalized words in the results are presented on Table 5.10. Under this list contains corrections on shortcut texts, typographical errors, and Filipino colloquialisms.

Table 5.10: Normalization Samples

Original – Normalized		
andyan – nandiyan	khit – kahit	palang – pa lang
anu – ano	kng – kung	pano/pnu – paano
anung – anong	kona – ko na	pg – pag
aq – ako	konting – kaunting	pls – please
atleast – at least	kpag – kapag	pmunta – pumunta
bgay – bagay	kya – kaya	pra – para
bgo – bago	lage/lgi – lagi	pwd– puwede
bhay – bahay	meron – mayroon	q – ko
bng – bang	mg – mag	qng – kong
cla – sila	mg – mga	s – sa
di – hindi	mging – maging	sakin – sa akin
dont – do not	mki – maki	san – saan
dpat – dapat	my – may	sma – sama
facebook – Facebook	n - na	tas – tapos
ganun/ganon – ganoon	naten – natin	tsaka – at saka
im – i am	nla – nila	tv – television
kana – ka na	nmin – namin	wag – huwag
kase – kasi	npo – na po	xa – siya
kelangan – kailangan	p – pa	yung – iyong

Even though the coverage of the normalizer was sufficient to correct the responses, not all were normalized correctly. Since the normalizer was built to be heavily dependent on a statistical model, some instances resulted undesirable insertions and replacements. An instance of insertion is evident on this phrase "as early as possible", which included an extra 'it' in between 'as' and 'possible'. Another is, "ayusin ang" which has "metro rail" succeeding it.

Instances for replacement were evident on words that are considered as colloquialisms or interlingual homographs – words that exists on both English and Filipino language. In the English phrase "seminar for pre or post...", the prefix *pre-* was found to be a shortcut for the colloquialism *pare* (buddy). In this

case, *pre* is also an interlingual homograph. Other mistakes are 'kits' in "medical kits" were considered as a typographical error for *kita* (you or salary), to into *ito* (this), non into *noon* (previously), and my into *may* (there, have, or with). Unfortunately, some repercussions of these mistakes removed words from clusters.

With incorrect normalizations, there are also those that were not normalized. There were merged words that was not covered by the normalizer such as 'atpagbigay', 'sumunodkapag', 'sakunamaaari', and 'dahilbansa'. Another is a typographical error variant that made use of letter 'q' as a 'g' such as 'paqdating' and 'paqaabiso'. Moreover, there are also shortcut variants, specifically the omission of vowels, that were not present in the statistical model such as 'ngbbgay', 'dhlan'. 'magki2ta', 'mlman', 'gwen', and 'magsgwa'.

Observing the effect of the normalizer as compared to the base OAE, frequency counts fluctuated into increasing and decreasing values, shifting the order of clusters, but did not affect the order of the top five. What has been evident from the normalized version is there are words that were previously included in the clusters that are shortcuts which was then removed, and new or corrected words appeared.

A few of these which were removed are 'pra', 'cla', 'xa', and 'lage', most of which are included in Table 5.10. Given this, there have been a number of instances that shortcuts as such were tagged as nouns and post-normalization were tagged otherwise.

As part of the normalization task, joining Filipino/Tagalog prefixes with their separated root words caused a set of words to appear as insights, and in action and target fields. In this instance, the prefix *mag-* was joined with *karoon* which resulted into *magkaroon*, a valid member of a proposed action cluster. Provided with more examples, joined prefixes found on the experiment are the following: *magplano*, *nagpeperform*, *pagpapadala*, *pagpapaalala*, *paguusap*, *pagbigay*, *paganunsyo*, and many more.

Provided with the changes, highly used verbs remained the same, which suggested ideas regarding procurement (e.g., magkaroon, pagbibigay, and providing), dissemination (e.g., pagiinform, ma-inform, and inform), sanitation (e.g., maglinis, linisin, and linisan), preparedness (e.g., prepare, preparing, ihanda, maghanda, maiwasan, and mkaiwas), and solidarity (e.g., magtulong, makipagtulongan, help, and helping).

Threshold Adjustments

Decreasing and increasing the similarity threshold from 50% to 20% and 80% changed the members of clusters. Reducing the threshold signifies a loose acceptance in determining if distance between two words are similar. The assumption is since the condition is looser, there may be more related (variants) words captured in the clusters. Increasing the threshold on the other hand, tightens it, thus producing harder but more closely similar clusters. The assumption is since the conditions is stricter, unrelated words will be filtered, meaning producing more accurate or closely related words in the clusters.

In OAE-T20, the most frequent suggestion is a cluster that consists of inflected verbs with the prefix *mag-* or suffix *-ing*. From the word *maging* (be), members of the clusters include the following: *magturo* (teach), *magsgwa* (magsagawa / perform), *magtayo* (build), fixing, giving, telling, messaging, calling, helping, knowing, and more.

Pointing out the highly used verbs, the set for OAE-T20 are not the same with OAE that provided per cluster a theme such as procurement, dissemination, sanitation, and more. The verbs were mostly grouped through their similarities with either the affixes or root words. Aside from the example with the most frequent suggestion, others include groups such as *papadala* (deliver) with *papaalam* (inform), and *naipapataasan* (raise), and *magtulungan* (help) with *pagtulungan* and *tutulongan*.

With this information, lexicalization also included target words to have more clusters or members. The members were joined not through the meaning of a word but in orthographic means. Instances grouped house with household, *kita* with *balita*, *kalamidad* (calamity) with *kalamid* and *kaalaman* (knowledge), seminar with *semninar* and seminars, and many more.

Despite this, there still were instances that the groupings coincidentally made sense semantically. Examples for these are *komunikasyon* (communication) with *organisasyon* (organization) and *impormasyon* (information), *ka-barangay* with *kabarangay* and *barangay*, and information with dissemination. In addition, the low threshold value enabled the clustering process to capture variants with far distances that were not clustered in the base OAE (e.g., pagkakaiisa with kaisa, and kanal with imburnal).

In comparing OAE-T80 with the base OAE, instead of words being clustered together, there are instances that initially clustered are separated, even if the difference is just a letter. Since Dice's coefficient runs through the strings with a set of three letters or trigram, values for the comparisons differ based on letter

order or positioning, and string length. Backed by the formula, Dice's coefficient computes the similarities by the common trigrams as numerator, and trigram counts of the two strings as denominator.

Visualizing this, the word *perform* and *performs* resulted into a similarity score above the 80% threshold, as the 's' character was present at the end of the word (works also if at the start) and comparing both through trigram differs at only the last trigram 'rms'. For the pair *barangay* and *baragay*, however, their similarity score is below the threshold as the 'n' letter difference is position in the middle, causing it to have more trigram differences as compared to the previous example.

Elaborating on the string length, the lesser the size, the least likely it would be to have a higher score given that a pair only differs one letter. Provided with a progression of the word *magikot* (roam) from its prefix *mag-*, which has a length from three to six, and comparing it with the last character replaced with 'x' (i.e., mag-max, magi-magx, ..., magikot-magikox); the resulting values for string similarity increases, starting with 0 and following with 0.5, 0.67, 0.75, and so on, so forth.

Negative samples for this restriction was unable to cluster the following pairs: kit-kits, training-taraining, and basura-basurahan. Positive samples, on the other hand, separated the following pairs: evacuation-elevation, drill-drills, and seminar-seminars. Moreover, there were others that the separation produced better clusters; before under one cluster are *pagbaha* (flood), *pagbabaha*, and *pagbara* (clog), then after threshold increase created two clusters with pairs pagbaha-pagbabaha and pagbara-pagbabara.

Generally, for this experiment, it proves that the assumption of increasing or decreasing the threshold could filter out, include, or basically place words in more appropriate clusters. Although, a fact is excessive amounts could decline the quality of clusters.

Clustered per Response Categories

The ORC experiments divided and spread out all the entries for which categories the responses are under. There are nine response categories in total: Information Campaign and Capacity Building, Disaster Relief, Community-wide Logistic Support for Disaster Response, Infrastructure Maintenance and Management, Early Warning System, Preparedness for Emergency, Local Government Accountability, Filipino Values, and Others, where each have their own highly suggested ideas.

Analyzing the clusters in this experiment, target/noun clusters are considered similar with OAE. So, the quality of the clusters was dependent on grouping actions/verbs. Since, Dice's coefficient groups together words orthographically, variants properly belonged with each other and pertain to a single action; with the assertion of response categories, entries can be related to them, as to the needs or actions to be done under that category.

ORC using Dice's coefficient and under Information Campaign and Capacity Building, focuses on actions that the community must have (dapat), which includes the necessary items or programs, preparations, support, and logistics involved in information dissemination. Key insights highlighted conducting programs such as seminars, drills, and assemblies. As well as the use of infographic materials such as signages, posters, and leaflets. Suggested content consists of reminders or tips on what to do before, during, and after the calamity, while the target for these are family members.

Disaster Relief contain clusters that mentioned receiving (pagbibigay) or providing assistance, goods, food or grocery (pagkain), medicine (medisina), and evacuation option. As a matter of fact, the highly clustered verbs pertain to the same idea, but orthographic clustering was not able to merge them all into one.

Similarly, Community-wide Logistic Support for Disaster Response contain clusters that suggests having safety gears, sirens, and shelter for the operations. It has also been suggested to add more budget, equipment (kagamitan) and volunteers. Expounding on the equipment, several responses grouped together medical kits and flashlight. Moreover, there was another cluster that pointed out boats and storage facility are a must have.

For Infrastructure Maintenance and Management, most of the suggestions were about cleaning up (maglinis) the surroundings (kapaligiran), specifically the streets (daanan), sewers (kanal), rivers (ilog), and garbage waste (basura). Cleaning these areas in the minds of the community would ensure prevention (maiwasan) of floods (pagbaha) and clogs (pagbara). Furthermore, in avoidance to throwing trash everywhere, one of the top suggestions mentioned proper place (lugar) or containers (tapunan) for garbage.

As stated for Early Warning System, clusters contain responses with insights that involves information dissemination. There should be (dapat) proper communication (komunikasyon), alert, news (balita) and updates, and radio. Grouping the information (pagiinform), it should be about the disaster, specifically the typhoon, and announced to the public, people (tao), citizens, and residents. Another top cluster had the same idea, that is to alert if there are (may) calamities (kalamidad), catastrophe (sakuna), disaster, typhoon, communication, support,

and assembly. However, given the same reason, the two clusters have different verbs nor even a variant of each other for them to be merged.

Under Preparedness for Emergency, clusters were in a form of a reminder, with verbs grouped such as maging (become), pagiging, magiging, and palaging (always). Target clusters for this set is to alert and attentive (atentibo) with nature (kalikasan), news (balita), and officials (opisyal). Another cluster suggests to be reminded of being aware and updated with the same target or nouns specified previously. Ideas as to where people could be reminded is through watching the weather forecast or news in television. In addition to this, other things to prepare are the following: news, evacuation plan, officials, management, unit, and the community.

For Local Government Accountability, these are the target ideas that the government should be accountable for: disasters, evacuation, posters, case, and society. It is also expected for the government to be ready (kahandaan), cooperative (mgsma/magsama and mgusap/magusap), and able to show (hrpin/harapin) and send (maiparting/maiparating) help (tulong). In light with this, there was a suggestion that the government should be (dapat) active.

Regarding Filipino Values, clusters pointed out two main ideas and these are to help and cooperate with each other. In terms of the first idea, help should be observable in preparing (paghahanda), families (magkakapamilya), and community (komunidad); while the other pointed out being cooperative with duties (tungkulin), plans (plano), and preparation. Other than the two, separate entries have verbs that mentioned tidiness (malinis), readiness (handa), equality (pantay-pantay), and kindheartedness (magmalasakit).

Under Others category, there were mixed ideas to improve disaster prevention and mitigation. There are a few clusters that called out corruption, which mentioned the act of putting valuables in pockets. Some endorsed their satisfaction with the decision makers, encouraging to continue (ipagpatuloy) their work or activities (gawain). There are also suggestions about minor and major entities in disasters, that there has to be communication between deaf, citizen, and responders.

Overall, using Dice's coefficient grouped together variants, but there are others more that could have been included in the clusters. Causes could be far string similarity distances or connection between words are through their meanings. A few of these are magkaisa-makiisa, handa-mapaghandaan, maglinis-clean, fixing-fix, nagkakabit-naglalagay, and create-make.

5.2.3 Experiments Clustered by Word2Vec

In this experiment, responses were clustered semantically through Word2Vec, which makes use of vector distances to determine if words are related to each other. In OAE, the most frequent suggestion clustered verbs that seem to be the essentials in disaster response. Sample verbs are to be, put, have, do, provide, make, create, know, help, cover, check, give, avoid, visit, support, contain, update, and more. From this verb collection, target nouns were training, news, garbage, evacuation, drills, flood, devices, supplies, and more. It is apparent that there are a lot of suggestions in this cluster pertains to objects that are a "must have" in the barangay. A few of these are boats, equipment, facilities, electricity, kits, gears, megaphones, goods, signage, storage, and dumpster.

One notable difference between Dice's coefficient and Word2Vec is vectors are positioned based on usage, so words that operate the same way are close together. Having said, in clusters, there were synonyms present such as make-create, help-support, have-contain, and provide-give. Moreover, there were also tense variants such as make-making, be-been, and need-needed. Lexicalizing the given targets, there was a large cluster under the topic of 'training' which consists of the following words: community, disaster, times, typhoon, plan, things, programs, government, technology, effects, management, events, case, info, society, emergency, food, help, assembly, warning, sign, advance, areas, week, gym, days, question, people, map, part, place, center, check, needs, information, aid, class, house, project, drive, household, proper, object, council, supply, heart, relief, and systems. On it are different topics and participants that can be the focus of trainings.

Listing other major clusters advises actions regarding *logistics* (e.g., magkaroon, magamit, maglagay, magbigay, ayusin, panatilihin, tanggalin, ilabas, malaman, gawin, magbibigay, mabigyan, handa, gagawin, matulungan, ibigay, malalaman, bigyan, iwasan, ipagpatuloy, ilagay, hikayatin, makakatulong, and magkakaroon), *dissemination* (e.g., inform), *sanitation* (e.g., linisin), *preparation* (e.g., prepare), and *solidarity* (e.g., tumulong, gumawa, magsagawa). Under logistics, aside from generally covering it, there are other top clusters that indicated movement (e.g., dumating, pumunta, and lumikas), procurement (e.g., giving), and expectations (e.g., maayos, dapat, mabawasan, epektibong, and inaasahan).

Under these topics, noun for logistics indicated sub-clusters about supplies (e.g., signal, gamut, komunikasyon, basura, and pagkain), areas (e.g., tahanan, lugar, bahay, and paaralan), information (e.g., detalye, plano, problema, kaalaman, ideya), and situation (e.g., sitwasyon, kalinisan, kalagayan). In spite of these related sub-clusters, there were also lexicalized instances that does not make sense such as joining food, warning, peace, report, notice, and government.

Dissemination topics recommended to point out the consequences of disasters to people, citizens, residents, neighbor, subordinate, and barangay. Sanitation then mentioned cleaning up garbage from sewage, river, and streets. Next, in terms of preparation, a place for seminars and alarms was let out. Last is for solidarity that pointed out helping the organization or community in activities or programs such as seminars, drills, orientations, and the likes.

Encapsulating the Word2Vec approach, there were a number of samples that proved to be sensible, with cluster members having clear relationship with each other. Providing further examples, notable instances include bagyo-baha, month-week, balita-ulat, sakit-kapansanan, organisasyon-pagpupulong, typhoon-storm, bagyo-lindol, people-public-community, harap-paligid, napinsala-tinamaan, and mataas-malaki. Extending this, it includes orthographic variants as instances like barangay-baranggay, kapaligiran-paligid, kabataang-bata, nakarating-pagdating, and pagtulong-tulong were grouped together.

However, relatedness does not always mean it produces the ideal groupings. There were clusters that produced antonyms like tao-bagay and sakuna-sanhi. Furthermore, Word2Vec missed words that should have been clustered together like prepare-preparing, giving-pagbibigay, maglinis-clean, announce-inform, and linisin-maglinis; and although under one cluster already because of merging their verbs, there are instances that should be lexicalized like kanal-imburnal, barangay-brgy, typhoon-flood, and gamit-bagay.

Normalized Evaluation

The underlying successes and issues of normalization discussed on Dice's coefficient is present in OAE-N experiment for Word2Vec. Some clusters had increased values, and some decreased because of it. As a result, there were shifts in the insights as to the verbs and nouns extracted, affecting the generated clusters.

Even with normalization, the shift did not prevent Word2Vec in overlooking words as cluster members. The assumption was, with normalization, more verbs will rise and be placed more appropriately on the vector space, while nouns will be correctly pointed out by the part-of-speech tagger and information extraction's pattern matching. However, the fact that most normalizations affected verbs inflected with prefixes; at the most, it can only add a few responses with the similar prefix or root word into some clusters and unfortunately was not able to significantly manipulate the vector's usages or positions in the space.

Concerning cluster composition, the changes with some of the groups from the most frequent clusters alone are provided. From 'training' sub-cluster, the keywords 'events', 'info', 'week', 'world', 'aid', 'household', and 'relief' moved into the 'news' sub-cluster. Another, from *sitwasyon* sub-cluster containing *kalinisan* and *kalagayan*, the members *kaligtasan*, *epekto*, *kalikasan*, and *ideya* was added. Then, the *samahan* sub-cluster was disbanded and removed. From a verb cluster regarding logistics, magkaroon was clustered with pagkakaroon and *nagkakaroon*, *gumawa* with *magsagawa*, *magdagdag* with *dagdagan*, and *iwasan* with *maiwasan*. Observing the rest, here are notable examples that new clusters was made: *kaalaman* with *problema*, *komunikasyon*, *kalinisan*, *gawain*, *paraan*, *kaligtasan*, *karanasan* with *epekto*, and *gamit* with *kagamitang*.

Threshold Adjustments

In OAE-T20, the most frequent suggestion hoarded and absorbed verbs from other clusters. Under this cluster, ideas relating to logistics were grouped together. Initially with the theme of essentials in disaster response, most of its contents were transferred to come up with a collective idea towards logistics such as concerns with its movement and expectations. In this new cluster, suggested actions such as *magkaroon*, *tumulong*, *maayos*, *dapat*, *maiwasan*, *maglagay*, *magbigay*, *panatilihin*, *mabawasan*, *mabilis*, *epektibong*, *paparating*, *ilabas*, *malaman*, *magpadala*, *magturo*, *malinis*, *dagdagan*, and more were grouped.

Loosening the threshold clustered more related words that were not joined before. Instances include verb pairs such as magkaroon-nagkakaroon, nakakatulong-makakatulong, maayos-ayusin, nalaman-malaman, paligid-daan, dagdagan-add, mabigyan-provide, and more. However, the contents in one cluster are general or vague, mixing up the ideas under one large topic. Visible with sub-clusters in nouns, there were lexicalized groups that mixed medicine (gamot) with cleanliness (kalinisan), barangay and typhoon (bagyo), and cause (sanhi) and food (pagkain).

Unaffected by the absorption, there were highly suggested clusters (e.g., linisin, prepare, and giving) that at the most changed only on the noun sub-clusters. Sample of this change added sewage (kanal), garbage (basura), and pathway (daan) with the original sub-cluster of word variants of surroundings (kapaligiran and paligid).

Contrary to OAE-T20, OAE-T80 dispersed cluster members in the base OAE. From the most frequent suggestion with actions that indicates essentials to possess, it has been divided into two entries. Although both have the same idea, distances in the vector space did not cut out for the threshold. This effect re-

occurred throughout the whole output, verb and noun clusters alike. A number of clusters was left with only one verb (e.g., magkaroon, pagbibigay, dagdagan, handa, makakatulong, and malinis), which means verbs must be exactly the same to be clustered together.

Due to dispersed verb groups, target fields have lesser appended nouns. As a result, it also lessened the sub-clusters or lexicalized ones. The 80% similarity threshold restricted into joining its members, that is why pairs like harap (front) and paligid (surroundings) were not lexicalized anymore but remained under the same cluster.

OAE-T80's effect however is not all negative. Since the restriction ensures that words are 80% and above close in the vector space, clusters clearly manifested the relationship between them. A good example for this is 'government' being clustered to only 'assembly' and 'council', which depicts a group of people. Another joined 'training' with 'community' and about 'disaster', which are the elements for disaster training.

Clustered per Response Categories

Similar to OAE-T80, ORC experiments divided responses by their designated categories. In this case, a balanced threshold was used for grouping similar ideas together. Analyzing the grouping of actions/verbs and target/nouns, there are certain representative topics that can be taken out of the clusters. Under Information Campaign and Capacity Building, the most frequent ideas consist of verbs that brings out the necessary actions involved (based on have, tell, create, avoid, and give), intended content and delivery medium (based on nais, dapat, malaman, kailangan, and sana), receiving end (based on mabigyan, maging, magkaroon), and decision makers (based on magbigay, magturo, magsagawa, magtayo, and talakayin) of the information.

Nouns involved for the necessary actions are the following: drills, programs, officials, meeting, siren, duty, and tips. In the intended contents and medium for the information, nouns included calamity, method (paraan), seminar, schools (paaralan), and Disaster Risk Reduction Management. For the receiving end of the information, neighbors (kapitbahay) and people (tao) in general must be aware, invited, disciplined (disiplina), and knowledgeable (kaalam). Then for decision makers, they are recommended to conduct programs such as seminars, drills, assemblies (pagpupulong), and orientation.

Under Disaster Relief, the top clusters mostly involve which items the community needs. One sub-cluster combined nouns containing food, aid, supply, relief, and case, then another with food (pagkain) and medicine (gamot). Unfortunately, even with almost the same set of nouns, there were verbs such as giving, provide, magbibigay and pagbibigay (give) that have not been merged together by Word2Vec.

In the same way, Community-wide Logistic Support for Disaster Response provided top suggestions with the same topic. It pointed out clusters specific to equipment and vehicles that can be used to support disaster response. Sub-clusters present groups about emergency, where the following words are included: place, aid, disaster, areas, food, center, people, and technology.

Under Infrastructure Maintenance and Management, most of the highly suggested ideas involve sanitation (cleaning and supplying). A sub-cluster with clear relationship between members are about flooding (pagbaha), that includes catastrophe (sakuna), pathway (daanan), road (kalsada), and flood (baha). In addition, there is a sub-cluster that mentioned the kapaligiran (surroundings) with lalagyan (place), daanan (pathway), and pagtaas (elevate). Moreover, in this category there were instances that lexicalization included orthographic similarities like clustering kapaligiran and paligid together.

In Early Warning System, highly suggested verb clusters indicated ideas that in this category must have. The cluster with highest frequency put up a bunch of actions words where their relationship are not easily distinguishable such as warning, do, make, be, have, coming, drive, is, are, has, eat, visit, update, give, avoid, said, watch, provide. The fact is there are keywords that relates to actions to be implemented for this category.

Focusing on target clusters, one sub-cluster collected ideas that seems to be describing a workshop; members of this include training, technology, community, disaster, warning, sign, typhoon, days, people, house, food, events, and emergency. More notable examples of sub-cluster paired up warning (babala) with typhoon (bagyo), situation (sitwasyon) with detail (detalye), typhoon with flood (baha), and radio with update. Provided with examples, there are cases wherein the orthographic similarities are evident on the vector space such as *maagang* (early) and *maaga*. Within this vector space, there are also cases that opposites were merged such as *mababang* (low) and *mataas* (high).

Under Preparedness for Emergency, a set of ideas on how to act in situations were presented. Word2Vec was able to combine essential actions related to preparedness which are *maayos* (fix), *malaman* (know), *magpadala* (send), *matugunan* (address), and *maiwasan* (avoid). Distinguishable topics in lexical-

ized sub-clusters are about readiness (paghahanda, pangangailangan, kaligtasan, pagkain), news (balita, ulat, programa / disaster, typhoon, week, times), time (oras, araw), and planning (plan, things, management, unit, community, time, proper, case, council, emergency).

Similarly with Early Warning System, in Local Government Accountability category, the cluster with highest frequency indistinguishably combined words such as help, be, are, want, working, make, have, know, having, and feed. Analyzing its target words, a sub-cluster lexicalized with help (people, map, part, government, case) was provided. In line with it are the nouns disasters, barangay, officials, personnel, evacuation, society. Basing on these, the idea for the top cluster signifies recommendation to either help the decision makers or make decision makers focus on helping the people. Moreover, there was a sub-cluster that grouped together problem (problema) with policy (patakaran), method (paraan), and attention (pansin).

In Filipino Values, it would be beneficial to encourage each other to help. With regards to clustering, recognizable positive samples are the following: samahan-tulong, tahanan-bahay, bagyo-baha, and baranggay-barangay. In another view, there are entries that could have been clusters with other entries. Example for these are *magkaisa* and *makiisa*, *tutulong* and *magtutulungan*, *matutong* and *matutunang*, and etc.

Last category is Others. Under this has not been much on both insight and clusters quality. For verbs, examples with clear relationships are humingi-magbigay, dapat-nararapat, and wala-walang; while for sub-clusters are sign-object, emergency-people, typhoon-disaster, warning-device.

Synthesizing ORC experiment using Word2Vec, examples showed its ability to use the vector space into providing semantic relationships between words. It was able to cluster orthographic variants, thematic similarities, usages, and even antonyms. However, given this algorithmic ability, there were high frequency clusters that has members with relationship indistinguishable from each other. In addition, there were some obvious instances that could have been included in either verb or noun clusters.

5.2.4 Experiments Clustered by FastText

Grouping responses using FastText attempted to produce clusters that are semantically related. In OAE experiment, the highly suggested entry has verbs that are about actions to be done in disaster response. In terms of quantity, majority of

the verbs are in English and as a whole, this cluster is larger than Word2Vec. Sample English suggested actions include maximize, alert, improve, prepare, enforce, inform, clean, provide, minimize, remind, implement, install, ensure, gather, educate, join, create, communicate, fix, teach, and more. A few Filipino actions include *maiaannounce*, *ma-inform*, *linawin*, and *ialarm*.

Among these verbs, there are instances that are proven to be synonymous with each other. Pairs include enforce-implement, establish-create, educate-teach, contain-hold, support-help, and tell-announce. At the same time, there are also antonyms such as minimize-maximize, let-prevent, spread-gather, add-reduce, and give-take. Other semantically related members describe communication through messaging, texting, and calling.

One special characteristic in FastText that has made its way to be evident in providing orthographically related words is the use of subword information (character n-grams) as representation. Cluster members included verb tenses such as improve, improved, and improving. Furthermore, there were intra-word code-switching connected to each other. Example pairs for this are inform-mainform, provide-magprovide, participate-magparticipate, and alert-ialarm.

Under the same cluster, two of the largest sub-clusters relates to disaster (with awareness, dissemination, consequence, evacuation, etc.) and sirens (with laws, theft, alert, gear, etc.). Smaller sub-clusters still provided clear relationships with each other, with pairs such as responders-response, assembly-house, news-radio, trash-risk, and people-aid.

Analyzing the rest of the clusters, they showed the same kind of relationships in groupings. In fact, on the second largest cluster, most of its verbs were closely related based on tenses. The set includes *magkaroon*, *maging*, *pagkakaroon*, *magtulong*, *maipaabot*, *maiwasan*, *maglagay*, *nagkakaroon*, *magbigay*, *mabawasan*, *maglinis*, *maghanda*, *magbibigay*, *mabigyan*, *magtulong2*, *magpasagawa*, *mabigyang*, *nagbbigay*, *makatulong*, *bigyan*, *bigyang*, *magtanim*, *matugunan*, *magsagawa*, *mabigay*, *mapagbigay-alam*, *magtulongan*, *maibigay*, *ipagbigay*, and more.

Provided with this example, the shortcut words *nagbbigay* and *magtulong2* were able to join the cluster with *magbigay* and *magtulongan* – where Dice's coefficient was also able to but not Word2Vec. On another view, instances that Dice have not covered orthographically but was clustered by FastText are the verb clusters of *magturo* (teach), fixing, *paalalahanan* (remind), *mabawasan* (reduce), *pagtibayin* (fortify), and more. In the sense, FastText effectively combined the two approaches as to covering orthographically similar words and using the vector space as basis for relationships.

Gathering ideas from other clusters, those with high frequency collected ideas regarding dissemination (e.g., pagbibigay, pagiinform, magtawag, and pagpapaalala), solidarity (e.g., magkaisa, tumulong, and magsama), preparedness (e.g., lessen, maagap, and maagang), and maintenance (e.g., tanggalin, palitan, and ilagay). Running through these ideas, one limit with FastText is there were still fragments of word variants scattered across different clusters. Case in point, from the base word *tulong* (help), there were entries that on another cluster contains *tumulong*, and on another is *makakatulong*, which should have been on a single cluster. Reflecting on this, the primary cause is the summed vectors' positioning in the space, which is determined by their usage.

Normalized Evaluation

In OAE-N experiment for FastText, some entries were affected by the shift of words created post-normalization. Shifts in the sense that shortcuts, typographical errors, and separated prefixes were standardized and those that were incorrectly tagged as an insight was replaced with a different set. A few of these changes are the normalized verbs *meron* (have) into *mayroon*, and joined prefixes *magplano* (plan), *magschedule* (schedule), *magreport* (report), *maglaan* (allocate), and *magdagdag* (add), which all are under the same cluster.

In the same way, target clusters were affected, where some were removed rather than replaced. In one of the clusters, the shortcuts *mg*, *nmin*, *hrpin*, and *dn* were gone from the OAE-N report. Another case added and removed some members in the lexicalization of targets. Positive samples for this include meetings-conduct added 'citizens' and responders-respondents added 'respondihan'. For new merges, komunikasyon (communication) was clustered with *impormasyon* (information), *samahan* (organization) with *komunidad* (community) and *pagpupulong* (assembly), and *daluyan* (pathway) with *kanal* (sewer) and *daanan* (road). Removals on the other hand were caused by changes in extracted insights or disbanding in clusters.

It is important to note that even with the change, there are clusters that remained the same in count, but some still changed in lexicalization or its sub-cluster members. In this case, the change in extracted insights are present, specifically on either the verbs which can change entry frequency counts or nouns which can change the target cluster and sub-cluster members.

Similarly with Dice and Word2Vec, OAE-N experiments did not eliminate but reduced instances of responses that were not clustered but should be. Instances like *turuan* (teach), *paghahanda* (ready), *magimbak* (store), and *ibalita* (report)

proved this. Regardless, using FastText in general increased the clusters made (decreased the single frequency entries) and decreased the number of entries as compared to the other two approaches by more than half.

Threshold Adjustments

The result of FastText's OAE-T20 showed the gravity of loosening the threshold. Initially from OAE's 114 entries, its value dropped to six entries, reaching about 99% of the responses clustered. Provided with this statistic, almost each of the clusters collected a large amount of actions and target (presuming the same effect on lexicalizations), generalized with topics about disasters.

The outliers for this experiment, however, are the last two clusters. With the rest of the clusters having a hundred or more frequency counts, the lowest only have a single insight, with the proposed action *nangyayaring* (happening) and target *barangay*. Next to it has two responses, with proposed actions *lumawak* (expand) and transport, and targets *kaalaman* (knowledge) and vehicle.

From the threshold of 20%, each pass of the clusters piled loads of responses together, and as one cluster is created, the next would have fewer selections until there is no more. However, FastText still was unable to include these outliers even though there are keywords that could have been potential members.

The reason for this exclusion is the algorithm works by choosing a base word that would be compared to the rest of the verbs. In this case, cluster one's *magkaisa* (unite), cluster two's *wastong* (proper), cluster three's put, and cluster four's *pagtawag* (call) as compared to *nangyayaring*, *lumawak* and transport has lower similarity values - visualizing them on opposite "corners" in the space. As a result, they are on separate clusters.

One solution to merge these clusters is to use other members from existing clusters as the base word. However, doing so might result into having one cluster all in all. Since the main idea of this research is to extract and organize the responses to generate a report that could be easy to interpret and implement, the problem with a single huge cluster is it would be harder to understand; it would represent a vague topic about disasters, which is similar to reading all of the responses in the data.

Tightening the clustering condition, OAE-T80 split the large clusters from OAE. Frequency counts and cluster orders shifted, with more specific topics in clusters. Instead of huge topics about logistics or disasters in general, some of the specific topics of action include procurement (e.g., provide), dissemination (e.g.,

inform), preparedness (e.g., prepare), sanitation (e.g., linisin), and avoidance (e.g., maiwasan). A downside with the spread of clusters or increase of entries however is there are ideas within separate clusters that duplicates the ideas. Nevertheless, these type of clusters makes it easier to interpret the idea behind each.

Similarly with Word2Vec, OAE-T80 created clusters with only a verb, which means verbs joined has to be exactly the same to be under one clustered. Examples for these are *magkaroon* (have), *linisin* (clean), *maging* (become), *kailangan* (need), give, *tumulong* (help), and more. Regarding target clusters, it is clear that at 80% mark, there is a high number of sub-clusters that joined words (mostly in pairs) with orthographic similarity. At the same time, FastText still included instances of semantic similarity such as before-after (antonym/preposition) and for-of (preposition).

Clustered per Response Categories

ORC for FastText produced high frequency clusters despite having the responses be segregated into their corresponding categories. Clusters have mixed topics, where some are specific and other are generic. Examined each category exhibited key insights grouped together by the approach.

First category is Information Campaign and Capacity Building. Inside it vaguely represents a multitude of actions that could be involved in disaster strategies. Among the highest cluster, verbs include alert, remind, gather, give, help, prepare, conducting, teach, provide, making, focusing, participate, reduce, ready, and more; while nouns include ideas, flood, place, sirens, seminars, tips, orientation, garbage, disposal, assembly, family, class, project, LGU, and more. As the same with other experiments, FastText was able to cluster this set with distinct relationship with each other. Other ideas from low frequency entries includes education or dissemination, faster actions, assistance, and construction.

Second, Disaster Relief in total have a few responses under it. Majority of its responses are under one cluster that indicated the need for support in the community. Suggestions under this relate to providing supplies like food and medical kits. It is noticeable that beneath the target field, there have been sub-clusters that would be more appropriate to be clustered than its current grouping. One example is the pair 'aid' and 'need'. The noun 'aid' could be clustered with 'response' or 'assistance' but are either non- or members of a different sub-cluster.

Third and in a similar case as Disaster Relief, Community-wide Logistic Support for Disaster Response accumulated a lot of responses for its cluster with the highest number of frequency counts. Within this cluster involves verbs and

nouns that indicates the things needed to be provided or prepared. Instances for the nouns grouped emergency with facility and assistance, supplies with shelter, evacuation, equipment and food, and disaster with facilities and for typhoon and storms. Other ideas that belonged to the same idea but were on another cluster mentioned building or buying an area or place, adding budget and community volunteers, and communicate weather predictions.

Fourth is Infrastructure Maintenance and Management which highlighted ideas for sanitation and repair. There were three major clusters, one that pertains to the primary subjects for maintenance or management, another is for those in need of improvement and prevention, and one of which to incorporate in this category.

Regarding the primary subjects, these are to clean and fix waste, garbage, and sewage. In improvement and prevention, target subjects are drainage (that comes with its sub-clusters areas, streets, canals, dumpster, etc.), system, rules, flow of flood, plan, and community. It is also notable how FastText was able to cluster dumpster with garbage, bins, and *garbagetrash*. Regarding which nouns to incorporate for maintenance and management, specific to providing (magkaroon or magbigay) and reducing (mabawasan), here are the following suggested sub-clusters: *basurahan* or garbage (for floods and clogging), *pagtitipon* (gathering), training (or seminars), and *puno* (trees). It is safe to note that *pagtitipon* could be clustered into training, but similarity seemed to be below the threshold. In addition, there could have been other low frequency clusters, especially the single ones, that FastText should merge. Samples for these are lessen, *dagdagan* (add), and *ngbbgay* (nagbibigay or provide).

Fifth is Early Warning System, another category that has a large number of responses. Under this has one cluster with more than a hundred cluster members, while the rest follow with less than 25. The essence of the highly grouped verbs is to provide ideas relating to Early Warning System, which includes the following: inform, alert, messaging, texting, *namemegaphone* (use of megaphone), update, utilize, provide, and more. In its target/noun list, there is a large sub-cluster that was lexicalized under theft. Its members are: plenty, citizens, places, beforehand, floods, incoming, troubles, people, preparedness, sms, alert, constituents, news, person, everyone, theveryone, damage, way, needs, need, weather, changes, things, loss, early, happenings, weeks, and more. Based on this, the lexicalization might not have been appropriate as this was chosen randomly. It would be better if nouns closely related to theft are the only ones included (e.g., troubles, people, damage, loss, things, news, alert, etc.). In another view, there is a sub-cluster that paired 'media' and 'devices', which would be more appropriate if the nouns 'sms', 'news', 'need', and 'things' are under them.

Sixth, the list of highly suggested actions under Preparedness for Emergency are the following: *magtulong* (help), *magkaroon* (have), *maghanda* (ready), *malaman* (know), *mapagbigay-alam* (inform), and more. A few of the nouns under these are *balita* (news), *gamit* (things), *disiplina* (discipline), *tulong* (help), emergency plan, and more. Although some of the contents have distinguishable connections with each other, there are also some that are indistinguishable to the category. Example is pairing up *atentibo* (attentive) with *kagamitin* (kagamitan or things), *kapit-bahay* (neighbor) with *pagkain* (food), and *bagay* (thing) with *kasanyan* (kasanayan or skill).

Rest of the clusters showed positive samples such as clustering news with week, radio and times, flood with weather, condition, and calamity, and *balita* (news) with *ulat* (report). Negative samples on the other hand could be combined with existing clusters such as *makipagtutulungan* (help), and *ihanda/handa* (ready) with the top cluster, *ibahagi* (share) with *ibalita* (report), and *maiwasan* (avoid) with *makaiwas*.

Next is Local Government Accountability that indicates the responsibility of the government in disaster planning and response. Under it has the following keywords as its top cluster: enforce, hold, gather, facilitate, surrounds, make, raise, and more. Targets under it pertains to trash, map, response, and laws about (as specified in the sub-cluster) disasters, awareness, officials, news, help, and evacuation. Undeniably, these ideas, especially the last one, can give light to the positive and potential use of the government's power to reinforce the nation's disaster prevention and mitigation.

Then, under Filipino values, clusters highlighted solidarity, that is to keep everyone united and participative in helping each other. The cluster with highest frequency indicated ways to help, with majority of its verbs as variants of its Filipino word *tumulong* (tutulong, magtulong2, matulungan, magtulungan, makatulong, magtulong, tulongan, hikayatin, makipagtulongan, maitutulong, tutulongan, magtulongan, and makakatulong). Subjects in helping are community, volunteer, *bata* (child), *pagkain* (food), *magkakapamilya* (families), and more. On the cluster about unity, traits of Filipinos or traits that should be are as follows: concern (malasakit), peace, order, and support (suporta). The rest of the clusters, some positive examples grouped *napinsala* (damaged) with *apektado* (affected) and *nasiraan* (damaged), volunteer with duty, and *pakiki-isa* (solidarity) with *komunidad* (community). Negative examples on the other hand paired share-trick and peace-my.

Last category is Others, where its clusters contain mixed ideas about disasters. In terms of clustered words, examples paired dapat-nararapat, walawalang, humingi-manghingi, tulung-tulong, and humingi-maibigay (antonym).

Conversely, it failed to pair maayos-pagsasaayos, emergency-responders, barangay-community, barangay-tao, and the likes. Furthermore, there were samples that clusters have indistinguishable relationships such as pockets-disasters, tas-corrupt, deaf-flashfloods, and train-permission.

Synthesizing FastText clustering for ORC, as it combines certain characteristics in Dice's coefficient and Word2Vec, it could be compared to both results. In fact, results in terms of characteristics in positive and negative aspects are similar, but quality of the clustering has changed. Since FastText has more characteristics taken from the two, there were more combinations as to the resulting clusters; specifically, being able to join orthographic and semantic (thematic similarities, usages, and even antonyms) similarity. At the same time, it also suffered from having indistinguishable relationships and missing some potential responses to be merged with others.

5.3 Survey on the API and Report

In evaluating the outputs of this study, survey was performed with questions pertaining to their quality and discussions on user feedback was provided.

5.3.1 API Functionalities

Application Programming Interface (API) is a collection of functions which is shown at Appendix B. It has nine parts that represents the tool's modules, namely Data Utilities, Normalization, Language Identification, Filipino Part-of-Speech Tagger, Information Extraction, Information Organization, Information Clustering, Information Ranking, and Report Generation.

Data Utilities module (see Appendix B.1) contains 10 functions. These functions enable the user to process files outside the program. Main functionalities permit the user to read and write on text or excel files.

Normalization module (see Appendix B.2) contains 10 functions, that could be used to utilize or customize the normalizer. There are two normalizers that can be used in this API, namely Nocon et al.'s (2018) normalizer and another that joins prefixes with root words using Oco and Borra's (2011). As default, both are used. There are two ways that normalizations could be done, one is per string or sentence, and another through a list or by batch. The rest of the functions act as means to modify the configuration, that is by setting file paths.

Language Identification module (see Appendix B.3) contains four functions. These can be used to indicate the language a particular string is under. There are two ways it could be used, one is using a string as input (per sentence evaluation), and another using string or object lists (by batch evaluation). Either way, its output provides a tuple of language and confidence value. Additional functionality enables the user to modify the coverage of languages for identification.

The Filipino Part-of-Speech Tagger module (see Appendix B.4) contains six functions, that makes use of FSPOST (Go & Nocon, 2017). Three kinds of functions can be seen in the list, which are about modifying the file path (to call the tagger), tagging options (per string, by object or string list), and formatting options (Part-of-Speech only or Stanford word|tag Format). By default, tagging format displays a word and Part-of-Speech tuple.

Information Extraction module (see Appendix B.5) contains only two functions. These functions enable the user to extract insights in two formats. One is insight phrases which extracts a string starting from a Verb up to a Noun. Another does the same process but formats it with only the Verb and Nouns inside a sub-list or tuple. It is safe to note that on this module, the extractions were made specific to Malasakit responses. Extractions are performed in an object with the following attributes: Response ID, the Response itself, its Response Category, Language identifier, FSPOST tags, container for the extracted insights, and location (a field that can be added by users).

Information Organization module (see Appendix B.6) contains three functions that sets the formatting style of the clusters and report. Main functionalities enable the user to organize their extractions or results all in all or uses a per category style of formatting.

Information Clustering module (see Appendix B.7) contains 11 functions. Three parts can be taken from this list. First is the main function that invokes the clustering algorithm (i.e., Dice's Coefficient, Word2Vec, or FastText). Then, supporting functions that can retrieve insights from the Malasakit object, remove duplicates in clusters, flatten insights in the cluster, and cluster/lexicalize target/noun words. Last is a list of functions that computes for distance or similarity values between two strings using the selected approach.

Information Ranking module (see Appendix B.8) contains only two functions. A function that ranks the clusters by frequency and arranges them in descending order (highest count first, lowest comes last); and a function that ranks by cluster categories, arranging the order of categories (category prioritization has been determined beforehand) and per categories ranks them by frequency in descending order.

Report Generation module (see Appendix B.9) contains six functions. Its main function generates the report in a Microsoft Word document. The other five are functions that was used as support in generating the report. Examples for this includes adding a timestamp, divider, title, and setting the document margins and page columns. The idea for separating or having these functions is for future applications that intends to create their own format in the report.

As a whole, the functions listed are intended to be useful in future researches or application not necessarily within Malasakit that involves the tasks of data processing, information extraction, language identification, part-of-speech tagging, word clustering, and text ranking.

5.3.2 Report Formatting

The report generated by the tool is a two-column Microsoft word document, with extracted insights/suggestions organized in two ways, organized all entries (OAE) by frequency (see Figure C.2) and organized per response category (ORC) and frequency (see Figure C.1). Each report contains three parts: Introduction, Insight List, and the Malasakit Response List (see Figure C.3).

In the Introduction, a title can be seen above the document's production timestamp (in Month-Day-Year and HH:MM:SS format). Below them is a short description which informs the readers that the suggestions that has been provided was automatically extracted and organized.

In the Insight List, Entries or also considered as clusters are numbered. Under that entry heading, fields such as Sentence ID numbers (of cluster members), Frequency Counts (number of responses under the cluster), Proposed Action (verbs extracted and joined together), and Target (nouns under those verbs clustered) were included.

Moreover, lexicalization, a process in placing a word that can represent a cluster, has been applied in Target fields, resulting into sub-clusters enclosed in parentheses. The only difference between OAE and ORC in terms of format is ORC's category heading enclosed with two horizontal column-length lines. The length of this part varies, depending on the experiment (approach and configurations used).

In the Malasakit Response List, the full responses in the data are provided. It is formatted in a table containing two columns, one for Sentence ID or row number in the data, and the next with the responses (sentences of suggestions). The length for this part is 33 pages.

5.3.3 Survey Procedures

In conducting the survey, several steps were followed for its completion. Prior to answering the questionnaires, an informed consent form (see Appendix D) was provided indicating the purpose, procedures, duration, participation and confidentiality notes, risks, benefits, contact information, and consent signatures.

Under the purpose of the survey, it has been indicated details about the research (what is it about or what is it for) and how the respondents relate to it or why are they chosen to partake in it. For procedures, a step-by-step on how the survey is going to be performed was iterated. In duration, an expected time for completion was provided. For participation, it has been noted that the survey is voluntary and that respondents can withdraw at any time. In confidentiality, assurances and steps that will be done to protect the respondents was described. For risks and benefits, it showed how respondents will be responsible for the effects and if there are negative ones, they will be addressed immediately. In contact information, details about Research Ethics Committee in De La Salle University was provided. Finally, are the concluding remarks and proof of participation in the survey.

After signing the consent form, materials for the survey such as supporting documents and API were provided. The documents include the copy of the consent form for both parties, survey questionnaires and API functions list (see Appendix B). There are two questionnaires (see Appendix E), one intended for assessing the API and another for the report.

The API questionnaire consists of two parts: a quantitative and qualitative part, modified from the USE Questionnaire (Lund, 2001) and NormAPI (Nocon, Cuevas, Magat, Suministrado, & Cheng, 2014, as cited in Regalado et al., 2015) version of the USE Questionnaire. In the quantitative part, every question is measured by numbers from one to five, where it indicates in the same order strongly disagree, disagree, neutral, agree, and strongly agree. It has been divided under four themes, namely usefulness (e.g., it is effective partnered with other software tools), ease of use (e.g., it is user friendly), ease of learning (e.g., I easily remember how to use it), and satisfaction (e.g., I would recommend it to be used in the future). In qualitative, there are three items that needed opinions about. The statement is to provide the functions used (or functions that will be most likely useful to me), comments and suggestions about the API, and negative aspects (if there are any).

Uniformly, the Report questionnaire has two parts and similar assessment measurement. It has been created from the TAM Model (Davis, Bagozzi, & Warshaw, 1989) that measures a tool's perceived usefulness and ease of use. It has been indicated in the survey the primary targets for its quantitative part are focused in terms of design (e.g., the report's design is acceptable), quality (e.g., the information fields are appropriate and enough to make a decision or action), format (e.g., the information is easy to interpret), efficiency (e.g., using the report in my job would enable me to accomplish tasks more quickly), and potential (e.g., the report would enhance my effectiveness on the job). For its qualitative assessment, it has been stated to indicate the organizational preference (which approach and format), comments and suggestions about the report, and its negative aspects.

5.3.4 Survey Results

The survey was conducted on five (5) Malasakit team members as its respondents. They were chosen to assess the content of the generated report and the developed software tool. Particularly, the report's aesthetics and information quality, and the tool's usability. Their feedback determined the impact of the research, specifically its overall usability, and was able to provide ideas for improving the report and tool (see Appendix F for their answers).

API Assessment

In assessing the API, quantitative scores were provided with criteria under Usefulness (see Table 5.11), Ease of Use (see Table 5.12), Ease of Learning (see Table 5.13), and Satisfaction (see Table 5.14). The format in tallying the result was based on Nocon et al. (2014), which accommodates the scores regardless of the number of participants.

In each row displays the description or questions under a criterion, while numbers one to five are the scores representing strongly disagree to strongly agree. Under the scores indicate how many respondents chose that value (blank fields count as zero), rather than putting scores per respondent. At the last column, average scores per description was provided.

Table 5.11: API Results on Usefulness

Description	1	2	3	4	5	Avg.
It is effective partnered with other software tools			1	1	3	4.4
It can help raise the productivity rate when used in conjunction with other software tools				2	3	4.6
It is useful for my tasks			2	1	2	4.0
It makes it easier to accomplish my tasks			2		3	4.2
It helps save time				2	3	4.6
It does everything I would expect it to do			2	1	2	4.0

As a whole, the API was rated with 4.07 out of five score. Particularly, its overall rating in usefulness criterion produced a value of 4.3 (see Table 5.11). It has been described to excel in providing increased productivity rate when partnered with other tools and reduces time in accomplishing tasks. Moreover, applying it to other tools was deemed effective. Lowest ratings for this criterion got the average of 4.0, a point lower to the highest score, which described how useful the tool was to the participants' tasks and if it runs how they expect it to be.

Table 5.12: API Results on Ease of Use

Description	1	2	3	4	5	Avg.
It is easy to use			1	2	2	4.2
It is simple to use			2	1	2	4
It is user friendly		1	1	3		3.4
It requires the fewest steps possible to accomplish what I want to do with it			2	2	1	3.8
It is flexible			1	4		3.8
Using it is effortless		1	2	2		3.2
I can use it without written instructions		1	2	2		3.2
I don't notice any inconsistencies as I use it			2	2	1	3.8
Both occasional and regular users would like it			1	3	1	4
I can recover from mistakes quickly and easily			2	2	1	3.8
I can use it successfully every time			1	2	2	4.2

In terms of Ease of Use, its overall rating garnered 3.76 – the lowest among all criterion (see Table 5.12). With this in mind, unfavored ones described the API as difficult or complicated to use, especially without proper documentation. Furthermore, there were counts with a participant rating them as low as 2 points. It comes with the same value count on user-friendliness. Despite this, there are participants that still found the API easy and simple to use. In addition, it

also runs successfully when they use it. Even having in mind that with these characteristics, occasional and regular users would like its functionalities. Other distinguishable characteristic pertains to the modularity of the API's functions, where it got four out of five participants agreeing that it is flexible.

Table 5.13: API Results on Ease of Learning

Description	1	2	3	4	5	Avg.
I learned to use it quickly		1		4		3.6
I easily remember how to use it			1	1	3	4.4
Learning how to use it is easy		1		4		3.6
I quickly became skillful with using it			2	3		3.6

For Ease of Learning, it got an overall rating of 3.8 (see Table 5.13). Supporting this, three descriptions under this criterion got the same average score of 3.6. They are regarding the learning curve involved in using the tool; where in terms of time invested and difficulty, there were four out of five participants that agreed to it to be fast and easy, while one found it hard. Correspondingly, applying it in their programs, most have been skillful in doing so. As a matter of fact, the highest description under this criterion is how easy a user can be accustomed to the API.

Table 5.14: API Results on Satisfaction

Description	1	2	3	4	5	Avg.
I am satisfied with it			1		4	4.6
I would recommend it to be used in the future				1	4	4.8
It works the way I want it to work			1	4		3.8

Last criterion is on Satisfaction. It got 4.4 overall rating, the highest among other criteria (see Table 5.14). It describes how satisfied the users are, if it works as intended, and if it would be recommended to others. Majority of the participants were strongly satisfied and positive with recommending it. Additionally, most agreed that the API worked the way they want or expected it to be. There are, however, an account that the participant is neutral with the expectations and being satisfied.

On another part of the survey form, a qualitative section was provided. It has three fields which asked for the participants' functions that were used in the evaluation or those likely useful to them, comments and suggestions about the tool, and its negative aspects, if there are any. Under this are answers that shed light upon ideas on improvements for the API.

Listing the functions used, every module was utilized, spread across the five participants. All of them were able to try out the organization or clustering modules. Specifically mentioned under this module are the functions for organizing response categories and sub-lists. Apart from that, the major tasks (i.e., Part-of-Speech Tagging, Information Extraction, and Information Ranking) in the tool was also tested. Specific to Part-of-Speech Tagging, formatting options was applied. For Information Extraction, participants tried out extracting word sets. In ranking module, ranking by response categories was tested. Additionally on these major tasks, supporting tasks such as Data Utilities (e.g., read excel file, refresh excel cells, and write report), Language Identification (e.g., identify language of a string) and Normalization (e.g., normalize a list, normalize a string, and translate Filipino colloquialism) was utilized.

Taking the respondents' comments and suggestions, there are a lot of inputs to consider. One of the highlights is their appreciation with the tool. Quoting from one of the respondents, "...this can be very useful especially that this is tested on a domain in the Filipino language. Users can now have a toolkit that can be used for preprocessing and information extraction for their Filipino dataset." Adding from another comment, it has been stated that the functions created can be "... used externally for other data processing tasks."

In addition, there were positive comments about the API being properly documented and readable. Even included a comment where atomic functions were very detailed. However, not all were satisfied with this documentation. Describing the current documentation, outside the API, respondents were provided with a list of functions and its description. While inside the API, each function consists of block comments that describes what it does, its parameters, and return values. Not to mention that during execution of the functions, there are progress updates to provide awareness on the events happening inside the program. Despite this, based on the comments provided, these are not enough.

Suggestions to improve documentation contain three main ideas. First is to make a README file that provides a brief overview on the API and state tasks that indicates its intended use. Second is to include a requirements list – these are Python modules or packages that is needed to be installed in order to properly use the API. Last, is to provide premade or sample scripts that utilizes the functions, specifying its input, the set of codes to run it, and how the output will be shown. In fact, one of the negative aspects stated its lack of requirements and instructions on how to use it. Rounding up the ideas about documentation, development of these documents would boost the low criteria ease of use and learning. One note is to make use of API documentation tools to accomplish this.

Following up the suggestions, respondents listed options in the future to extend this API/tool that addresses improvements in ease of use. One is to commercialize it by making it into a RESTful API, using HTTP requests; for reference, REST (Representational State Transfer) is an architecture for web APIs. Another is to package it in a way that utilizes pip install. Last is to introduce a Graphical User Interface (GUI).

For issues and negative aspects of the API, aside from documentations, a participant noticed tracing prompts on the runtime updates, which indicated "No insights (words) extracted at Response #: <response_ID>". In the participant's perspective, it appeared as errors, but in this case indicated that the Part-of-Speech tagger and Information Extraction's pattern matching were not able to capture such ideas. One way to mend this is to remove tracing prompts but leave the module updates intact. Another issue, in one of the participant's account, language identification was unable to run as it was not recognized in the program. This proves the importance of having the README and requirements file, to prevent instances such as the one provided.

Report Assessment

Table 5.15: Report Survey Results

Description	1	2	3	4	5	Avg.
The report's design is acceptable			1	3	1	4
The different elements of the report (e.g., title, insights list, and Malasakit response list) is necessary				3	2	4.4
The information fields are appropriate and enough to make a decision or action				4	1	4.2
The information is clear and readable				4	1	4.2
The information is easy to interpret		1	1	3		3.4
The information is useful in my job			1	1	3	4.4
The information is displayed in an organized manner			1	1	3	4.4
Using the report in my job would enable me to accomplish tasks more quickly				3	2	4.4
The report would enhance my effectiveness on the job			1	1	3	4.4
I can make decision/s based on the information provided				3	2	4.4
I am satisfied with the report				2	3	4.6

In assessing the generated report, 11 descriptions were provided for its quantitative evaluation (see Table 5.15). The format of presenting the results is similar to the quantitative evaluation of the API. Overall, the report has been rated 4.25, a value that resides with agreeable to strongly agreeable elements.

Based on the results, the highest average score garnered 4.6, where all participants agreeing to being satisfied with the report. It then was followed with six descriptions tied for the value of 4.4, in which answers mixed counts on either agree or strongly agree. Descriptions involved the appropriateness of the elements in the report, its impact to the participant's job and tasks, presentation or organization style of the information, and usefulness of the information.

The lowest score on the other hand, got 3.4 in average. It states that interpreting the information was found to be easy for most of the participants, but there were some that were neutral and even disagree with the level of difficulty. Despite having this, participants agreed that contents are clear, readable, and sufficient make decisions based on the information. With this, it goes to show the need to provide a background on what to expect in the report and instructions on how to do interpretations given the information – to conveniently push users to easily learn making use of the report.

Exploring ideas to improve the report, three fields were provided to take these inputs namely, to provide their organizational and approach preference, comments and suggestions, and negative aspects of the report. In organizational preference, most preferred organized by response categories (ORC), where each response is organized per categories first then by frequency.

Although, one of the participants noticed an important element in clustering the entries entirely or using organized all entries (OAE); quoting, "having a frequency only ranking for the information also has its merits since it will give the users an idea on which category is most important followed by the rest." In this perspective, the participant was able to point out the importance of OAE, which is to show the urgent topic or category, actions, and target subjects that is in need of prioritization in disaster planning.

On another perspective, there was one preference that indicated a reverse order, grouping all entries by frequency first then order by categories. In this case, using the response categories may be inappropriate as one cluster could belong to multiple response categories. The task that would be more appropriate for this is applying a topic modeling task; where given a set of clusters, they will be labeled depending on a topic they are generally under. Nonetheless, this is an idea for future extensions.

Regarding the participants' preference in the clustering approach. The setup prior to assessment provided six sets of report with a combination of the organizational format (i.e., OAE and ORC) and clustering approaches (i.e., Dice's Coefficient, Word2Vec, and FastText). The approaches were labeled A, B, and C, respectively, to remove bias on the innovative approaches.

Based on the results, four out of five participants preferred how the information were clustered through Dice's Coefficient. Due to the fact that it displays a clearer relationship on the actions and targets through its orthographic similarities, as compared to semantic similarities which have instances of vaguely related and diverse clusters. Complementing with ORC, the layout looked more presentable and easier to interpret. Quoting from one of the answers, "...even though the proposed action is limited, insights are better gained using this approach by being specific on what the proposed action is". One participant, however, have a different opinion and pointed out FastText's output to be easier and clearer.

Collecting their comments and suggestions, the reports were judged to be "aesthetically formal and proper to look at." The information is understandable and actionable. However, some initially found it hard to understand, which took time before fully understanding what to do with the information. Having said, the report was not as intuitive as expected. Factors for this are the length of pages and contents in the reports.

With regards to the pages, participants found it overwhelming at it contains pages that stretch around 30 or more pages. Suggestions to reduce this include the removal of entries with frequency counts of one. As stated by one of the participants, it is not necessary as those could be redundant ideas from top or highly frequent clusters. For the same reason, entries could also be limited into the top 5, 10 or 25 entries. Another idea is to add a layer of generalization to the clusters. It could be through lexicalization of actions (and omitting members) or placing topic labels to aid categories whilst summarizing contents of the cluster.

Alternatively, a different way of displaying the information can be supplied, not as replacement but as aid. The idea of showing keywords, by only looking at the action and its target subject, was not easily interpreted by some. There might be a need for showing context with less effort than redirecting from sentence numbers to Malasakit Response list. In this situation, it could be an infographic or visualization that would give an overview in the contents of the report – particularly urgent steps to prevent and mitigate disasters. With this in mind, it would seem that the current report will be used when the user is ready for the specifics. Example suggestion to accomplish this is through "... simple generated graphs such as word clouds or any frequency-based visualization", applying User Interface Design or User Experience design methodologies.

With regards to the contents, few of the respondents indicated improvements in clustering. Even though the clusters were said to be understandable, they found the proposed actions broad and disconnected with the target nouns. As a result, there were verbs that lack additional, relatable information. Take for example the word 'mag', that since it is a prefix for Filipino verbs, it covers a wide range of words that it could be under. One solution for this is to implement the normalizer in the report or filter the clustered words to reduce and narrow down the ideas. Granted, these actions will improve the value of clustered contents, not just for disaster planning's benefit, but also for developers that would implement the tool.

5.4 Test on News Dataset

In terms of data, there was a test on another dataset in another domain. The assumption is that since the solution processes texts, it should be able to handle inputs regardless of the domain. This test is a proof of concept that it can handle any text given the current implementation. The domain of choice was News.

The News dataset was taken from a Philippine language resource collection (Oco, Syliongka, Allman, & Roxas, 2016). Sources used for this experiment are from *Pang-Masa* and *Pilipino Star Ngayon* 2015 which are sister newspapers under the latter. Both are in Filipino and has collected 576 and 1,013 articles, respectively. Moreover, the two are considered as the leading tabloid newspaper in the Philippines which makes it ideal as subject for this experiment.

2,000 sentences were randomly taken from each of the categories under each newspaper. Pang-Masa has been labeled with Movies, *Punto Mo* (Your Point), Sports, and Metro, while Pilipino Star Ngayon has *Bansa* (Nation), Metro, *Opinyon* (Opinion), *Palaro* (Sports), *Probinsya* (Province), and Showbiz. As part of the experiment, these categories were merged and labeled into four main categories based on their topic or theme, namely Entertainment (for Movies and Showbiz), Opinion (for Your Point and Opinion), Sports (for Palaro and Sports), and World (for Metro, Nation, and Province). Having each category with 200 sentences, the highest number of contents is World category, with 800.

In this news dataset, sentences were processed through the main tasks, Information Extraction (making use of Language Identification and Part-of-Speech Tagger) and Information Organization/Clustering. Organization were implemented to process by category with category prioritization set by alphabetical order. Similar to previous experiments, in terms of clustering, the dataset undergone Dice's Coefficient, Word2Vec, and FastText clustering.

5.4.1 General Statistics

There were three runs on this experiment, one for each clustering approach. As this is a qualitative analysis, the only statistics provided indicates the runtime and number of pages. As for the extracted insight phrases and word sets, and entry/cluster counts, it is provided on their respective sections.

Generally, processing the 2,000 sentences dataset took more than an hour to finish running all the modules. Among these tasks, the longest processing time is the Part-of-Speech Tagger with around 50 minutes to an hour to complete. Two other tasks also contribute to lengthening the time, that is the Information Clustering and Report Generation.

Specifically, processing through Dice's Coefficient completed its execution time with one hour, three minutes and one second. With the number of sentences and entries produced, Report Generation took 8 minutes and 58 seconds to complete. Other than the two, the rest of the tasks were under 11 seconds. It produced 114 pages worth of clusters/insights and adding 77 pages for a list of the 2,000 sentences, the total pages for this report is 191.

Another, using Word2Vec, its total execution time was one hour, 10 minutes, and 48 seconds. The report was generated in 10 minutes and six seconds, while its clustering task took four minutes and 34 seconds. It produced 108 pages worth of clusters/insights, which in total is 185 pages. A smaller number of pages, given that the extractions are consistent, means that there were more sentences clustered as compared to Dice's.

The third approach used FastText. Its execution time lasted for one hour, 31 minutes, and 40 seconds. Report generation took less than 10 minutes (exactly nine minutes and 14 seconds), while its clustering task took almost 30 minutes (exactly 28 minutes and 14 seconds). Among the approaches, FastText took the longest time in completing the whole task. It produced 52 pages worth of clusters/insights, which in total has 129 pages. By far, FastText took the longest but in turn provided lower number of pages. That having said, more ideas were clustered in this approach.

5.4.2 Information Extraction

Expectation for this task is to produce examples that indicates an action and a target that is the subject of that action. Based on the results, the information extracted was consistent, regardless of the clustering approach. There are two types of formatting, namely insight phrases and word sets. For insight phrases, it produced 3,490 entries from 2,000 sentences. Whereas, there were 3,503 entries for word sets. Phrases proves to be usable by providing readability for analyzing extracted ideas, while word sets are for clusters. Together, they point into the same ideas that can be taken from the news snippet.

Table 5.16: Extracted Information in News Dataset

Category	**Examples**
Entertainment	Humihingi na siya ng pambili ng pagkain
	Magkaroon ng healthy lifestyle
	i-promote ang teleserye
	Nag-tweet si Vice
	natuwa ang fans
Opinion	NAGULAT ang mga kidnaper
	masagot ang nasabing mga tanong
	hilingin ni Pope Francis
	Lumalabas ang sintomas
	nakuha ang plaka
Sports	sumabak si Pacquiao
	Tumanggap diumano ng 3 million
	sinimulan na ang fitness test
	mapapanood ng live
	idineklarang may injury
World	binili ng Ecowaste Coalition
	inaprubahan ang bail petitions
	Ituturo sa lahat ang tamang paghuhugas
	nakaresponde ang mga bumbero
	patay sa ligaw na bala

The algorithm for extraction makes use of Part-of-Speech patterns. It looks for a verb tag and records it until it reaches a noun group. Among the insights, this extraction algorithm exhibited decent results. It shows that as long as the Part-of-Speech tagger is reliable, it would be able to process texts that can point out the actions found on a sentence and record that phrase until its subject, which is a noun is found. Example of these phrases taken from each category are shown

at Table 5.16. In addition, as the tool covers English, there are positive instances of extracting English phrases. Few of these are "controlled the game", "received proper medical attention", "plays the title role", "worked hard for the movie", and "uniting our people".

However, not all ranges of verbs to nouns provide a legitimate verb to noun entry. In some cases, the Part-of-Speech tagger failed to label the words correctly, producing incorrect entries such as "asul na van" (blue van), "liblib na lugar" (secluded place), "bandang alas-7" (around 7), "33-anyos na suspek" (33 year old suspect), "nationwide sa January" (nationwide on January), and "nakaraang week" (last/past week). These examples do not point to an action instead describes a noun. Moreover, there are some that does not exhibit enough idea, meaning there are lacking elements to it (e.g., am Maldives, sa semis, ani Chulani, is what St Paul, taus puso, and more). Furthermore, out of 2,000 sentences, only 1,689 sentences have insights extracted, that is 311 sentences without insights.

On the condition that extracting information in the news domain has been successful to capture actions and targets, the main question is its potential beneficial use in the news/media setting. A few of the ideas is insight phrases can provide a summary or gist of the contents in an article. By taking parts of the article, specifically the actions or events in it, readers would have an idea on what already happened in the article. At the same time, word sets can be used as keywords or tags, displaying the main occurrences (e.g., pinatay, nadakip, nakaresponde, mapatalsik, nangunguna, etc.) and involved subjects (e.g., which celebrity, victim, government official, sports team, area/country, etc.) of the article. Regardless, this experiment showed the potential in being applied to other domains.

5.4.3 Information Clustering

Three approaches were used for this experiment, namely Dice's Coefficient for string similarity and Word2Vec and FastText for semantic similarity. Discussions about the quality and contents of the clusters are provided.

Using Dice's Coefficient

In this clustering approach, it produced a total of 1,663 entries spread amongst four categories (shown at Table 5.17). The highest number of sentences clustered together is 51, exhibiting action words or ideas used in this category is closely related. In terms of cluster entry counts (CEC), over 25% of the entries have at least two news sentences or frequency in it. Highest CEC percentage is under

World with 41.41%. On the other hand, cluster insight counts (CIC) percentages were above 55%, which means at least half of the sentences were clustered into an entry. Highest CIC percentage is 77.52% under World category.

Table 5.17: Report Composition of News through Dice's Coefficient Clustering

Category	**Total Entries**	**CEC**	**CIC**	**Highest Freq.**	**Total Freq.**
Entertainment	352	26.14	58.73	27	623
Opinion	356	27.81	55.69	24	580
Sports	332	41.27	71.15	21	676
World	623	41.41	77.52	51	1624

Each category produced clusters that aimed to connect two or more words together based on their orthographic similarity. In Entertainment category, its top cluster joined the exact verbs *may* (to possess or have). Its targets pointed to articles with topics that indicated possessing: *plano* (plan), lovescenes, crush, *problema* (problem), birthday, *laban* (fight/game), and more. Although the clusters were orthographically joined, consolidating the ideas can be represented by the verbs it is under. Beside this, lexicalizing combined nouns under a cluster, which produced a notable pair ugali-galit (habit-anger) coincidentally showing semantic similarity.

Other clusters or ideas in Entertainment showed actions that a target has become (naging) something, does not have (walang) something, is with or together with (nakasama or makakasama) someone, huge (malaking) physical or emotional aspect, been seen (makikita), is attractive (maganda), and more. Other target or nouns provided names of celebrities (e.g., Vice, Sarah Geronimo, and Gary Valenciano), politicians/positions (e.g., chairman, senator, and presidente), characteristics (e.g., happy, healthy, and kalungkutan), and other related keywords in Entertainment (e.g., aktor, direktor, ratings, fans, and teleserye).

Identically for Opinion, the most frequent cluster contain the verb *may*. In this case, target contains assorted ideas due to its category where articles are based on author's perspective or judgement on a matter. Having said that, the nouns found for this cluster indicates what the articles have, such as there is a cobra, rally, hidden camera, internet, *terorista* (terrorist), *reklamo* (complaint), and more.

Other highly frequent clusters have the following base verbs (verbs that was compared): *nawala* (lost), *kailangan* (need), *maging* (become), *dapat* (should), *mayroon* (there is), *bagong* (new), *sinabi* (told), *nangyari* (happened), and more. Nouns on the other hand have distinct orthographic composition, to the point that there was not a single cluster with a lexicalized or sub-clustered target.

For Sports, the most frequent cluster contain a pair of verbs *matapos* (finish or after) and *matatapik* (tap). Under this cluster pointed out targets that talked about a specific event (e.g., competition, laro, round, quarterfinals, and more) or athlete/teams (e.g., Mayweather, Tropang Texters, D' Angelo Russel, Pirates, and more).

Other clusters with high frequency have base verbs of *may*, *sunod* (following), *nasabing* (said), *nakaraan* (previous), *kailangan* (need), *naging* (become), *dating* (before), and more. Positively on one of the clusters grouped prefixes with *pinaka-* (e.g., pinakamalaki, pinakamabigat, pinakamasamang, pinakamaraming, pinakamahabang, etc.); although they are not semantically related, it is one with a large, yet distinct set of words with similar strings.

Generally, in target and lexicalization, the approach was not able to produce a lot of sub-clusters, due to nouns in this category involved names (e.g., Cleveland, Pacquiao, Romero, NBA, etc.) and things (e.g., medalya, tiket, record, season, etc.) related to sports. In some that mentioned the same nouns, unfortunately they are on different clusters. Despite this, there are still some examples of sub-clusters which are manlalaro-manlalarong (player/s), player-players, mar-mark (names of players), kampeon-kampeong (champions), and alas-9-alas-2 (time).

In World news, the cluster with highest number of frequency count is the same as most, the verb *may*. As contents concern updates with the entire world, its targets have mixed nouns pertaining to different topics. A few of these indicated that there are *armas* (weapons), MERS-CoV, water, inmates, tanks, cargo, shabu, *pondo* (funds), fiesta, and more. There are also samples of lexicalized entries, which are the pairs apartment-compartment, marking-markings, and dbb-11-db-12.

World category indeed contain a huge number of sentences. The top 10 clusters contain at least 20 counts with the following base verbs: *wala* (nothing or gone), *maging* (become), *nasabing* (said), *matapos* (after), *sinabi* (said), *kinilala* (known), *patay* (dead), *nabatid* (realized), and *dating* (previous). It is noticeable that in this selected dataset, there are a number of accounts that pertain to deaths. Extending the top into 20, aside from *patay*, other verbs related to that crime have the words *nasawi* (casualty), *sinaksak* (stabbed), *nakaratay* (bedridden), and *natagpuan* (found).

For target, since there are a lot of sentences under the category, this is also the category with the most sub-clusters. Instances of these paired biktima-biktimang (victim), imbestigasyon-pag-iimbestiga (investigation), psupt-supt (superintendent), kasong-kaso (case), national-international, infomercial-commercial, and even have samples of semantic relevance (e.g., permit-permiso, pulisya-pulis, suspek-suspect, hospital-ospital, and insidente-akdidente).

Furthermore, there is a particular set of instances that joined targets that relates to time, specifically those with a prefix of *ala-/alas-* followed by a number. It has spread through different clusters, and to visualize it is in this example, alas-900 was paired with alas-915, alas-4, alas-6, and alas-10.

Taking from these results, Dice's coefficient was able to cluster verbs mainly but was ineffective to targets. It is due to a lot of the clusters containing distinct set of nouns that made string distances farther from each other. However, given the chance, it could cluster nouns that has been generally used such as victim, suspect, case, and the likes.

Using Word2Vec

Results of clustering using Word2Vec can be seen at Table 5.18. It produced 1,522 entries in total, about a hundred less than Dice's. The highest frequency under this experiment is 93, under World News. Aside from the highest frequency, World category also gained the highest percentage value in CIC. CEC on the other hand, more clusters were made on the Sports category. Overall, CEC and CIC values are above 15% and 58%, respectively.

Table 5.18: Report Composition of News through Word2Vec Clustering

Category	**Total Entries**	**CEC %**	**CIC %**	**Highest Freq.**	**Total Freq.**
Entertainment	306	15.36	58.43	49	623
Opinion	291	16.84	58.28	44	580
Sports	303	22.44	65.24	46	676
World	622	20.42	69.52	93	1624

Analyzing its clusters, it is expected that sentences are joined by their semantic relationship. In the Entertainment category, the highest cluster from the base verb *malalaman* (know) produced different ways to communicate or give information. Example of its members include *makikilala* (meet), *makita* (see), *narinig* (hear), *mapapansin* (notice), *sinabi* (told), *hinahanap* (looking for), *importante*

(important), *magkasama* (together), and more. It is also important to note that under Entertainment, these are actions mostly done by the subject in the topics.

Forward with targets, there are nouns that were lexicalized that has relatable members. A few of these are about franchise (with actor, character, teleserye, ratings, fans, kumpetisyon, etc.), celebrity names (with Nora, Vilma, Sharon, Herbert, Enrique, Gary, Martin, etc.), places (with Quezon, city, and mall members), and other contextual similarities like kuwento-buhay (story-life), aktres-pelikula (actress-film), and kaibigan-kapatid (friend-sibling). However, even with sub-clusters as such, there still are members that were not merged along with them.

Checking on the other highly frequent clusters, they showed verb clusters that showed action in events such as *kinanta* (sang), *dumalo* (visited) and *ipinakilala* (introduced), and features or characteristics such as *maganda* (beautiful) with *matanda* (old), *malaking* (huge) and *mahina* (weak). Other distinguishable sub-clusters combined Daniel-Padilla, Manny-senador, San-Juan, ina-ama, Araneta-coliseum, Muntinlupa-city, Facebook-account, Cebu-Pacific, music-video, acting-career, aktor-aktres, pari-obispong, final-episode, over-acting, emosyonal-problema, and problema-pagsubok-sitwasyon.

In the Opinion category, the highly frequent cluster exhibited verbs that pertains to statements indicating belief. The verbs described here are *sana* (with hope / should be), *kailangan* (need), *sabi* (said), *inisip* (thought), *gusto* (want), *nais* (desire/want), *pwede* (can), and more. Under this cluster, noun sub-clusters contained pairs such as supreme-commission, sampaguita-bakuran, pasahero-sakay, pamahalaan-desisyon, and more. Other members that could be joined include taumbayan-tao, pamahalaan-otoridad, traffic-enforcers, banko-tax, and more.

The rest of the clusters contain a wide distribution of cluster members depending on their base verb. Some examples from the highly frequent ones are the following: *maiwasan* (with huminto, magpadala, mabawasan, mabilis, kumilos, inihanda, ipagpatuloy, etc.), *nawala* (with dumating, nangyari, Nakita, bumalik, nananatili, iniwan, etc.), *nagulat* (with nakatakas, nahuli, pinadala, binaril, nasangkot, nagsalita, malungkot, etc.), and more. While, target sub-clusters' notable examples are pairs such as Aquino-Roxas, Andres-Bonifacio, opisina-trabaho, department-government, camera-picture, pulis-terorista, kaso-criminal, gamot-sintomas, balita-impormasyon, and more.

In Sports, the highest verb cluster is comprised of mostly auxiliary verbs. These are words such as 'am', 'are', 'be', 'do', 'had', 'has', 'have', 'is', 'were', 'was', and the likes. Inside this cluster, target words indicated major sub-clusters relating to the base noun coach (with players, team, championship, league, plan,

win, etc.) and time (with tournament, year, and game). Other members include referees, intensity, teams, experience, Lebron, owner, Macau, and more. Provided, it is observable that there are words that could be placed on some of the lexicalized nouns such as teams under coach and time under experience.

Aside from the highly clustered example, other verb clusters were grouped that indicated actions that thematically is related to Sports. Instances for this are the pairs tinapos-tinalo, matapos-sinimulan, napatalsik-nabigo, nakatakda-inaasahan, pinamumunuan-namuno, nakaraang-naunang, maabot-makapasok, and nakuha-nakamit. Turning to nouns, distinguishable lexicalizations pointed to subjects that are related to each other like Sabado-Linggo, Setyembre-Enero, Malaysia-Singapore, San-Miguel, Manny-Pacquiao, manlalaro-miyembro, laban-labanan, conference-cup, finals-kampeonato, and more.

In the context of World news, the cluster with highest frequency contained keywords of those appropriate for headlines. Take for example using the following verbs to start or at least provide a gist of the article: *kinasuhan* (sued), *nasawi* (death), *inaresto* (arrested), *pumatay* (killed), *nagpalabas* (issued), *nilagdaan* (signed), *nasangkot* (involved), *nadiskubre* (discovered), and many more. The topics under this mixed noun about crime (e.g., suspek, pulis, rebelde, and biktima), politics (e.g., president, secretary, and Moreno), and other issues and announcements for the public.

Analyzing the rest, there were distinguishable clusters that provided closely related verbs. Instances involved those about movement (e.g., lumisan, tumakas, iniwan, dinala, umakyat, umalis, humiwalay, dumating, etc.), suggestions (e.g., mangyari, magsagawa, magkaroon, magbibigay, maiwasan, makamit, simulant, siyasatin, etc.), events (e.g., may, mayroong, etc.), and more.

The lexicalization of the targets also expressed the capability of Word2Vec to be able to make use of the vector space in measuring similarities in between nouns. Even on distinct orthographic cases, it still provided relationships such as *mag-asawa* (married couple) with *ina* (mother), *anak* (child), and *lalaki* (male), as members of the family; *eroplano* (airplane) with *sakay* (aboard), *kotse* (car), and *pasahero* (passenger), as subjects about transportation; *sakuna* (catastrophe) with *sunog* (fire), *trapiko* (traffic), *krimen* (crime), and *aksidente* (accident), as mishaps; and more.

These clusters have frequency counts with two-digit values until the 28th entry. In spite having large members count, there still are some entries that could have been included in those clusters. Take the case of *maaresto* (arrested), *naaresto* and *arestado* which could be under a crime related cluster or simplistically clustered with each other, because they are under the same root word. In addition, there are lexicalized instances from Dice's Coefficient that were not found to be close vector distances in Word2Vec. One of the examples is the *ala-/alas-* prefixes, where Word2Vec was not able to lexicalize.

Comparing Word2Vec with Dice's coefficient, it has been proven that both were able to cluster verbs and nouns. However, Word2Vec produced more members for both fields. Word2Vec merged words based on its usage and there are an ample number of examples that exhibited semantic similarity. Extending this, it also covers some clusters with orthographic similarity. One flaw in this approach is there are some words that were not captured in the cluster, as its vector distance is far from each other even with obvious semantic similarities – for example are proper names.

Using FastText

Applying FastText, this approach produced 547 total entries as shown at Table 5.19, the lowest among the three. A smaller number of entries, in this case, mean that there have been more sentences clustered together. As a matter of fact, the highest frequency among all categories is 234. Supporting this, CEC and CIC values are above 60% and 91%, respectively – an amount generally higher than the other approaches. Specifically for CEC, the highest value garnered was 70.52%; whereas, in CIC, 96.86% of the sentences were clustered. Both of these values are under the World category. It signifies that under this approach, it is appropriate to combine Metro, National, and Province news together to produce a larger quantity in the category that substantiates similar properties in reporting news under this consolidated category; thus, being able to cluster more sentences.

Table 5.19: Report Composition of News through Word2Vec Clustering

Category	**Total Entries**	**CEC %**	**CIC %**	**Highest Freq.**	**Total Freq.**
Entertainment	120	63.33	92.94	47	623
Opinion	130	60.00	91.03	32	580
Sports	124	62.10	93.05	72	676
World	173	70.52	96.86	234	1624

Observing cluster contents in Entertainment, its highly frequent verb cluster collected words that indicates events happening within the category. It specified that targets are *ine-endorse*, *nakumbinse* (convinced), *natsismis* (gossip), *naka-schedule*, *nag-cancel*, *nag-extend*, and more. Basing on a few of these verbs, most pertains to status of the shows or film. In terms of its targets, words collected are movie, commercial, episode, shooting, press, *produksyon* (production), *programa* (program), *eksena* (scene), and more.

In lexicalization, there were a few sub-clusters that showed clear relationships such as life-people, movie-shooting, entertainment-music, final-season, and more. Even with these, there are members in the cluster that was not lexicalized such as eksena-scene, pamilya-anak, skin-collagen, episode-season, and more. Furthermore, there were inexplicit relationships in the sub-clusters such as collagen-bet, fans-go, leaf-day, na-taong, and credit-wansapanataym.

The following clusters within Entertainment, provided status (e.g., naging, nanatiling, naging, nagkaron, etc.), characteristics (e.g., mabait, matangkad, mahirap, kalmado, masama, etc.), and incidents (e.g., nag-viral, siniraan, lumaylay, nagkukuwento, etc.). There were also instances that mixed the clustered verbs with orthographic similarity such as *makikita* (see), *nakikita*, *pinapakita*, and *nagkita*. Adding semantic relationships, under this cluster included the words *ipinapanuod* (watch) and *mapapansin* (notice).

Other positive instances for nouns paired the following: pelikula-aktor, ratings-happy, emosyonal-damdamin, GMA-bulaga, century-year, buwang-buwan, Smart-Araneta, Muntinlupa-city, reserved-seat, film-festival, Facebook-account, fresh-fruits, direktor-aktres and more. Negative instances on the other hand, in the sense that the relationship is not obvious are the following: crush-cubao, march-scratches, Instagram-tirik, pagkakasakit-pagtaas, issue-welcome, and more.

Under Opinion, top cluster touched ideas that explicitly showed subjects to possess (i.e., may and mayroong). Target words under this are camera, *testigo* (witness), rally, *reklamo* (complaint), *pagkain* (food), *himig* (song), and more. Distinguishable targets showed relationship between internet-email, lungga-hidden, and lalaki-sanggol.

Following this, more verbs clustered contained mixed and diversed set of action words. sinabi-nagsalita, kailangan-mahalaga, nawala-nagkaroon, and ginagawa-nangyayari. There was even a cluster that contained a large number of verbs that starting with the word *nagbibiruan* (joke), and clustered together *nagtatanong* (ask), *nagtaksi* (took a taxi), *nagbigay* (give), *pagbibitbit* (carry), *nagpaalam* (said goodbye), *naghubad* (undress), and more.

For nouns, positive instances consist of the following sample pairs: opisina-gobyerno, manpower-highways, taumbayan-pamahalaan, sakay-sasakyan, MRT-LRT, kapulisan-terorista, airport-seaport, kasong-kriminal, highway-patrol, toxic-hazardous, and more. On the other hand, negative examples are luha-paradahan, pagpapawis-prosecutors, pananalita-mamasapano, bumuwelo-corridor, and many more.

Under Sports category, its cluster with the highest frequency produced groups with indistinguishable relationship. From the base forged, some of the cluster members are prepared, *ipinoste* (posted), ranking, evaluating, deliver, breaking, uniting, fostering, mens, Benilde, and other auxiliary verbs such as 'do', 'were', 'is', 'had', and 'been'. Mixing verbs with nouns may be caused by inaccuracy in the Part-of-Speech tagger module, however adding auxiliary verbs made this cluster hazier than it already is. It is also surprising how the words 'forged' and 'mens' or 'Benilde' are close in distance in the vector space to be clustered together.

Although there is a variety on its verb clustering, contents in target combined ideas resulted into having large lexicalized sub-clusters, wherein from the word 'challenge' it was able to come up with 45 members. Sample members for this sub-cluster are time, message, experiences, referees, barriers, intensity, tournament, mistake, adjustment, tiredness, years, and more.

Subsequent verb clusters also provided similar diversity in its clusters but were more specific as compared to the top cluster. There were clusters that focused on the progression (e.g., matapos, makaraan, kasunod, etc.), responses (e.g., sinabi, nangako, inihayag, sisiguraduhin, etc.), and status (e.g., umusad, makabangon, inilunsad, nabigo, etc.) of the sport events.

Positive instances of target sub-clusters showed the following relationships: laro-game, points-round, lider-chairman, national-pambansang, players-koponan, kabiguan-pagkatalo, siko-braso, Olympics-medalya, Malaysia-Singapore, MVP-famous, Mavericks-Heat, Setyembre-Enero, point-guard, and many more. On the other hand, negative examples paired offensive-no, plan-tickets, duda-swerte, fans-contract, fight-president, and more.

The category with the highest frequency amongst all is World category. As compared to the other approaches FastText was able to cluster 234 ideas. Under this cluster contain actions relating to World events; sample of these are *nasuspinde* (suspended), *abandonadong* (abandoned), *patay* (dead), *isinailalim* (undergone), *sinunog* (burned), *madugong* (bloody), *kinumpiska* (confiscated), *pagkakabangga* (crash), *kuwestiyonable* (questionable), *nag-organisa* (organized), *inoobserbahan* (observed), *nasaksihan* (witnessed), and many more.

Provided with that set of verbs, nouns present on those topics involved the following: *bomba* (bomb), *biktima* (victim), *pagamutan* (hospital), *bangkay* (corpse), *suspek* (suspect), *lindol* (earthquake), compound, city, and many more. By counting the number of sub-clusters, under this cluster alone have 39. Largest sub-cluster have 62 members, merging commissioner, requirement, surveillance, cam, murder, bail, proceedings, interrogation, arson, SUV, telephone, rollback, and other nouns. Notable lexicalized pairs joined bahay-silid, suspek-kasong, anak-ama, kaalaman-impormasyon, operation-operatiba, ulo-katawan, hospital-medical, batay-resulta, oras-minuto and more.

Succeeding the top cluster, highly frequent clusters have verb groups that concerns with bumaba 'drop' (with nahulog, nakaratay, bumulagta, nagpabagsak, tumaas, etc.), iniulat 'report' (with kinasuhan, inaresto, napatay, kinumpirma, inalam, etc.), iniwan 'left' (with napansin, naalarma, nakilala, pinasok, binalikan, etc.), and matapos 'after' (with nasabing, sumunod, nakalipas, pagkatapos, etc.) base verbs. Observing the rest of the clusters' lexicalized nouns, some examples that displayed clear relationships are provided; recognized pairs are the following: milyon-million, river-ilog, Filipino-Pilipino, bansa-Pilipinas, suspek-biktima, awtopsiya-inspeksyon, kamay-paa, pangulo-pinuno, gunman-shot, pagulan-tagtuyot, pera-alahas, and more.

Additionally, comparing to Word2Vec, FastText was able to group *ala-/alas-* prefixes, which evidently showed the effectiveness of using n-gram vectors. Even though n-gram vectors prove to be effective on word variants, there are clusters wherein words are not exactly related to each other. Take the case of residente-residue, where it indeed showed orthographic similarity, but its meaning did not match up.

Examining the approach entirely, the most compelling quality of FastText is its ability to be able to capture both orthographic and semantic similarities. Having said, positive instances of Dice's Coefficient and Word2Vec approaches was covered or present. Although this is the case, their negative qualities are also passed down, where it was unable to combine closely related terminologies and instances that have uncertain relationship with each other were still clustered. Regardless, in this experiment, it has been shown the extent of relationships that FastText was able to cover.

Moreover, with this coverage, there were large quantity of sentences that were clustered, that positively designated more sentences in clusters, but negatively was harder to interpret for its vague relationships. Other than that, it is important to remember its capability to be able to group words through a combination of vector space and n-grams which produced an approach that complements previous approaches.

Chapter 6

Conclusion and Recommendations

In this paper, the development of an automated insight extraction and organization was discussed. It collected ideas or actionable points from textual data, specifically Malasakit community responses. It is then presented in a list report, ordered by highly suggested ideas, that serves as medium that can connect local communities with respective decision makers in disaster planning and response.

Results showed that the use of Part-of-Speech Information Extraction achieved satisfactory marks in collecting these insights. It is measured through standard metrics such as Precision (P), Recall (R), Accuracy (A), and F-Measure (F). In extracting insight phrases scores were recorded with P = 70.09, R = 80.87, A = 72.57, and F = 75.09. Whereas on word sets, scores achieved P = 62.14, R = 74.06, A = 51.03, and F = 67.58.

There are two options available in organizing the extracted insights, where one can organize all entries or organize by response categories. Under these formatting, three clustering approaches were applied, namely Dice's Coefficient, Word2Vec, and FastText. Undoubtedly, all approaches were able to join similar ideas together and some instances formed one, interpretable idea. At the same time, the three approaches still have room for improvement, especially in capturing the right balance of relationships between words. Even though each have their own advantages and disadvantages, in one of the assessments, organizing by response categories and using Dice's Coefficient as clustering approach was the preferred combination in presenting the results.

Experimenting on the modules, lexicalization, normalization, and threshold adjustments were implemented. Results showed the effectivity of placing a word that represents a cluster, and that there could be other suitable representatives in the group. In normalization, changes were evident in words and through shifts in Part-of-Speech tags. On threshold adjustment of clustering approaches, primary learning is it controls how general and specific the contents of the clusters could be. Furthermore, another experiment changed the domain of the data. The whole process was tested on a News dataset, where it was able to extract and organize ideas under topics of Entertainment, Opinion, Sports, and World-related articles.

In assessing the entirety of the tool and its generated report, a survey was conducted. The tool was rated 4.07 out of five and the report got 4.25 out of five. The tool excelled in usefulness and satisfaction, while the report on appropriateness, impact, presentation, usefulness, and satisfaction. Areas for improvement with regards to the tool is on its ease of use and ease of learning. Whereas for the report, content readability and interpretability need work. Nonetheless, participants appreciated the benefit and potential of having these two outputs and provided feedback on possible improvements.

Future directions of this study involve improving the heuristics of the extractor, exploring more novel clustering approaches, adding Graphical User Interface in the API, including other report formats such as infographics or visualizations, commercializing the tool, integrating the tool on other software applications, and studying the effects of applying the report in disaster planning and response.

Appendix A

Filipino Part-of-Speech (POS) Tagset

MGNN TAGSET

Total of 230 Tags (69 Basic and 161 Compound)
Updated as of March 1, 2017

Part of Speech	Tag Name	Example
Noun (Pangngalan)	**NN (4)**	
Common Noun (count noun)	NNC	papel, tao, pag- + verb, kapalit
Proper Noun	NNP	Pilipino, Lasaliano
Proper Noun Abbreviation	NNPA	Dra., Bb., G., Kgg., etc.
Common Noun Abbreviation	NNCA	in, km, m, cm, measurements, et al, etc.
Pronoun (Panghalip)	**PR (10)**	
as Subject (Palagyo)/Personal Pronouns Singular	PRS	ako, ikaw, ka, siya, ko, mo, niya, kita, nya
Personal Pronouns (Plural)	PRP	kami, tayo, kayo, sila, nila, naming, natin, ninyo
Possessive Subject (Paari)	PRSP	akin, iyo, kanya, amin, atin, inyo, kanila
Pointing to an Object Demonstrative/(Paturol/Pamatlig)	PRO	ito, iyan, iyon, iri/e, niyan, niyon/noon, nito, naroon, nariyan, yaon
Question/Interrogative (Pananong)/Singular	PRQ	sino, saan, alin, ilan, gaano, kanino, magkano
Question/Interrogative Plural	PRQP	sinu-sino, saan-saan, alin-alin, ilan-ilan, gaa-gaano, kani-kanino, etc.
Location (Panlunan)	PRL	dito, doon, diyan, riyan, roon, rito, nandito, etc.
Comparison (Panulad)	PRC	ganyan, ganito
Found (Pahimaton)	PRF	ayto, heto, hayan, ayon, yun, hayun
Indefinite	PRI	kuwan, iba, kapwa, isa, lahat, marami, kaunti, sinuman, alinman, anuman, kalahatan, kabuuan
Determiner (Pantukoy)	**DT (4)**	
for Common Noun	DTC	ang
for Common Noun Plural	DTCP	(ang) mga, (ng) mga
for Proper Noun	DTP	si, ni, kay
for Proper Noun Plural	DTPP	sina, nina, kina
Lexical Marker	**LM (1)**	ay
Conjunctions (Pang-ugnay)	**CC (6)**	
	CCT	o, saka, ni-, maging, pero, subalit, ngunit, bagkus, kundi, imbes, kahit, halip, maliban, sa, sa pamamagitan ng, bilang, bagamat, datapwat, samantala, habang, para
	CCR	kaya (tuloy), kaya (nga ba), kaya (ngayon), kasi, dahil sa, dahil kasi, kung dangan kasi, papaano kasi, sapagkat, kasi, dahilan sa, palibhasa
	CCB	at saka, at gayon din, at...rin, kasama, upang, ng, nang gayundin, palibhasa, sa sandaling, basta't
	CCA	at, pati
Ligatures (Pang-angkop)	CCP	na, -ng, -g
Preposition (Pang-ukol)	CCU	laban sa, dagdag pa
Verb (Pandiwa)	**VB (14)**	
Neutral/Infinitive	VBW	mag-, ma-, mang-, sana, sabi, ka- + verb, mapag- + verb, makipag- + verb, maging
Auxiliary, Modal/Pseudo-verbs	VBS	kailangan, pwede, dapat, maari, gusto, ayaw, ibig, nais

Existential	VBH	mayroon, meron, may
Non-existential	VBN	wala, ala
Time Past (Perfective)	VBTS	nahulog, kumain, pinaalis, nag-, naging
Time Present (Imperfective)	VBTR	nahuhulog, kumakain, pinapaalis, nagiging
Time Future (Contemplative)	VBTF	mahuhulog, kakain, papaalisin, magiging
Recent past	VBTP	kahuhulog, kakakain, kapapaalis
Actor Focus	VBAF	-um-, mag-, ma-, mang-
Object/Goal Focus	VBOF	-in, -an, i-
Benefactive Focus	VBOB	i-, ipag-
Locative Focus	VBOL	-an, -in, pag…an
Instrumental Focus	VBOI	ipang-
Referential/Measurement Focus	VBRF	pinag-
Adjective (Pang-uri)	**JJ (6)**	
Describing (Panlarawan)	JJD	maganda, mabait, buo, masyado, bawat
Used for Comparison (same level) (Pahambing Magkatulad)	JJC	sing-, kasing, kapwa, pareho, magsing, magkasing, gangga, ga, tulad ng, gaya ng, kaysa sa
Comparison Comparative (more) (Palamang)	JJCC	mas, medyo, higit, lalo, lalong
Comparison Superlative (most) (Pasukdol)	JJCS	pinaka-, ubod, sakdal, ulo, labis, hari
Comparison Negation (not quite) (Di-Magkatulad)	JJCN	di-gasinong, di-gaano
Describing Number (Pamilang)	JJN	tatlong, labinlima
Adverb (Pang-Abay)	**RB (15)**	
Describing “How” (Pamaraan)	RBD	mabilis na tumakbo, masayang umuwi, pa + verb, sabay, naka- + verb
Number (Panggaano/Panukat)	RBN	nang limang libra, + apat na guhit
Conditional (Kondisyunal)	RBK	kung, sakali, pagka, kapag, pag
Causative (Pananhi)	RBP	dahil sa, dahil dito, kaya
Benefactive (Benepaktibo)	RBB	para sa, para kay
Referential (Pangkaukulan)	RBR	tungkol sa, ukol, hinggil, patungkol, ayon sa, ukol sa, hinggil sa, alinsunod sa, sabi ni, wika ni, tanong ni
Question (Pananong)	RBQ	bakit, paano, baga, kaya, gaano
Agree (Panang-ayon)	RBT	talaga, oo, tunay, mangyari, opo, oho, siyanga pala, sadya, maaaring, totoo
Disagree (Pananggi)	RBF	hindi nga, hinding-hindi, walang, huwag, ewan, aywan, ayaw, malay, wag, ayoko
Frequency (Pamanahon)	RBW	tuwing, muli, ngayon, laging, pagkatapos, noon, mamaya, parati, bihira, bago, uli, sandali, minsan, samantala, habang, kapag, buhat, mula ng, umpisa, hanggang, kahapon, kanina, bukas, araw-araw, galing
Possibility (Pang-agam)	RBM	baka, tila, marahil, yata, siguro, wari, malamang, maaaring
Place (Panlunan)	RBL	kina Thelma, nasa, sa + bahay, amin, ilalim, likod, itaas, harap, mula sa, kinaroroonan, tungo sa
Enclitics (Paningit)	RBI	na, pa, rin, din, man, muna, kaya, naman, sana, yata, ba, nga, daw, raw, kasi, lang, lamang, pala, tuloy
Interjections (Sambitla)	RBJ	hoy, aba, ay, aray, naku, ha
Social Formula (Pormularyong	RBS	Tao po!, Magandang umaga! Mano po., Salamat po.,

Panlipunan)		Pasensya na po., Sori po.
Cardinal Number (Bilang)	**CD (1)**	
Digit, Rank, Count	CDB	1, una, tatlo, II
Topicless (Walang Paksa)	**TS (1)**	Umuulan., Alas dos na., May tao., Ang tapang mo pala.
Foreign Words	**FW (1)**	English, Spanish, Latin
Punctuation (Pananda)	**PM (6)**	
Period	PMP	"."
Exclamation Point	PME	"!"
Question Mark	PMQ	"?"
Comma	PMC	","
Semi-colon	PMSC	";"
Symbols	PMS	"@, /, +, *, (,), ",', ~, &, %, $, #, =, -, :"

Compound Tags	**<tag1>_<tag2>_…_<tagN>**			
CCB_CCP	JJCS_VBRF_CCP	PRI_CCT	RBL_JJD	VBS_CCP
CCR_CCA	JJCS_VBTR	PRI_LM	RBL_JJD_CCP	VBTF_CCP
CCR_CCB	JJCS_VBTR_VBOF	PRL_CCP	RBL_NNC	VBTF_JJD
CCR_CCP	JJCS_VBTR_VBRF	PRL_LM	RBL_NNP	VBTF_VBAF
CCR_LM	JJCS_VBTS	PRO_CCB	RBL_NNPA	VBTF_VBOB
CCT_CCA	JJCS_VBW	PRO_CCP	RBL_NNP_NNP	VBTF_VBOF
CCT_CCP	JJC_CCB	PRO_LM	RBL_PRL	VBTF_VBOF_CCP
CCT_LM	JJC_CCP	PRP_CCB	RBM_CCP	VBTR_CCP
CCU_DTP	JJC_JJD	PRP_CCP	RBM_LM	VBTR_VBAF
CDB_CCA	JJC_PRL	PRP_LM	RBN_CCP	VBTR_VBAF_CCP
CDB_CCP	JJD_CCA	PRQ_CCP	RBP_CCP	VBTR_VBOB
CDB_LM	JJD_CCB	PRQ_LM	RBQ_CCB	VBTR_VBOF
CDB_NNC	JJD_CCP	PRSP_CCP	RBQ_CCP	VBTR_VBOF_CCP
CDB_NNC_CCP	JJD_CCT	PRS_CCB	RBQ_LM	VBTR_VBRF
JJCC_CCP	JJD_NNC	PRS_CCP	RBR_DTP	VBTR_VBRF_CCP
JJCC_JJD	JJD_NNP	PRS_LM	RBS_CCP	VBTS_CCA
JJCN_CCP	JJN_CCA	RBD_CCB	RBT_CCB	VBTS_CCP
JJCN_LM	JJN_CCB	RBD_CCP	RBT_CCP	VBTS_JJD
JJCS_CCB	JJN_CCP	RBD_LM	RBT_CCT	VBTS_LM
JJCS_CCP	JJN_NNC	RBF_CCP	RBT_LM	VBTS_VBAF
JJCS_JJC	JJN_NNC_CCP	RBF_JJD	RBW_CCA	VBTS_VBOB
JJCS_JJC_CCP	NNC_CCA	RBF_JJD_CCP	RBW_CCB	VBTS_VBOF
JJCS_JJD	NNC_CCB	RBF_LM	RBW_CCP	VBTS_VBOF_CCP
JJCS_JJD_CCB	NNC_CCP	RBF_RBW	RBW_DTP	VBTS_VBOL
JJCS_JJD_CCP	NNC_LM	RBF_VBTR	RBW_LM	VBTS_VBRF
JJCS_JJD_NNC	NNC_PMC	RBF_VBW_CCP	RBW_RBI	VBW_CCB
JJCS_JJN	NNP_CCA	RBI_CCA	VBAF_CCP	VBW_CCP
JJCS_JJN_CCP	NNP_CCP	RBI_CCP	VBH_CCB	VBW_CDB
JJCS_RBF	PRC_CCB	RBI_LM	VBH_CCP	VBW_LM
JJCS_VBAF	PRC_CCP	RBJ_CCP	VBN_CCP	
JJCS_VBAF_CCP	PRI_CCB	RBK_LM	VBOB_CCP	
JJCS_VBN_CCP	PRI_CCP	RBL_CCP	VBOF_CCP	
JJCS_VBOF	PRI_CCP_NNP	RBL_CCP_NNP	VBRF_CCP	

Tagset used at Nocon, N. and Borra, A.'s *"SMTPOST: Using Statistical Machine Translation Approach in Filipino Part-of-Speech Tagging"* (2016) from De La Salle University, Manila, Philippines. (https://www.aclweb.org/anthology/Y/Y16/Y16-3010.pdf)

Appendix B

Application Programming Interface (API) Functions

Table B.1: Data Utilities Module

Function Name	Description
refresh_excel	Clears out values in excel, excluding values under a protected_cell variable.
read_candidate_excel	Reads the values in the candidate's excel file and stores the value in a list.
read_gold_standard_excel	Reads the values in the gold standard's excel file and stores the value in a list.
read_excel	Reads the values in an excel file and stores the first two columns (response and tag) into the MalasakitResponse object.
write_excel	Writes the system output in an excel file.
text_to_list	Transforms a given text file into a list of list [s1 [w1, w2, ..., wN], ..., sN [w1, w2, ..., wN]].
text_to_list_without_stopwords	Transforms a given text file into a list of lists removing Tagalog/English stopwords in the process.
write_text_file	Writes the strings in a list to a text file.
read_text_file	Reads the strings in a file and transfer them into a list.
get_stopwords_from_file	Transforms stop words in a given file to a list.

Table B.2: Normalization Module

Function Name	Description
normalize_object	Normalizes the MalasakitResponse object and updates the object after.
normalize_list	Normalizes a given list of strings and returns the normalized list.
normalize_string	Normalizes a given string and returns the normalized string.
join_prefix_word	Joins the prefixes that are separated with a word by whitespace. More prefixes can be added in the tl_prefixes.txt file.
translate_filipino_colloquialism	Runs the Filipino Colloquialism Translator or Normalizer through command prompt. File path parameters can be changed by the user.
set_moses_file_path	Sets Moses' executable file path with the one provided by the user.
set_model_file_path	Sets Moses' model configuration file path with the one provided by the user.
set_input_file_path	Sets Moses' input text file path with the one provided by the user.
set_output_file_path	Sets Moses' output text file path with the one provided by the user.
set_prefix_file_path	Sets a user-provided prefix list text file.

Table B.3: Language Identification Module

Function Name	Description
set_language	Changes the scope of languages.
identify_language_string	Identifies language (ISO 639-1 code) of a given string. Returns a (language, confidence) tuple.
identify_language_object_list	Identifies language between Tagalog or English of MalasakitResponse object's responses and updates the language field in the object.
identify_language_string_list	Identifies language of a sentence list. Returns a list of languages respective to the sentences.

Table B.4: Filipino Part-of-Speech Tagger Module

Function Name	Description
set_java_path	Sets the java path to make Stanford POS Tagger work.

Table B.4 continued from previous page

Function Name	Description
tag_string	Tags a sentence/string. Returns a (word, pos) tuple.
tag_object_list	tagging a list of MalasakitResponse object's sentence. This updates the MalasakitResponse object.
tag_string_list	Tags a sentence list. Returns a list of (word, pos) tuple.
format_pos	Formats a tuple into a POS-only string.
format_stanford	Formats a tuple into Stanford word|tag string.

Table B.5: Information Extraction Module

Function Name	Description
extract_insights_phrases	Extracts phrase insights (action word to target/s). The MalasakitResponse object is updated after.
extract_insights_words	Extracts word insights or word sets (action word and target/s). The MalasakitResponse object is updated after.

Table B.6: Information Organization Module

Function Name	Description
organize_sublist	Organizes a given sublist (a single category or the current category).
organize_by_response_categories	Organizes the information based on (or per) response categories.
organize_all_entries	Organizes the entire information (per entry).

Table B.7: Information Clustering Module

Function Name	Description
string_similarity_fasttext	Computes FastText's vector similarity (high value is better) between two strings.
string_distance_fasttext	Computes FastText's vector distance (low value is better) between two strings.
string_similarity_word2vec	Computes Word2Vec's vector similarity (high value is better) between two strings.
string_distance_word2vec	Computes Word2Vec's vector distance (low value is better) between two strings.
string_similarity_dice	Computes Dice's Coefficient similarity (high value is better) between two strings.

Table B.7 continued from previous page

Function Name	Description
string_distance_dice	Computes Dice's Coefficient distance (low value is better) between two strings.
collect_all_insights_from_object	Retrieves all insights in MalasakitResponse object and stores them in one list.
merge_cluster_insights	Merges the insights in one cluster into a single line.
remove_duplicate	Removes duplicate strings in a list (cluster).
cluster_words	Clusters target/noun words. Given a list it will join similar words using the 'word_1 (word_2, ..., word_N)' notation.
cluster_information	Clusters text using either Srensen-Dice Coefficient (String Clustering), Word2Vec, or FastText Word Embeddings (Semantic Clustering) and returns a list of clusters.

Table B.8: Information Ranking Module

Function Name	Description
rank_clusters_by_frequency	Ranks the clusters based on their frequency counts (descending order: highest count first).
rank_by_response_categories	Ranks the clusters (rearranges the groups) based on their response category prioritization order. Categories follow the Malasakit Codebook 4.7.

Table B.9: Report Generation Module

Function Name	Description
add_timestamp	Adds a timestamp in the document. Follows Month-Date-Year Hours-Minutes-Seconds format (e.g., Jan-01-2020 23:59:59).
add_divider	Adds a divider in the document that is made from a 1x1 table object.
add_title	Adds the title in the document and formats it for display.
set_document_margin	Sets the document's margin (in inches).
set_number_of_page_columns	Sets the number of columns in a section through xpath.
write_report	Generates the report in word document (.docx) format. Default filename: Report.docx

Appendix C

Report Screenshots

FILIPINO TEXT ANALYSIS TOOL REPORT

Mar-24-2020 20:24:54

The information below were extracted and organized automatically.

INFORMATION CAMPAIGN AND CAPACITY BUILDING

Entry 1

ID/s: 26|208|209|339|507|576|580|649|762|766|811|813|836|852|854|885

Frequency: 20

Proposed action: dapat

Target: barangay, seminar, oras, prepared, kalamidad, sakuna, posters, paalala, drill, like, for, example, about, paraan, encourage, before, during, and, after, of, the, calamity, my, weekly, mg, roong

Entry 2

ID/s: 13|46|208|236|243|307|311|598|603|618|631|651|758|760|766|854|903|925

Frequency: 19

Proposed action: maging, palaging, laging

Target: kapitbahay, tao, disaster, mamamayan, aware, kabarangay, kabaro, kalamidad, darating, beforeafter, and, during, pra, bagyo, trahedya, gawim, paalala

Entry 3

ID/s: 33|68|209|289|307|310|311|339|696|716|762|787|800|847|885|926|930

Frequency: 19

Proposed action: magkaroon, magkaron, magkakaroon, karoon

Target: seminars (seminar, seminarsdrill), about, kaalaman (kaalam), disaster, drill, sos, program, regarding, and, iinvite, emergency, kits, training, progma, pra, disiplina, mamamayan, weekly, meeting, organisasyon, orientation, barangay

Entry 4

ID/s: 80|121|132|149|156|169|215|222|234|340|585|654|794|831|929

Frequency: 15

Proposed action: be

Target: advantage, possibilities, calamities, dont, times (time), drills, typhoon, disaster, preparedness (prepare), programs, officials, instructions, orientation, effects, duty

Entry 5

ID/s: 130|215|245|249|259|266|340|390|794|838

Frequency: 12

Proposed action: have

Target: assembly, disaster, drill, place, representative, check, emergency, needs, training (taraining), barangay, officials, seminar, meeting

Entry 6

ID/s: 169|222|303|331|343|358|385|614|627|654|661

Frequency: 11

Proposed action: help

Target: prepare, families, disasters (disaster), outcomes, community, idea, seminars, people, signage, calamity

Entry 7

ID/s: 101|104|169|287|333|343|347|396|583|644

Frequency: 10

Proposed action: preparing, prepare

Target: typhoon, disaster, seminar, times

Entry 8

Figure C.1: Word Report: First Page (By Categories)

FILIPINO TEXT ANALYSIS TOOL REPORT

Mar-04-2020 19:40:07

The information below were extracted and organized automatically.

Entry 1

ID/s:
26|28|31|39|58|69|73|90|148|151|167|203|204|208|209|211|306|339|341|342|366|436|440|448|455|495|506|507|510|529|554|576|580|612|629|643|649|673|732|743|757|762|766|767|777|791|793|811|812|813|821|836|850|851|852|853|854|885|888|890|891|892|894|896|899|900|901|902|922|923

Frequency: 80

Proposed action: dapat, sapat

Target: barangay (baragay, baranggay), active, pakiki-isa, komunidad, sakuna, eg, komunikasyon, kita, kalinisan, mamamayan, disaster, balita, evacuation, center, aware, pamamagitan, seminar, oras, anunsiyo, prepared, updated (update), kanal, pangongolekta, lugar, alert, tao, araw, kalamidad, alirto, radio, abiso, saknila, posters, paalala, official, ugnayan, membro, i, lage, panahon, drill, like, for, example, about, paraan, truck, encourage, pagbabahahindi, dn, before, during, and, after, of, the, calamity, my, weekly, paligid, mg, roong, mgkaisa, ulat, darating, pra, programa (program), pagkain, pangangailangan

Entry 2

ID/s:
6|7|13|16|19|41|46|122|128|208|236|243|307|311|341|365|419|439|443|447|457|471|502|513|557|598|603|611|616|618|621|626|631|651|660|690|714|721|728|731|747|748|753|758|760|766|783|785|786|806|815|817|820|823|824|830|833|854|889|903|925

Frequency: 63

Proposed action: maging, palaging, messaging, laging, pagiging, magiging, nagiging

Target: tao, kapitbahay, bagay, bagyobaha (bagyo), darating (daratinga), disaster, mamamayan, aware, oras, sakuna, paglaki, pra, kalagayan, alertoat, barangay (kabarangay), tagapag, handa, pamaraan, kalamidad (kalamid), agrisibo, kabaro, atentibo, balita, cla, brgys, pkiking, beforeafter, and, during, kalikasan, kagamatin, opisyal, sanhi, kasanyan, xa, trahedya, media, etc, gawim, paalala, prepared, dahilan

Entry 3

ID/s:
80|112|121|123|125|132|137|139|140|145|146|149|153|154|156|165|169|175|192|195|198|199|215|222|233|234|235|248|285|292|308|309|318|340|371|392|575|585|619|654|755|794|795|816|831|859|861|863|868|909|928|929|932|934

Frequency: 56

Proposed action: be

Target: advantage, training, possibilities, news, plenty, calamities, community, beforehand, incoming, disaster (disasters), officials, time (times), dont, publicsoundnotifsystem, happenings, typhoon, aware, garbage, evacuation, plan, drills, things, preparedness (prepare), programs, constituents, flood, devices, instructions, government, technology, need, orientation, effects, management, response, unit, barangay, events, posters, case, duty, info, society

Entry 4

ID/s:
3|6|7|8|11|14|20|27|33|35|40|44|50|66|68|209|289|307|310|311|321|339|341|368|467|478|488|550|555|696|716|752|762|779|787|800|847|885|926|930

Frequency: 42

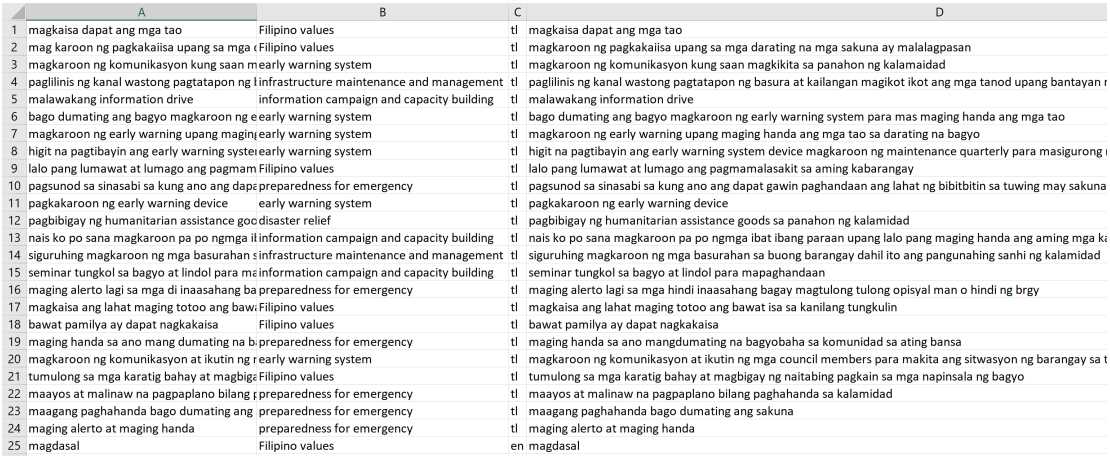
Figure C.2: Word Report: First Page (All Entries)

MALASAKIT RESPONSES REFERENCE LIST

ID	Response
1	magkaisa dapat ang mga tao
2	mag karoon ng pagkakaiisa upang sa mga darating na mga sakuna ay malalagpasan
3	magkaroon ng komunikasyon kung saan magkikita sa panahon ng kalamaidad
4	paglilinis ng kanal wastong pagtatapon ng basura at kailangan mag ikot ikot ang mga tanod upang bantayan mga gamit ng tao
5	malawakang information drive
6	bago dumating ang bagyo magkaroon ng early warning system para mas maging handa ang mga tao
7	magkaroon ng early warning upang maging handa ang mga tao sa darating na bagyo
8	higit na pagtibayin ang early warning system device magkaroon ng maintenance quarterly para masigurong maayos ito bago dumating ang isang kalamidad
9	lalo pang lumawat at lumago ang pagmamalasakit sa aming ka-barangay
10	pagsunod sa sinasabi sa kung ano ang dapat gawin paghandaan ang lahat ng bibitbitin sa tuwing may sakuna
11	pagkakaroon ng early warning device
12	pagbibigay ng humanitarian assistance goods sa panahon ng kalamidad
13	nais ko po sana magkaroon pa po ngmga ibat ibang paraan upang lalo pang maging handa ang aming mga kapitbahay po
14	siguruhing magkaroon ng mga basurahan sa buong barangay dahil ito ang pangunahing sanhi ng kalamidad
15	seminar tungkol sa bagyo at lindol para mapaghandaan
16	maging alerto lagi sa mga di inaasahang bagay magtulong tulong opisyal man o hindi ng brgy
17	magkaisa ang lahat maging totoo ang
17	bawat isa sa kanilang tungkulin
18	bawat pamilya ay dapat nagkakaisa
19	maging handa sa ano mang dumating na bagyobaha sa komunidad sa ating bansa
20	magkaroon ng komunikasyon at ikutin ng mga council members para makita ang sitwasyon ng barangay sa tuwing may kalamidad
21	tumulong sa mga karatig bahay at magbigay ng naitabing pagkain sa mga napinsala ng bagyo
22	maayos at malinaw na pagpaplano bilang paghahanda sa kalamidad
23	maagang paghahanda bago dumating ang sakuna
24	maging alerto at maging handa
25	magdasal
26	dapat ang barangay ay sanayin ang mga naninirahan sa kanilang lugar tungkol sa drrm na may sapat na pangangailangan sa pagsapit ng bagyobaha
27	magkaroon ng maayos na komunikasyon gaya ng paggamit ng public address system para mabilis ang pagpaparating ng inpormasyon
28	mabuti ang aming barangay at nakatutulong sa amin pag may problema dapat mas maging active pa ang ibang opisyal ng barangay kung maari 100 performance na maipaabot ang serbisyo sa mga tao
29	bahay-bahay na pag-inform tungkol sa sakuna
30	mabilis na pagiinform ng chairman upang mabilis na mapalaganap ang inpormasyon sa aking mga ka-barangay
31	dapat may pakiki-isa sa barangay para kapag may sakunang dumating mas makakahanda sa anumang kalamidad na darating

Extracting and Organizing Disaster-related Philippine Community Responses for Aiding Nationwide Risk Reduction Planning and Response (N. Nocon, 2019)

Figure C.3: Word Report: Malasakit Responses List

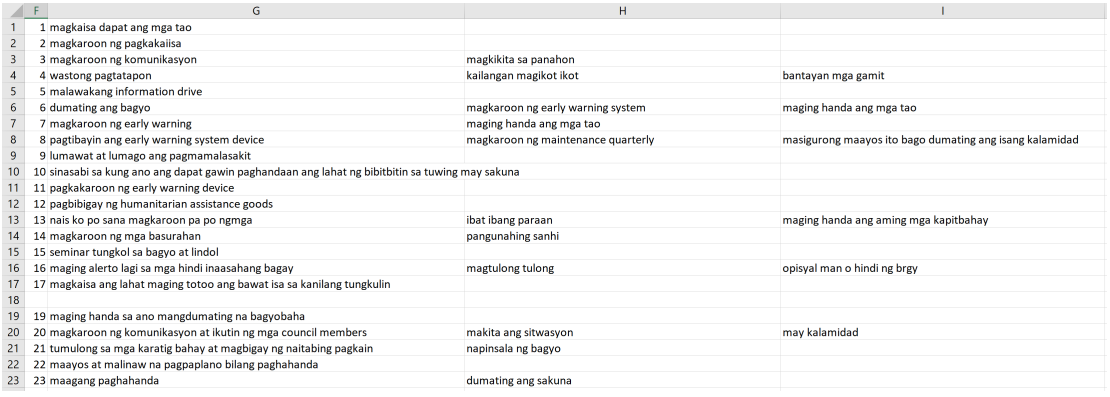


	A	B	C	D
1	magkaisa dapat ang mga tao	Filipino values	tl	magkaisa dapat ang mga tao
2	mag karoon ng pagkakaiisa upang sa mga (	Filipino values	tl	magkaroon ng pagkakaiisa upang sa mga darating na mga sakuna ay malalagpasan
3	magkaroon ng komunikasyon kung saan m	early warning system	tl	magkaroon ng komunikasyon kung saan magkikita sa panahon ng kalamaidad
4	paglilinis ng kanal wastong pagtatapon ng l	infrastructure maintenance and management	tl	paglilinis ng kanal wastong pagtatapon ng basura at kailangan magikot ikot ang mga tanod upang bantayan
5	malawakang information drive	information campaign and capacity building	tl	malawakang information drive
6	bago dumating ang bagyo magkaroon ng e	early warning system	tl	bago dumating ang bagyo magkaroon ng early warning system para mas maging handa ang mga tao
7	magkaroon ng early warning upang magin	early warning system	tl	magkaroon ng early warning upang maging handa ang mga tao sa darating na bagyo
8	higit na pagtibayin ang early warning syste	early warning system	tl	higit na pagtibayin ang early warning system device magkaroon ng maintenance quarterly para masigurong
9	lalo pang lumawat at lumago ang pagmam	Filipino values	tl	lalo pang lumawat at lumago ang pagmamalasakit sa aming kabarangay
10	pagsunod sa sinasabi sa kung ano ang dapa	preparedness for emergency	tl	pagsunod sa sinasabi sa kung ano ang dapat gawin paghandaan ang lahat ng bibitbitin sa tuwing may sakuna
11	pagkakaroon ng early warning device	early warning system	tl	pagkakaroon ng early warning device
12	pagbibigay ng humanitarian assistance goo	disaster relief	tl	pagbibigay ng humanitarian assistance goods sa panahon ng kalamidad
13	nais ko po sana magkaroon pa po ngmga il	information campaign and capacity building	tl	nais ko po sana magkaroon pa po ngmga ibat ibang paraan upang lalo pang maging handa ang aming mga k
14	siguruhing magkaroon ng mga basurahan s	infrastructure maintenance and management	tl	siguruhing magkaroon ng mga basurahan sa buong barangay dahil ito ang pangunahing sanhi ng kalamidad
15	seminar tungkol sa bagyo at lindol para ma	information campaign and capacity building	tl	seminar tungkol sa bagyo at lindol para mapaghandaan
16	maging alerto lagi sa mga di inaasahang ba	preparedness for emergency	tl	maging alerto lagi sa mga hindi inaasahang bagay magtulong tulong opisyal man o hindi ng brgy
17	magkaisa ang lahat maging totoo ang bawa	Filipino values	tl	magkaisa ang lahat maging totoo ang bawat isa sa kanilang tungkulin
18	bawat pamilya ay dapat nagkakaisa	Filipino values	tl	bawat pamilya ay dapat nagkakaisa
19	maging handa sa ano mang dumating na b	preparedness for emergency	tl	maging handa sa ano mangdumating na bagyobaha sa komunidad sa ating bansa
20	magkaroon ng komunikasyon at ikutin ng r	early warning system	tl	magkaroon ng komunikasyon at ikutin ng mga council members para makita ang sitwasyon ng barangay sa t
21	tumulong sa mga karatig bahay at magbiga	Filipino values	tl	tumulong sa mga karatig bahay at magbigay ng naitabing pagkain sa mga napinsala ng bagyo
22	maayos at malinaw na pagpaplano bilang p	preparedness for emergency	tl	maayos at malinaw na pagpaplano bilang paghahanda sa kalamidad
23	maagang paghahanda bago dumating ang	preparedness for emergency	tl	maagang paghahanda bago dumating ang sakuna
24	maging alerto at maging handa	preparedness for emergency	tl	maging alerto at maging handa
25	magdasal	Filipino values	en	magdasal

Figure C.4: Excel Report: Response Information

	E
1	magkaisa|VBW dapat|VBS ang|DTC mga|DTCP tao|NNC
2	magkaroon|VBAF ng|CCB pagkakaiisa|NNC upang|CCB sa|CCT mga|DTCP darating|NNC na|CCP mga|DTCP sakuna|NNC ay|LM malalagpasan|VBTF
3	magkaroon|VBAF ng|CCB komunikasyon|NNC kung|RBK saan|RBQ magkikita|VBTF sa|CCT panahon|NNC ng|CCB kalamaidad|NNC
4	paglilinis|NNC ng|CCB kanal|NNC wastong|JJD_CCP pagtatapon|NNC ng|CCB basura|NNC at|CCA kailangan|VBS magikot|VBW ikot|NNC ang|DTC mga|DTCP tanod|NNC upang|CCB ba
5	malawakang|JJD_CCP information|FW drive|FW
6	bago|RBW dumating|VBAF ang|DTC bagyo|NNC magkaroon|VBW ng|CCB early|FW warning|FW system|FW para|CCT mas|JJCC maging|VBW handa|JJD ang|DTC mga|DTCP tao|NNC
7	magkaroon|VBAF ng|CCB early|FW warning|FW upang|CCB maging|VBW handa|JJD ang|DTC mga|DTCP tao|NNC sa|CCT darating|NNC na|CCP bagyo|NNC
8	higit|JJCC na|CCP pagtibayin|VBOF ang|DTC early|FW warning|FW system|FW device|FW magkaroon|VBAF ng|CCB maintenance|FW quarterly|FW para|CCT masigurong|VBW_CCP m
9	lalo|JJCC pang|RBI_CCP lumawat|VBAF at|CCA lumago|VBAF ang|DTC pagmamalasakit|NNC sa|CCT aming|PRSP_CCP kabarangay|NNC
10	pagsunod|NNC sa|CCT sinasabi|VBTR sa|CCT kung|RBK ano|RBQ ang|DTC dapat|VBS gawin|VBOF paghandaan|VBOF ang|DTC lahat|PRI ng|CCB bibitbitin|VBTF sa|CCT tuwing|RBW ma
11	pagkakaroon|VBW ng|CCB early|FW warning|FW device|FW
12	pagbibigay|VBW ng|CCB humanitarian|VBTR assistance|FW goods|FW sa|CCT panahon|NNC ng|CCB kalamidad|NNC
13	nais|VBS ko|PRS po|RBS sana|VBS magkaroon|VBW pa|RBI po|RBS ngmga|NNC ibat|JJD ibang|PRI_CCP paraan|NNC upang|CCB lalo|JJCC pang|RBI_CCP maging|VBW handa|JJD ang|D
14	siguruhing|RBD_CCP magkaroon|VBW ng|CCB mga|DTCP basurahan|NNC sa|CCT buong|PRI_CCP barangay|NNC dahil|CCR ito|PRO ang|DTC pangunahing|JJD_CCP sanhi|NNC ng|CCB
15	seminar|JJD tungkol|RBR sa|CCT bagyo|NNC at|CCA lindol|NNC para|CCT mapaghandaan|VBW
16	maging|VBW alerto|JJD lagi|RBW sa|CCT mga|DTCP hindi|RBF inaasahang|VBTR_CCP bagay|NNC magtulong|VBW_CCP tulong|NNC opisyal|JJD man|RBI o|CCT hindi|RBF ng|CCB brgy|
17	magkaisa|VBW ang|DTC lahat|PRI maging|VBW totoo|RBT ang|DTC bawat|PRI isa|PRI sa|CCT kanilang|PRSP_CCP tungkulin|NNC
18	bawat|PRI pamilya|NNC ay|LM dapat|VBS nagkakaisa|VBTR
19	maging|VBW handa|JJD sa|CCT ano|PRO mangdumating|VBTF na|CCP bagyobaha|NNC sa|CCT komunidad|NNC sa|CCT ating|PRSP_CCP bansa|NNC
20	magkaroon|VBAF ng|CCB komunikasyon|NNC at|CCA ikutin|VBOF ng|CCB mga|DTCP council|FW members|FW para|CCT makita|VBW ang|DTC sitwasyon|NNC ng|CCB barangay|NNC
21	tumulong|VBAF sa|CCT mga|DTCP karatig|JJD bahay|NNC at|CCA magbigay|VBAF ng|CCB naitabing|VBTS_CCP pagkain|NNC sa|CCT mga|DTCP napinsala|VBTS ng|CCB bagyo|NNC
22	maayos|JJD at|CCA malinaw|JJD na|CCP pagpaplano|VBW bilang|CCT paghahanda|NNC sa|CCT kalamidad|NNC
23	maagang|JJD_CCP paghahanda|NNC bago|RBW dumating|VBAF ang|DTC sakuna|NNC
24	maging|VBW alerto|JJD at|CCA maging|VBW handa|JJD
25	magdasal|NN

Figure C.5: Excel Report: Part-of-Speech (Stanford Format)

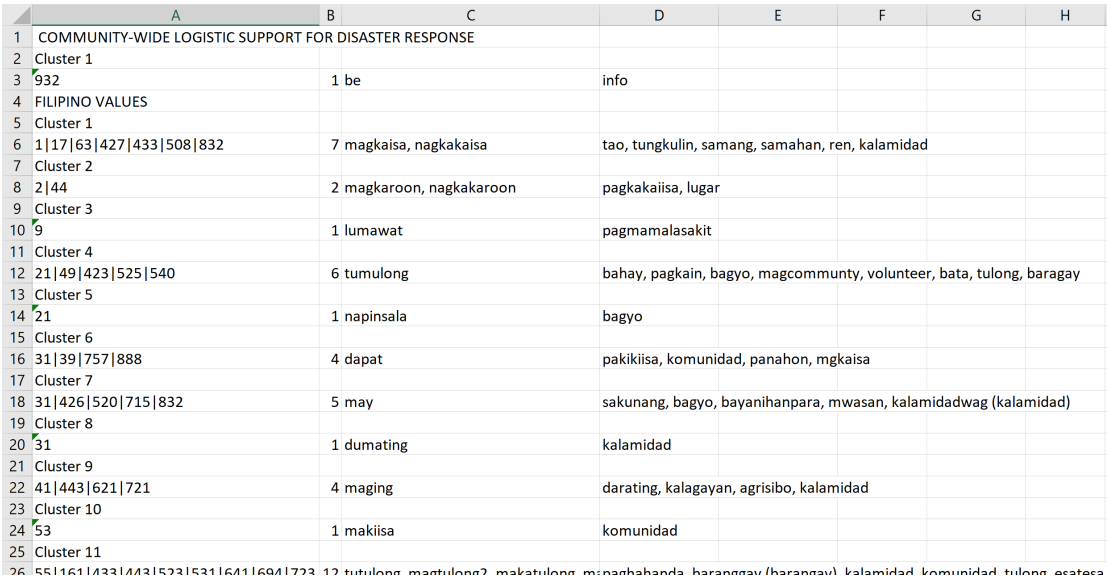


	F	G	H	I
1	1	magkaisa dapat ang mga tao		
2	2	magkaroon ng pagkakaiisa		
3	3	magkaroon ng komunikasyon	magkikita sa panahon	
4	4	wastong pagtatapon	kailangan magikot ikot	bantayan mga gamit
5	5	malawakang information drive		
6	6	dumating ang bagyo	magkaroon ng early warning system	maging handa ang mga tao
7	7	magkaroon ng early warning	maging handa ang mga tao	
8	8	pagtibayin ang early warning system device	magkaroon ng maintenance quarterly	masigurong maayos ito bago dumating ang isang kalamidad
9	9	lumawat at lumago ang pagmamalasakit		
10	10	sinasabi sa kung ano ang dapat gawin paghandaan ang lahat ng bibitbitin sa tuwing may sakuna		
11	11	pagkakaroon ng early warning device		
12	12	pagbibigay ng humanitarian assistance goods		
13	13	nais ko po sana magkaroon pa po ngmga	ibat ibang paraan	maging handa ang aming mga kapitbahay
14	14	magkaroon ng mga basurahan	pangunahing sanhi	
15	15	seminar tungkol sa bagyo at lindol		
16	16	maging alerto lagi sa mga hindi inaasahang bagay	magtulong tulong	opisyal man o hindi ng brgy
17	17	magkaisa ang lahat maging totoo ang bawat isa sa kanilang tungkulin		
18				
19	19	maging handa sa ano mangdumating na bagyobaha		
20	20	magkaroon ng komunikasyon at ikutin ng mga council members	makita ang sitwasyon	may kalamidad
21	21	tumulong sa mga karatig bahay at magbigay ng naitabing pagkain	napinsala ng bagyo	
22	22	maayos at malinaw na pagpaplano bilang paghahanda		
23	23	maagang paghahanda	dumating ang sakuna	

Figure C.6: Excel Report: Insight Phrases

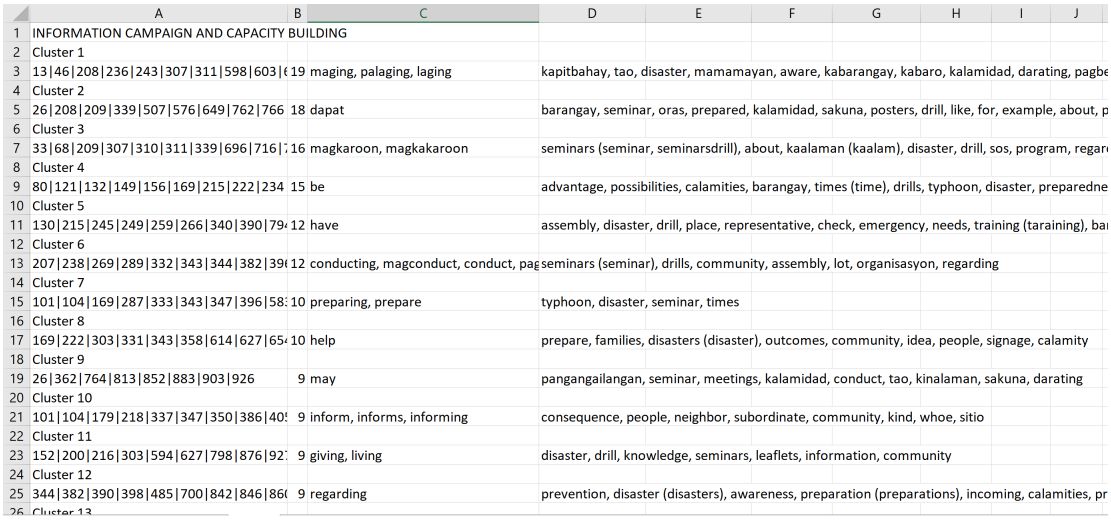
	A	B	C	D	E	F
1	1	magkaisa	tao			
2	2	magkaroon	pagkakaiisa			
3	3	magkaroon	komunikasyon			
4	3	magkikita	panahon			
5	4	wastong	pagtatapon			
6	4	kailangan	ikot			
7	4	bantayan	gamit			
8	5	malawakang	information	drive		
9	6	dumating	bagyo			
10	6	magkaroon	early	warning	system	
11	6	maging	tao			
12	7	magkaroon	early	warning		
13	7	maging	tao			
14	8	pagtibayin	early	warning	system	device
15	8	magkaroon	maintenance	quarterly		
16	8	masigurong	kalamidad			
17	9	lumawat	pagmamalasakit			
18	10	sinasabi	sakuna			
19	11	pagkakaroon	early	warning	device	
20	12	pagbibigay	assistance	goods		
21	13	nais	ngmga			
22	13	ibat	paraan			
23	13	maging	kapitbahay			
24	14	magkaroon	basurahan			
25	14	pangunahing	sanhi			
26	15	seminar	bagyo	lindol		

Figure C.7: Excel Report: Insight Word Sets



	A	B	C	D	E	F	G	H
1	COMMUNITY-WIDE LOGISTIC SUPPORT FOR DISASTER RESPONSE							
2	Cluster 1							
3	932	1	be	info				
4	FILIPINO VALUES							
5	Cluster 1							
6	1|17|63|427|433|508|832	7	magkaisa, nagkakaisa	tao, tungkulin, samang, samahan, ren, kalamidad				
7	Cluster 2							
8	2|44	2	magkaroon, nagkakaroon	pagkakaiisa, lugar				
9	Cluster 3							
10	9	1	lumawat	pagmamalasakit				
11	Cluster 4							
12	21|49|423|525|540	6	tumulong	bahay, pagkain, bagyo, magcommunty, volunteer, bata, tulong, baragay				
13	Cluster 5							
14	21	1	napinsala	bagyo				
15	Cluster 6							
16	31|39|757|888	4	dapat	pakikiisa, komunidad, panahon, mgkaisa				
17	Cluster 7							
18	31|426|520|715|832	5	may	sakunang, bagyo, bayanihanpara, mwasan, kalamidadwag (kalamidad)				
19	Cluster 8							
20	31	1	dumating	kalamidad				
21	Cluster 9							
22	41|443|621|721	4	maging	darating, kalagayan, agrisibo, kalamidad				
23	Cluster 10							
24	53	1	makiisa	komunidad				
25	Cluster 11							
26	55|161|433|443|523|531|641|694|723	12	tutulong, magtulong2, makatulong, m	pagbabanda, baranggay (barangay), kalamidad, komunidad, tulong, esatesa				

Figure C.8: Excel Report: Cluster List



	A	B	C	D	E	F	G	H	I	J
1	INFORMATION CAMPAIGN AND CAPACITY BUILDING									
2	Cluster 1									
3	13|46|208|236|243|307|311|598|603|6	19	maging, palaging, laging	kapitbahay, tao, disaster, mamamayan, aware, kabarangay, kabaro, kalamidad, darating, pagbe						
4	Cluster 2									
5	26|208|209|339|507|576|649|762|766	18	dapat	barangay, seminar, oras, prepared, kalamidad, sakuna, posters, drill, like, for, example, about, p						
6	Cluster 3									
7	33|68|209|307|310|311|339|696|716|7	16	magkaroon, magkakaroon	seminars (seminar, seminarsdrill), about, kaalaman (kaalam), disaster, drill, sos, program, regar						
8	Cluster 4									
9	80|121|132|149|156|169|215|222|234	15	be	advantage, possibilities, calamities, barangay, times (time), drills, typhoon, disaster, preparedne						
10	Cluster 5									
11	130|215|245|249|259|266|340|390|79	12	have	assembly, disaster, drill, place, representative, check, emergency, needs, training (taraining), ba						
12	Cluster 6									
13	207|238|269|289|332|343|344|382|39	12	conducting, magconduct, conduct, pag	seminars (seminar), drills, community, assembly, lot, organisasyon, regarding						
14	Cluster 7									
15	101|104|169|287|333|343|347|396|58	10	preparing, prepare	typhoon, disaster, seminar, times						
16	Cluster 8									
17	169|222|303|331|343|358|614|627|65	10	help	prepare, families, disasters (disaster), outcomes, community, idea, people, signage, calamity						
18	Cluster 9									
19	26|362|764|813|852|883|903|926	9	may	pangangailangan, seminar, meetings, kalamidad, conduct, tao, kinalaman, sakuna, darating						
20	Cluster 10									
21	101|104|179|218|337|347|350|386|40	9	inform, informs, informing	consequence, people, neighbor, subordinate, community, kind, whoe, sitio						
22	Cluster 11									
23	152|200|216|303|594|627|798|876|92	9	giving, living	disaster, drill, knowledge, seminars, leaflets, information, community						
24	Cluster 12									
25	344|382|390|398|485|700|842|846|86	9	regarding	prevention, disaster (disasters), awareness, preparation (preparations), incoming, calamities, pr						
26	Cluster 13									

Figure C.9: Excel Report: Ranked Cluster List

Appendix D

Informed Consent Form

EXTRACTING AND ORGANIZING DISASTER-RELATED PHILIPPINE COMMUNITY RESPONSES FOR AIDING NATIONWIDE RISK REDUCTION PLANNING AND RESPONSE

Informed Consent Form

Philippine-California Advanced Research Institute: Malasakit Team Members

Nicco Louis S. Nocon
College of Computer Studies, De La Salle University, Manila

PURPOSE OF THE STUDY

You are being invited to take part in a research study. Before you decide to participate in this study, it is important that you understand why the research is being done and what your participation will involve. Please read the following information carefully and feel free to ask the researcher if there is anything that is not clear or if you need more information.

The purpose of the study is to automatically extract key insights from community responses and organize that information to be used as a list recommendations or guide in improving the nation's disaster risk reduction planning and response strategies. As developers of Malasakit, you are chosen as respondents to this research who will assess the content of the generated report and/or the developed software tool.

STUDY PROCEDURES

Initially, materials for assessment will be provided to you – these are the report, tool and supporting document/s such as the tool's function list. In assessing the report, you are to provide your opinions regarding its content quality, design or formatting, usability, satisfaction, and organizational preference. In assessing the tool, questions included are about its usefulness, ease of use, ease of learning, satisfaction, and functionalities used. At the latter portion of both forms, comments and suggestions on how to improve them and negative aspects that you have discovered will be asked.

DURATION

Answering either or both forms are good for less than thirty (30) minutes. Unless necessary, there is no need for a follow-up regarding your answers.

VOLUNTARY PARTICIPATION

Your participation in this study is voluntary. It is up to you whether or not you decide to participate. If you decide to participate, you will be asked to sign this consent form. After you sign this consent form, you are still free to withdraw at any time and without giving a reason. Withdrawing from this study will not affect the relationship you have, if any, with the researcher. If you withdraw from the study before data collection is completed, your data will be destroyed.

RISKS

There are no foreseeable risks involved in answering the questionnaires. Your feedback will not be disclosed with your personal information. However, if there are questions that you may feel uncomfortable with answering, you may decline to answer any or all questions and you may withdraw your participation at any time if you choose.

BENEFITS

Initially, your feedback will determine the impact of the research, specifically its overall usability. By participating in this study, you will be able to provide ideas for improving the report and tool. The final product of this research would be used by decision makers in strategizing and executing the nation's disaster risk reduction prevention and mitigation. Successfully utilizing the report will improve the status of your community in handling disasters and actions will be evident among society as a whole. Moreover, the success of this research will benefit you as it would expand the applications of your work. Having said that, researchers and developers in particular, will be able to discover and make use of the tool in creating more applications.

CONFIDENTIALITY

Your responses in this research will be anonymous. Every effort will be made by the researcher to preserve your confidentiality, including the following: personal identifiable information will not be included in research notes and documents, and as for this consent form, it will be stored and accessed digitally in a device that only the principal investigator has access to.

CONTACT INFORMATION

This study was approved by the Research Ethics Review Committee of De La Salle University. If you have any questions at any time about this study, or if you experience any non-normative sensations as a result of participation, you may contact the researcher whose contact information is on the first page. If you have any questions regarding your rights as a research participant, or if problems arise which you do not feel you can discuss with the Principal Investigator, please feel free to contact the Director of the Research Ethics Office, Dr. Nelson B. Arboleda, Jr., at REO@dlsu.edu.ph or by calling (632) 524-4611 local 513.

CONSENT

I have read the provided information, or it has been read to me. I have had the opportunity to ask questions about it and any questions I have been asked have been answered to my satisfaction. I understand that I will be given a copy of this form, and the researcher will keep another copy on file. I consent voluntarily to be a participant in this study.

Print Name of Participant _____
Signature of Participant _____
Date _____
Day/month/year

Print Name of Researcher **Nicco Louis S. Nocon**
Signature of Researcher _____
Date _____
Day/month/year

Appendix E

Survey Forms

FILIPINO TEXT ANALYSIS TOOL FOR DISASTERS: REPORT SURVEY	
Value Representation 1- Strongly Disagree, 2- Disagree, 3- Neutral, 4- Agree, 5- Strongly Agree	
1. Aesthetics (design): The report's design is acceptable	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
2. Content (quality): The different elements of the report (e.g., title, insights list, and Malasakit response list) is necessary	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
3. Content (quality): The information fields are appropriate and enough to make a decision or action	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
4. Readability (design): The information is clear and readable	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
5. Understandability (format): The information is easy to interpret	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
6. Usefulness of Information (extraction quality): The information is useful in my job	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
7. Organization (organization quality): The information is displayed in an organized manner	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
8. Usability (efficiency): Using the report in my job would enable me to accomplish tasks more quickly	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
9. Usability (potential): The report would enhance my effectiveness on the job	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
10. Report (overall quality): I can make decision/s based on the information provided	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
11. User Satisfaction (overall measurement): I am satisfied with the report	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
Organization Preference	
Do you prefer organizing the information by frequency (all entries and ranked by frequency only), per response categories (grouped by categories first then ordered by frequency), or something else?	
Comments and Suggestions	
Negative Aspects	

FILIPINO TEXT ANALYSIS TOOL FOR DISASTERS: API SURVEY	
Value Representation 1- Strongly Disagree, 2- Disagree, 3- Neutral, 4- Agree, 5- Strongly Agree	
Usefulness	
1. It is effective partnered with other software tools	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
2. It can help raise the productivity rate when used in conjunction with other software tools	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
3. It is useful for my tasks	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
4. It makes it easier to accomplish my tasks	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
5. It helps save time	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
6. It does everything I would expect it to do	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
Ease of Use	
1. It is easy to use	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
2. It is simple to use	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
3. It is user friendly	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
4. It requires the fewest steps possible to accomplish what I want to do with it	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
5. It is flexible	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
6. Using it is effortless	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
7. I can use it without written instructions	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
8. I don't notice any inconsistencies as I use it	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
9. Both occasional and regular users would like it	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
10. I can recover from mistakes quickly and easily	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
11. I can use it successfully every time	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
Ease of Learning	
1. I learned to use it quickly	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
2. I easily remember how to use it	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
3. Learning how to use it is easy	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]

4. I quickly became skillful with using it	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
Satisfaction	
1. I am satisfied with it	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
2. I would recommend it to be used in the future	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
3. It works the way I want it to work	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [ ]
Functions Used (Functions that will most likely be useful to me)	
Comments and Suggestions	
Negative Aspects	

Appendix F

Survey Results and Feedback

FILIPINO TEXT ANALYSIS TOOL FOR DISASTERS: API SURVEY	
Value Representation 1- Strongly Disagree, 2- Disagree, 3- Neutral, 4- Agree, 5- Strongly Agree	
Usefulness	
1. It is effective partnered with other software tools	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [X]
2. It can help raise the productivity rate when used in conjunction with other software tools	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [X]
3. It is useful for my tasks	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [X]
4. It makes it easier to accomplish my tasks	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [X]
5. It helps save time	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [X]
6. It does everything I would expect it to do	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
Ease of Use	
1. It is easy to use	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
2. It is simple to use	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
3. It is user friendly	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
4. It requires the fewest steps possible to accomplish what I want to do with it	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
5. It is flexible	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
6. Using it is effortless	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
7. I can use it without written instructions	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
8. I don't notice any inconsistencies as I use it	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
9. Both occasional and regular users would like it	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
10. I can recover from mistakes quickly and easily	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [X]
11. I can use it successfully every time	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
Ease of Learning	
1. I learned to use it quickly	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
2. I easily remember how to use it	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [X]
3. Learning how to use it is easy	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]

4. I quickly became skillful with using it	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
Satisfaction	
1. I am satisfied with it	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [X]
2. I would recommend it to be used in the future	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [X]
3. It works the way I want it to work	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]

Functions Used (Functions that will most likely be useful to me)

- Cluster
- Data Utilities
- POS Taggers
- Normalize

Comments and Suggestions

1. Most of the functions in modules are properly documented and readable. Atomic functions are very detailed.
2. The functions can be used externally for other data processing tasks.
3. It did not come with any README file or a requirements.txt file to give users a brief overview on how to run the application and its required Python modules. Having these files would ease the use of the API.
4. Example scripts using a few of the functions provided by the API would help users in understanding how it works.
5. Not necessarily a requirement but it would be nice if a Graphical User Interface (GUI) would be integrated in the future for the API.
6. One module, the lang_id, was not recognized by the thesis_software.py program.

Negative Aspects

FILIPINO TEXT ANALYSIS TOOL FOR DISASTERS: REPORT SURVEY	
Value Representation 1- Strongly Disagree, 2- Disagree, 3- Neutral, 4- Agree, 5- Strongly Agree	
1. Aesthetics (design): The report's design is acceptable	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
2. Content (quality): The different elements of the report (e.g., title, insights list, and Malasakit response list) is necessary	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
3. Content (quality): The information fields are appropriate and enough to make a decision or action	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
4. Readability (design): The information is clear and readable	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
5. Understandability (format): The information is easy to interpret	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
6. Usefulness of Information (extraction quality): The information is useful in my job	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [X]
7. Organization (organization quality): The information is displayed in an organized manner	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [X]
8. Usability (efficiency): Using the report in my job would enable me to accomplish tasks more quickly	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
9. Usability (potential): The report would enhance my effectiveness on the job	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
10. Report (overall quality): I can make decision/s based on the information provided	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [X]
11. User Satisfaction (overall measurement): I am satisfied with the report	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
Organization Preference	
Do you prefer organizing the information by frequency (all entries and ranked by frequency only), per response categories (grouped by categories first then ordered by frequency), or something else? I prefer grouping the information first by category then by frequency. However, having a frequency-only ranking for the information also has its merits since it will give the users an idea on which category is most important followed by the rest. I prefer the layout and formatting of A and A – Category compared to the others.	
Comments and Suggestions	
1. The reports are aesthetically formal and proper to look at. 2. It might take some time for the users to fully obtain actionable results from the report since usually it spans more than 20+ pages.	

3. Some simple automatically generated graphs such as word clouds or any frequency-based visualization might help the user in understanding the information extracted in partner with the generated report.
Negative Aspects

FILIPINO TEXT ANALYSIS TOOL FOR DISASTERS: API SURVEY	
Value Representation 1- Strongly Disagree, 2- Disagree, 3- Neutral, 4- Agree, 5- Strongly Agree	
Usefulness	
1. It is effective partnered with other software tools	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
2. It can help raise the productivity rate when used in conjunction with other software tools	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
3. It is useful for my tasks	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
4. It makes it easier to accomplish my tasks	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
5. It helps save time	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
6. It does everything I would expect it to do	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
Ease of Use	
1. It is easy to use	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
2. It is simple to use	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
3. It is user friendly	1 [ ] 2 [X] 3 [ ] 4 [ ] 5 [ ]
4. It requires the fewest steps possible to accomplish what I want to do with it	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
5. It is flexible	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
6. Using it is effortless	1 [ ] 2 [X] 3 [ ] 4 [ ] 5 [ ]
7. I can use it without written instructions	1 [ ] 2 [X] 3 [ ] 4 [ ] 5 [ ]
8. I don't notice any inconsistencies as I use it	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
9. Both occasional and regular users would like it	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
10. I can recover from mistakes quickly and easily	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
11. I can use it successfully every time	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
Ease of Learning	
1. I learned to use it quickly	1 [ ] 2 [X] 3 [ ] 4 [ ] 5 [ ]
2. I easily remember how to use it	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
3. Learning how to use it is easy	1 [ ] 2 [X] 3 [ ] 4 [ ] 5 [ ]

4. I quickly became skillful with using it	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
Satisfaction	
1. I am satisfied with it	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
2. I would recommend it to be used in the future	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
3. It works the way I want it to work	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
Functions Used (Functions that will most likely be useful to me)	
API function groups 1 - 8	
Comments and Suggestions	
API could have been a RESTful API using HTTP requests and use API documentation tools for the developer guide. Another option is to make it a Python package (installable through pip) and have proper web developer guide to document each API endpoint with the expected request parameters and request format. However, this can be very useful especially that this is tested on a domain in the Filipino language. Users can now have a toolkit that can be used for preprocessing and information extraction for their Filipino dataset.	
Negative Aspects	

FILIPINO TEXT ANALYSIS TOOL FOR DISASTERS: REPORT SURVEY	
Value Representation 1- Strongly Disagree, 2- Disagree, 3- Neutral, 4- Agree, 5- Strongly Agree	
1. Aesthetics (design): The report's design is acceptable	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
2. Content (quality): The different elements of the report (e.g., title, insights list, and Malasakit response list) is necessary	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
3. Content (quality): The information fields are appropriate and enough to make a decision or action	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [X]
4. Readability (design): The information is clear and readable	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
5. Understandability (format): The information is easy to interpret	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
6. Usefulness of Information (extraction quality): The information is useful in my job	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
7. Organization (organization quality): The information is displayed in an organized manner	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
8. Usability (efficiency): Using the report in my job would enable me to accomplish tasks more quickly	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
9. Usability (potential): The report would enhance my effectiveness on the job	1 [ ] 2 [ ] 3 [X] 4 [ ] 5 [ ]
10. Report (overall quality): I can make decision/s based on the information provided	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
11. User Satisfaction (overall measurement): I am satisfied with the report	1 [ ] 2 [ ] 3 [ ] 4 [X] 5 [ ]
Organization Preference	
Do you prefer organizing the information by frequency (all entries and ranked by frequency only), per response categories (grouped by categories first then ordered by frequency), or something else? Organize by response categories then frequency. A – all A – category	
Comments and Suggestions	

Clustering must be improved. Although most clusters are easily understandable, the proposed action (verbs) are still too broad and not every verb in each cluster can be linked to the target nouns. It will also be cool if there is a report that lists the top 10 opinions by the community as to what should be done during the disaster, and the steps needed to turn the clusters into this list. This way, developers can see deeper value that the information clusters generated is usable in their own report / software.
Negative Aspects

FILIPINO TEXT ANALYSIS TOOL FOR DISASTERS: API SURVEY	
Value Representation 1- Strongly Disagree, 2- Disagree, 3- Neutral, 4- Agree, 5- Strongly Agree	
Usefulness	
1. It is effective partnered with other software tools	1 [ ] 2 [ ] 3 [x] 4 [ ] 5 [ ]
2. It can help raise the productivity rate when used in conjunction with other software tools	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
3. It is useful for my tasks	1 [ ] 2 [ ] 3 [x] 4 [ ] 5 [ ]
4. It makes it easier to accomplish my tasks	1 [ ] 2 [ ] 3 [x] 4 [ ] 5 [ ]
5. It helps save time	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
6. It does everything I would expect it to do	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
Ease of Use	
1. It is easy to use	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
2. It is simple to use	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
3. It is user friendly	1 [ ] 2 [ ] 3 [x] 4 [ ] 5 [ ]
4. It requires the fewest steps possible to accomplish what I want to do with it	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
5. It is flexible	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
6. Using it is effortless	1 [ ] 2 [ ] 3 [x] 4 [ ] 5 [ ]
7. I can use it without written instructions	1 [ ] 2 [ ] 3 [x] 4 [ ] 5 [ ]
8. I don't notice any inconsistencies as I use it	1 [ ] 2 [ ] 3 [x] 4 [ ] 5 [ ]
9. Both occasional and regular users would like it	1 [ ] 2 [ ] 3 [x] 4 [ ] 5 [ ]
10. I can recover from mistakes quickly and easily	1 [ ] 2 [ ] 3 [x] 4 [ ] 5 [ ]
11. I can use it successfully every time	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
Ease of Learning	
1. I learned to use it quickly	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
2. I easily remember how to use it	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
3. Learning how to use it is easy	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]

4. I quickly became skillful with using it	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
Satisfaction	
1. I am satisfied with it	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
2. I would recommend it to be used in the future	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
3. It works the way I want it to work	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
Functions Used (Functions that will most likely be useful to me)	
Clustering part of noisy data (responses)	
Comments and Suggestions	
I would like to recommend for a graphical user interface for ease of use.	
Negative Aspects	
None.	

FILIPINO TEXT ANALYSIS TOOL FOR DISASTERS: REPORT SURVEY	
Value Representation 1- Strongly Disagree, 2- Disagree, 3- Neutral, 4- Agree, 5- Strongly Agree	
1. Aesthetics (design): The report's design is acceptable	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
2. Content (quality): The different elements of the report (e.g., title, insights list, and Malasakit response list) is necessary	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
3. Content (quality): The information fields are appropriate and enough to make a decision or action	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
4. Readability (design): The information is clear and readable	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
5. Understandability (format): The information is easy to interpret	1 [ ] 2 [x] 3 [ ] 4 [ ] 5 [ ]
6. Usefulness of Information (extraction quality): The information is useful in my job	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
7. Organization (organization quality): The information is displayed in an organized manner	1 [ ] 2 [ ] 3 [x] 4 [ ] 5 [ ]
8. Usability (efficiency): Using the report in my job would enable me to accomplish tasks more quickly	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
9. Usability (potential): The report would enhance my effectiveness on the job	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
10. Report (overall quality): I can make decision/s based on the information provided	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
11. User Satisfaction (overall measurement): I am satisfied with the report	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
Organization Preference	
Do you prefer organizing the information by frequency (all entries and ranked by frequency only), per response categories (grouped by categories first then ordered by frequency), or something else? Group by frequency first then ordered by categories. A is better for me.	
Comments and Suggestions	
The output should be formatted in such a way non-technical background can easily understand.	
Negative Aspects	
I had a hard time understanding the output at first.	

FILIPINO TEXT ANALYSIS TOOL FOR DISASTERS: API SURVEY	
Value Representation 1- Strongly Disagree, 2- Disagree, 3- Neutral, 4- Agree, 5- Strongly Agree	
Usefulness	
1. It is effective partnered with other software tools	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
2. It can help raise the productivity rate when used in conjunction with other software tools	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
3. It is useful for my tasks	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
4. It makes it easier to accomplish my tasks	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
5. It helps save time	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
6. It does everything I would expect it to do	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
Ease of Use	
1. It is easy to use	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
2. It is simple to use	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
3. It is user friendly	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
4. It requires the fewest steps possible to accomplish what I want to do with it	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
5. It is flexible	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
6. Using it is effortless	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
7. I can use it without written instructions	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
8. I don't notice any inconsistencies as I use it	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
9. Both occasional and regular users would like it	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
10. I can recover from mistakes quickly and easily	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
11. I can use it successfully every time	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
Ease of Learning	
1. I learned to use it quickly	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
2. I easily remember how to use it	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
3. Learning how to use it is easy	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]

4. I quickly became skillful with using it	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
Satisfaction	
1. I am satisfied with it	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
2. I would recommend it to be used in the future	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
3. It works the way I want it to work	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]

Functions Used (Functions that will most likely be useful to me)

- extract_insights_words
- organize_by_response_categories
- translate_filipino_colloquialism
- normalize_list
- normalize_string
- read_excel
- write_report
- Clustering Module Functions
- Ranking Module Functions

Comments and Suggestions

- The user is aware of what is happening during the execution of the program because the program was able to provide enough updates regarding its progress.

Negative Aspects

- When I run the program, I noticed some errors like *No insights (words) extracted at Response #: <response_ID>* then I checked the actual responses and there are some valuable insights found there that might also affect the generated reports. There were more or less 50 of such errors.

FILIPINO TEXT ANALYSIS TOOL FOR DISASTERS: REPORT SURVEY	
Value Representation 1- Strongly Disagree, 2- Disagree, 3- Neutral, 4- Agree, 5- Strongly Agree	
1. Aesthetics (design): The report's design is acceptable	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
2. Content (quality): The different elements of the report (e.g., title, insights list, and Malasakit response list) is necessary	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
3. Content (quality): The information fields are appropriate and enough to make a decision or action	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
4. Readability (design): The information is clear and readable	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
5. Understandability (format): The information is easy to interpret	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
6. Usefulness of Information (extraction quality): The information is useful in my job	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
7. Organization (organization quality): The information is displayed in an organized manner	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
8. Usability (efficiency): Using the report in my job would enable me to accomplish tasks more quickly	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
9. Usability (potential): The report would enhance my effectiveness on the job	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
10. Report (overall quality): I can make decision/s based on the information provided	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
11. User Satisfaction (overall measurement): I am satisfied with the report	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
Organization Preference	
Do you prefer organizing the information by frequency (all entries and ranked by frequency only), per response categories (grouped by categories first then ordered by frequency), or something else? ➢ I prefer to have the responses organized per response categories. I prefer approach A – category, even though the proposed action is limited, insights are better gained using this approach by being specific on what the proposed action is.	
Comments and Suggestions	
➢ Entries with only 1 frequency I think is not anymore necessary to be included in the reports since most of these entries doesn't make sense and is probably included already in other entries with higher frequency.	

Negative Aspects
➢ The length of the generated reports were kind of overwhelming but given the amount of information provided, it is understandable.

FILIPINO TEXT ANALYSIS TOOL FOR DISASTERS: API SURVEY	
Value Representation 1- Strongly Disagree, 2- Disagree, 3- Neutral, 4- Agree, 5- Strongly Agree	
Usefulness	
1. It is effective partnered with other software tools	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
2. It can help raise the productivity rate when used in conjunction with other software tools	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
3. It is useful for my tasks	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
4. It makes it easier to accomplish my tasks	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
5. It helps save time	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
6. It does everything I would expect it to do	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
Ease of Use	
1. It is easy to use	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
2. It is simple to use	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
3. It is user friendly	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
4. It requires the fewest steps possible to accomplish what I want to do with it	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
5. It is flexible	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
6. Using it is effortless	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
7. I can use it without written instructions	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
8. I don't notice any inconsistencies as I use it	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
9. Both occasional and regular users would like it	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
10. I can recover from mistakes quickly and easily	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
11. I can use it successfully every time	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
Ease of Learning	
1. I learned to use it quickly	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
2. I easily remember how to use it	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
3. Learning how to use it is easy	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]

4. I quickly became skillful with using it	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
Satisfaction	
1. I am satisfied with it	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
2. I would recommend it to be used in the future	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
3. It works the way I want it to work	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
Functions Used (Functions that will most likely be useful to me)	
read_excel, refresh_excel, organize_sublist, identify_language_string_list, format_pos, rank_by_response_categories, extract_insights_words	
Comments and Suggestions	
Instructions must be provided to enable the user to use it to do it's job/purpose. Also, functions need some example inputs or arguments to feed into the function.	
Negative Aspects	
No instructions provided if there are requirements needed to install and on how to use it.	

FILIPINO TEXT ANALYSIS TOOL FOR DISASTERS: REPORT SURVEY	
Value Representation 1- Strongly Disagree, 2- Disagree, 3- Neutral, 4- Agree, 5- Strongly Agree	
1. Aesthetics (design): The report's design is acceptable	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
2. Content (quality): The different elements of the report (e.g., title, insights list, and Malasakit response list) is necessary	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
3. Content (quality): The information fields are appropriate and enough to make a decision or action	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
4. Readability (design): The information is clear and readable	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
5. Understandability (format): The information is easy to interpret	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
6. Usefulness of Information (extraction quality): The information is useful in my job	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
7. Organization (organization quality): The information is displayed in an organized manner	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
8. Usability (efficiency): Using the report in my job would enable me to accomplish tasks more quickly	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
9. Usability (potential): The report would enhance my effectiveness on the job	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
10. Report (overall quality): I can make decision/s based on the information provided	1 [ ] 2 [ ] 3 [ ] 4 [x] 5 [ ]
11. User Satisfaction (overall measurement): I am satisfied with the report	1 [ ] 2 [ ] 3 [ ] 4 [ ] 5 [x]
Organization Preference	
Do you prefer organizing the information by frequency (all entries and ranked by frequency only), per response categories (grouped by categories first then ordered by frequency), or something else? I prefer organizing per response categories with C then ordered by frequency to present a clearer insight and easier interpretation on the information shown.	
Comments and Suggestions	
Words like "mag" in the proposed action must contain other information for narrowing down some actions.	

Negative Aspects
The reports generated are too much to interpret and a generalization of the words is needed to provide a broader and faster reports. Either it is full of information that make its purpose done or a generalization of ideas are needed based from the informations from each categories

Appendix G

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