Detecting Frames and Causal Relationships in Climate Change Related Text Databases Based on Semantic Features

by

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ABSTRACT

The subliminal impact of framing of social, political and environmental issues such as climate change has been studied for decades in political science and communications research. Media framing offers an "interpretative package" for average citizens on how to make sense of climate change and its consequences to their livelihoods, how to deal with its negative impacts, and which mitigation or adaptation policies to support. A line of related work has used bag of words and word-level features to detect frames automatically in text. Such works face limitations since standard keyword based features may not generalize well to accommodate surface variations in text when different keywords are used for similar concepts.

This thesis develops a unique type of textual features that generalize <subject,verb, object> triplets extracted from text, by clustering them into high-level concepts. These concepts are utilized as features to detect frames in text. Compared to uni-gram and bi-gram based models, classification and clustering using generalized concepts yield better discriminating features and a higher classification accuracy with a 12% boost (i.e. from 74% to 83% F-measure) and 0.91 clustering purity for Frame/Non-Frame detection.

The automatic discovery of complex causal chains among interlinked events and their participating actors has not yet been thoroughly studied. Previous studies related to extracting causal relationships from text were based on laborious and incomplete hand-developed lists of explicit causal verbs, such as "causes" and "results in." Such approaches result in limited recall because standard causal verbs may not generalize well to accommodate surface variations in texts when different keywords and phrases are used to express similar causal effects. Therefore, I present a system that utilizes generalized concepts to extract causal relationships. The proposed algorithms overcome surface variations in written expressions of causal relationships and discover the domino effects between climate events and human security. This semi-supervised approach alleviates the need for labor intensive keyword list development and annotated datasets. Experimental evaluations by domain experts achieve an average precision of 82%. Qualitative assessments of causal chains show that results are consistent with the 2014 IPCC report illuminating causal mechanisms underlying the linkages between climatic stresses and social instability.

DEDICATION

This thesis is dedicated to the memory of my parents, Abdullah and Sultanah. I miss them every day, but I am glad that my mother saw this process at the beginning of my study, offering unlimited support to make it possible. To my wife, Reem, my son, Mishary, my brothers and sisters for their love, support, and encouragement.

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INTRODUCTION

Climate change has provoked heated debates on global political and media arenas. Media framing offers an "interpretative package" for average citizens on how to make sense of climate change and its consequences to their livelihoods, how to deal with its negative impacts, and which mitigation or adaptation policies to support (Chong and Druckman, 2007; Nisbet, 2009; Shehata and Hopmann, 2012). News frames encourage salient interpretation of debated issues through the usage of rhetorical devices (e.g. words, repetitive phrases, and metaphors). Increasingly, governments and international communities are concerned about the security implications of climate change as empirical research has documented that climate change is linked to increased risk of violent conflict (Barnett and Adger, 2007). For example, in May 2015, U.S. President Barack Obama asserted that extreme weather is a threat to national security and elevates the risk of global instability and conflict. Some popular press adopted security threat frames to gain public attention. Therefore, systematic detection of news frames related to climate change offers better understanding of stakeholders and their competing perspectives.

Politicians have used framing on hotly debated issues to shift public opinion, gain support and pursue their agenda. A **frame** is the bundling of a component of oratory to urge certain perceptions and to dishearten others (Alashri *et al.*, 2015). Framing is accomplished when a choice of words, expressions, subjects and other logical gadgets support one understanding of an arrangement of realities, and debilitate other interpretations. One of those framed issues is climate change. Internet created a public space for politicians and stakeholders to frame climate change and related issues to push for their agenda. Online tools such as blogsphere, microblogging and social media streams have increased the availability of data on climate change related debate and made it feasible for researchers to analyze them.

Framing research requires qualitative analysis of a number of texts by subject matter experts to identify and code a set of frames. This is a time consuming process that does not scale well. In order to address the scalability problem, machine learning techniques can be utilized to detect and classify frames. In this study we propose a system for automatic detection of frames in sentences in a climate change related corpus, and map them to one of four expert-identified frame categories: solution, problem threat, cause, and motivation. Our problem here can be described as a multi-level multi-class classification problem where we first classify each sentence as *Frame* or *Non-Frame*. Then, the *Frame* sentences are further mapped into one of four predefined frame categories. In particular, we show that if a sentence is <subject,verb,object> patterned then using generalized concepts and relations as features produced significant results compared to classical textual features (e.g. uni-grams and bi-grams) while detecting and categorizing *Frame/Non-Frame* sentences. In the unsupervised frame learning approach, we experimented with k-means (Arthur and Vassilvitskii, 2007) and its results aligned with our development of the four frame categories using theories discussed later in Section 4.3. In the supervised frame learning approach, we experimented with SVM (Cortes and Vapnik, 1995), Random Forests (Breiman, 2001) and Sparse Logistic Regression (Liu *et al.*, 2009a) classifiers, and identified sparse logistic regression as the best performing classifier for these tasks. Once we detect framed sentences, we investigate the causality among actors/entities to discover the causal relationships.

The generalized concepts approach extracts high-level information from text as relationships and concepts forming a semantic network. It first uses shallow seman-

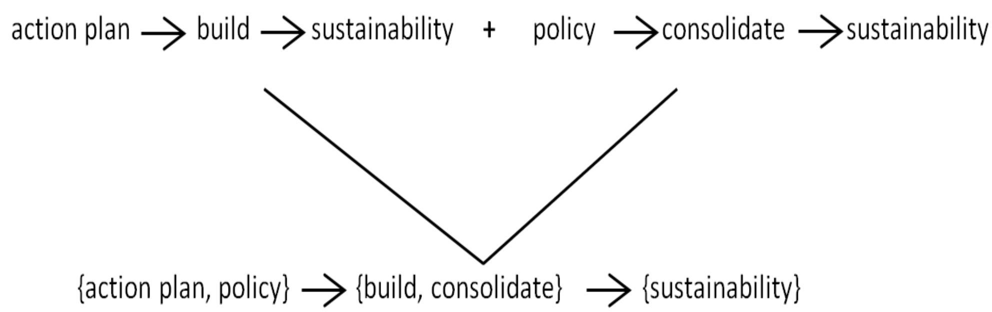

Figure 1.1 Example of Merging Two Related Concepts

tic parser to generate POS tags to obtain semantic triplets <subject,verb,object> from text. Next, it utilizes a bottom-up agglomerative clustering approach to merge and generalize those triplets into concepts. In NLP, shallow parsing is the task of extracting the *subjects*, *predicates* or *verb phrases*, and *objects*. Figure 1.1 shows how two related triplets could be merged into a higher level generalized concept. In this figure, two extracted triplets: ⟨*action plan*→*build*→*sustainability*⟩ and ⟨*policy* →*consolidate*→*sustainability*⟩ are merged to form a high level generalized concept and relationship as: ⟨{*action plan, policy*}→{*build, consolidate*}→ {*sustainability*}⟩ by discovering contextual synonyms such as {*action plan, policy*} and {*build, consolidate*}. Here the definition of contextual synonyms is not based on the one in the traditional dictionary. Rather, they correspond to phrases that may occur in similar semantic roles and associate with similar contexts. In Figure 1.1 the two triplets share the same object {*sustainability*} and semantically similar verbs; hence, we can merge their subjects {action plan,policy} as contextual synonyms.

"All reasonings concerning matter of fact seem to be founded on the relation of Cause and Effect," (Hume and Beauchamp, 1904). Causal relationships are central to human reasoning for individuals (Riaz and Girju, 2014; Zhao *et al.*, 2016; Khemlani *et al.*, 2014) and policy makers to address significant global problems that pose threats to human security. Despite scientific evidence suggesting the potential linkages between climate change impacts and human security (Adger *et al.*, 2014), results from social and physical sciences offer ambivalent explanations of the causal mechanisms. The *domino effect* describing linear or nonlinear relationships between climate extremes and sociopolitical impacts is not well documented. Understanding the security repercussions triggered by climate shocks and stresses can motivate decision-makers to build adaptive capacity at global and local level. Therefore, there is an urgent need to develop data intelligence system to demystify causes and consequences of climate change risks in various sources of textual information. Enhancing causality extraction is extremely helpful in detecting interlinked drivers for social unrest and identifying opportunities for policy intervention. A recent meta-analysis examining 50 quantitative studies demonstrated that warm temperature and extreme precipitation increase the risk of violent conflict (Hsiang and Burke, 2014).

Causal relationships, defined as "the relationship between cause and effect," [1] are central to our life. Given the complex climate risks and human security interactions, it is challenging for citizens and political leaders to grasp the indirect consequences of extreme weather events on livelihoods efficiently. As a result, computational linguistics researchers have proposed approaches to help automate this task. Such approaches were developed for a variety of applications ranging from medicine (Khoo *et al.*, 2000; Vandenbroucke *et al.*, 2016), to environmental science (Araúz and Faber, 2012), law (Thagard, 2004), and question-answering systems in computer science (Girju, 2003; Chang and Choi, 2004; Higashinaka and Isozaki, 2008).

The 2014 Intergovernmental Panel on Climate Change (IPCC) fifth assessment report (Adger *et al.*, 2014) firstly summarizes a systematic framework to reflect how climate change poses risks to human safety and sociopolitical instability. The framework discusses associations between climate stresses and potential impacts on human

[1] Oxford English dictionary online

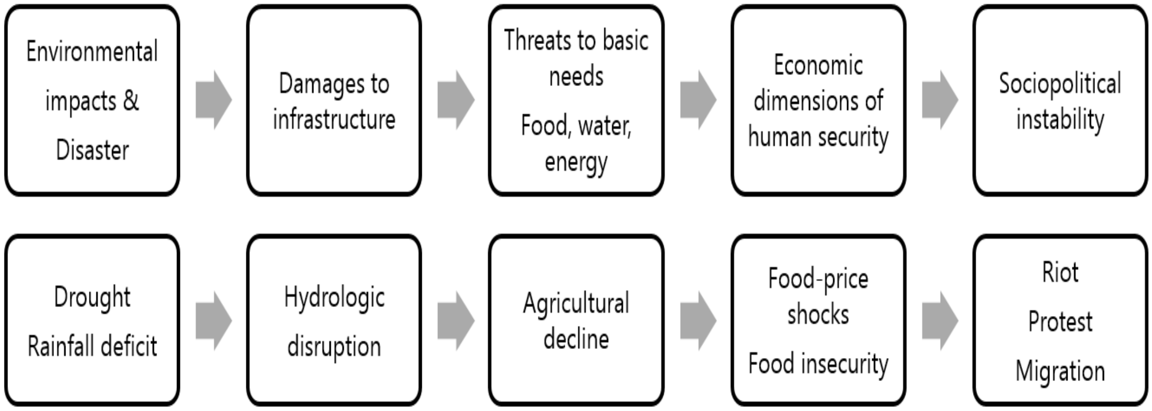

Figure 1.2 Causal Chains of the Relationship Between Climate Change and Human Security

health, economic conditions, and violent conflicts intensifying global or regional instability (Scheffran *et al.*, 2012a; Lu *et al.*, 2016, 2017; Scheffran *et al.*, 2012b). Guided by the IPCC fifth assessment report, we use a set of novel algorithms for causality identification to disentangle climate-security linkages from vast amounts of textual data. Our approach is more robust for understanding the causal processes between climate systems, natural resources, human security, and social instability. Figure 1.2 provides an illustrative overview of *domino effect* of climate change on key dimensions of human security. Sea surface temperature or heat would lead to prolonged droughts. Rainfall deficits cause hydrologic disruption, posing threats to basic needs. Agricultural crop yields will be affected adversely. Food-price shocks increase the likelihood of foot riots or conflict over resource scarcity (e.g., protest and migration). One of the objectives of this thesis is to develop a series of computational models for causality extraction to illustrate how climate stresses result in multifaceted threats to economic, social and political outcomes essential to human security.

In contrast to previous studies, our generalized concepts approach discovers the interlinked causal relationships in English texts by considering linguistic and contex-

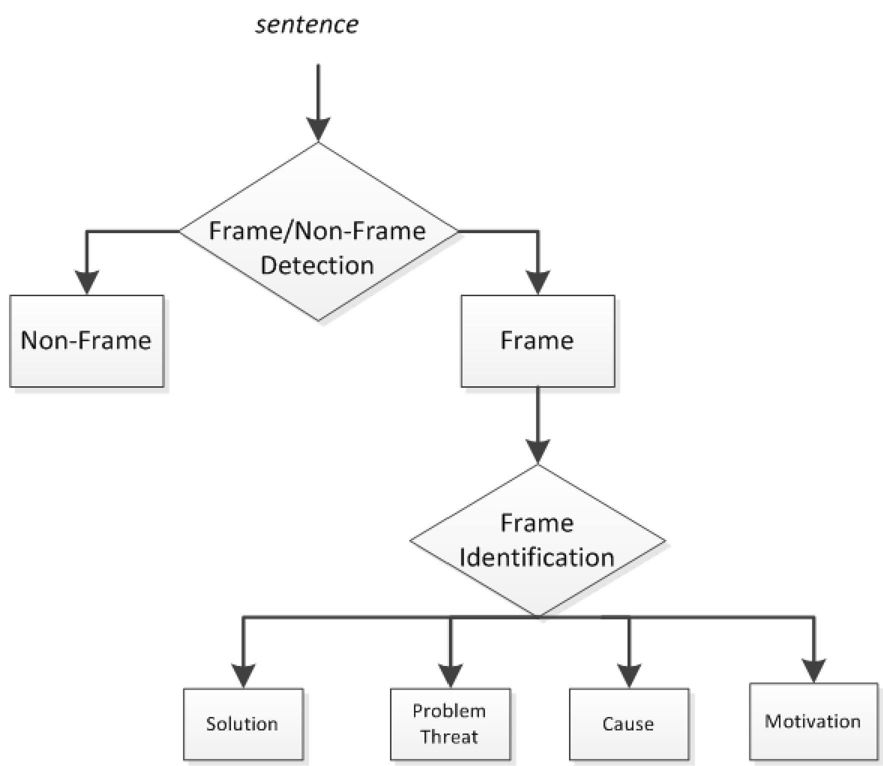

Figure 1.3 Multi-level Multi-class Classification

tual features. We investigate the interconnected processes in the context of climate change and human security by analyzing causal connections between entities through concept generalization techniques. An entity is defined as an extreme weather event, human action or outcome.

1.1 Problem Definition

Given a set of documents $\{D_1,...,D_M\}$ where each document contains one or more paragraphs; first, we split documents into sentences $\{S_1,...,S_N\}$. Next, using sentences as data points, we aim to resolve whether a sentence S_i contains a frame or not. And, if the sentence contains a frame, then we aim to identify its frame category, as one of: {*Solution, Problem Threat, Cause, Motivation*}. Figure 1.3 shows our multi-level multi-class problem for a given sentence. Next, we aim to mine climate-change related

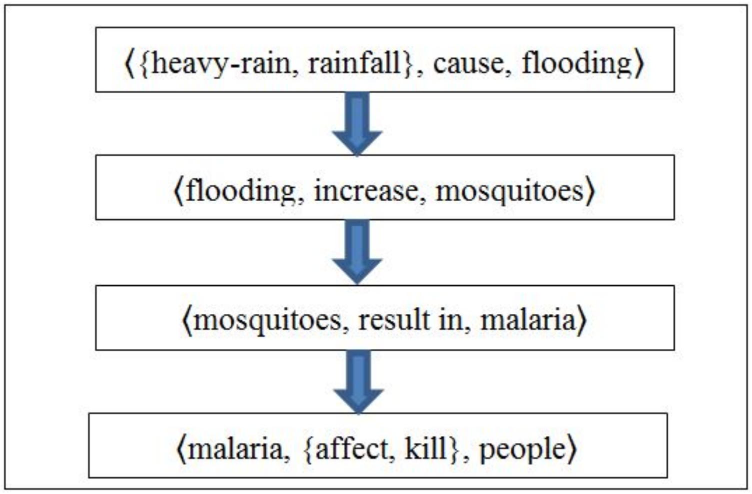

Figure 1.4 Example of Causal Chain of Concepts

sentences to derive spatially and temporally tagged causal relationships among events, effects, and impacts on actors. Figure 1.4 shows an example of this causal chain of concepts.

1.2 Challenges

1. **Incomplete sentences or informal English:** When extracting generalized concepts, the sentences have to be complete formal sentences so that <subject,verb, object> can be extracted. In other words, it might not be possible to use informal English dataset (such as Twitter) where users typically write in an informal way.

2. **Small Dataset size:** If the dataset is small, then the resultant generalized concepts will be sparse. Using a 10,000 documents dataset would yield more generalized concepts as compared to a 100 documents. The definition of "small" dataset is subjective, and as a rule of thumb we suggest a minimum of 1,000 documents.

1.3 The Contributions

Our unique contributions are threefold:

1. Extracting new textual features (Generalized Concepts) from large corpora and utilizing them in document classification.

2. Starting with a seed set of causal verbs, we apply a concept generalization technique to extract causal relationships and their participating actors automatically.

3. The ability to reveal the domino effect of climate change risks to human security within large corpora.

1.4 Thesis Structure

This dissertation is structured into several chapters as follows:

Chapter 2: Literature Review

This chapter reviews related work in media framing, framing research in computer science, and causal relationships.

Chapter 3: Methodology

In this chapter we show the components of our system: climate change corpus, pre-processing, feature extraction, supervised and unsupervised frame learning, and causal relationships extraction.

Chapter 4: Experimental Evaluation

After discussing our system, we show quantitative and qualitative evaluations. Subject matter experts analyzed the results and provided more insights.

Chapter 5: Conclusion and Future Work

Finally, we conclude the thesis and point out its limitations and directions for future work.

Chapter 2

LITERATURE REVIEW

2.1 Media Framing

Mainstream media serve as the main arena where international governments, social and political actors, scientists, social movement organizations interact and make competing claims about climate change issues (Hilgartner and Bosk, 1988). Communication surrounding climate change can inhibit or support science and policy interactions, propagate consensus or disagreements (Hulme, 2009), and ultimately facilitate social change (Boykoff, 2011; Moser and Dilling, 2006), depending on how messages about climate change have been framed (Boykoff, 2011).

Media representation of climate change plays a vital role in shaping ongoing policy discourse, public perception and attitudes. (Carvalho, 2007) suggests that prominent political actors frame climate risk for their own purposes, and align frames with their interests and perspectives through media feedback processes of representing climate change risk. Studies have shown that the lay people learn about climate change mainly through consuming mainstream media news (Brulle *et al.*, 2012). Consequently, (Nisbet, 2009) argued news media framing can catalyze public engagement and help trigger collective concern of climate change. Put differently, media framing is a powerful tool to highlight different aspects of the policy options, and promote specific interpretations or evaluations that influence decision making (Entman, 1993).

Existing typologies of climate change framing, focusing on dichotomous categories, are limited by their inability to link framing processes with movement interaction. We argue that, in order to understand how the media reflect different organizations interests in addressing climate change as a social problem, it is necessary to supplement the social movement focus on resource mobilization to framing processes of collective action problems. To do that, this study develops a nuanced typology for studying climate change framing and its adequacy for supporting social movements that would be necessary to overcome the collective action problem. Our typology provides a holistic map to evaluate how climate change media framing can enable appropriate social and policy actions that ultimately can mitigate risks of social unrest. We apply this framework to examine framing of climate change in media and social media texts collected from the Niger Basin region over seven months, from August 2014 to February 2015, using a novel coding technique to assess diagnostic, prognostic, and motivational framing described by (Benford and Snow, 2000) as the keys to effective social movements.

2.2 Framing Research in Computer Science

Jang et al. (Jang and Hart, 2015) examined the role of media framing in shaping public opinion expressed on twitter. In (Stalpouskaya and Baden, 2015), authors went further to distill agenda from news and link them to actions. Content analysis of frames in news is performed either by (1) manual frame coding by expert coders, which is costly and not scalable, or by (2) utilizing machine learning techniques to detect frames automatically after training a learning model (Burscher *et al.*, 2014). A line of related work has used word-level features to detect frames automatically in text. Odijk *et al.* (Odijk *et al.*, 2013) utilized bag of words, n-grams, and topic models to classify news articles and map them to a set of frames. Others, employed POS-tags (Baumer *et al.*, 2015) and named entities (Finkel *et al.*, 2005) as features to detect and classify frames. However, such works face limitations since their features may not generalize well to accommodate surface variations in text when different keywords are used for similar concepts. In (Ceran *et al.*, 2012), they experimented with triplet <subject,verb,object> based features to detect story paragraphs in extremists corpus and showed how these features performed better in classification compared to standard keyword based features. In (Ceran *et al.*, 2015), they developed generalized concepts which outperformed their previous work in detecting story paragraphs. In our work, we improved their generalized concepts and utilized them as features to detect and categorize frames in climate change corpus. We worked on sentence level classification and clustering compared to their paragraph level, which made the extraction of triplets more challenging. Therefore, we developed triple-extraction techniques where we can extract more features and incorporate a larger percentage of sentences into the learning model (i.e. 80% of sentences compared to 40%). Next, the extracted features are used in a multi-level multi-class learning model where we first examine if a sentence contains a frame, and then we identify which category of four frame categories it belongs to.

2.3 Causal Relationships

Previous studies on causality mining attempted to extract explicit cause-effect relations from text using hand-coded patterns (Joskowicz *et al.*, 1989; Kaplan and Berry-Rogghe, 1991). Two main drawbacks of this approach should be noted. It requires extensive human effort; it does not scale up for large corpora, limiting the predictive ability of forecasting long-term impacts brought by climatic risks.

Recent studies (Girju *et al.*, 2002; Chang and Choi, 2006) attempted to automate the extraction of causal relations using lexico-syntactic patterns within one sentence in the form of <NP-Cause, Verb, NP-effect>. Girju (Girju, 2003) proposed an enhancement of these patterns by searching causal verbs on the Internet and WordNet (Miller, 1995); results showed a precision of 73.91% for causality extraction. Chang and Choi (Chang and Choi, 2006) replaced Girju (Girju, 2003) causal verbs approach with "cue phrases" to link cause and effect events. They defined a cue phrase as "a word, a phrase, or a word pattern which connects one event to the other with some relation (e.g. caused by, because, as the result of)." The "cue phrases" approach showed a precision of 81% for extracting causality within one sentence. The limitation of these approaches is that they only extracted relations based on explicit causal verbs or phrases. Our system extracts both explicit and implicit causal relationships across multiple sentences.

Extracting causal chains of events is understudied. To our knowledge, Sizov and Öztürk (Sizov and Öztürk, 2013) made the first attempt to extract causal chains to explain an isolated event, limiting its generalization to inform the public of a threat multiplier that would cause substantial harm to basic needs and human security. The authors aimed to fill the reasoning graphs from aviation investigation related reports to understand the relationship between an aircraft incident and its root causes. In their approach, they extracted structural relations, similarity relations, and causal relations to derive a reasoning graph for a given incident. However, their approach does not unpack the causal relations between different events. Rather, it constructs the relations (Part of, Contains, Similar, and Cause) between different pieces of text, i.e. pairs of sentences. Our focus in this paper is novel in not only understanding entities involved in causing and being impacted by the inherent complexity of climate change, but also unpacking the cascading causal relationships.

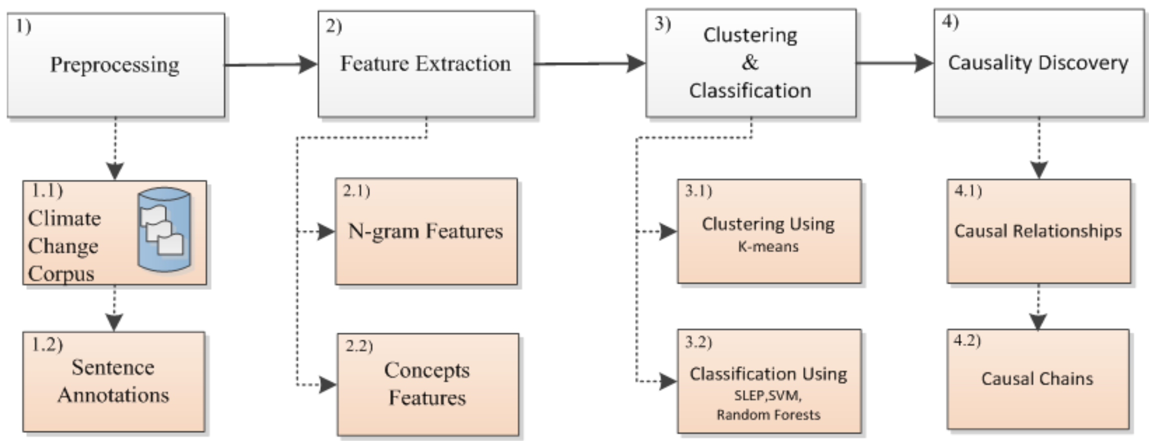

Figure 3.1 System Architecture

Chapter 3

METHODOLOGY

3.1 Overall System Model

Figure 3.1 shows the main components of our system. The overall system consists of documents collected from nearly 100 RSS feeds that are related to climate change in the Niger Delta region. We also perform sentence splitting of documents, identification of key frames and their categories by expert coders, feature extraction (uni-grams, bi-grams, and generalized concepts), identification of discriminative features, a predictive model to detect and identify the frame categories for sentences containing frame references, and a causality discovery model to mine causal relationships and construct their chains.

Table 3.1 Distribution of Sentences per Frame Category

Cause	**Problem Threat**	**Solution**	**Motivation**
2,542	7,595	4,509	1,404

3.2 Climate Change Corpus

Our climate change corpus is comprised of nearly $45,054$ sentences extracted from news and social media websites, that are related to climate change topics in the Niger Basin region over a seven month period from August, 1^{st} 2014 to February, 15^{th} 2015. There are $16,050$ sentences coded as *Frame* sentences and $29,004$ coded as *Non-Frame* sentences by domain experts. *Frame* sentences are further categorized into one of four categories: Solution, Problem Threat, Cause, and Motivation. Table 3.1 summarizes the distribution of sentences into the four categories.

3.3 Development of Four-class Typology of Media Framing

Existing typologies of climate change framing, focusing on dichotomous categories, are limited by their inability to link framing processes with movement interaction. We argue that, in order to understand how media reflect different organizations interests in addressing climate change as a social problem, it is necessary to supplement the social movement focus on resource mobilization to framing processes of collective action problems. To do that, this study develops a nuanced typology for studying climate change framing and its adequacy for supporting social movements that would be necessary to overcome the collective action problem. Our typology provides a holistic map to evaluate how climate change media framing can enable appropriate social and policy actions that ultimately can mitigate risks of social unrest. We apply this framework to examine framing of climate change in media and social media texts collected from the Niger Basin region, using a novel coding technique to assess diagnostic, prognostic, and motivational framing described by (Benford and Snow, 2000) as the keys to effective social movements.

3.3.1 Media Framing, Collective Action, and Social Movements

In the field of social movement studies, framing has primarily been used to discuss challenges of strategy formation that implementation activists face (Knight and Greenberg, 2011). Social movement scholars define framing as a process aimed at aligning movement meanings with the ideological perspectives of relevant audiences, including the general public, the media and policy makers (Benford and Snow, 2000) in order to produce action in support of ideological goals. Understanding climate change as a collective action problem makes a social movement approach to framing relevant, as framing "plays a central role in the need to mobilize resources, recognize and respond to opportunities and threats, and exercise pressure and influence by means of communication" (Knight and Greenberg, 2011). This approach moves the study of framing beyond the limits of previous research with its focus on dichotomies, and highlights instead the potential impact of overarching framing strategies. As a complex social issue requiring engagement with multiple stakeholders and audiences (e.g. international organizations, local governments, NGOs, scientists, and the general public), climate change in developing countries, such as West Africa, provides fertile ground on which to explore the effectiveness of framing in propelling social movements in response to collective action problems.

Benford and Snow (Benford and Snow, 2000) develop a typology of social movement frames to explore signification strategies in the context of collective action. The authors assert that the more central the framing is to the ideology of the targets of mobilization, the greater the hierarchical salience within their larger system of belief (Snow and Benford, 1992). This hierarchy relies on the concept of narrative fidelity (Fisher, 1984): The more a frame "rings true" to the audience, the greater the salience of the frame, and the more potential it carries to influence collective action. The authors argue that "frames help render events or occurrences meaningful and thereby function to organize and guide action" (Benford and Snow, 2000). This process occurs through the development, generation, elaboration, and contestation of three types of collective action frames: diagnostic, prognostic, and motivational.

The first type, diagnostic framing, seeks to remedy or alter some problematic situation or issue by identifying the source of causality, blame, and/or culpable agents (Benford and Snow, 2000). The second type, prognostic framing, attempts provide a solution or plan of attack for the identified problem. While the first two functions seek to create a consensus in the audience, the third, motivational framing, is a call to action. According to (Benford and Snow, 2000), motivational framing attempts to engage the audience in ameliorative collective action. That is, motivational frames supply the impetus for public actions that go beyond diagnosis and prognosis, and include compelling vocabularies of severity, urgency, efficacy, and propriety (Benford, 1993). To engage the public in solving social problems, organizations need to establish the severity of a particular situation, emphasize a sense of urgency of the threat, stress the likelihood of change or efficacy of taking actions, or highlight moral responsibility. This process occurs within a multi-organizational realm that includes opponents, audiences, media, bystanders, and within the organization itself.

We argue that messages encouraging collective action are most effective when they combine these three types of frames. While Benford and Snow (Benford and Snow, 2000) do not address this issue, a story combining problem, solution, and motivation touches all the elements of the narrative arc (Abbott, 2008), and is therefore more

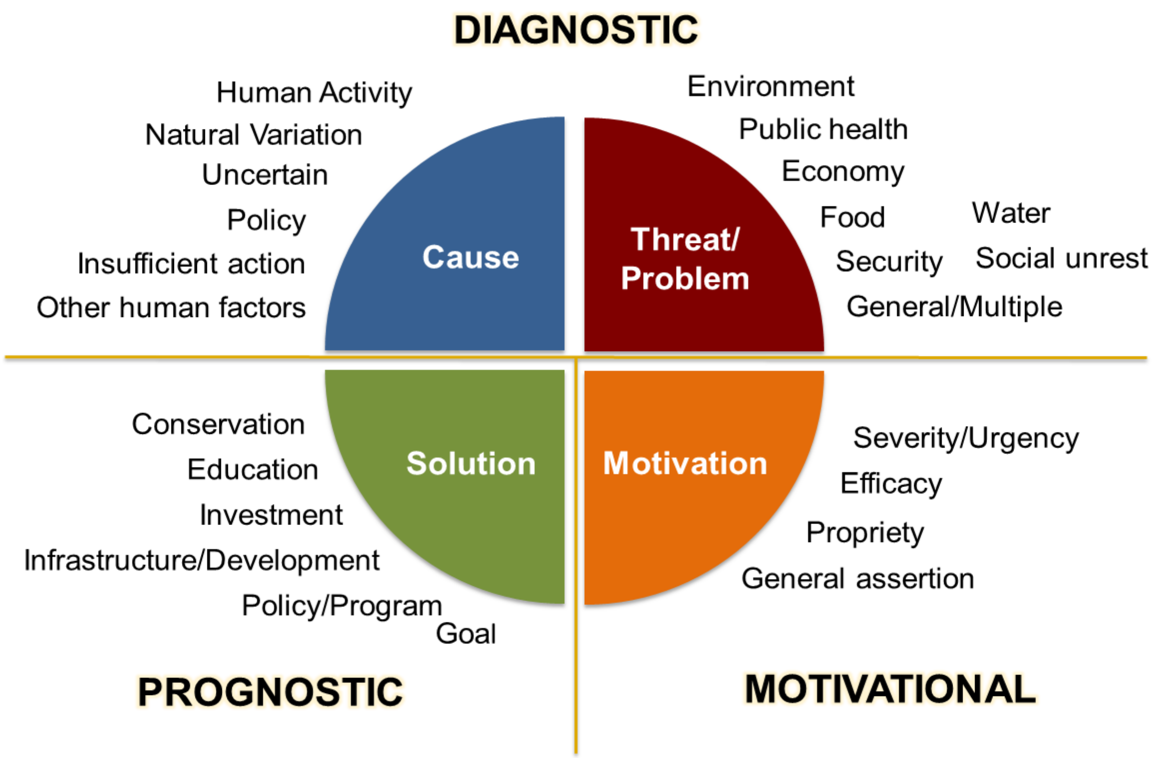

Figure 3.2 Four-class Typology

likely to be perceived as coherent (Fisher, 1984). Separating these elements in different messages relies on the audience to integrate them from different sources, a process vulnerable to effects of memory and involvement.

3.3.2 A Four-class Typology of Media Framing

Drawing from Benford and Snow (Benford and Snow, 2000) collective action frames for social movements, Tsai *et al.* (Tsai *et al.*, 2015) developed a four-class typology of climate change framing to capture three functions: diagnostic, prognostic, and motivational. As discussed earlier, those three functions of framing play an essential role in social actors' resource mobilization and participation in the political processes. Guided by Benford and Snow's framework, Tsai *et al.* (Tsai *et al.*, 2015) also incorporated and modified a handful of common frames applicable to climate change identified from prior research (e.g. (Nisbet, 2009), (ONeill *et al.*, 2015)). To ensure that the four-class typology captured a full spectrum of possible frames that emerged from the West African media discourse, they further adopted an inductive approach based on a preliminary scanning of relevant texts. The final typology consisted of four framing classes and a set of twenty-five subcategories germane to climate change impacts and solutions.

Figure 3.2 provides an overview of four-class typology. Though Benford and Snow (Benford and Snow, 2000) identify three classes of frames, (Tsai *et al.*, 2015) split the diagnostic frame into two sub-classes, cause and problem threat to capture the special diagnostic attention paid to causes in the climate change debate. Though West African discourse is likely different from Western discourse in this regard, singling out cause framing for special attention would provide maximum applicability of the four-class typology to other geographic contexts, and maintain a future basis for comparative analysis.

3.4 Feature Extraction

3.4.1 N-gram Features

As a baseline model, we experimented with both uni-gram and bi-gram features. We run a simple term frequency - inverse document frequency (TF-IDF) (Hartigan and Wong, 1979) based technique on the entire corpus to generate a large ranked list of stopword-eliminated uni-grams and bi-grams, and we experimented with them separately as features in our learning models.

3.4.2 Generalized Concepts Features

In (Ceran *et al.*, 2015), they extracted concepts from paragraphs where only 40% of the paragraphs generated concepts. In this thesis, since we are working on sentence level, we improved the concept extraction approach, by extracting more triplets by utilizing a larger number of triplet extractors and pre-processing their output to include about 80% of the sentences in our experimental evaluations.

Triplets Extraction

In order to extract <*subject,verb,object*> triplets, first we resolve co-references in the entire corpus using four state-of-the-art pronoun resolvers (Raghunathan *et al.*, 2010), (Lee *et al.*, 2011), (Lee *et al.*, 2013), (Recasens *et al.*, 2013). Since triplets extraction is an ongoing research topic in NLP, we proceeded to use four state-of-the-art triplets extraction tools: ClearNLP (Choi, 2012), Reverb (Fader *et al.*, 2011), Everest (EVE, 2013), AlchemyAPI (Alc, 2015) as complementary systems. Additionally, any triplet slots with phrases were segmented into stopword-removed keywords, and their Cartesian product were produced as additional triplets.

Concepts Generation

Triplets extraction algorithms typically produce noisy and sparse triplets. Therefore, we apply a hierarchical bottom-up clustering algorithm that generalizes triplets into more meaningful relationships. First, we apply a contextual synonyms algorithm (Section 3.4.2) to create the initial set of concepts C_0. Next, we cluster the concepts along with triplets based on both *syntactic* and *semantic* criteria (Section 3.4.2) to generalize them into high level concepts without *drift*.

Contextual Synonyms We create the initial set of concepts C_0 by finding three separate pairwise contextual similarity matrices for subjects, verbs and objects based on their co-occurrences with verb-object, subject-object, and subject-verb pairs respectively. In algorithm 1, the first *for-loop* (lines 3–5) iterate over all <subject,verb, object> triplets and create a list of unique <subject,verb>, <verb,object> and <subject,object> pairs. The next three *for-loops* iteratively expand the concept set C_0 by adding a unique pair along with a set of all co-occurring words.

Algorithm 1 Find concepts with unique pairs

1: **procedure** FIND CONCEPTS W/ UNIQUE PAIRS(T)

2: C_{sv}, C_{vo}, $C_{so} \leftarrow \emptyset$

3: **for all** $\langle s_i, v_j, o_k \rangle \in T$ **do**

4: Find and add unique pairs to:

$C_{sv} \leftarrow C_{sv} \cup \{\langle s_i, v_j \rangle\}$

$C_{vo} \leftarrow C_{vo} \cup \{\langle v_j, o_k \rangle\}$

$C_{so} \leftarrow C_{so} \cup \{\langle s_i, o_k \rangle\}$

5: **end for**

6: **for all** $\langle s_i, v_j \rangle \in C_{sv}$ and $\langle s_i, v_j, o_k \rangle \in T$ **do**

7: $C_0 \leftarrow C_0 \cup \{\langle s_i, v_j, O \rangle\}$ where $o_k \in O$.

8: **end for**

9: **for all** $\langle v_j, o_k \rangle \in Y$ and $\langle s_i, v_j, o_k \rangle \in T$ **do**

10: $C_0 \leftarrow C_0 \cup \{\langle S, v_j, o_k \rangle\}$ where $s_i \in S$.

11: **end for**

12: **for all** $\langle s_i, o_k \rangle \in Z$ and $\langle s_i, v_j, o_k \rangle \in T$ **do**

13: $C_0 \leftarrow C_0 \cup \{\langle s_i, V, o_k \rangle\}$ where $v_j \in V$.

14: **end for**

15: **end procedure**

Algorithm 2 Calculate contextual similarity

procedure CALCULATE CONTEXTUAL SIMILARITY(C_0)
    $Sim_S, Sim_V, Sim_O \leftarrow 0$
    for all $c \in \mathcal{C}_0$ **do**
        if $c = \langle S, v, o \rangle$ **then**
            $Sim_S(i,j) \leftarrow Sim_S(i,j) + 1, \forall s_i, s_j \in S.$
        else if $c = \langle s, V, o \rangle$ **then**
            $Sim_V(i,j) \leftarrow Sim_V(i,j) + 1, \forall v_i, v_j \in V.$
        else if $c = \langle s, v, O \rangle$ **then**
            $Sim_O(i,j) \leftarrow Sim_O(i,j) + 1, \forall o_i, o_j \in O.$
        end if
    end for
end procedure

Next, we apply a corpus-based contextual similarity measure in algorithm 2 to calculate pairwise contextual similarity for subjects, verbs and objects in C_0. We create similarity matrices Sim_S for subjects, Sim_V for verbs, and Sim_O for objects. The similarity between a pair of words is defined as the number of common co-occurring unique contexts, i.e. if any of the two subjects, verbs or objects appear with the same verb-object, subject-object or subject-verb pair respectively, then we increase similarity count between two words by one.

Clustering Concepts and Triplets In order for the information to propagate between clusters of relations, we apply a hierarchical bottom-up clustering algorithm (Kok and Domingos, 2008). High level concepts and relations are merged to form clusters. In algorithm 3, each concept in C_0 is compared with the rest in order to create a set of candidates for merging based on the syntactic criteria described in the next section. Next, we process each candidate concept and prune the words that do not satisfy the semantic criteria described in the following sections. Iteratively, we expand our candidate concepts by adding the elements that satisfy both criteria.

Algorithm 3 Bottom-Up Clustering Algorithm

CLUSTER CONCEPTS$(T, Sim_S, Sim_V, Sim_O, C_0)$
    $C \leftarrow C_0$
    while $flag = 1$ **do**
        $flag \leftarrow 0$
        for all $c \in C_0$ **do**
            Find related concepts C_r using ***Syntactic Criteria***
            if $|C_r| \geq 1$ **then**
                $flag \leftarrow 1$
                for all $r \in C_r$ **do**
                    $\{c\} \leftarrow \{c\} \cup \{r\}$
                    Prune c using ***Semantic Criteria***.
                    $C \leftarrow C \cup \{c\}$
                end for
            end if
        end for
    end while
end

Syntactic Criteria: To allow for meaningful merging of related concepts, we only merge concepts that have a common context in all semantic arguments (i.e. subject, verb, object). For example, given two concepts $C_1 = \langle \{s_1, s_2\}, v_1, o_1 \rangle$ and $C_2 = \langle s_1, v_1, \{o_1, o_2\} \rangle$, we can merge them into a more generalized concept $C_3 =$

$\langle \{s_1, s_2\}, v_1, \{o_1, o_2\} \rangle$. To justify this merge: 1) C_3 adds a new object, o_2, to C_1; thus, C_1 and C_2 must have a common context, i.e. the intersection of C_1 and C_2 subject and verb sets, $\{S_1 \cap S_2\}$ and $\{V_1 \cap V_2\}$, is not empty, and 2) C_3 adds a new subject, s_2, to c_2 subject set; thus, the intersection of C_1 and C_2 verb and object sets, $\{V_1 \cap V_2\}$ and $\{O_1 \cap O_2\}$, should be not empty. In general, the syntactic criteria is defined as follows:

Two concepts $C_1 = \langle S_1, V_1, O_1 \rangle$ and $C_2 = \langle S_2, V_2, O_2 \rangle$ are merged if the following is satisfied:

- $\{S_1 \cap S_2 = \emptyset\}$ and $\{V_1 \cap V_2 \neq \emptyset\}$ and $\{O_1 \cap O_2 \neq \emptyset\}$
- $\{V_1 \cap V_2 = \emptyset\}$ and $\{S_1 \cap S_2 \neq \emptyset\}$ and $\{O_1 \cap O_2 \neq \emptyset\}$
- $\{O_1 \cap O_2 = \emptyset\}$ and $\{S_1 \cap S_2 \neq \emptyset\}$ and $\{V_1 \cap V_2 \neq \emptyset\}$

Semantic Criteria: We apply semantic criteria to ensure that only the most similar candidate keywords can be added to the expanded concept. This would allow the concepts to grow without drift. The criteria utilizes the contextual similarity measure (algorithm 2) that relates subjects, verbs, and objects among themselves. The semantic criteria is defined as follows:

We merge two concepts $C_1 = \langle S_1, V_1, O_1 \rangle$ and $C_2 = \langle S_2, V_2, O_2 \rangle$ into a third concept C_3 as follows:

- C_3 initially contains the intersection of C_1 and C_2 (i.e. $S_3 = \{S_1 \cap S_2\ \}$, $V_3 = \{V_1 \cap V_2\ \}$, $O_3 = \{O_1 \cap O_2\ \}$)
- we expand C_3 by adding words from the complement of C_2 and C_3 that are among the closest contextual synonyms of words in the initial intersection sets (i.e. for C_3 subjects we add from $(S_1 \setminus S_2) \cup (S_2 \setminus S_1)$), and similarly for C_3 verbs and objects).

3.5 Unsupervised Frame Learning

Unsupervised learning aims to draw inferences from given dataset where labels (i.e. classes) are hidden or unknown. It focuses on how the model can learn to represent particular input patterns in a way that reflects the statistical structure of the dataset. We utilized this approach to assist in benchmarking different features: generalized concepts, uni-grams and bi-grams in the clustering process. Our goal is to investigate which feature set will produce the best clusters. In unsupervised learning, comparing different features sets will give a hint about the best feature set to be used in the classification task. Additionally, unsupervised learning will help us in determining whether the rationale and theoretical background for the development of four frame categories will align with our dataset or not. Utilizing k-means (Arthur and Vassilvitskii, 2007) we cluster the entire dataset into two clusters to see if they form *Frame/Non-Frame* clusters, and then the *Frame* sentences are clustered into four clusters mimicking the four frame categories {Solution, Problem Threat, Cause, and Motivation}.

3.6 Supervised Frame Learning

To classify each sentence as *Frame/Non-Frame* and identify its relevant frame category we utilize sparse learning framework (Liu *et al.*, 2009a), with the underlined motivation to select a subset of discriminating concepts that can (1) identify sentences containing frame references and (b) classify a sentence into a frame category. The following steps describe our algorithm:

1. Generate features from the entire corpus
2. Filter the features $\times$ sentences matrix to include only resultant generalized concepts/features

3. Formulate the problem in a general sparse learning framework (Liu *et al.*, 2009a). In particular, the logistical regression formulation presented below fits this application, since it is a dichotomous frame classification problem (i.e. each sentence classified as *Frame/Non-Frame*), and multi-class classification problem (i.e. each *Frame* sentence is further classified as one of four frames {Solution, Problem Threat, Cause, and Motivation}):

$$\min_x \sum_{i=1}^{m} w_i \log(1 + \exp(-y_i(x^t a_i + c))) + \lambda|x| \tag{3.1}$$

In formula 3.1, a_i is the vector representation of the i^{th} sentence, w_i is the weight assigned to the i^{th} sentence ($w_i = 1/m$ by default), and $A = [a_1, a_2, \ldots, a_m]$ is the features $\times$ sentences matrix, y_i is the label of each sentence, and the x_j , the j^{th} element of x, is the unknown weight for each feature, ($\lambda \geq 0$) is a regularization parameter that controls the sparsity of the solution, $|x|_1 = \sum |x_i|$ is 1-norm of the x vector. We used the SLEP (Liu *et al.*, 2009b) sparse learning package that utilizes the gradient descent approach to solve the above convex and non-smooth optimization problem. The features with non-zero values on the sparse x vector yield the discriminant factors for classifying a sentence.

3.7 Causality Discovery

3.7.1 Causal Relationship Extraction

Simple Causatives Model

Our baseline model for extracting causal relationships is based on “Simple Causatives.” In linguistics, Nedjalkov and Silnickij (Nedjalkov and Silnickij, 1973) categorized causative verbs into:

Table 3.2 List of Simple Causative Verbs (V_{simple})

Simple Causatives Verbs			
cause	result in	raise	lead to
produce	create	bring about	begin
originate	engender	spawn	occasion
affect	bring to	bring on	precipitate
prompt	provoke	kindle	trigger
make	spark	touch off	stir up
whip up	induce	inspire	promote
increase	foster	generate	

- *Simple causatives*: linking verbs that explicitly express causal links, typically synonyms of "cause". An example of simple causatives is: *fossil-fuel causes greenhouse gases.*

- *Resultative causatives*: linking causal verbs that include resulting situations, e.g. kill (cause death). Some examples from our data are: *extreme weather events kill more people each year.*

- *Instrumental causatives*: linking causal verbs that include an event and its result, e.g. poison (kill by poisoning). For example: *heavy rainfall flooded homes.*

In the baseline model we use simple causative verbs [1] in table 3.2 to extract explicit causal relationships.

[1]Oxford English dictionary online

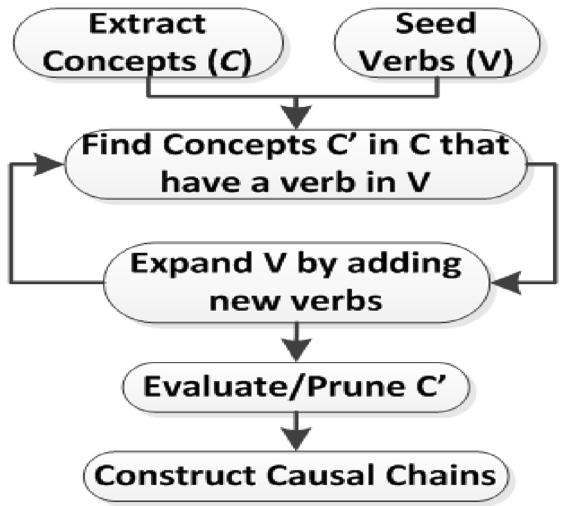

Figure 3.3 Main Components of the Concepts Based Model

Concepts Based Model

Figure 3.3 shows the main components of our system to extract causal relationships. The system comprises of novel techniques to extract *generalized concepts*, identify concepts with causal relationships, and lastly construct causal chains. We will describe each component in detail.

In the baseline model we utilized only explicit causal verbs which could result in limited recall because standard causal verbs may not generalize well to accommodate surface variations in texts when different keywords and phrases are used to express similar causal effects. Therefore, we apply our concepts generalization algorithm (discussed in section 3.4.2) to extract generalized concepts and utilize them to mine causal relationships. Our algorithm for the automatic discovery of causal relationships and chains is based on the extraction of inter- and intra- sentential patterns of the form <subjects,verbs,objects>. The proposed model is able to extract explicit and implicit causal relationships from text.

For each of the four frame categories we apply the following procedure:

1. Start with a seed set of simple causative verbs $\boldsymbol{V}$=V_{simple} to get all concepts $\boldsymbol{C}$=$\{c_1,c_2,...,c_q\}$ that contain at least one simple causative verb.

2. Add to the set $\boldsymbol{V}$ the verbs $\{v_1,v_2,..., v_k\}$ that are in concept $c_i \in \boldsymbol{C}$.

3. Extract the concepts that contain verb $v_j \in \boldsymbol{V}$ and add them to the set $\boldsymbol{C}$.

4. Repeat 2 and 3 until no further verbs and concepts are added to their sets.

In the above algorithm, we start a seed set of simple causative verbs (table 3.2) and iteratively expand it in step 2 by adding more verbs, and in step 3 we extract more concepts based on these verbs. We repeat until the sets do not change. This greedy algorithm has a worst case time complexity of $O(n)$, where n is the number of concepts. For all four frame categories, the algorithm requires less than 100 steps of iterations to reach convergence.

Next, we evaluate the extracted concepts $c_i \in \boldsymbol{C}$ to keep only causative related ones based on algorithm 4. In this procedure, line 2 checks if a concept contains at least one simple causative verb. If that criterion is met, the concept is retained. Otherwise (lines 3 to 11), we evaluate its verbs to determine if any of them is semantically similar to a simple causative verb with similarity score above 0.5 (range is in [0,1]). When we set this threshold to higher values, results become more sparse. When we use lower values threshold, results become more noisy. Similarity score is computed using the UMBC Semantic Similarity measurement (Han *et al.*, 2013). If none of the verbs are similar to a simple causative, its concept is removed accordingly.

Algorithm 4 Concepts Evaluation

procedure CONCEPTS EVALUATION(C)

    for each $c_i \in C$ **do**:

    if $v_i \cap V_{simple} \neq \emptyset$ where $v_i \in c_i$, **then**, keep c_i

    else, evaluate each verb $v_{ij} \in c_i$ by applying the following Semantic Constraints:

        Set FLAG=0

        for each verb $v_{ij} \in c_i$ **do**:

        find top N semantically similar verbs (V_N) with similarity score > 0.5

        if $V_N \cap V_{simple} \neq \emptyset$, **then** FLAG=1, **break**

        end if

        end for

        if FLAG=0, **then** remove concept c_i from C

        end if

    end if

    end for

end procedure

3.7.2 Causal Chains Construction

Once we extract and evaluate the set of concepts $\boldsymbol{C}$ for each frame category, we construct the causal chains (algorithm 5). In this iterative procedure, we start with a concept C_s and connect it to the next concept C_t if the two conditions (lines 5 to 7) are satisfied: 1) the intersection of Objects set O_s of C_s and Subjects set S_t of C_t is not empty, and 2) their semantic similarity is the maximum compared to other concepts other than C_t. As suggested above, the similarity between the two sets of connected concepts (O_s ,S_t) are measured by using UMBC Semantic Similarity (Han *et al.*, 2013).

Algorithm 5 Construct Causal Chains

1: **procedure** CAUSAL CHAINS(C)

2: **for each** $c_s \in C$ **do**:

3: find all acyclic paths that start from c_s:

4: $c_s \rightarrow c_t \rightarrow c_b \rightarrow \ldots$ such that concept c_s is connected to $c_t \in C$ - $\{c_s\}$, if the following is satisfied:

5: $O_s \cap S_t \neq \emptyset$

6: AND

7: $max_{s \neq t}$ sim(O_s,S_t)

8: **end for**

9: **end procedure**

Chapter 4

EXPERIMENTAL EVALUATION

4.1 Sentence Annotation

Our experts developed four categories of climate change related frames as follows:

- **Solution framing (prognostic)**: Covering the prognostic function of defining what should be done about problems, *solution* framing refers to actions taken to prevent further impact of climate change effects or further impact of the causes of climate change, such as greenhouse gas emissions. Solutions can also emphasize ongoing measures to deal with existing effects of climate change. Six frames capture an array of mitigation and adaptation efforts: conservation, education, investment, infrastructure and development, creation or implementation of policy and programs, and goal.

- **Problem Threat framing (diagnostic)**: This diagnostic framing class stresses on how climate change or outcomes of climate change impact various actors, industries, human health, and the environment. Eight codes capture negative consequences and threats brought by climate change, including environmental systems and ecosystem, public health, economic development, food security, water scarcity, national security, social unrest, and general or multiple impacts. Both *cause* framing and *problem threat* framing comprise the diagnostic function in defining social problems.

- **Cause framing**: This group of diagnostic frames focus on attributing the blame for causing climate change to either human activity, natural variation or other reasons. Six subcategories captured different explanations for causal attribution of climate change: (a) human activity, (b) natural variation, (c) scientific uncertainty, (d) policy causes, (e) insufficient actions, and (f) human disruption to mitigate climate change impact.

- **Motivation framing (motivational)**: Motivational framing refers to statements that explicitly call for definitive course(s) of action and explain why the audience should make an effort to enact solutions (Benford and Snow, 2000). In other words, *motivational* frames elaborate on the rationale for action that goes beyond diagnosis and prognosis, and include vocabularies of severity, urgency, efficacy, and propriety (Benford, 1993). We added a general category to analyze statements that call for actions without providing readers with above-mentioned reasons.

We assigned sentence annotation to three different expert coders. To evaluate the agreement between coders we utilize Fleiss' Kappa measure (Fleiss, 1971). We define the following variables:

n= the number of sentences,

k= the number of frame categories,

m=the number of coders for each sentence.

For each sentence i=*1,2,...,n* and frame category j= *1,2,...,k*, let x_{ij} the number of coders that annotated sentence i with frame category j. The proportion of pairs of coders that agree in their annotation of sentence i is defined as:

$$p_i = \frac{\sum_{j=1}^{k} x_{ij}(x_{ij}-1)}{m(m-1)} = \frac{\sum_{j=1}^{k} x_{ij}^2 - \sum_{j=1}^{k} x_{ij}}{m(m-1)} = \frac{\sum_{j=1}^{k} x_{ij}^2 - m}{m(m-1)} \tag{4.1}$$

The average of p_i is then,

$$p_a = \frac{1}{n} \sum_{i=1}^{n} p_i \tag{4.2}$$

We calculate the error p_e as follows:

$$p_\varepsilon = \sum_{j=1}^{k} q_j^2 \tag{4.3}$$

$$where\ q_j = \frac{1}{mn} \sum_{i=1}^{n} x_i j \tag{4.4}$$

The Fleiss' Kappa is therefore,

$$k = \frac{p_a - p_\varepsilon}{1 - p_\varepsilon} \tag{4.5}$$

For *Frame/Non-Frame* annotation, the percentage of agreement is 0.93 and the Fleiss' Kappa value is 0.9, indicating strong (almost perfect) inter-coder agreement (Landis and Koch, 1977). For the four frame categories *Solution, Problem threat, and Cause*, the percentage of agreement is 0.87 and the Fleiss' Kappa value is 0.8, indicating substantial inter-coder agreement (Landis and Koch, 1977).

4.2 Unsupervised Frame Learning

Experimenting with unsupervised learning reveals dataset structure and can infer relations among data points. In this experiment, we ignored labels and clustered our dataset using three sets of features (i.e. uni-gram keywords, bi-gram terms, and generalized concepts) separately as features, and the k-means (Arthur and Vassilvitskii, 2007) as a clustering algorithm. We experimented with different k values and found the best results when k=2 for the entire dataset, and k=4 for the *Frame* sentences. To evaluate k-means clustering results, we utilized SSE (sum of squared error), purity, precision, recall, and F-measure.

Table 4.1 Clustering into Two Clusters

Method	SSE	Purity
Concepts	**54,322.08**	**0.91**
Bi-grams	720,044.21	0.71
Uni-grams	306,124.03	0.68

Table 4.2 Clustering into Four Clusters

Method	SSE	Purity
Concepts	**34,397.75**	**0.98**
Bi-grams	139,124.43	0.91
Uni-grams	292,812.30	0.51

Table 4.1 shows the SSE and purity for clustering the entire dataset into two clusters using different features. Using generalized concepts as features, the resultant SSE (54,322.08) and purity (0.91) outperform those with uni-grams, SSE (306,124.03) and purity (0.68) as well as bi-grams, SSE (720,044.21) and purity (0.71).

Table 4.2 presents the SSE and purity for clustering the frame sentences into four clusters using different features. Using generalized concepts as features, the resultant SSE (34,397.75) and purity (0.98) outperform those with uni-grams, SSE (292,812.30) and purity (0.51) as well as bi-grams, SSE (139,124.43) and purity (0.91).

Since we know the labels, the unsupervised frame learning can also be evaluated using precision, recall, and F-measure. According to (Zafarani *et al.*, 2014), in clustering, precision is defined as the fraction of pairs that were correctly assigned to the same cluster. Recall is defined as the fraction of pairs that were assigned to the same cluster among the pairs that should be in the same cluster. To compute *Precision, Recall, and F-measure* for Frame/Non-Frame clustering (i.e. clustering the entire dataset into two clusters) we compute TP, FP, FN, and TN based on the proposed method in (Zafarani *et al.*, 2014) as follows:

Clustering the entire dataset into two clusters using concepts yielded the following clusters. In cluster 1, there are 14,591 sentences labeled as Frame sentences, and 2,611 sentences labeled as Non-Frame sentences. In cluster 2, there are 26,393 sentences labeled as Non-Frame sentences and 1,459 sentences labeled as Frame sentences.

To compute TP, we calculate the number of pairs that have the same label and are clustered in the same cluster:

$$TP = \underbrace{(\binom{14591}{2} + \binom{2611}{2})}_{\text{cluster 1}} + \underbrace{(\binom{26393}{2} + \binom{1459}{2})}_{\text{cluster 2}} = 459,194,339$$

To compute FP, we calculate the number of dissimilar pairs that are in the same cluster:

$$FP = \underbrace{(14591 * 2611)}_{\text{cluster 1}} + \underbrace{(26393 * 1459)}_{\text{cluster 2}} = 76,604,488$$

To compute FN, we calculate the similar labels that are in different clusters:

$$FN = \underbrace{(14591 * 1459)}_{\text{Frame label}} + \underbrace{(26393 * 2611)}_{\text{Non-Frame label}} = 90,200,392$$

For TN, we calculate the number of dissimilar pairs in different clusters:

$$TN = \underbrace{(14591 * 26393) + (2611 * 1459)}_{\text{clusters 1 and 2}} = 388,909,712$$

Table 4.3 Clustering into Two Clusters: Precision, Recall, and F-measure

Method	Precision	Recall	F-measure
Concepts	**0.86**	**0.83**	**0.85**
Bi-grams	0.62	0.58	0.60
Uni-grams	0.60	0.57	0.58

Next, we compute precision, recall , and F-measure for clustering the entire dataset into two clusters as follows:

$$Precision = \frac{TP}{TP + FP} = 0.86$$

$$Recall = \frac{TP}{TP + FN} = 0.83$$

$$F - measure = 2.\frac{P.R}{P + R} = 0.85$$

Table 4.3 presents the precision, recall and F-measure for clustering the entire dataset into two clusters using different features. Using generalized concepts as features, the resultant F-measure of 85% outperforms those with uni-grams (58%) and bi-grams (60%), respectively.

Similarly, table 4.4 reports the precision, recall and F-measure for clustering the frame sentences into four clusters using different features. Using generalized concepts as features, the resultant F-measure of 97% outperforms those with uni-grams (37%) and bi-grams (89%), respectively.

Table 4.4 Clustering into Four Clusters: Precision, Recall, and F-measure

Method	Precision	Recall	F-measure
Concepts	**0.98**	**0.96**	**0.97**
Bi-grams	0.85	0.94	0.89
Uni-grams	0.38	0.36	0.37

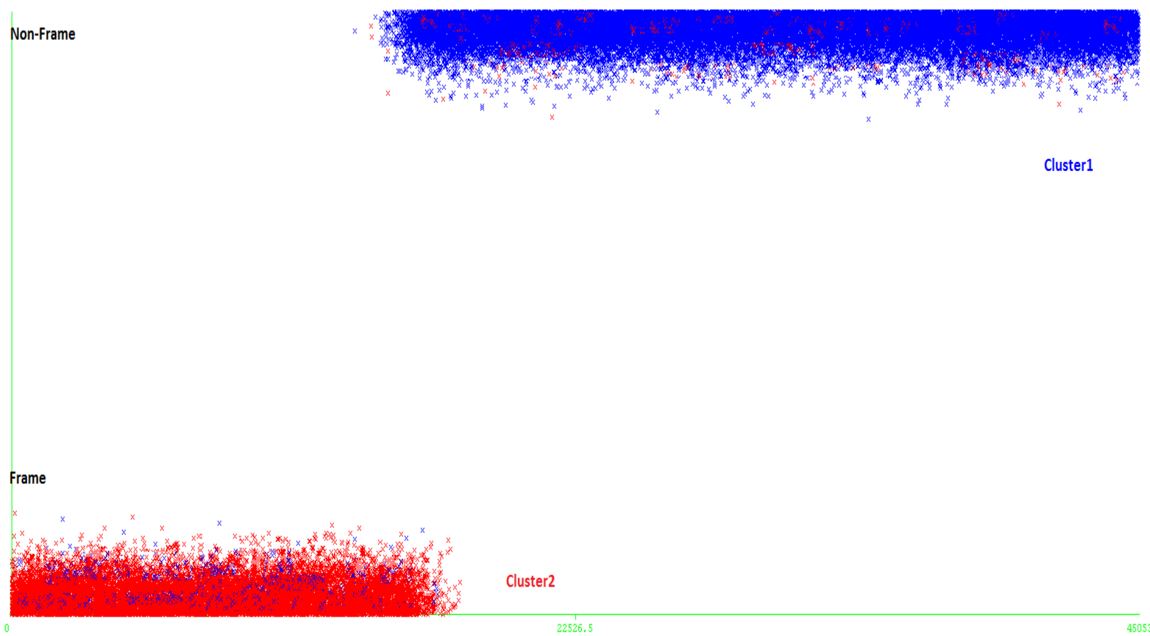

Figure 4.1 Clustering All Sentences into Two Clusters Using Concepts

Figures 4.1, 4.2, and 4.3 show the resultant clusters of the entire dataset into two clusters using concepts, bi-grams, uni-grams as features, respectively. In these figures we have the ground truth (i.e. which sentence belongs to which label) by using sentence *id* in x-axis and the corresponding label in y-axis. Cluster 1 corresponds to Non-Frame sentences, and cluster 2 represents Frame sentences. From these figures, we can see that clustering using concepts yielded better and more pure clusters compared to bi-grams and uni-grams.

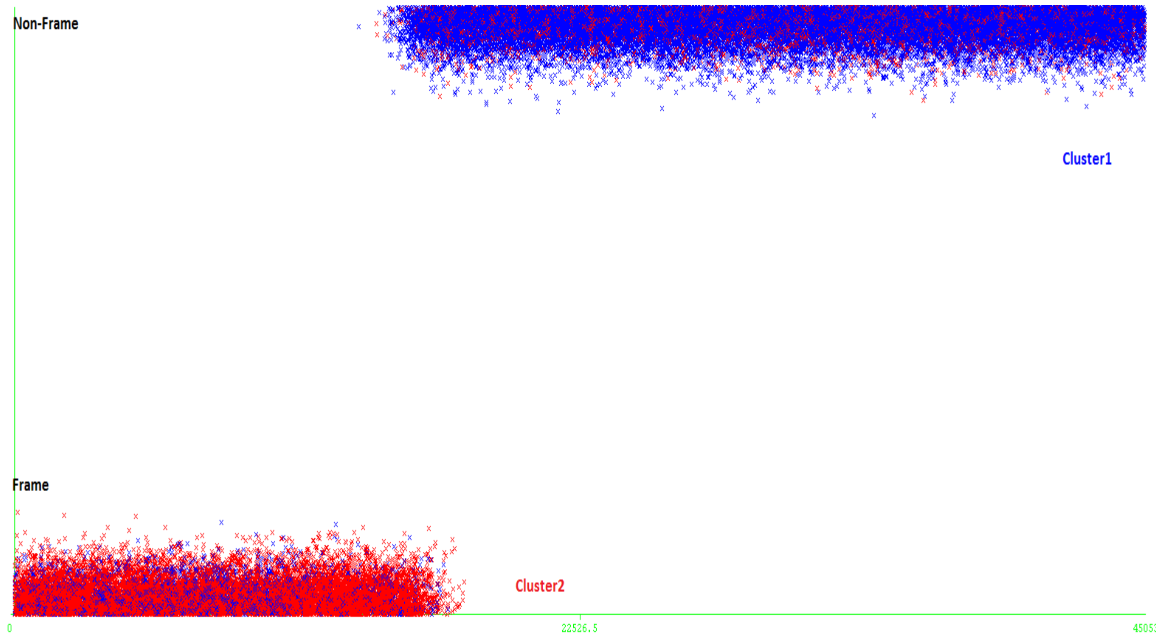

Figure 4.2 Clustering All Sentences into Two Clusters Using Bi-grams

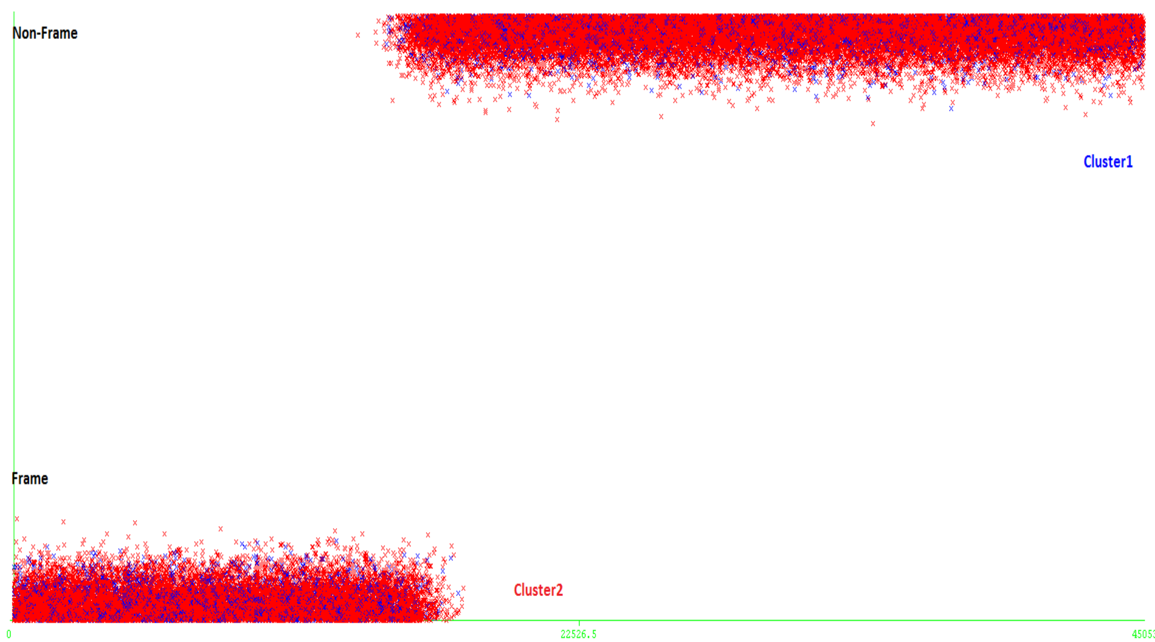

Figure 4.3 Clustering All Sentences into Two Clusters Using Uni-grams

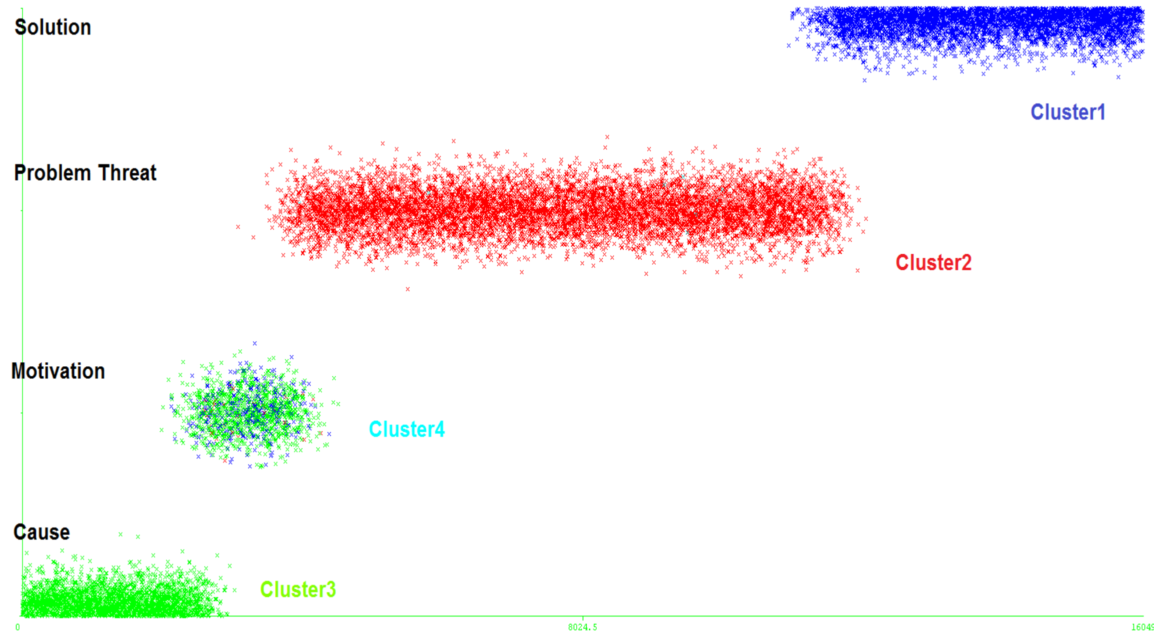

Figure 4.4 Clustering Frame Sentences into Four Clusters Using Concepts

Figures 4.4, 4.5, and 4.6 show the resultant clusters of frame sentences using concepts, bi-grams, uni-grams as features, respectively. Clustering frame sentences using concepts yielded better and more pure clusters compared to bi-grams and uni-grams. In figure 4.4 the three clusters (1,2,3) corresponding to frames *Solution, Problem threat,* and *Cause* are well clustered in terms of purity. The *Motivation* frame in cluster 4 is a mixture of the other three clusters (1,2,3). Our interpretation for this impurity is that in motivational framing, typically people show the cause of a problem and propose a solution. As a result, a sentence belonging to motivation frame category could carry other frame categories *Solution, Problem threat,* and *Cause.*

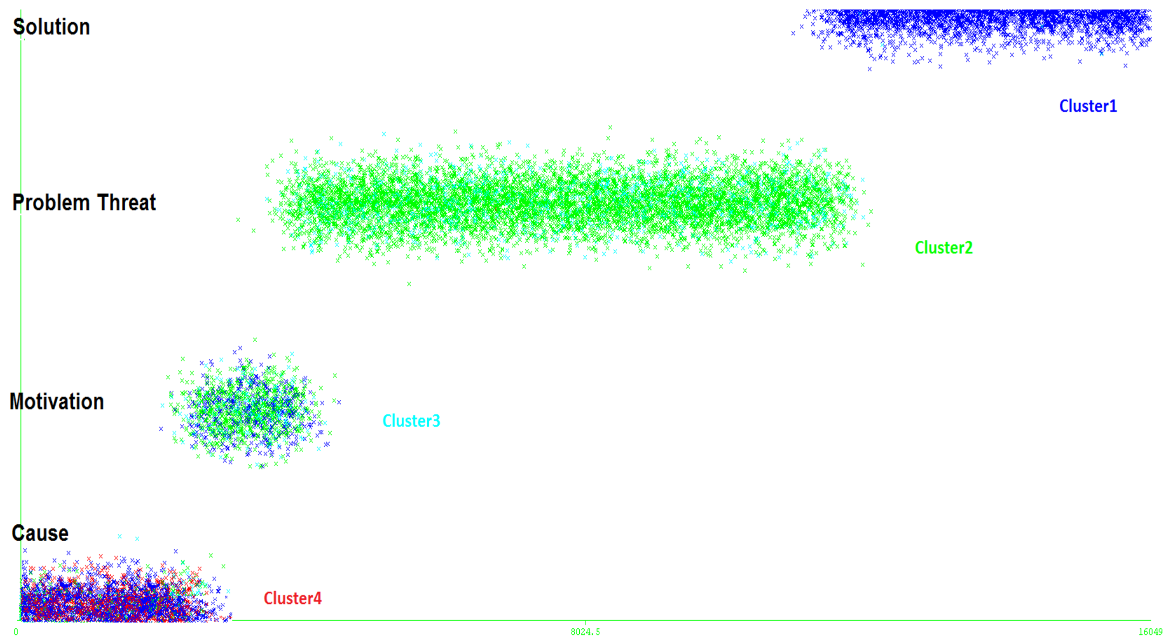

Figure 4.5 Clustering Frame Sentences into Four Clusters Using Bi-grams

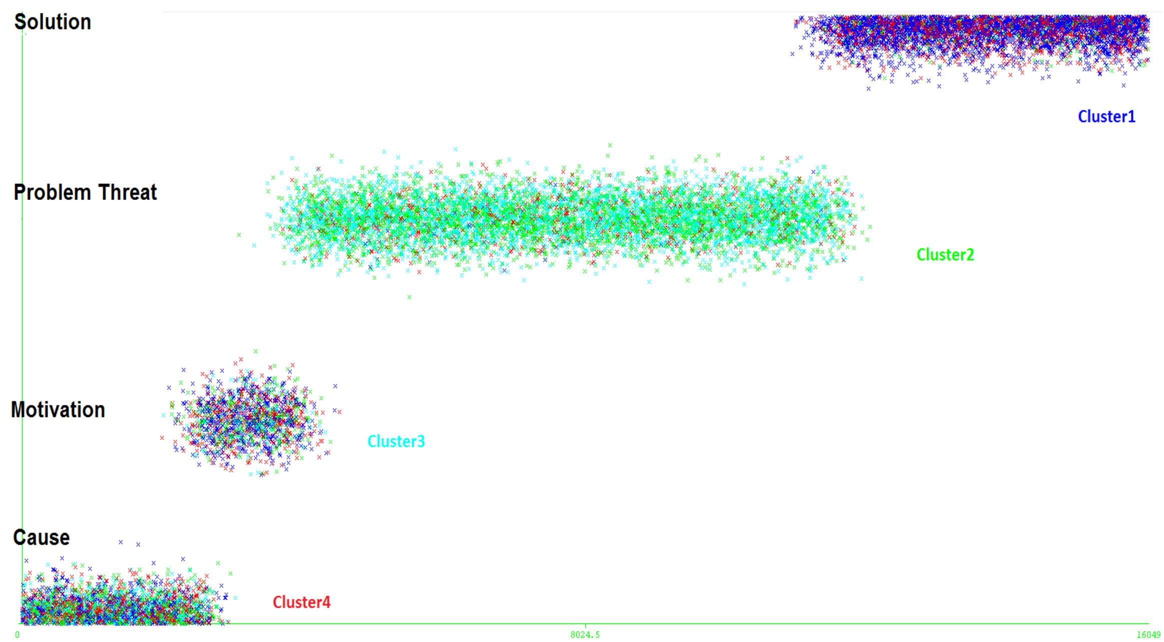

Figure 4.6 Clustering Frame Sentences into Four Clusters Using Uni-grams

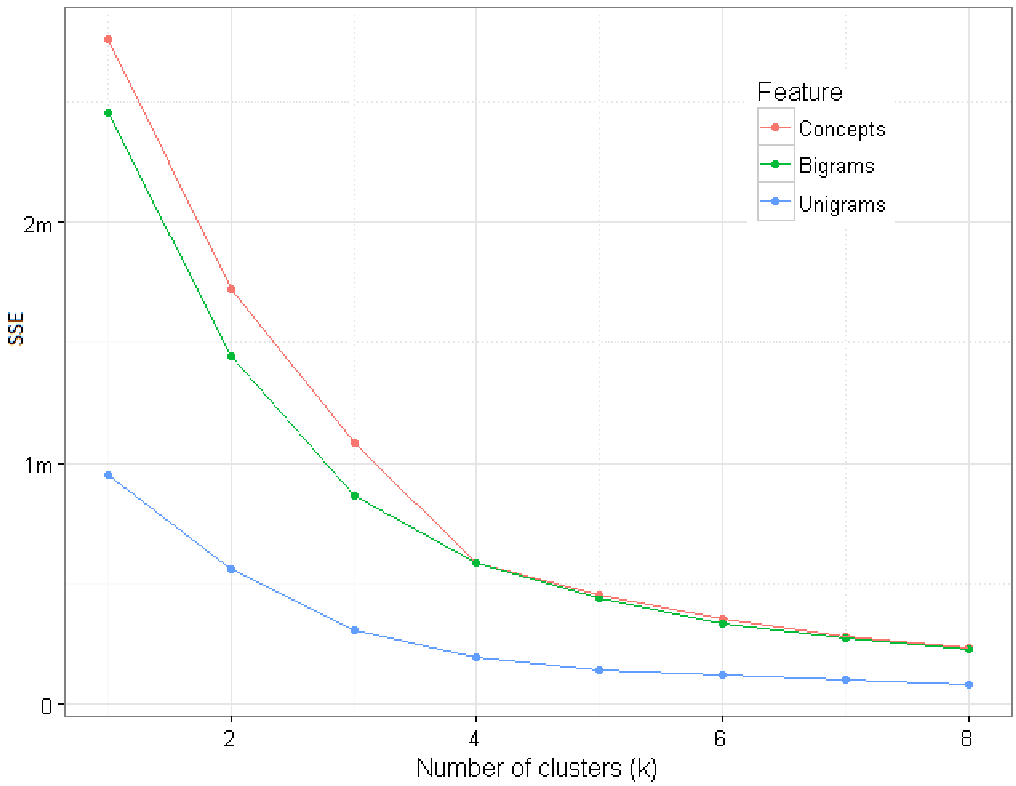

Figure 4.7 Elbow Method for Determining the Number of Clusters

Determining the number of clusters when using K-means is one of the most challenging problems in unsupervised learning. To overcome this problem, we used the Elbow method (Thorndike, 1953), which uses the percentage of variance as a function of the number of clusters K. For each K, it calculates the SSE and plots a line chart. For example, figure 4.7 shows how Elbow method can help to find the optimal K for clustering the *Frame* sentences using different features (Concepts, Bi-grams, Uni-grams). Experimenting with different K values $\{1,2,3,\ldots,8\}$, we found that clustering by using concepts as features is optimal at K=4, due to lower SSE. We also found that clustering using Bi-grams or Uni-grams can have K as 4. Larger values of K ($\geq$5) show marginal return on reducing SSE.

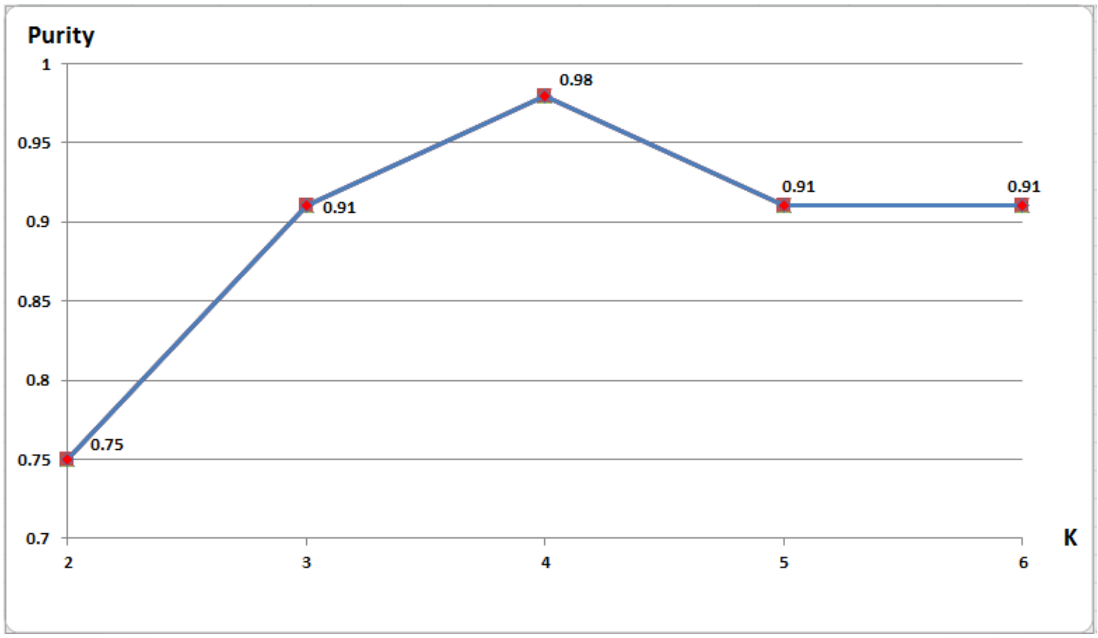

Figure 4.8 Experimenting Different Values of K

Additionally, we show how the purity changes when experimenting with different K values. In figure 4.8, using concepts as features on the *Frame* sentences yielded the highest purity of 0.98 when K=4, which aligns with the development of the four frame categories {Solution, Problem Threat, Cause, and Motivation} discussed in Section 4.1.

Appendix B provides additional visualizations for clustering the dataset into Frame/Non-Frame as well as clustering the Frame sentences into four categories.

4.3 Supervised Frame Learning

4.3.1 Quantitative Evaluation

In this approach, we use the labeled dataset. Once sentences are labeled as *Frame/Non-Frame* and categorized with their corresponding frame category, we utilize uni-gram keywords, bi-gram terms, and generalized concepts separately as features and the sparse logistical regression classifier SLEP (Liu *et al.*, 2009b) to identify weighted discriminative features and classify sentences. We experimented with three different classifiers: SVM (Cortes and Vapnik, 1995), SLEP (Liu *et al.*, 2009b), Random Forests (Breiman, 2001); and found that SLEP outperformed both these other classifiers. Using different types of features generated from the entire corpus, we perform ten-fold cross-validation for measuring the classifier's predictive accuracy to detect *Frame/Non-Frame* sentences. Next, using features generated from frame sentences only, we train a multi-class model to classify sentences into their corresponding frame category. We report precision, recall, and F-measure as quantitative evaluation metrics. In the subsequent tables we report the results of SLEP classifier, and in appendix C we report the results of other classifiers (i.e. SVM and Random Forests). Qualitative analysis of the identified discriminating concepts is also presented in the next section.

Table 4.5 presents the accuracies for detecting *Frame/Non-Frame* sentences using different features. Using the generalized concepts approach as features, the resultant average accuracy (F-measure of 83%) outperforms both accuracies with uni-grams (74%) and bi-grams (68%) features by 12% and 22%, respectively.

Table 4.5 *Frame/Non-Frame* Classification

Method	**Class Label**	**Precision**	**Recall**	**F-measure**
Concepts	*Frame*	0.80	0.88	0.84
	Non-Frame	0.87	0.77	0.82
	Average	**0.83**	**0.83**	**0.83**
Bi-grams	*Frame*	0.75	0.42	0.54
	Non-Frame	0.74	0.92	0.82
	Average	**0.74**	**0.67**	**0.68**
Uni-grams	*Frame*	0. 75	0.48	0.59
	Non-Frame	0.76	0.91	0.89
	Average	**0.75**	**0.70**	**0.74**

Table 4.6 shows the accuracies for identifying the corresponding frame category. Using generalized concepts, these accuracies vary between 73% and 83% (F-measure) for different categories. In this table, utilizing generalized concepts yields slightly better performance compared to both uni-grams and bi-grams with an overall average accuracy (F-measure) of 79%.

Table 4.6 Frame Classification into Four Categories

Method	Frame Category	Precision	Recall	F-measure
Concepts	Solution	0.75	0.93	0.83
	Problem Threat	0.77	0.84	0.79
	Cause	0.85	0.77	0.80
	Motivation	0.89	0.62	0.73
	Average	**0.82**	**0.79**	**0.79**
Bi-grams	Solution	0.87	0.77	0.81
	Problem Threat	0.84	0.77	0.80
	Cause	0.86	0.73	0.76
	Motivation	0.90	0.58	0.71
	Average	**0.87**	**0.71**	**0.77**
Uni-grams	Solution	0.78	0.87	0.82
	Problem Threat	0.81	0.81	0.81
	Cause	0.83	0.62	0.82
	Motivation	0.85	0.57	0.64
	Average	**0.82**	**0.72**	**0.77**

In the previous two tables, the best performance for Frame/Non-Frame classification using concepts is achieved when λ=0.0001 (λ is a regularization parameter that controls the sparsity of the solution, $0 \leq \lambda \leq 1$). For the four frame classification using concepts, the best performance is achieved when λ=0.03.

In the following table (table 4.7) we show how accurcies change when using different λ values to classify sentences into Frame/Non-Frame using generalized concepts as features.

Table 4.7 Different λ Values for *Frame/Non-Frame* Classification Using Concepts

λ	**Class Label**	**Precision**	**Recall**	**F-measure**
0.00	*Frame*	0.79	0.87	0.83
	Non-Frame	0.87	0.77	0.82
0.0001	*Frame*	**0.80**	**0.88**	**0.84**
	Non-Frame	**0.87**	**0.77**	**0.82**
0.001	*Frame*	0.79	0.88	0.83
	Non-Frame	0.87	0.77	0.82
0.03	*Frame*	0.78	0.88	0.83
	Non-Frame	0.86	0.77	0.81
0.1	*Frame*	0.78	0.88	0.83
	Non-Frame	0.86	0.76	0.81
0.25	*Frame*	0.78	0.87	0.83
	Non-Frame	0.86	0.76	0.81
0.5	*Frame*	0.77	0.87	0.82
	Non-Frame	0.86	0.75	0.80
1.00	*Frame*	0.75	0.89	0.81
	Non-Frame	0.86	0.69	0.77

Table 4.8 (next page) reports how accurcies change when using different λ values to classify sentences into one of the four frame categories using generalized concepts as features.

Table 4.8 Different λ Values for Four Frame Classification Using Concepts

λ	**Frame Category**	**Precision**	**Recall**	**F-measure**
0.00	Solution	0.72	0.94	0.82
	Problem Threat	0.66	0.94	0.77
	Cause	0.91	0.64	0.75
	Motivation	0.89	0.51	0.64
0.0001	Solution	0.71	0.95	0.82
	Problem Threat	0.65	0.94	0.76
	Cause	0.91	0.64	0.75
	Motivation	0.89	0.49	0.63
0.001	Solution	0.71	0.94	0.81
	Problem Threat	0.65	0.92	0.76
	Cause	0.92	0.61	0.73
	Motivation	0.87	0.55	0.67
0.03	Solution	**0.75**	**0.93**	**0.83**
	Problem Threat	**0.77**	**0.84**	**0.79**
	Cause	**0.85**	**0.77**	**0.80**
	Motivation	**0.89**	**0.62**	**0.73**
0.1	Solution	0.70	0.95	0.81
	Problem Threat	0.66	0.95	0.78
	Cause	0.93	0.60	0.72
	Motivation	0.96	0.47	0.63
0.25	Solution	0.68	0.97	0.80
	Problem Threat	0.64	0.97	0.77
	Cause	0.95	0.55	0.69
	Motivation	0.95	0.46	0.62
0.5	Solution	0.67	0.98	0.80
	Problem Threat	0.63	0.98	0.76
	Cause	0.97	0.53	0.68
	Motivation	0.96	0.41	0.57
1.00	Solution	0.59	0.99	0.75
	Problem Threat	0.58	0.98	0.73
	Cause	0.96	0.34	0.50
	Motivation	0.96	0.29	0.44

4.3.2 Qualitative Analysis of Resultant Concepts

Table 4.10 shows top five discreminative concepts for each frame category. Our team of experts explored the highly significant generalized concepts germane to four-class framing in media discourse surrounding climate change across West African RSS feeds and provided qualitative evaluations as follows:

Table 4.10 Top Five Generated Concepts for Each Frame Category

Cause	**Problem Threat**	**Solution**	**Motivation**
{Greenhouse, Emissions, Gases} ↓ {Cause,Attribute to} ↓ {Global warming}	{Flood} ↓ {Associate, Create} ↓ {Poverty, Disease}	{Action plan, Policy} ↓ {Build, Consolidate} ↓ {Sustainability, Resilience future}	{International, Community} ↓ {Urge,Warn} ↓ {Threat}

{Industry, Anthropogenic} ↓ {Raise} ↓ {Earth temperature, CO2, CO5}	{Heavy rainfall, Torrential rain} ↓ {Create, Bring, Increase} ↓ {Flooding, Disaster, Landslide}	{Development, Sustainability, National program} ↓ {Enhance} ↓ {Community}	{Agreement, Leaders, World} ↓ {Help} ↓ {Future,Hope}
{Fossil fuel} ↓ {Impact,Harm} ↓ {Planet, Environment, Weather}	{Drought} ↓ {Cause, Impact, Reduce} ↓ {Food-shortage, Food-production, Crop}	{Brown} ↓ {Sign} ↓ {Local legislation, CA groundwater, Management framework}	{USA, EU, China} ↓ {Recognize, Reduce} ↓ {Emissions}

{Coal combustion, Diesel, Man-Made} ↓ {Create} ↓ {Extreme weather, Temperature-up}	{Sea-level rise} ↓ {Result in, Cause} ↓ {Tsunami, Damage, Flood}	{Sustainability, Energy} ↓ {Can help, Improve} ↓ {Food security, Households}	{Africa} ↓ {Need, Implement} ↓ {Policy, Awareness, Partnership}
{Truck, Car} ↓ {Rise} ↓ {Carbon pollution, Pollute}	{Extreme Weather, Hailstorm} ↓ {Cause, Affect} ↓ {Mudslide, Floods, Farming}	{Smart agriculture, Africa countries} ↓ {Meet, Breathe} ↓ {Life}	{Nigerian} ↓ {Apply, Take} ↓ {Measures, Renewable Energy, Policy}

Cause Framing

Causal responsibility of climate change and its effects was often attributed to anthropogenic activities, particularly man-made greenhouse gas emissions, human-induced pollution, and fossil fuel use. Carbon dioxide and greenhouse gas emission emerged as highly significant concepts, as indicated by high weight value. Media texts often associated global warming with carbon dioxide emissions using the following triplets to construct a cohesive story:

- Scientific research indicates that atmospheric carbon dioxide increases to ever higher levels.
- Cars and trucks were major sources of air pollution and carbon dioxide emissions, which directly increased local temperature.

Problem Threat Framing

Next, we turned our attention to identify the dominant concepts representing the problem and threat framing of climate change. Media texts tended to highlight devastating environmental impacts caused by climate change, such as floods, prolonged drought, loss of landmass and soil, desertification, sea-level rise, storm surge, heat waves, and more. Flooding, in particular, is a severe concern as nine out of sixteen triplets of high weight values explicitly mentioned the negative impacts of heavy or torrential rainfall. Consequently, economic conditions and food insecurity were influenced, infrastructure was damaged, and diseases were exacerbated by the increased intensity and frequency of floods.

Solution Framing

The most representative discourse of solution framing is discussed next in the Visualizing Concepts section.

Motivation Framing

When discussing motivation for why policy actors and citizens should act upon the most salient concepts emphasized that international communities (e.g. U.S., EU, and China) should negotiate a legal agreement to reduce greenhouse gas emissions at the end of 2015. There is little attention to stating specific reasons for offering localized adaptation strategies that people can undertake. Although the awareness of climate change impacts among African government officials was generally high, the prevailing generalized concept of calling for international actions on mitigation from mainstream media discourse reflected a lack of effective national and local polices.

Visualizing Concepts

To visualize the generalized concept and relation clusters, we utilize a semantic network (Quillian, 1968) of nodes (V) and edges (E) to describe the semantic space of the underlying texts. Circle nodes represent *subjects/objects* and square nodes represent *verbs*. Edges represent relations between concepts. In such a network, distinct combinations of actors (subjects) perform or recommend various sets of actions (verbs) on distinct combinations of targets (objects). The sample semantic network in Figure 4.9 illustrates how *sustainability* emerges as a concept that is central to addressing climate change impacts. The semantic network represents the contextual relationships between generalized triplets relating to strategies for sustainable adaptation. In the media discourse, sustainable adaptation is predominantly framed as an effective solution to reduce impacts of climate change and contribute to social, economic, and environmental development. As shown in Figure 4.9, developing sustainable national programs (or actions) can enhance local community resilience. According to the IPCC (Intergovernmental Panel on Climate Change) report, majority of rural

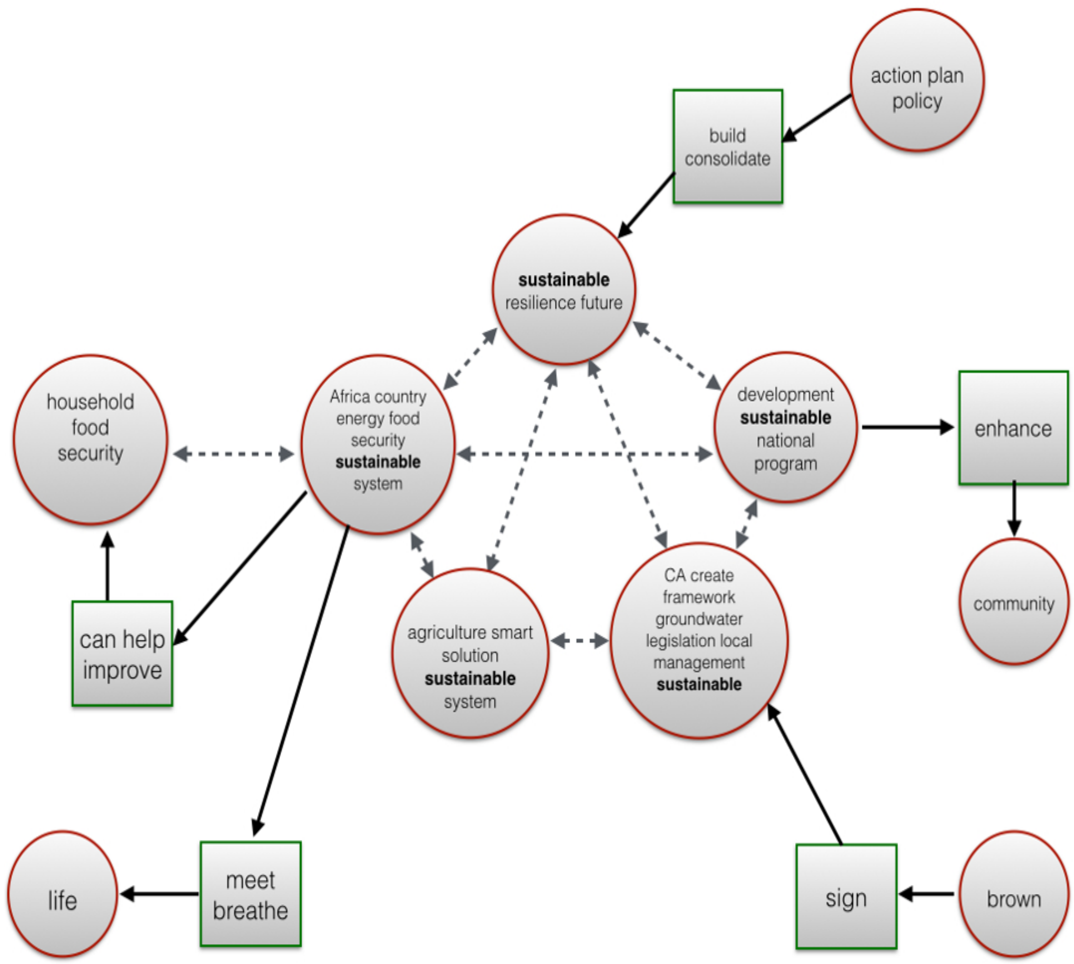

Figure 4.9 A Sample Semantic Network of Frame Concepts

communities rely on rain-fed agriculture to sustain their livelihoods in West Africa, the region worst affected by climate change. With changing rainfall patterns, prolonged droughts and flooding, sustainable systems for developing agriculture-smart technologies can help improve food security at the household level. Interestingly, the African media discussed that California Governor Jerry Brown has signed the most significant framework for regulating underground water resources to achieve sustainable development in September, 2014.

4.4 Causality Discovery

Next, we present the results of causal relationships extraction as well as the resultant causal chains. To evaluate the results, we present two types of evaluation: quantitative evaluation of accuracy and qualitative evaluation to examine if top extracted causal chains yield meaningful linkages between climate events and sociopolitical instability.

4.4.1 Quantitative Evaluation

Domain experts evaluated manually the extracted causal relationships from the two approaches: the baseline model (simple causatives) and concepts based model for each frame category. Quantitative evaluation of the causal relationships extraction performance is expressed in terms of true positive, false positive, and overall precision. Table 4.11 reports the accuracies of our causality mining approaches. The baseline model yielded higher overall average precision of 88% compared to overall average precision of 82%. However, the baseline model extracted only 1,714 causal relationships compared to 3,307 causal relationships extracted by the concepts based model. This indicates that the concepts based model outperformed the baseline model in terms of recall (93% boost). Quantitative results from our system successfully outperformed the precision of 73.91% reported in (Girju, 2003) and the precision of 81% reported in (Chang and Choi, 2006). Additionally, using the concepts based model, our system extracts both implicit and explicit causal relationships. Table 4.12 shows a list of resultant implicit causal verbs. In this list, there are corpus-based implicit causal verbs that were extracted using the generalized concepts approach. As we discussed in section 3.7.1, Nedjalkov and Silnickij (Nedjalkov and Silnickij, 1973) categorized causative verbs into: *simple causatives*, *resultative causatives*, and *instru-*

mental causatives. The last two categories are implicit causatives and our approach was able to extract them. Examples of *resultative causatives* from table 4.12 are: **kill**, **warm**, and **displace**. Examples of *instrumental causatives* from our results are: **erode**, **burn**, and **pollute**. Previous work on causal relationships extraction focused on simple causatives or hand-coded patterns which may not generalize well and produce results with limited recall. The proposed approach overcomes these limitations and produces more comprehensive results. However, it is worth mentioning that some resultant causal verbs are ambiguous. Table 4.13 shows a list of such verbs. Next, we provide qualitative assessments of the top resultant causal chains to better understand this approach's strengths and weaknesses.

Table 4.11 Accuracies of Extracted Causal Relationships

Approach	**Frame Category**	**TP**	**FP**	**Precision**
Simple Causatives	*Solution*	0.83	0.17	0.83
	Problem Threat	0.92	0.08	0.92
	Cause	0.88	0.12	0.88
	Motivation	0.90	0.10	0.90
	Average	0.88	0.12	0.88
Concepts	*Solution*	0.77	0.23	0.77
	Problem Threat	0.86	0.13	0.87
	Cause	0.80	0.20	0.80
	Motivation	0.83	0.16	0.83
	Average	0.82	0.18	0.82

Table 4.12 Example of Extracted Implicit Causal Verbs

Implicit Causal Verbs			
Drive	Worsen	Kill	Endanger
Displace	Erode	Destroy	Pollute
Entail	Escalate	Damage	Contribute to
Stave off	Associate	Stem	Emit
Account for	Trap	Degrade	Strengthen
Reduce	Enable	Provide	Deliver
Havoc	Prevent	Drive	Lift
Accelerate	Limit	Impact	Activate
Hit	Devastate	Attribute to	Force
Warm	Threaten	Grapple	Inundate
Brace	Mitigate	Hinder	Rise
Exacerbate	Remove	Burn	Mobilize
Contaminate	Linked to		

Table 4.13 Example of Extracted Ambiguous Verbs

Ambiguous Verbs			
Set	Add	Cut	Cover
Compile	Feed	Assure	Move
Warn	Mirror	Stimulate	Determine
Put	Blame	Implicate	Coordinate
React	Knock	Strike	Melt
Employ	Encompass	Experience	

4.4.2 Qualitative Analysis

We supplement quantitative evaluations with a qualitative analysis of the top identified causal chains for each frame category. The goal of qualitative analysis is to evaluate the practical validity of top extracted causal chains. We consider that a meaningful causal chain should explicitly explain the role of climate change risks in generating cascading effects on human security and societal instability. Qualitative assessments should provide evidence for the framework suggested by the IPCC fifth assessment report (Adger *et al.*, 2014) and Scheffran *et al.* (Scheffran *et al.*, 2012a). Findings of causal chains delineate the dynamic interactions between the climate conditions and social instability, and indirect environmental impacts on natural resources and human security, which in turn can amplify the probability of violent actions.

We adopt the definition of cascading effects inherent during natural disasters (Pescaroli and Alexander, 2016). Cascading effects represent the processes in which physical events (e.g., hurricanes, flooding) generate a sequence of events in human subsystems, thereby causing disruption to social and economic conditions. Three contributing factors determine the linear and non-linear path of a cascade: the interdependent nature of the human-environment systems, the context, and a triggering event. According to the 2014 IPCC report (Adger *et al.*, 2014), threats to human security systems can be attributed to climate-related events, impacts on material aspects of livelihood such as food, water, and energy, and disruption to damaged infrastructure. All of these negative impacts lead to migration and armed conflicts (Figure 4.10).

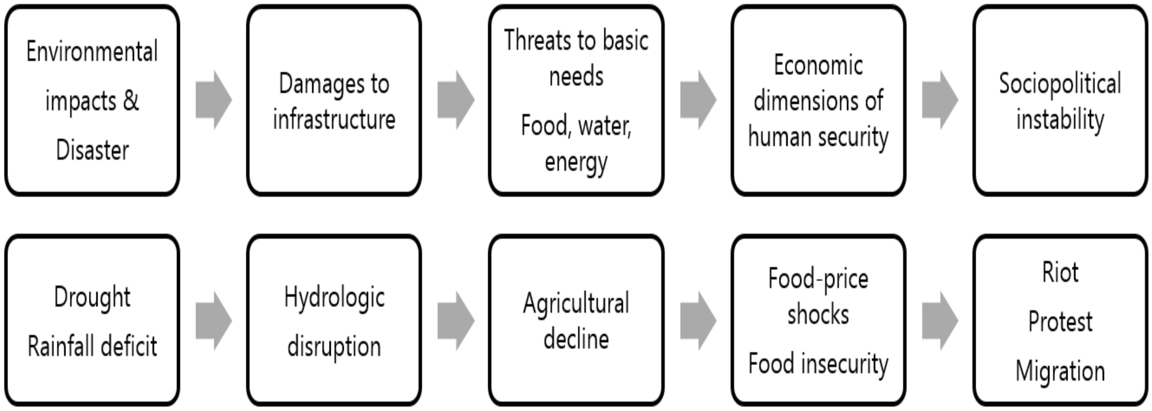

Figure 4.10 Causal Chains of the Relationship Between Climate Change and Human Security

Figure 4.11 presents the resultant causal chains for *Cause* framing of climate change. In this figure and subsequent figures, each large box numbered in red is a chain, and each chain is represented by grey boxes. Arrows are used to explain the cascading mechanisms (*domino effect*) through which one causal concept contributes to next interlinked concepts in the subsequent grey squares. Findings support the direct impacts linking human activities to environmental consequences and damaged natural resources. In *Cause* framing chains, examples show how human activities such as burning fossil fuels accounted for greenhouse gas emissions, which not only caused warming temperatures but also brought destruction to the natural ecosystems. Additionally, global warming temperatures escalated global environmental degradation and caused droughts in drier regions.

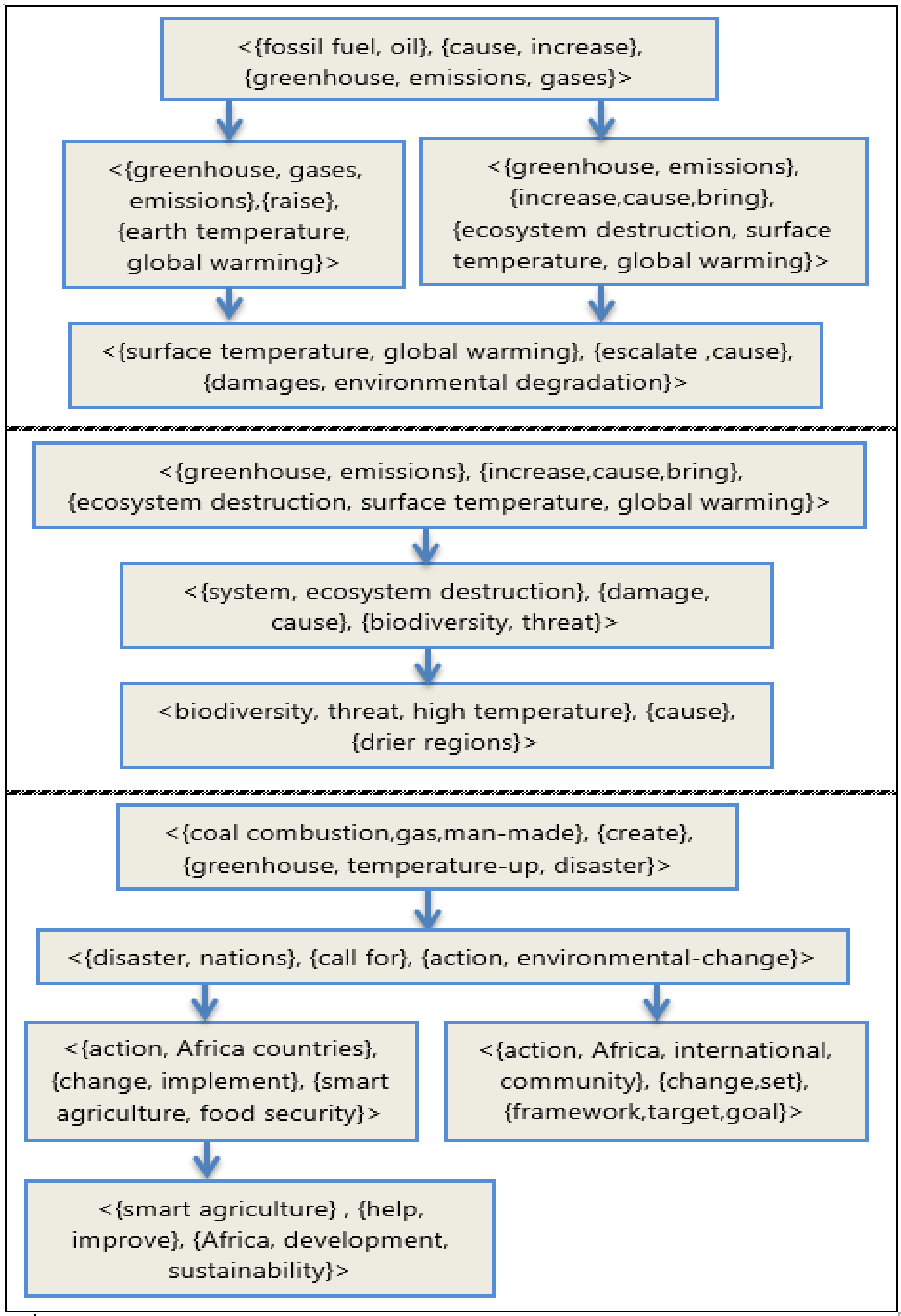

Figure 4.11 Example of Extracted Causal Chains from the *Cause* Frame

As illustrated in Figure 4.12, the *Problem Threat* framing chains explain the causal relationships between climate change and intensification of natural disasters. Heat absorption in the atmosphere leads to higher temperatures, which results in powerful hurricanes and storm surge. Intense hurricanes cause large scale flooding in coastal communities. These causal chains of contextually-related concepts exemplify complex pathways of how human activities change the climate system and ultimately cause negative consequences in the natural resources system.

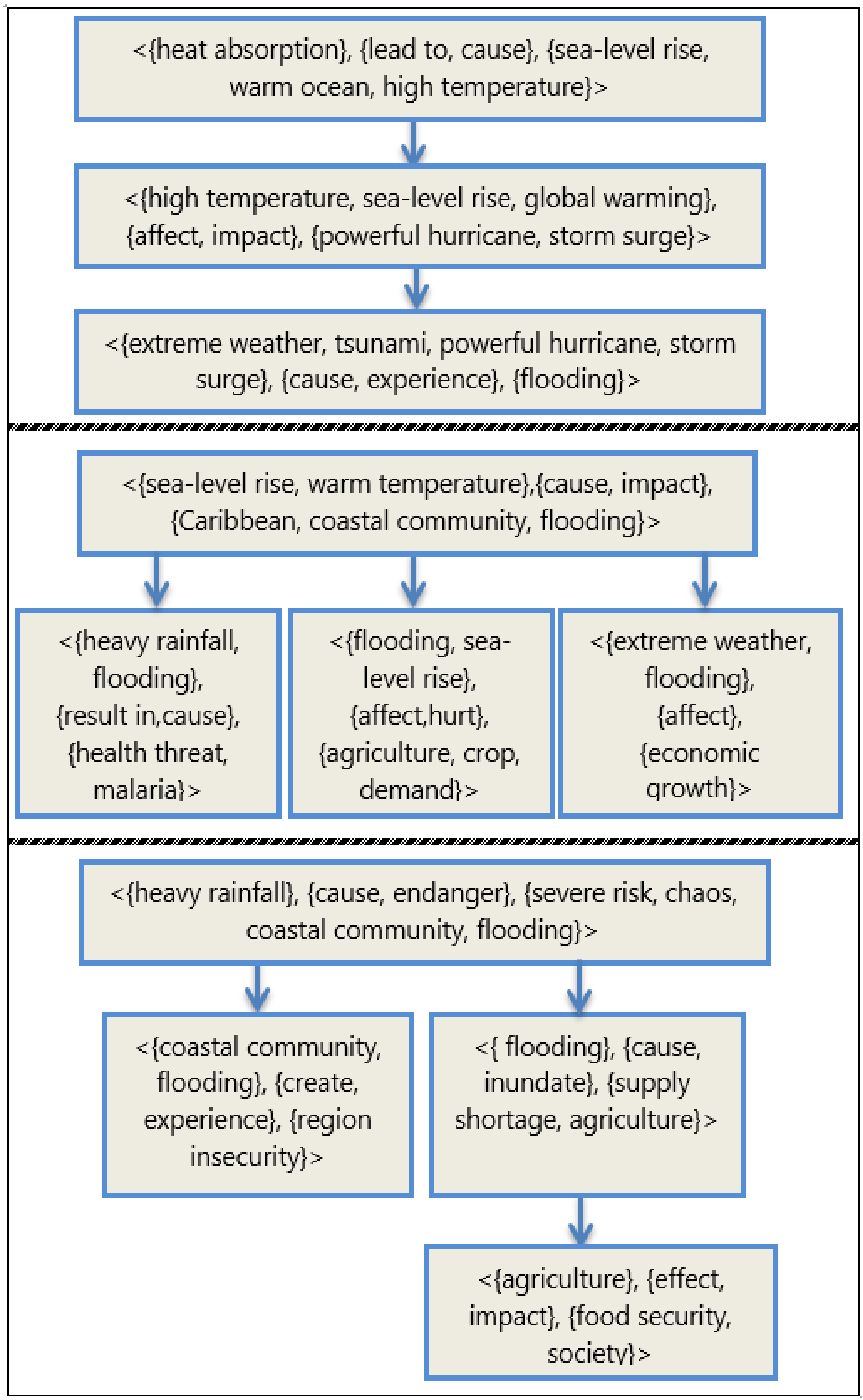

Figure 4.12 Example of Extracted Causal Chains from the *Problem Threat* Frame

To demonstrate the linkages between climate variability, natural resources, and dimensions of human security, top causal chains provide evidence that warming temperatures bring the greatest threats to biodiversity, thereby leading to inequitable distribution of drier and wetter regions. Moreover, these causal chains extracted from *Problem Threat* framing explicitly stress the direct impacts of extreme weather events causing disruption to social, health, and economic conditions. To explain, powerful hurricanes and storm surge result in coastal flooding. Flooding associated with dramatic amounts of rainfall increases the spread of malaria epidemics, affects crop yields in agriculture, causes food shortages and ultimately disrupts economic growth. These chains show how one extreme weather event can trigger cascading effects and affect human security through erosion of livelihood assets and infrastructure.

In this dataset, we found relatively scarce evidence to support the direct links between climate change and violent conflict. Examples extracted from intra and inter sentences focus on the security implications of natural disasters and heavy flooding. For instance, representative causal chains in *Problem Threat* framing (Figure 4.12) show that coastal flooding would cause food supply shortages, increase food insecurity, and elevate regional instability without explicitly suggesting that climate change contributes to violent conflict.

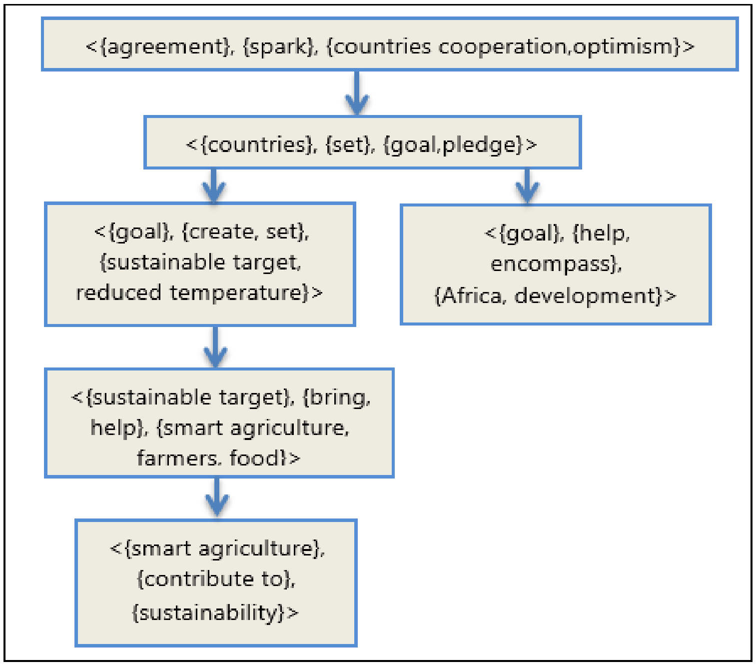

Figure 4.13 Example of Extracted Causal Chains from the *Solution* Frame

In response to threats to human security, international and domestic governments increasingly focus on building resilience and adaptive capacity at the local level. As summarized in Figure 4.13, causal chains extracted from Solution framing highlight intergovernmental efforts to respond to threats to human safety. For instance, the 2015 Paris agreement sparked a sense of optimism among international leaders in moving forward with cooperation, and setting goals for reducing carbon emissions to prevent rising temperature. In line with the UN's sustainable development goals, developed countries pledged to help African countries. Local governments planned to develop smart agriculture systems to help local farmers grow food, thereby contributing to environmental suitability.

Lastly, we examine top causality extraction from 1,404 sentences coded into *Motivation* framing (Figure 4.14). Findings reveal three major actors involved in calling for mitigation and adaptation efforts to address global climate change: grassroots organizations, Former U.S. President Obama, and local governments. Environmental movement groups placed the blame on large oil companies and called for international organizations to donate funding to help communities heavily impacted by natural disasters (flooding, hurricanes). Former President Obama called for international collaboration to combat rising temperatures and sea levels, and addressed the impacts of climate extremes on increasing precipitation and coastal flooding. In terms of local response, media discourse called for Nigerian policy makers to invest in affordable clean energy, public transportation systems, and renewable solutions. These efforts can help reduce carbon emissions.

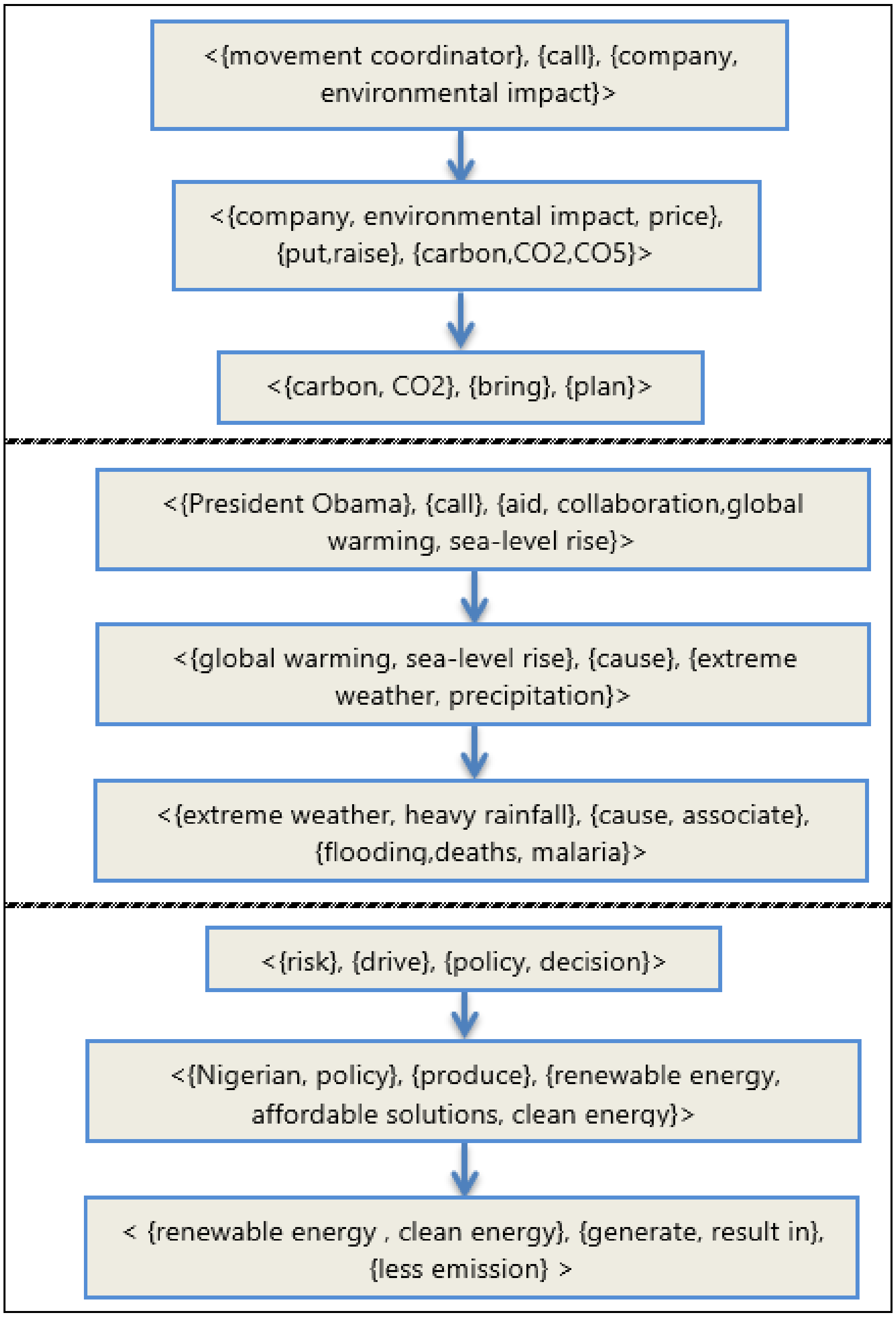

Figure 4.14 Example of Extracted Causal Chains from the *Motivation* Frame

Chapter 5

CONCLUSION AND FUTURE WORK

Climate change framing has pervasive influence, and this thesis presents a new computational approach based on generalized concepts to identify popular media frames and map them to different categories: solution, problem threat, cause, and motivation. A line of related work has used bag of words and word-level features to detect frames automatically in text. Such work face limitations since standard keyword based features may not generalize well to accommodate surface variations in text when different keywords are used for similar concepts. In this thesis, we developed a unique type of textual features that generalize <subject,verb,object> triplets extracted from text, by clustering them into high-level concepts. Compared to uni-gram and bi-gram based models, frame classification and clustering using our generalized concepts yielded better discriminating features with a 12% boost in accuracy (i.e. from 74% to 83% in f-measure) and 0.91 clustering purity for *Frame/Non-Frame* detection.

With more frequent and intense extreme events happening across the globe in recent years, identifying mitigation and adaptation strategies for coping with threats climate change poses to human security becomes the top priory for policy makers. We present a novel approach to extract causal relations and construct causal chains from large text corpora. The semi-supervised approach yields an average precision of 82%.

In contrast to previous work that mainly focuses on implicit lexical pattern matching our concepts-based approach extracts both explicit and implicit relations using *syntactic* and *semantic criteria* that are based on the corpus. It also extracts and clusters related actors across different news story documents that report significant effects of changing climatic conditions. The proposed approach can be utilized to construct causal chains of events in any text corpora. More importantly, in line with scientific studies of climate change impacts and human security, the qualitative evaluation of causal chains from the four categories of climate change framing lends strong support for the direct and indirect impacts of climate events on natural resources and economic conditions, which in turn can amplify the likelihood of sociopolitical instability and violent conflict. Top causal chains show meaningful linkages to enhance decision makers' understanding of the causes and cascading effects in the human-environment interaction.

As noted by Zhao *et al.* (Zhao *et al.*, 2016), constructing automatic recognition of causal relations is a fundamental and challenging task. Based on quantitative and qualitative assessments, our approach not only demonstrates improved performance, but also generates interpretable causal chains mostly consistent with the 2014 IPCC report (Adger *et al.*, 2014).

This thesis has several limitations that need to be acknowledged. First, we analyzed RSS feeds that are related to climate change, thus they are not fully reflective of the entirety of media outlets. Second, the proposed algorithms work on formal English with complete sentences and it might not be possible to apply informal English dataset (such as Twitter); where users typically write in an informal way. Additionally, if the dataset is small, then the resultant generalized concepts will be sparse and less meaningful. Lastly, in this thesis we are studying post-hoc analysis of data. Therefore, an analysis model of future activities is needed.

Following the promising results presented in this thesis, we intend to extend this work and build a predictive model of causal chains of events. Predictions of cascading effects will allow researchers to provide evidence to further establish the direct or indirect relationships between risks associated with climate change and sociopolitical instability.

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APPENDIX A

CONVERGENCE PLOTS FOR EXTRACTING CAUSAL CONCEPTS

Cause Frame

Figures A.1 and A.2 show the convergence curves for *Cause* frame concepts. The algorithm reached convergence at the 66^{th} iteration where the number of concepts and verbs did not change.

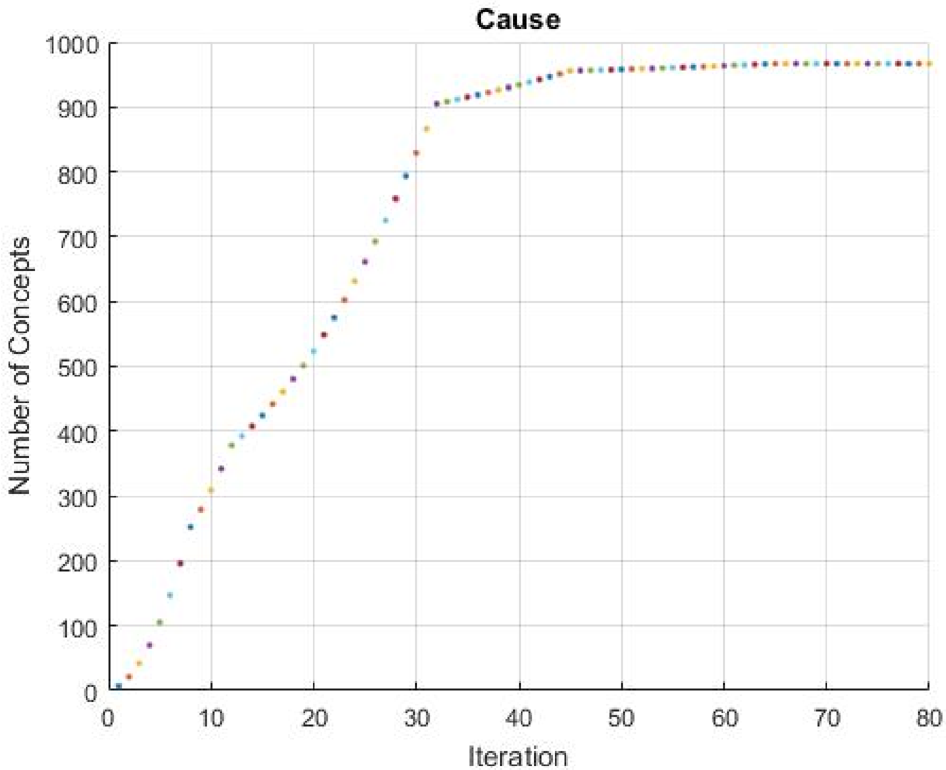

Figure A.1 Convergence of Extracting *Cause* Causal Concepts as a Function of Iteration Number and Number of Concepts

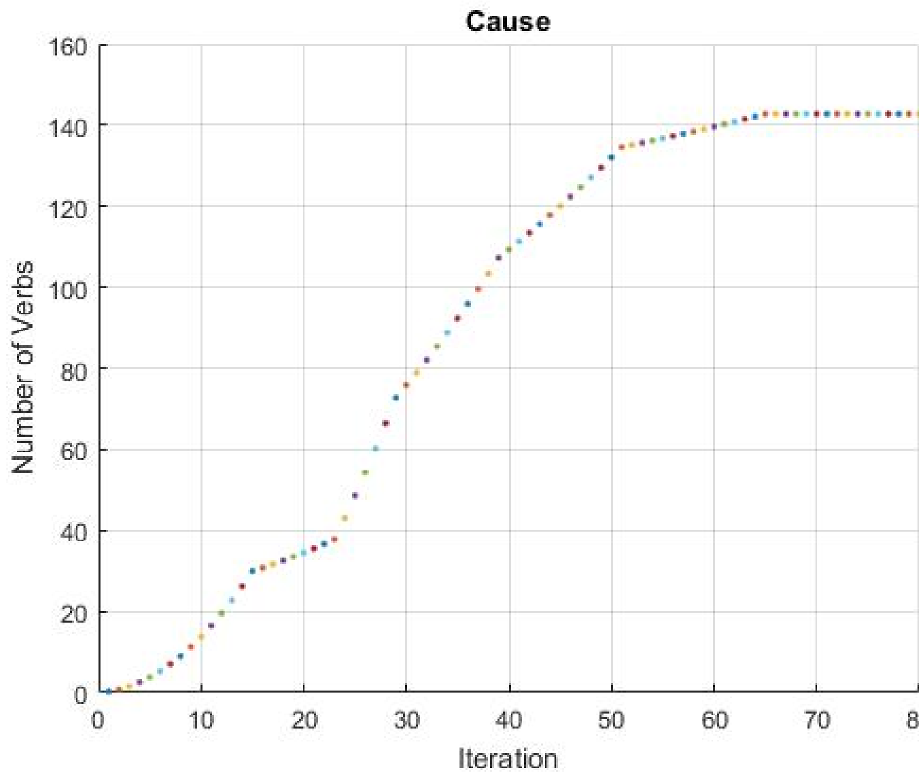

Figure A.2 Convergence of Extracting *Cause* Causal Concepts as a Function of Iteration Number and Number of Verbs

Problem Threat Frame

Figures A.3 and A.4 show the convergence curves for for $ProblemThreat$ frame concepts. The algorithm reached convergence at the 57^{th} iteration where the number of concepts and verbs did not change.

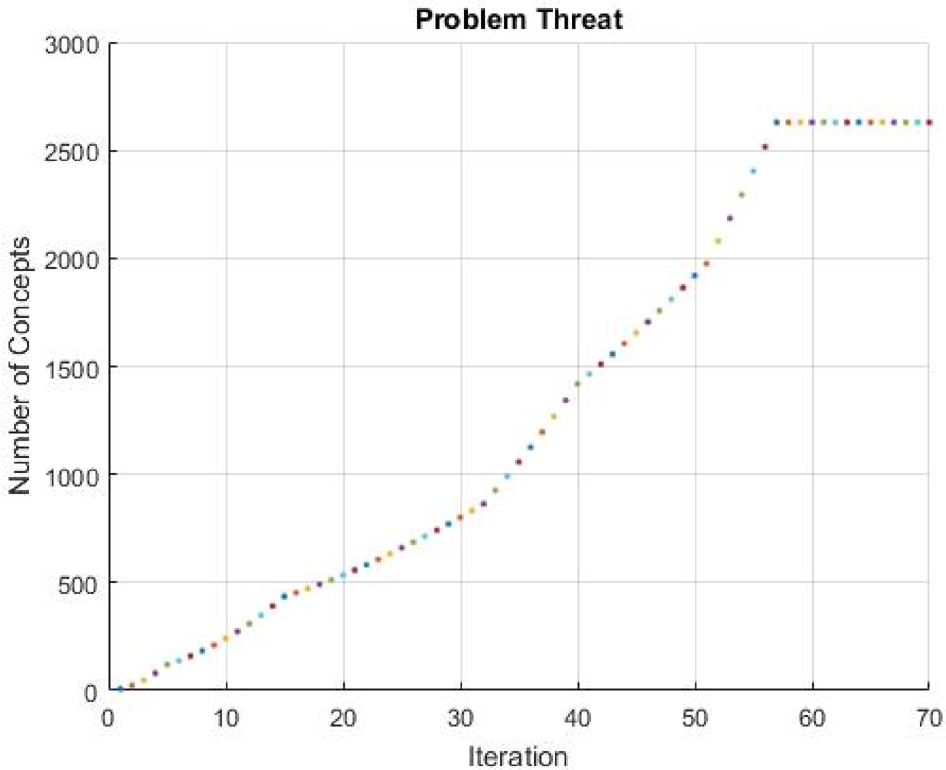

Figure A.3 Convergence of Extracting *Problem Threat* Causal Concepts as a Function of Iteration Number and Number of Concepts

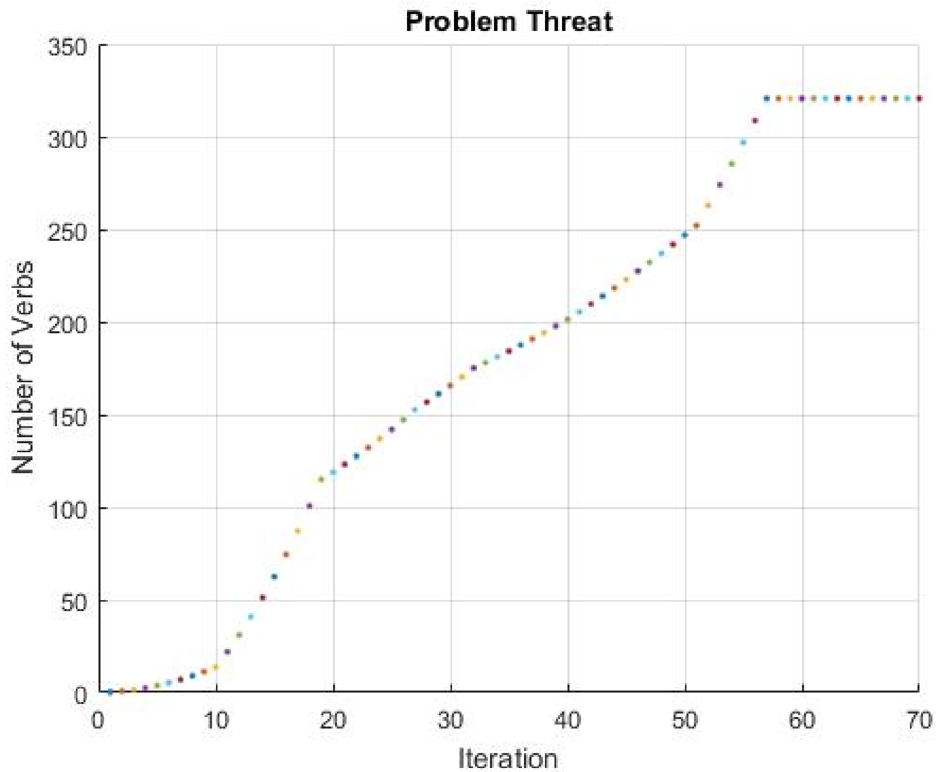

Figure A.4 Convergence of Extracting *Problem Threat* Causal Concepts as a Function of Iteration Number and Number of Verbs

Solution Frame

Figures A.5 and A.6 show the convergence curves for *Solution* frame concepts. The algorithm reached convergence at the 48^{th} iteration where the number of concepts and verbs did not change.

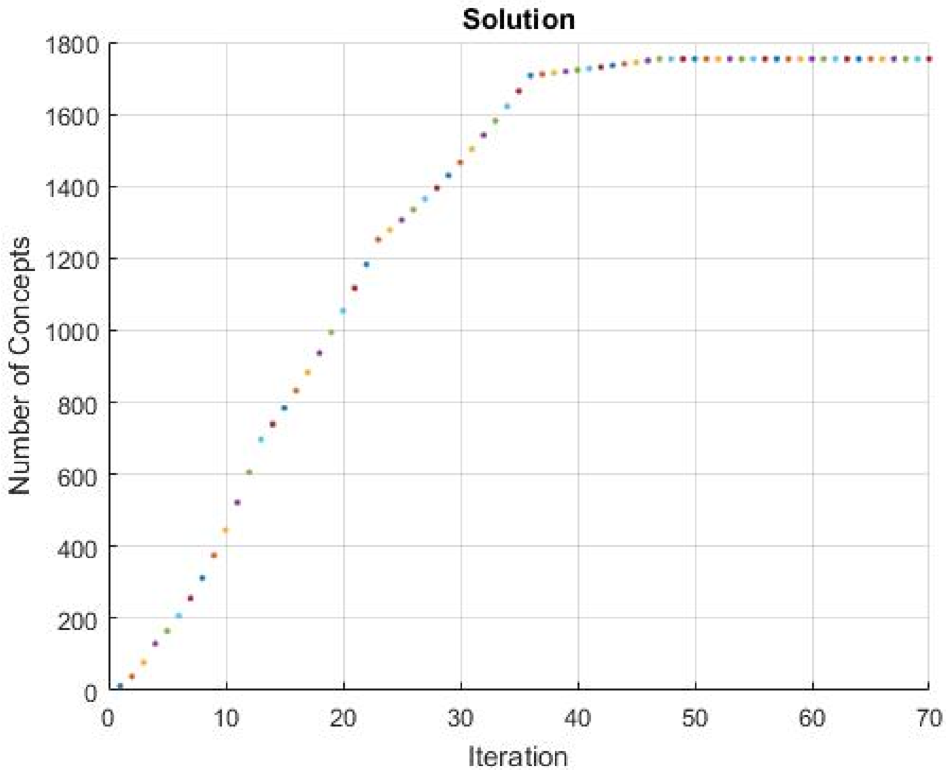

Figure A.5 Convergence of Extracting *Solution* Causal Concepts as a Function of Iteration Number and Number of Concepts

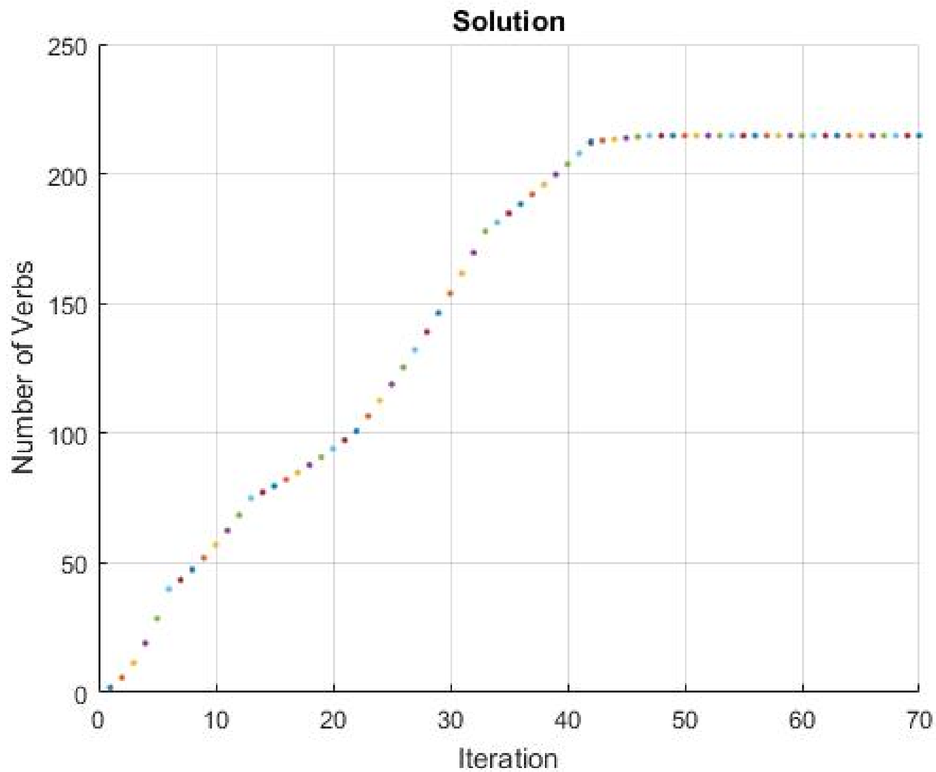

Figure A.6 Convergence of Extracting *Solution* Causal Concepts as a Function of Iteration Number and Number of Verbs

Motivation Frame

Figures A.7 and A.8 show the convergence curves for *Motivation* frame concepts. The algorithm reached convergence at the 35^{th} iteration where the number of concepts and verbs did not change.

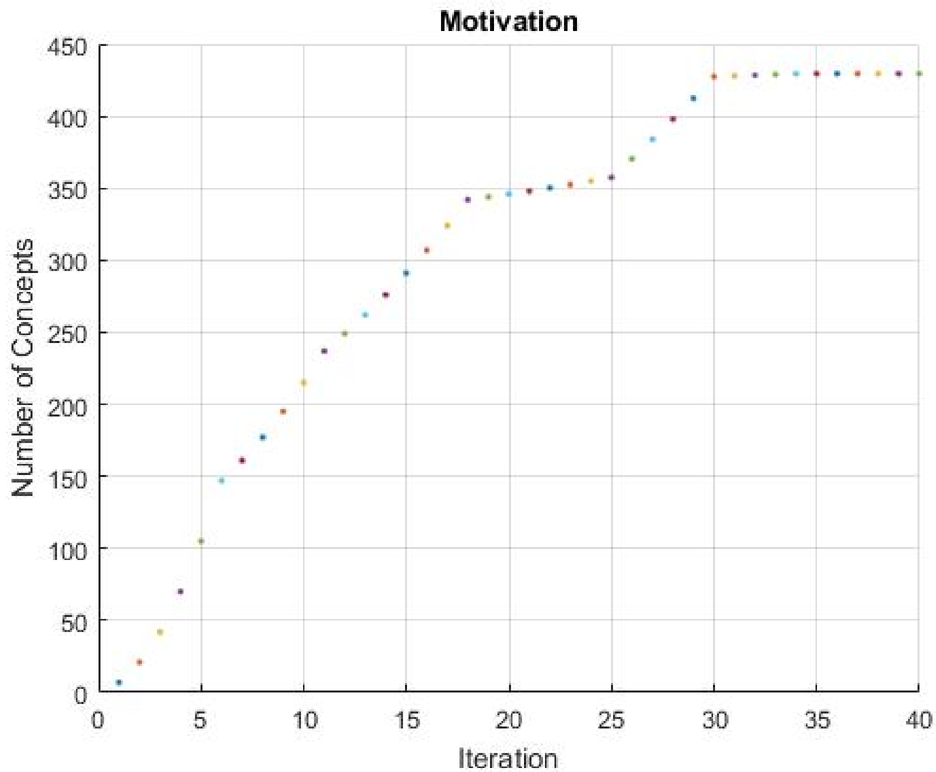

Figure A.7 Convergence of Extracting *Motivation* Causal Concepts as a Function of Iteration Number and Number of Concepts

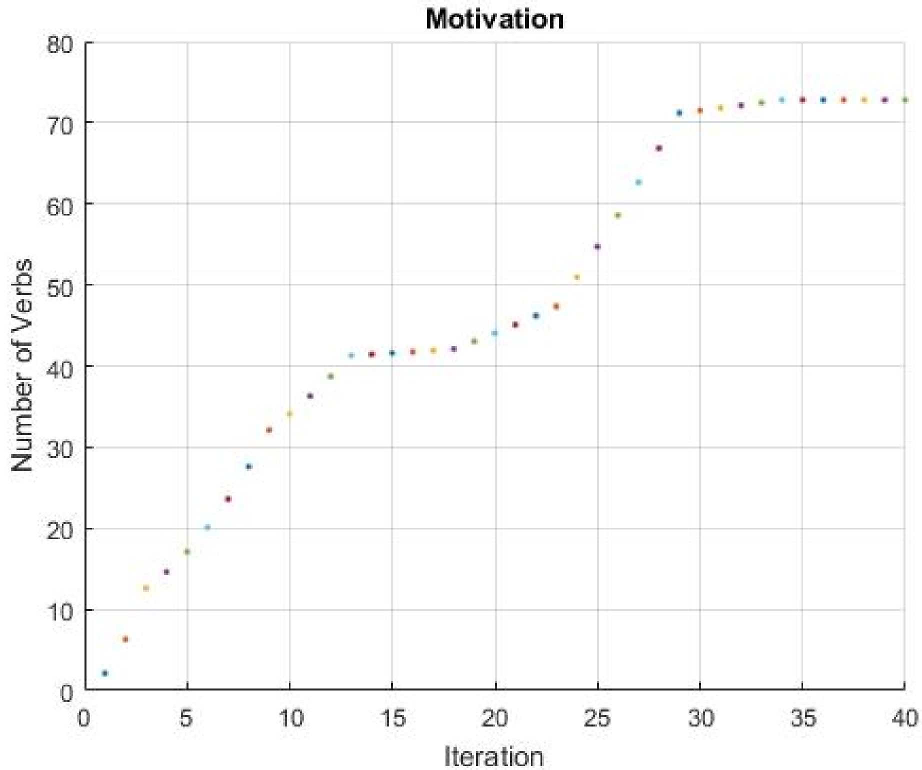

Figure A.8 Convergence of Extracting *Motivation* Causal Concepts as a Function of Iteration Number and Number of Verbs

APPENDIX B

CLUSTERS VISUALIZATION

We experimented with t-Distributed Stochastic Neighbor Embedding (t-SNE) dimensionality reduction technique (Maaten, 2009) to visualize the clusters in a better way and to examine if this method would produce better results.

Frame/Non-Frame Clusters

Figures B.1, B.2, B.3 show the resultant clusters after applying t-SNE to cluster the entire dataset into two clusters (Frame/Non-Frame) using different features (i.e. concepts, bi-grams, uni-grams). In these figures, we can see that clustering based on concepts is more pure compared to bi-grams and uni-grams.

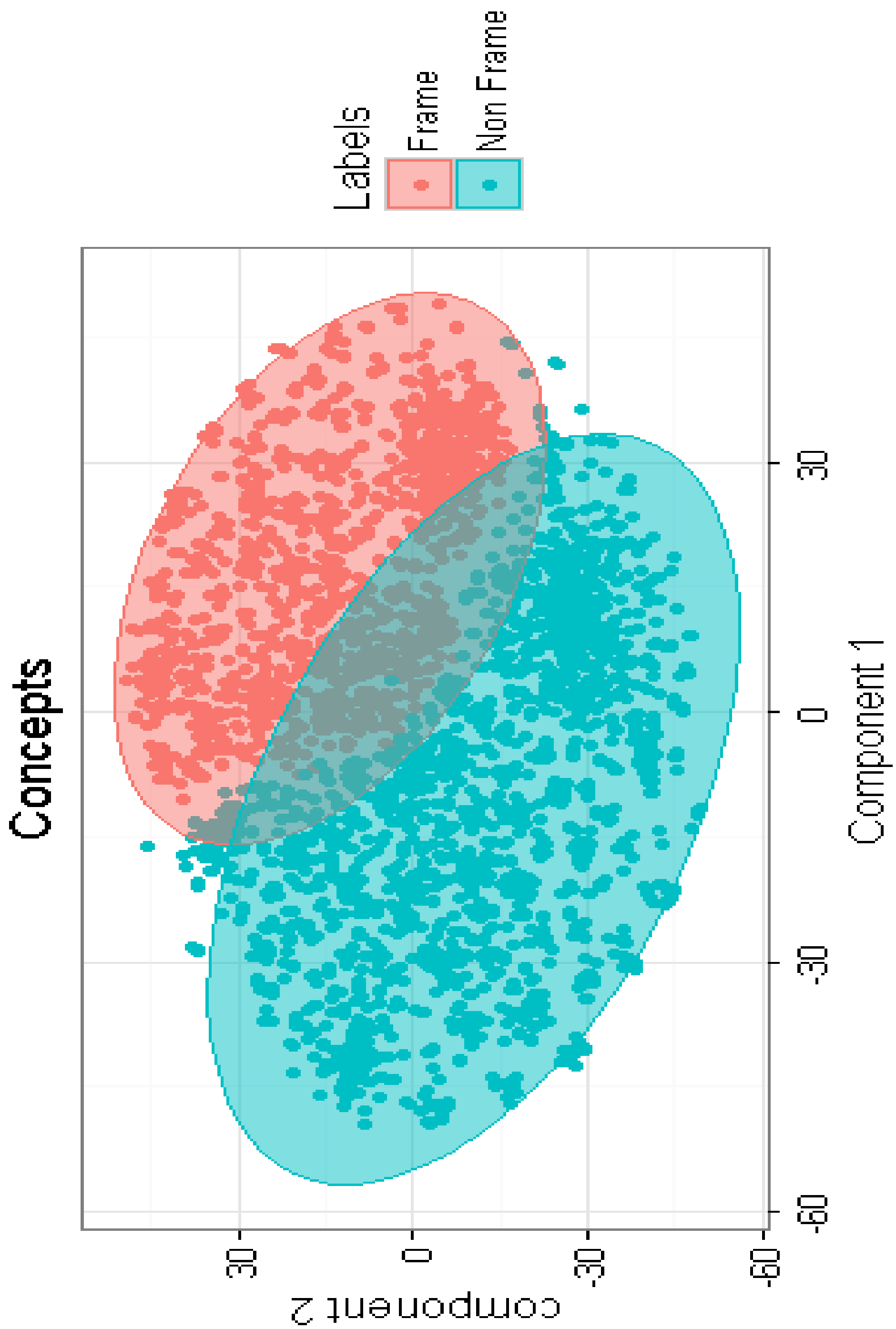

Figure B.1 Resultant Two Clusters after Applying t-SNE Using Concepts as Features

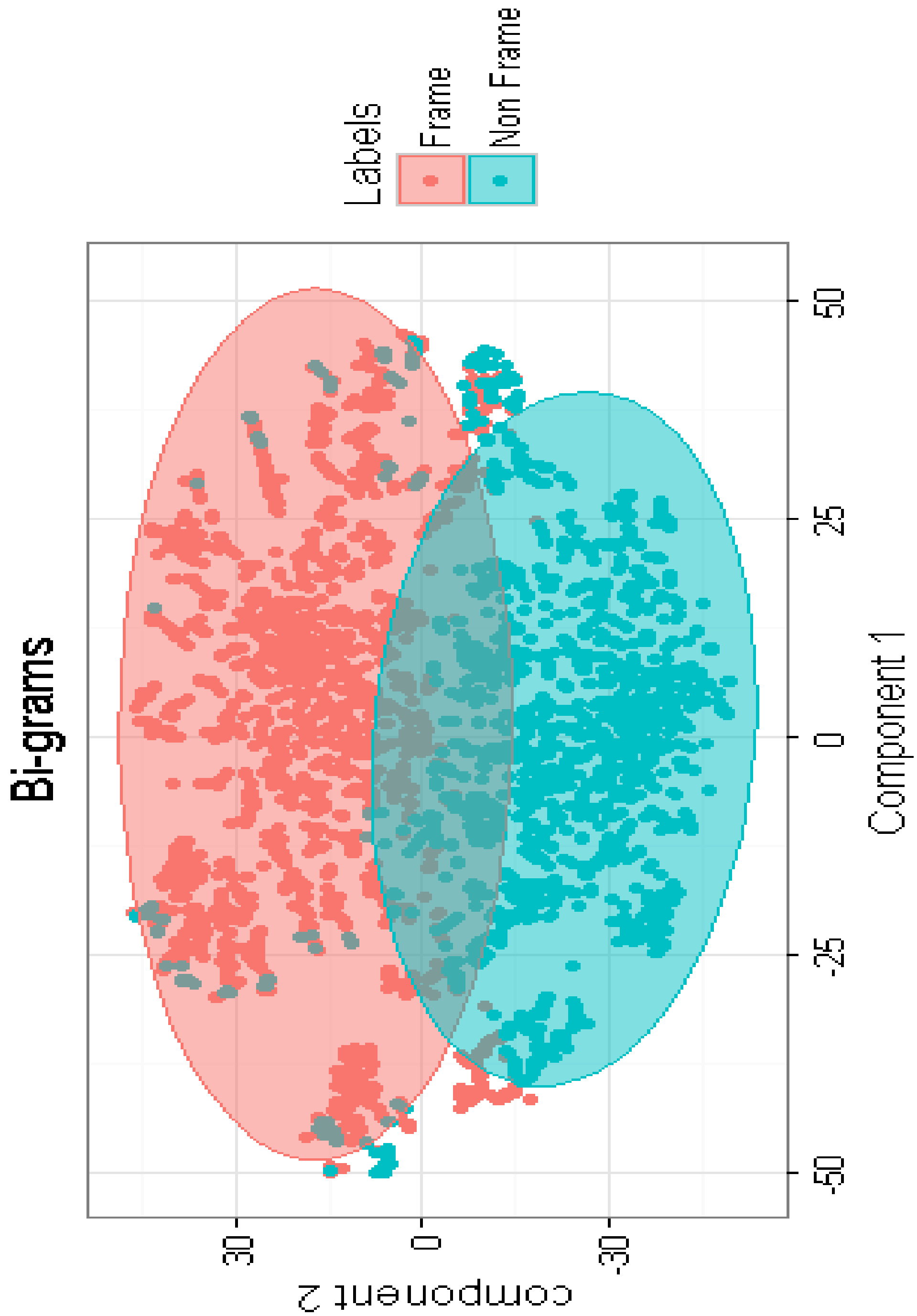

Figure B.2 Resultant Two Clusters after Applying t-SNE Using Bi-grams as Features

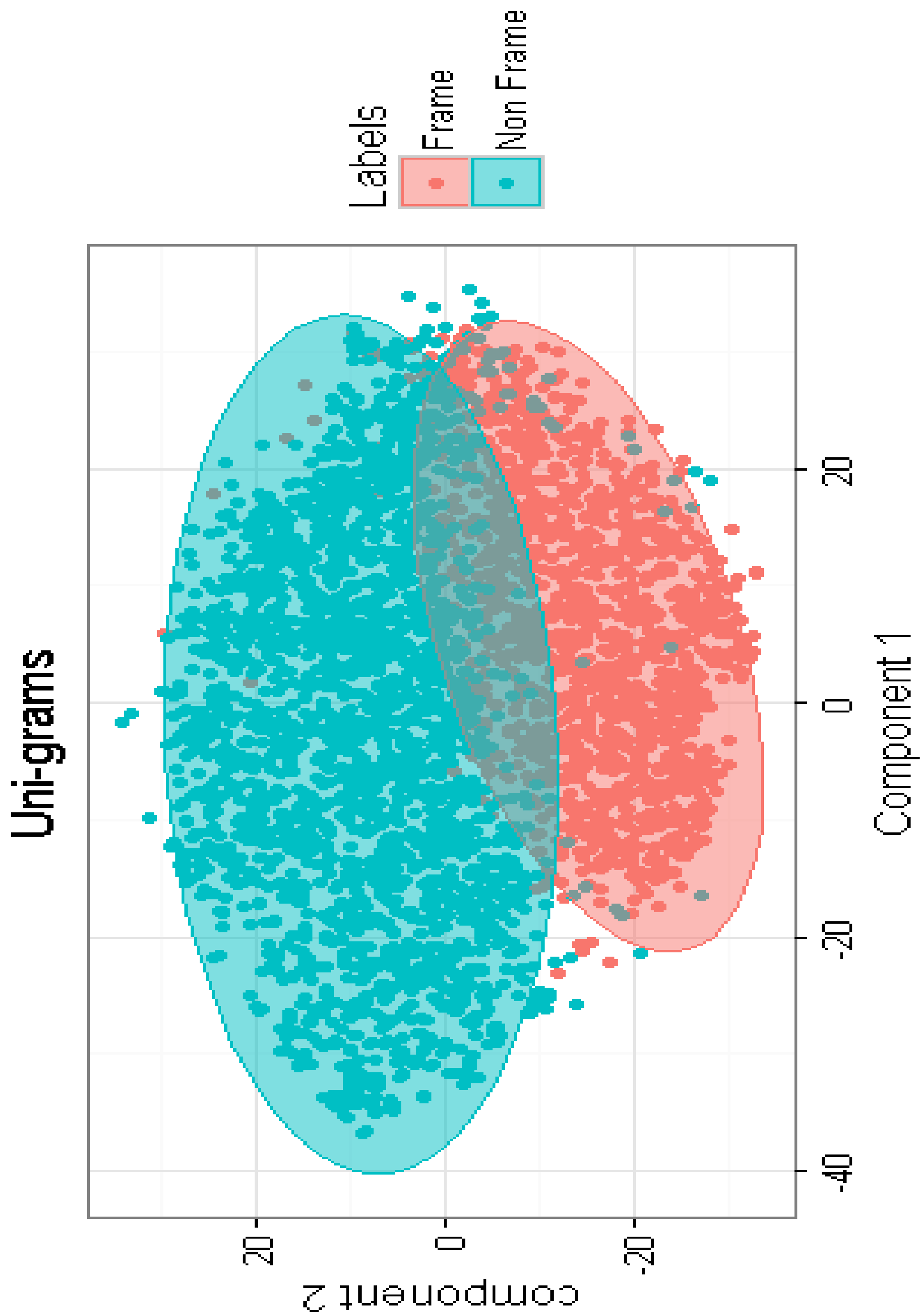

Figure B.3 Resultant Two Clusters after Applying t-SNE Using Uni-grams as Features

Four Frames Clusters

Figures B.4, B.5, B.6 show the resultant clusters after applying t-SNE to cluster the Frame sentences into four clusters (Solution, Problem Threat, Cause, Motivation) using different features (i.e. concepts, bi-grams, uni-grams). Clustering based on concepts produces more pure clusters compared to bi-grams and uni-grams.

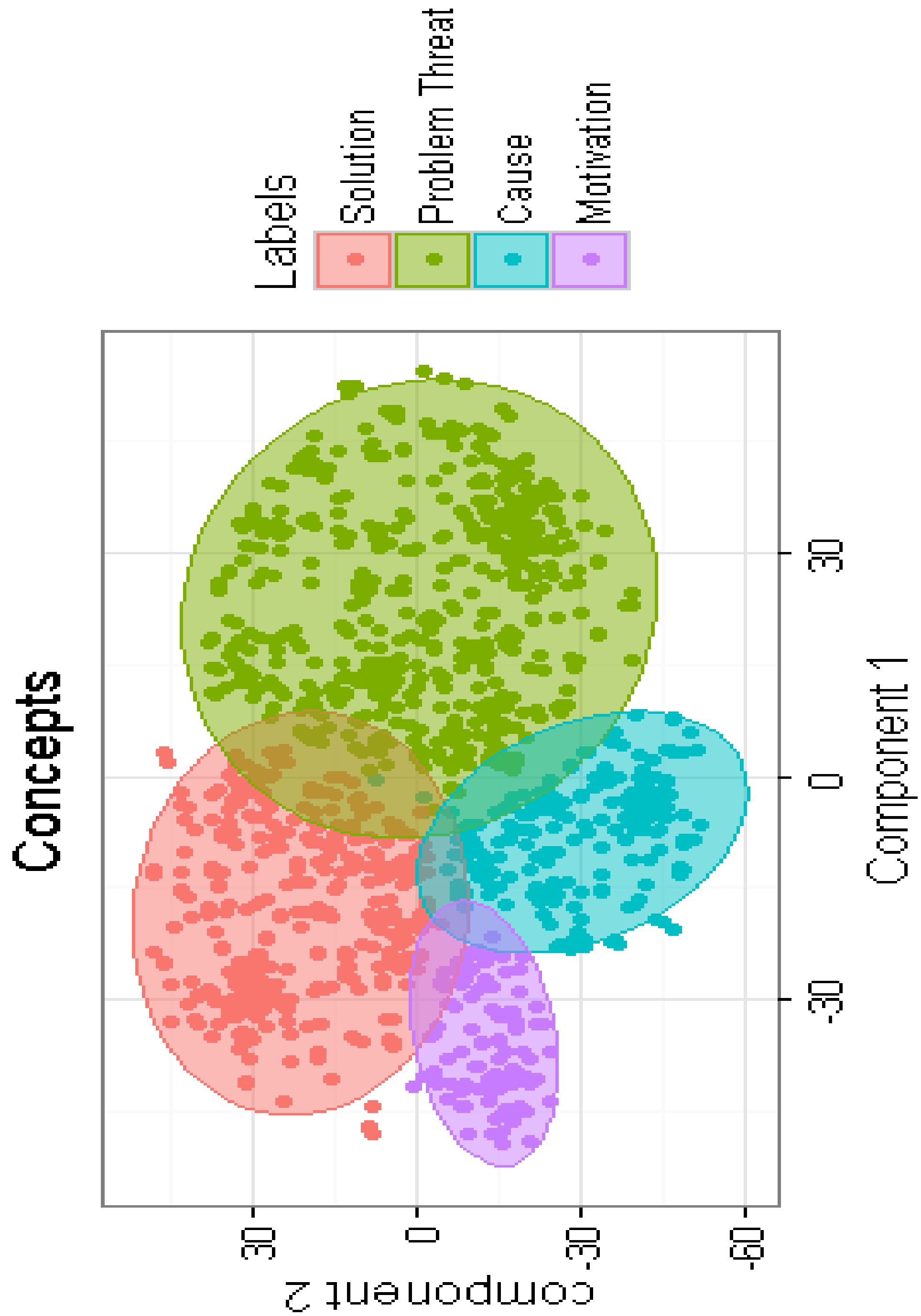

Figure B.4 Resultant Four Clusters after Applying t-SNE Using Concepts as Features

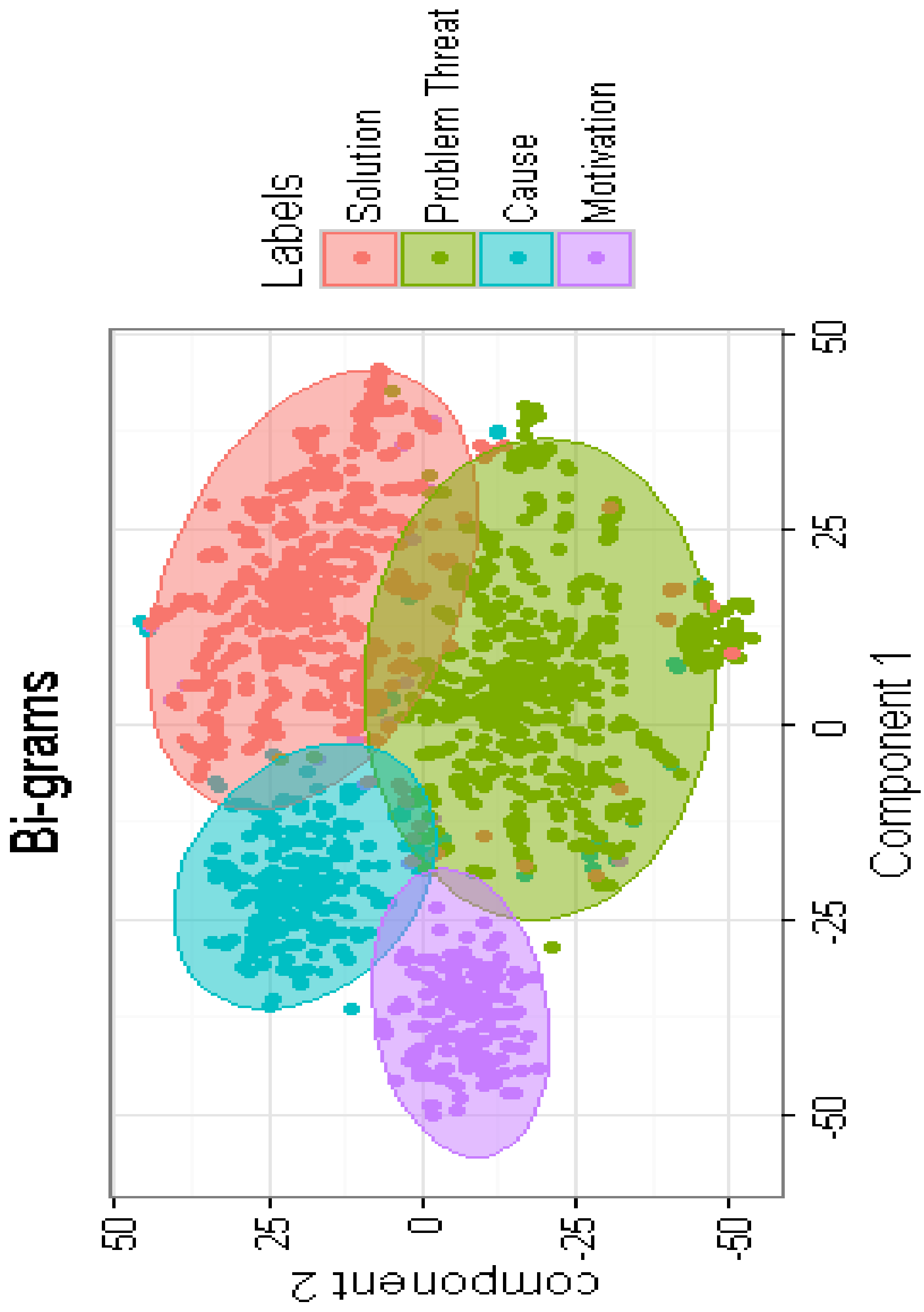

Figure B.5 Resultant Four Clusters after Applying t-SNE Using bi-grams as Features

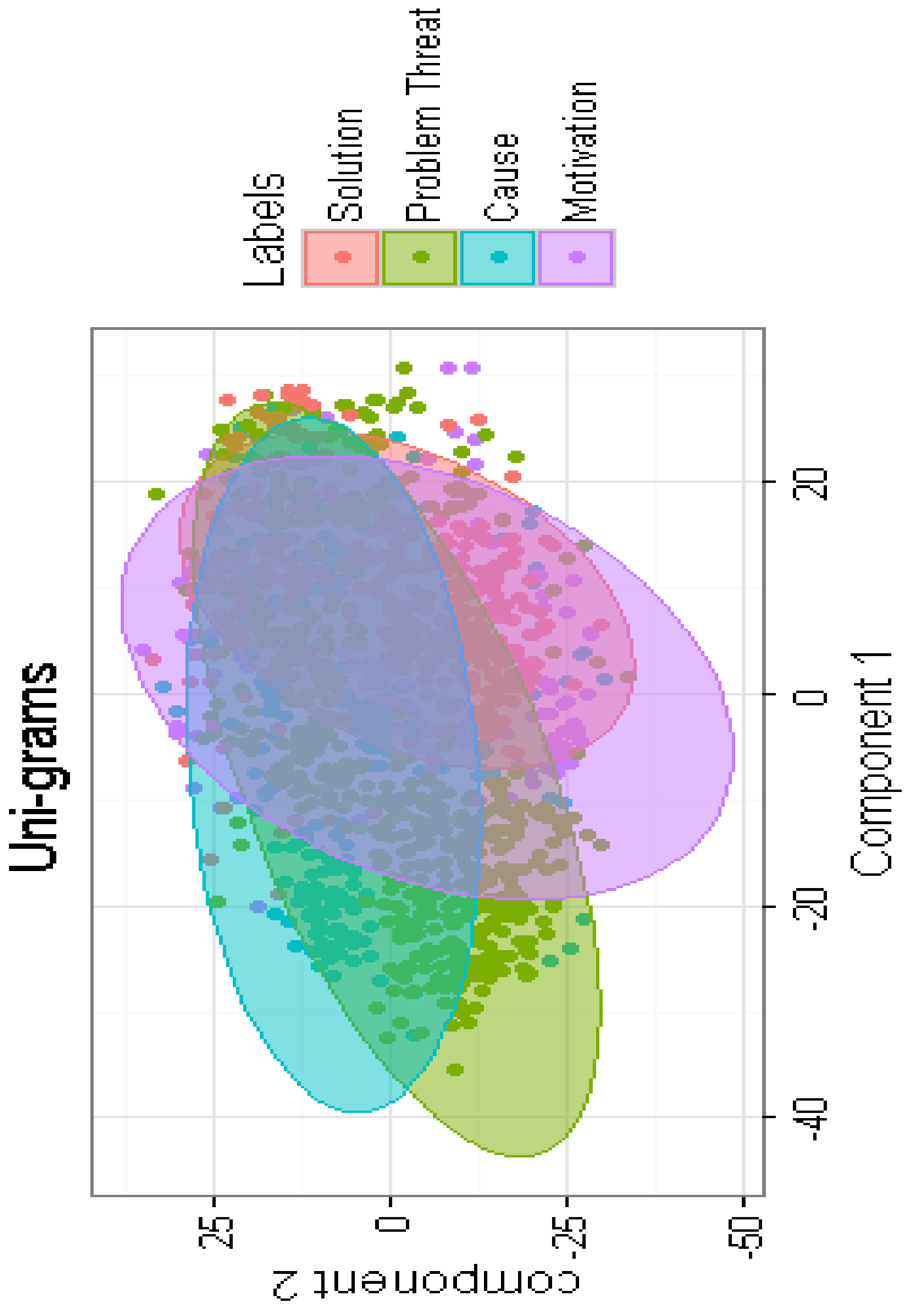

Figure B.6 Resultant Four Clusters after Applying t-SNE Using Uni-grams as Features

APPENDIX C

OTHER CLASSIFIERS PERFORMANCE

SVM

In this section we show the results of experimenting SVM (Cortes and Vapnik, 1995) classifier using different kernels: Linear, Radial basis function, and Polynomial. Kernel function specifies how the dot product is projected into higher feature space, without necessarily knowing that space.

SVM with Linear Kernel

Table C.1 *Frame/Non-Frame* Classification Using SVM with Linear Kernel

Method	**Class Label**	**Precision**	**Recall**	**F-measure**
Concepts	*Frame*	0.51	0.73	0.60
	Non-Frame	0.78	0.61	0.69
	Average	**0.64**	**0.67**	**0.64**
Bi-grams	*Frame*	0.45	0.56	0.50
	Non-Frame	0.68	0.71	0.69
	Average	**0.56**	**0.63**	**0.59**
Uni-grams	*Frame*	0.38	0.60	0.47
	Non-Frame	0.61	0.66	0.63
	Average	**0.49**	**0.63**	**0.55**

Table C.2 Frame Classification into Four Categories Using SVM with Linear Kernel

Method	**Frame Category**	**Precision**	**Recall**	**F-measure**
Concepts	Solution	0.63	0.65	0.64
	Problem Threat	0.69	0.66	0.67
	Cause	0.58	0.64	0.61
	Motivation	0.61	0.49	0.54
	Average	**0.63**	**0.61**	**0.62**
Bi-grams	Solution	0.69	0.61	0.65
	Problem Threat	0.64	0.69	0.67
	Cause	0.61	0.50	0.55
	Motivation	0.53	0.35	0.42
	Average	**0.62**	**0.54**	**0.57**
Uni-grams	Solution	0.59	0.63	0.61
	Problem Threat	0.67	0.62	0.64
	Cause	0.48	0.52	0.50
	Motivation	0.37	0.48	0.42
	Average	**0.53**	**0.56**	**0.54**

SVM with Radial Basis Function Kernel (RBF)

Using SVM with radial basis function (RBF) kernel yielded the best performance compared to other kernels. For Frame/Non-Frame classification the RBF-SVM yielded an average F-measure of 72% using concepts as features. This indicates that the dataset is non-linearly separable. For four frame classification, the RBF-SVM with concepts as features yielded an average F-measure of 67%.

Table C.3 *Frame/Non-Frame* Classification Using SVM with RBF Kernel

Method	Class Label	Precision	Recall	F-measure
Concepts	*Frame*	0.71	0.74	0.72
	Non-Frame	0.77	0.69	0.73
	Average	**0.74**	**0.71**	**0.72**
Bi-grams	*Frame*	0.73	0.59	0.65
	Non-Frame	0.71	0.75	0.74
	Average	**0.72**	**0.67**	**0.69**
Uni-grams	*Frame*	0.70	0.55	0.62
	Non-Frame	0.73	0.78	0.75
	Average	**0.71**	**0.66**	**0.68**

Table C.4 Frame Classification into Four Categories Using SVM with RBF Kernel

Method	**Frame Category**	**Precision**	**Recall**	**F-measure**
Concepts	Solution	0.71	0.67	0.69
	Problem Threat	0.77	0.72	0.74
	Cause	0.68	0.62	0.65
	Motivation	0.65	0.57	0.61
	Average	**0.70**	**0.64**	**0.67**
Bi-grams	Solution	0.64	0.70	0.67
	Problem Threat	0.68	0.61	0.64
	Cause	0.58	0.49	0.53
	Motivation	0.51	0.42	0.46
	Average	**0.60**	**0.56**	**0.58**
Uni-grams	Solution	0.61	0.58	0.59
	Problem Threat	0.63	0.69	0.66
	Cause	0.56	0.52	0.54
	Motivation	0.45	0.48	0.46
	Average	**0.56**	**0.57**	**0.57**

SVM with Polynomial Kernel

Table C.5 *Frame/Non-Frame* Classification Using SVM with Polynomial Kernel

Method	**Class Label**	**Precision**	**Recall**	**F-measure**
Concepts	*Frame*	0.65	0.71	0.68
	Non-Frame	0.79	0.64	0.71
	Average	**0.72**	**0.67**	**0.69**
Bi-grams	*Frame*	0.70	0.64	0.67
	Non-Frame	0.67	0.73	0.70
	Average	**0.68**	**0.68**	**0.68**
Uni-grams	*Frame*	0.65	0.63	0.64
	Non-Frame	0.74	0.76	0.75
	Average	**0.70**	**0.69**	**0.70**

Table C.6 Frame Classification into Four Categories Using SVM with Polynomial Kernel

Method	**Frame Category**	**Precision**	**Recall**	**F-measure**
Concepts	Solution	0.67	0.65	0.66
	Problem Threat	0.71	0.74	0.73
	Cause	0.63	0.67	0.65
	Motivation	0.60	0.54	0.57
	Average	**0.65**	**0.65**	**0.65**
Bi-grams	Solution	0.70	0.62	0.66
	Problem Threat	0.73	0.69	0.71
	Cause	0.52	0.58	0.55
	Motivation	0.44	0.42	0.43
	Average	**0.60**	**0.58**	**0.59**
Uni-grams	Solution	0.63	0.57	0.60
	Problem Threat	0.61	0.74	0.67
	Cause	0.59	0.55	0.57
	Motivation	0.39	0.49	0.44
	Average	**0.55**	**0.59**	**0.57**

Random Forests

In this section we show the results of experimenting the Random Forests (Breiman, 2001) classifier using different numbers of trees: 10, 20, 50, and 100. In Random Forests, as the number of trees grows, the computation time grows exponentially. It took a total of 38 hours to calculate the results for 100 trees. After experimenting with different numbers of trees, we found that the best performance in terms of F-measure is achieved when we set the number of trees to 50 trees.

Random Forests with 10 Trees

Table C.7 *Frame/Non-Frame* Classification Using Random Forests with 10 Trees

Method	**Class Label**	**Precision**	**Recall**	**F-measure**
Concepts	*Frame*	0.49	0.60	0.54
	Non-Frame	0.57	0.62	0.59
	Average	**0.53**	**0.61**	**0.57**
Bi-grams	*Frame*	0.36	0.47	0.41
	Non-Frame	0.41	0.54	0.47
	Average	**0.38**	**0.50**	**0.44**
Uni-grams	*Frame*	0.55	0.48	0.51
	Non-Frame	0.59	0.62	0.60
	Average	**0.57**	**0.55**	**0.56**

Table C.8 Frame Classification into Four Categories Using Random Forests with 10 Trees

Method	**Frame Category**	**Precision**	**Recall**	**F-measure**
Concepts	Solution	0.63	0.55	0.59
	Problem Threat	0.69	0.61	0.65
	Cause	0.64	0.55	0.59
	Motivation	0.61	0.51	0.56
	Average	**0.64**	**0.55**	**0.60**
Bi-grams	Solution	0.53	0.61	0.57
	Problem Threat	0.57	0.64	0.60
	Cause	0.52	0.48	0.50
	Motivation	0.46	0.37	0.41
	Average	**0.52**	**0.53**	**0.52**
Uni-grams	Solution	0.55	0.52	0.53
	Problem Threat	0.58	0.60	0.59
	Cause	0.51	0.54	0.52
	Motivation	0.48	0.50	0.49
	Average	**0.53**	**0.54**	**0.53**

Random Forests with 20 Trees

Table C.9 *Frame/Non-Frame* Classification Using Random Forests with 20 Trees

Method	**Class Label**	**Precision**	**Recall**	**F-measure**
Concepts	*Frame*	0.53	0.62	0.57
	Non-Frame	0.59	0.63	0.61
	Average	**0.56**	**0.62**	**0.59**
Bi-grams	*Frame*	0.41	0.48	0.44
	Non-Frame	0.44	0.56	0.50
	Average	**0.42**	**0.52**	**0.47**
Uni-grams	*Frame*	0.56	0.48	0.52
	Non-Frame	0.62	0.60	0.61
	Average	**0.59**	**0.54**	**0.56**

Table C.10 Frame Classification into Four Categories Using Random Forests with 20 Trees

Method	**Frame Category**	**Precision**	**Recall**	**F-measure**
Concepts	Solution	0.66	0.61	0.63
	Problem Threat	0.73	0.64	0.68
	Cause	0.67	0.58	0.62
	Motivation	0.65	0.56	0.60
	Average	**0.68**	**0.60**	**0.64**
Bi-grams	Solution	0.58	0.62	0.60
	Problem Threat	0.59	0.67	0.63
	Cause	0.55	0.49	0.52
	Motivation	0.48	0.40	0.44
	Average	**0.55**	**0.54**	**0.55**
Uni-grams	Solution	0.56	0.59	0.57
	Problem Threat	0.61	0.63	0.62
	Cause	0.55	0.57	0.56
	Motivation	0.51	0.54	0.52
	Average	**0.56**	**0.58**	**0.57**

Random Forests with 50 Trees

Table C.11 *Frame/Non-Frame* Classification Using Random Forests with 50 Trees

Method	**Class Label**	**Precision**	**Recall**	**F-measure**
Concepts	*Frame*	0.61	0.72	0.66
	Non-Frame	0.67	0.64	0.65
	Average	**0.64**	**0.68**	**0.65**
Bi-grams	*Frame*	0.44	0.49	0.46
	Non-Frame	0.47	0.57	0.52
	Average	**0.45**	**0.53**	**0.49**
Uni-grams	*Frame*	0.57	0.49	0.53
	Non-Frame	0.62	0.65	0.63
	Average	**0.59**	**0.57**	**0.58**

Table C.12 Frame Classification into Four Categories Using Random Forests with 50 Trees

Method	Frame Category	Precision	Recall	F-measure
Concepts	Solution	0.72	0.67	0.69
	Problem Threat	0.78	0.70	0.74
	Cause	0.71	0.65	0.68
	Motivation	0.68	0.61	0.64
	Average	**0.72**	**0.66**	**0.69**
Bi-grams	Solution	0.63	0.65	0.64
	Problem Threat	0.66	0.68	0.67
	Cause	0.59	0.51	0.55
	Motivation	0.51	0.45	0.48
	Average	**0.60**	**0.57**	**0.58**
Uni-grams	Solution	0.61	0.65	0.63
	Problem Threat	0.62	0.67	0.64
	Cause	0.58	0.60	0.59
	Motivation	0.53	0.57	0.55
	Average	**0.58**	**0.62**	**0.60**

Random Forests with 100 Trees

Table C.13 *Frame/Non-Frame* Classification Using Random Forests with 100 Trees

Method	**Class Label**	**Precision**	**Recall**	**F-measure**
Concepts	*Frame*	0.59	0.70	0.64
	Non-Frame	0.66	0.64	0.65
	Average	**0.62**	**0.67**	**0.64**
Bi-grams	*Frame*	0.43	0.45	0.44
	Non-Frame	0.48	0.52	0.50
	Average	**0.45**	**0.48**	**0.47**
Uni-grams	*Frame*	0.51	0.46	0.48
	Non-Frame	0.56	0.60	0.58
	Average	**0.53**	**0.53**	**0.53**

Table C.14 Frame Classification into Four Categories Using Random Forests with 100 Trees

Method	Frame Category	Precision	Recall	F-measure
Concepts	Solution	0.70	0.66	0.68
	Problem Threat	0.75	0.64	0.69
	Cause	0.68	0.64	0.66
	Motivation	0.65	0.56	0.60
	Average	**0.69**	**0.62**	**0.66**
Bi-grams	Solution	0.61	0.59	0.60
	Problem Threat	0.64	0.65	0.64
	Cause	0.58	0.50	0.54
	Motivation	0.48	0.46	0.47
	Average	**0.58**	**0.55**	**0.56**
Uni-grams	Solution	0.57	0.61	0.59
	Problem Threat	0.60	0.64	0.62
	Cause	0.52	0.58	0.55
	Motivation	0.50	0.52	0.51
	Average	**0.55**	**0.59**	**0.57**

Discussion of Classifiers Performance

When we compare the results of SVM and Random Forests, we found that SVM with radial basis function (RBF) kernel outperformed Random Forests for Frame/Non-Frame classification with an average F-measure of 72% using concepts as features.

However, for four frame classification, the Random Forests (with 50 trees) outperformed SVM (regardless of the used kernel). Random forests scored an overall average F-measure of 69% using concepts as features.

Lastly, using concepts as features typically yields higher average F-measure compared to uni-grams and bi-grams.