GENERATIVE CONTRASTIVE LEARNING
FOR STRUCTURAL FRAMING ANALYSIS

BY

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THESIS

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Abstract

Framing is the act of selecting "some aspects of a perceived reality and [making] them more salient in a communicating text" [1]. Framing has been widely used in journalism to influence public opinion. However, analysis of news framing has majorly relied on human expert efforts. Efforts have been put into developing automatic framing analysis via computational linguistic approaches. In this work, we propose a novel large-scale, multi-agency news dataset with crowd-sourced political stances and factuality labels to facilitate framing analysis. We propose two ways of conducting framing analyses on this dataset, the first is via learning a "switch" in the embedding space to change the generation trend, and the second utilizes a Generative Adversarial Network under a contrastive learning framework. We further create an interactive demo website to directly display results. Our code and dataset will be released to facilitate future research.

To my parents, for their love and support.

Acknowledgments

This endeavor would not have been possible without my research advisor Prof. Heng Ji and her priceless feedback and inspiration. She has been the perfect advisor, providing more support and guidance than I ever ask for.

I also could not have undertaken this journey without my mentors Manling Li and Chi Han, who generously helped me with their extraordinary knowledge and experience. Cooperating with them has been one of the most rewarding experiences of mine.

I am also grateful to my family and friends, for their belief in me has helped me stay motivated throughout this process. I would also like to thank my Syrian hamster, Jeremy, for all of the entertainment and emotional support.

Table of Contents

Chapter 1

Introduction

News is an important medium through which the members of society get to understand the world. However, despite the normative expectation of neutrality and objectivity [2], news articles covering the same event can vary among different news agencies. The same story can be covered from different perspectives, conventionally referred to as "frames" [1, 3, 4]. The act "to frame" is "to select some aspects of a perceived reality and make them more salient in a communicating text" [1]. As a linguistic technique, the practice of framing reflects the underlying preferences and intents of the covering news agency and is known to affect public opinion and political processes [5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15].

Prior work has proposed computational approaches for news framing analysis. One line of work focuses on recovering the underlying bias of the news agencies (*i.e.*, Political Viewpoint Identification) [16, 17, 18, 19, 20], and another line of work aims to locate the framing language and structures in the news articles [13, 14, 15, 21]. Recently, there are also efforts paid to generate texts with framing techniques, such as the task of reframing [22, 23].

In this work, we propose `MultiAgencyNews`, a novel large-scale, multi-agency news dataset with crowd-sourced political stances and factuality labels to facilitate framing analysis. Existing news aggregation platforms are utilized to collect metadata for recent social events with news article coverage from multiple news agencies. The metadata includes a series of labels including the news article URLs, news agency names, news agency political stance biases, and news agency factualities. The news articles are filtered with heuristics to balance the labels, guaranteeing that the comparison is fairly conducted.

We continue to propose two different methods of conducting framing analyses on this dataset, the first method, `SwitchLM`[1], learns a "switch" in a large

[1]The contribution of SwitchLM is led by Chi Han.

pre-trained language model's embedding space, the switch shifts the semantic embedding of specific words in a text prompt for text generation. The switch is a learnable parameterized matrix that projects embedding for each word to a linear subspace, where the semantics of corresponding dimensions align with the corresponding directions in a scaled manner.

The second method, `GenCo`, utilizes generative language models and contrastive learning. An initial configuration vector is inputted to a generator, which is a generative language model such as `T5`, `BART`, and `GPT`. Existing Information Extraction tools are then applied to extract the event structure of the generated news, where two levels of event graphs are involved: 1) the inter-subframe graphs which capture the coarse-grained semantics such as paragraphs, and 2) the intra-subframe graphs which capture the fine-grained semantics such as sentences. The generated event graph is then compared with texts sampled from corresponding news pools from the dataset for contrastive learning with a classifier. The generator and the classifier are collectively trained and mutually enhancing each other.

We further create an interactive demo application with `Streamlit` to directly display results. The application is live and hosted on a cloud server, which can be accessed with public IP. The application showcases two functionalities: 1) the *stance-guided generation* functionality, where the user gets to specify a stance on a continuous spectrum that will be used to guide the model on generating with stances, and 2) the *text stance scoring* functionality, where a user-specified piece of news article text can be inferred by a hosted trained model to profile the underlying political bias.

Chapter 2

Related Works

Previous relevant works have been focused on computational approaches of Political Viewpoint Indentification, framing mechanism, and the steerability of generative models.

2.1 Political Viewpoint Indentification

A line of work has been focused on automatic news framing analysis such as Political Viewpoint Identification (PVI) [16, 17, 18, 19, 20, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34]. The task of PVI is to infer the political stance of the writer news agency from the news article content under a classification setting. Earlier work with traditional feature engineering techniques utilizes features such as tf-idf [24], bag-of-words [24, 25, 26], and part-of-speech tags [25, 27, 28].

More recent work has put more effort to leverage the success of deep learning language models and techniques, with a variety of backbones ranging from LSTM and its variations [29, 30, 31] to transformer-based models [32, 33, 34]. This line of work relies more on word embedding and attention to capture the semantics behind news article contents.

2.2 Framing Mechanism

Another relevant domain is the analysis of the mechanism of framing. Earlier efforts have explored the task of framing language identification [13, 14, 15, 21]. This task mainly aims to conduct word-level binary classification for framing languages. However, this effort is subject to the elusive nature of the framing language and has difficulty in obtaining high-quality annotation.

Another recent line of work focuses more on understanding the framing strategies used [35, 36] and using the framing strategies for generation, with specific targets such as positive reframing [22] and controlled reframing [23].

Correspondingly, there have emerged open tools [37] to facilitate framing analysis for non-experts in computer science.

2.3 Steerability of Generative Models

Our method `SwitchLM` navigates the generative language models via learning a projection matrix in the word embedding space. This technique has been previously applied to visual edition [38, 39, 40, 41] to learn editing operations as linear trajectories in the latent space of Generative Adversarial Networks.

Previous applications include image dimension editing [38] where the output image can be parallelly or circularly shifted, facial feature finetuning and augmenting [39, 40] where the facial features can be finetuned or perturbed, and cognitive property transformation [41] where dimensions such as memorability, aesthetics, and emotional valence are altered.

Chapter 3

Methodology

In this chapter, the technical details of our methodology are described. We describe in §3.1 the process of collecting the dataset; in §3.2 the technique of our learned editing operations is elaborated; in §3.3 the details of the contrastive learning framework are presented.

3.1 `MultiAgencyNews` Data Collection

The data collection has two main phases:

1. Web scraping structured article metadata from `ground.news`

2. Collecting the full news article information from news agency websites.

We provide background information of `ground.news` in §3.1.1, details on these two phases in §3.1.2 and §3.1.3, and statistics in §3.1.4.

3.1.1 `Ground.news` Background Information

`Ground.news` is a News Aggregation platform, where news articles from different news agencies are aggregated and presented together. `Ground.news` has a *topic-story-article* hierarchy, a screenshot of which is shown in Figure 3.1. There are three levels in the hierarchy, namely:

1. *Topic* is the highest level, which can be one of the following four kinds:

    (a) abstract topics such as "politics" or "trade";

    (b) geopolitical concepts such as "iran" or "pakistan";

    (c) specific celebrities, such as "tim-cook" or "liz-truss";

    (d) news sources, such as npr or new-york-times.

2. *Story* is the middle level, an event that got coverage from different sources - *e.g.*, "elon-musk-and-twitter-discussed-price-cut-to-44-billion-takeover-in-recent-weeks" contains news articles covering the recent event that concerns the recently acquisition by Elon Musk.

3. *Article* is the lowest level, which contains the metadata of an article.

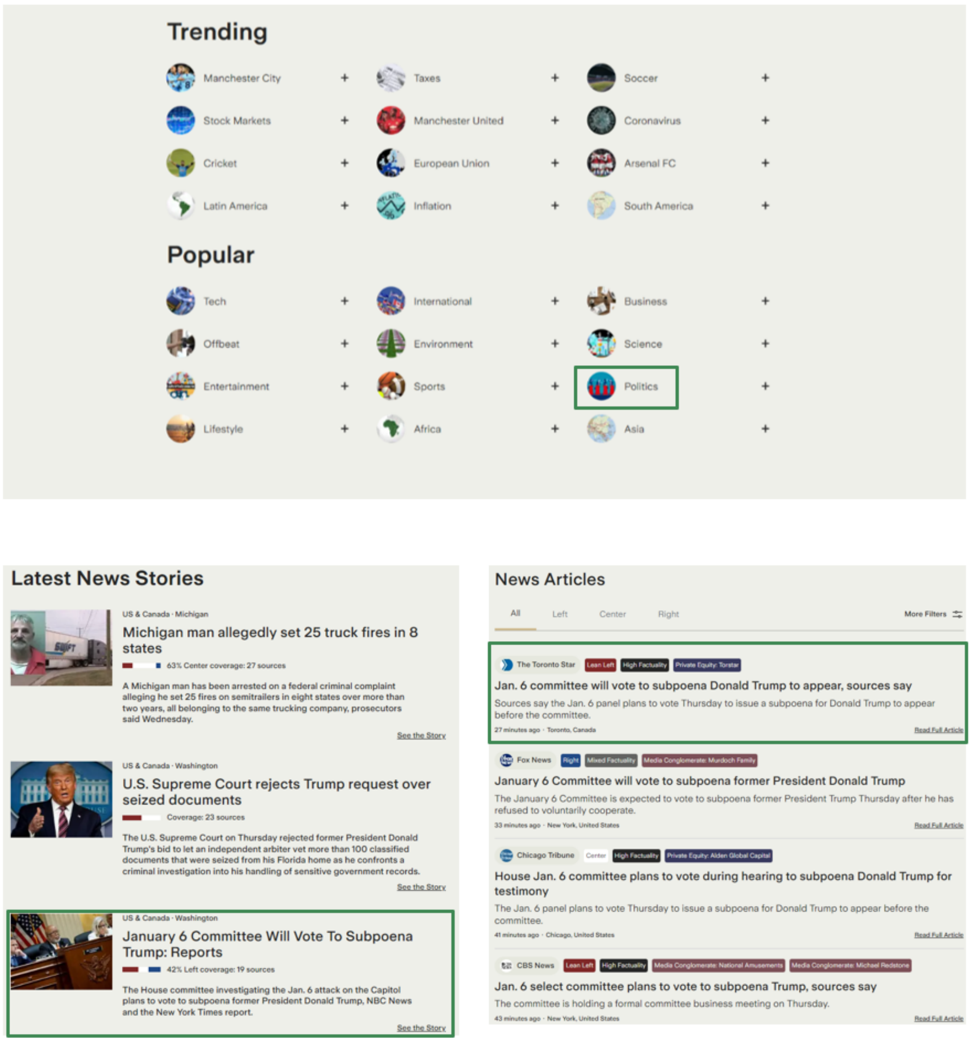


Figure 3.1: A screeshot of `ground.news` (https://ground.news). The top figure displays a non-exhaustive list of the topics covered. The left bottom figure displays a list of *stories* under the topic *Politics*. The right bottom figure displays a list of news *articles* from different news agencies for the *story* "January 6 Committee ... Reports," where metadata is provided.

3.1.2 Article Metadata

To collect the news data, we need to first obtain the article metadata. We create a web scraper[1] to collect article metadata from `ground.news`. The web scraper is based on the HTML parsing toolkit `BeautifulSoup` and the frontend testing toolkit `Selenium`. The web scraper starts with the root level of the topic list[2]. By mimicking the mouse-clicking events with `Selenium`, the sub-page of each topic is displayed. The web scraper further parses the related section of the current topic web page to obtain more topics. This process can be modeled as a multi-source Breadth-First-Search process.

Then the story pages on each topic page are collected, which are then used to find metadata for each specific article. Among the metadata provided by `ground.news`, three kinds of metadata serve our purposes most substantially:

1. *bias* is the political stance category of the current news agency labeled by `ground.news` (one of "Left," "Lean Left," "Center," "Lean Right," "Right," "Unknown")

2. *factuality* is the news reliability category of the current news agency labeled by `ground.news` (one of "High Factuality," "Low Factuality," "Mixed Factuality," "Unknown")

3. *URL* is the link to the original news web page.

Note that the original full text is not directly available to us. Thus, the *URL* obtained in §3.1.2 is further processed in §3.1.3 to obtain the full information of the news articles.

3.1.3 Full News Information Collection

We utilized the `news-please` toolkit[3] to extract the news content information from the *URL* provided by `ground.news` in §3.1.1. Namely, we collected the following attributes of the news articles:

1. *article_idx*: the index of the article within the story;

2. *name*: name of the news agency;

[1] https://github.com/liamjxu/ground_news_webscraper
[2] https://ground.news/my/discover
[3] https://github.com/fhamborg/news-please

3. *date_publish*: the date the article got published;
4. *image_url*: the URL to the news image (if any);
5. *language*: the language of the article;
6. *url*: the URL to the original article;
7. *source_domain*: the source domain of the original article;
8. *title*: the article title;
9. *maintext*: the main text of the article.

3.1.4 Dataset Statistics

When the data collection is finished, the final dataset has the following statistics shown in Table 3.1. The dataset is open-sourced [4].

Table 3.1: The Statistics of the Collected Dataset

Metric	**Number**
collected topics	544
collected stories	17,716
collected articles	187,479
unique urls	107,721
words in the unique articles	54,631,854

3.2 `SwitchLM` Functionality Suites

We propose to conduct framing analysis on the `MultiAgencyNews` dataset. Specifically, we aim to answer the following questions:

> *How to determine the underlying stance for news articles?*
> *How to generate text with pre-set stance?*

Correspondingly, we propose the `SwitchLM` Functionality Suites, which consist of the following two functionalities:

[4] https://github.com/blender-nlp/MultiAgencyNews

1. Stance categorization upon given input text.

2. Text generation controlled by input stance;

In §3.2.1, we elaborate our motivation behind this design. We further provide the design details in §3.2.2 and implementation details in §3.2.3.

3.2.1 Motivation

Different audiences with ranged stances can have varied perceptions of the same concept (*e.g.*, guns), however, within the fixed vocabulary of generative language models, the word embedding for the same word is static across stances. This counter-intuitive setting motivated us to design means of adding another degree of freedom to allow cross-stance dynamic embedding.

Inspired by the steerability demonstrated in visual deep generative models, we hypothesized that a linear subspace in the word embedding space exists for natural language generation models, where the latent embeddings corresponding to stance-shifting operations align, as shown in Figure 3.2.

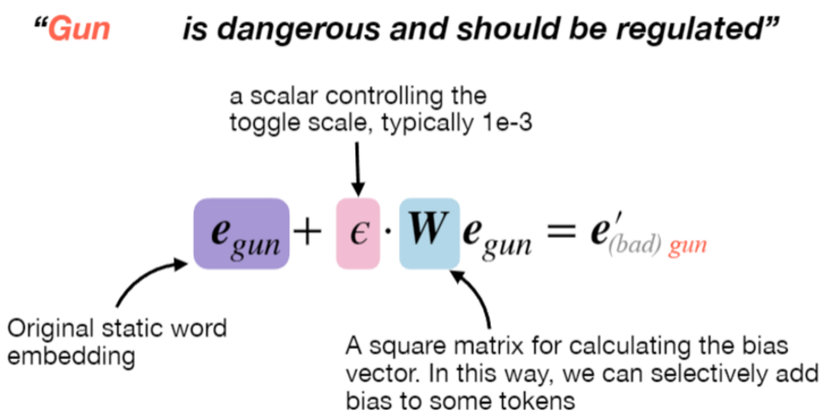


Figure 3.2: Learning a projection matrix for switching generative language models allows selective addition of stance shifts.

Here, e is the original static word embedding from the pre-trained generative language model, and e' is the stance-navigated word embedding. The projection matrix W maps the embedding of each word in the vocabulary into a basis of their specific editing subspace. The scalar ϵ then controls the scale of stance shifting.

This hypothesis allows us to achieve the two functionalities as proposed in §3.2, as elaborated in §3.2.2.

3.2.2 Model Design

We now describe our model design and explain how the functionalities in §3.2.2 can be unified under the hypothesis in §3.2.1 via this model design.

The high-level model architecture is shown in Figure 3.3. The linearly transformed word embeddings are only applied to the output layer of the generative models as a replacement for the original output embedding, and W is the only learnable parameter in our model, which guarantees the parameter efficiency of the method.

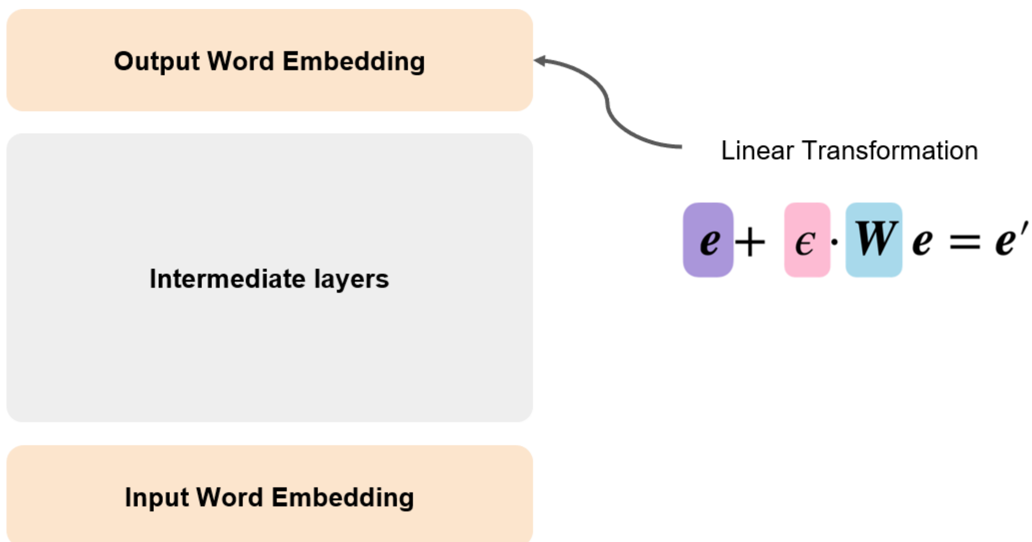


Figure 3.3: The Model Architecture of `SwitchLM`.

Corresponding to the two functionalities in §3.2, the model has two modes of application, shown in Figure 3.4. Under mode (a), the model conducts generation with a specified ϵ translated from the user input on a political stance spectrum. Under mode (b), the model operates under a frozen W and profiles the probability of generating the given input with different ϵ and treats that distribution as the stance likelihood distribution. In this way, the model serves both the stance-guided generation functionality and the stance detection functionality.

3.2.3 Implementation Details

The model backbone was GPT-neo-1.3B, we trained our model on our recently collected `MultiAgencyNews` dataset. The training objective is to max-

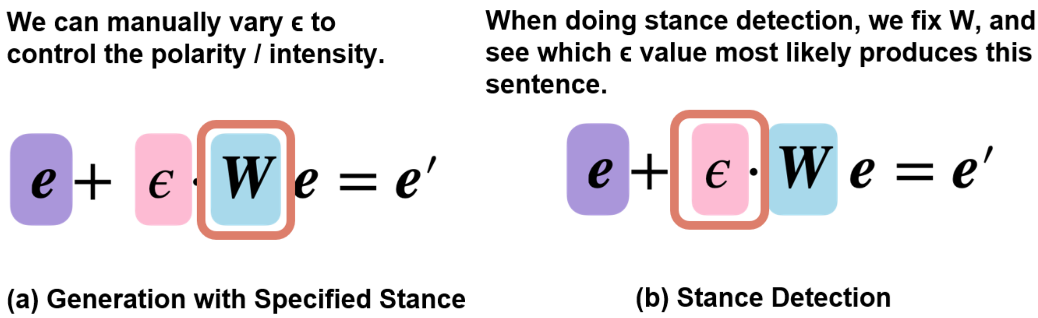


Figure 3.4: The Two Modes of `SwitchLM`.

imize the log-likelihood of texts conditioned on their stances. We trained our model on 1 NVIDIA V100 16G GPU card until convergence[5].

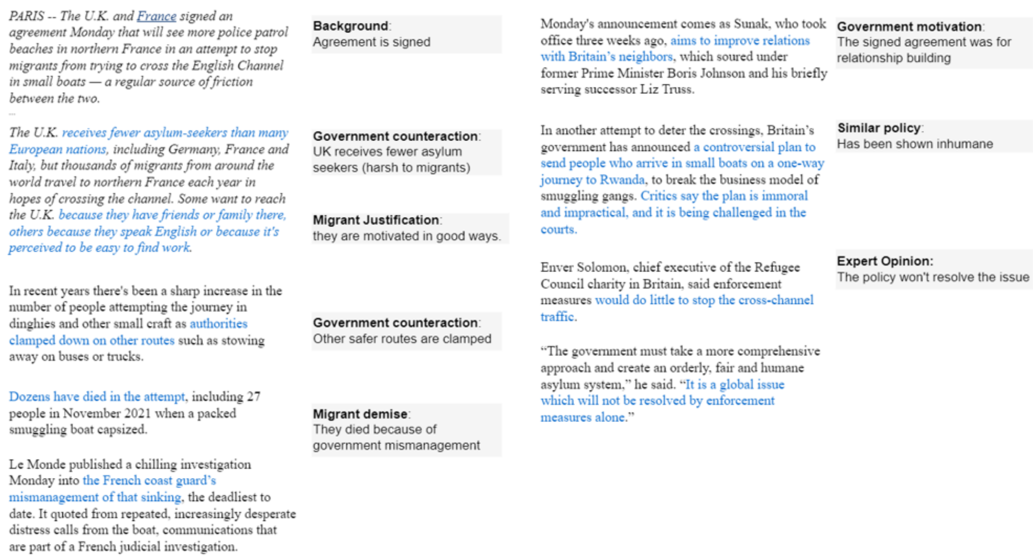
3.3 Contrastive Learning for Structural Framing Analysis

Another main goal of conducting framing analysis on the `MultiAgencyNews` dataset is to capture the framing strategies for subframe structures. We propose `GenCo` (**Gen**erative **Co**ntrastive Learning Framework for Framing Analysis) to achieve this goal. We provide the motivation in §3.3.1 and the model details in §3.3.2.

3.3.1 Motivation

One widely perceived framing strategy is leveraging the presentation order to create an uneven impression of the different frames covered in the news article. Figure 3.5 and Figure 3.6 show two news articles covering the same social events of a recent agreement between France and the UK to counteract illegal immigration. The article structures are different, as the left-wing news agency emphasizes the misbehavior of the governments, the justification of immigration, and the unfortunate experience of the migrants; while the right-wing news agency focuses on the policy details and how the policy will be beneficial to fight crime.

[5] https://github.com/Glaciohound/SwitchingLM


PARIS -- The U.K. and France signed an agreement Monday that will see more police patrol beaches in northern France in an attempt to stop migrants from trying to cross the English Channel in small boats — a regular source of friction between the two.

Background: Agreement is signed

The U.K. receives fewer asylum-seekers than many European nations, including Germany, France and Italy; but thousands of migrants from around the world travel to northern France each year in hopes of crossing the channel. Some want to reach the U.K. because they have friends or family there, others because they speak English or because it's perceived to be easy to find work.

Government counteraction: UK receives fewer asylum seekers (harsh to migrants)

Migrant Justification: they are motivated in good ways.

In recent years there's been a sharp increase in the number of people attempting the journey in dinghies and other small craft as authorities clamped down on other routes such as stowing away on buses or trucks.

Government counteraction: Other safer routes are clamped

Dozens have died in the attempt, including 27 people in November 2021 when a packed smuggling boat capsized.

Migrant demise: They died because of government mismanagement

Le Monde published a chilling investigation Monday into the French coast guard's mismanagement of that sinking, the deadliest to date. It quoted from repeated, increasingly desperate distress calls from the boat, communications that are part of a French judicial investigation.

Monday's announcement comes as Sunak, who took office three weeks ago, aims to improve relations with Britain's neighbors, which soured under former Prime Minister Boris Johnson and his briefly serving successor Liz Truss.

Government motivation: The signed agreement was for relationship building

In another attempt to deter the crossings, Britain's government has announced a controversial plan to send people who arrive in small boats on a one-way journey to Rwanda, to break the business model of smuggling gangs. Critics say the plan is immoral and impractical, and it is being challenged in the courts.

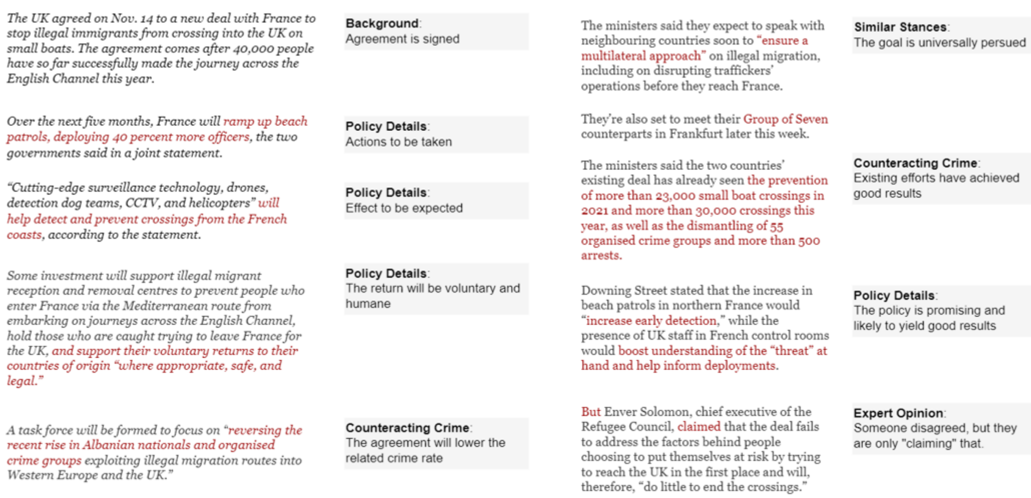
Similar policy: Has been shown inhumane

Enver Solomon, chief executive of the Refugee Council charity in Britain, said enforcement measures would do little to stop the cross-channel traffic.

Expert Opinion: The policy won't resolve the issue

"The government must take a more comprehensive approach and create an orderly, fair and humane asylum system," he said. "It is a global issue which will not be resolved by enforcement measures alone."

Figure 3.5: The Subframe-level Dissection of the News Article from a Left-wing News Agency.


The UK agreed on Nov. 14 to a new deal with France to stop illegal immigrants from crossing into the UK on small boats. The agreement comes after 40,000 people have so far successfully made the journey across the English Channel this year.

Background: Agreement is signed

Over the next five months, France will ramp up beach patrols, deploying 40 percent more officers, the two governments said in a joint statement.

Policy Details: Actions to be taken

"Cutting-edge surveillance technology, drones, detection dog teams, CCTV, and helicopters" will help detect and prevent crossings from the French coasts, according to the statement.

Policy Details: Effect to be expected

Some investment will support illegal migrant reception and removal centres to prevent people who enter France via the Mediterranean route from embarking on journeys across the English Channel, hold those who are caught trying to leave France for the UK, and support their voluntary returns to their countries of origin "where appropriate, safe, and legal."

Policy Details: The return will be voluntary and humane

A task force will be formed to focus on "reversing the recent rise in Albanian nationals and organised crime groups exploiting illegal migration routes into Western Europe and the UK."

Counteracting Crime: The agreement will lower the related crime rate

The ministers said they expect to speak with neighbouring countries soon to "ensure a multilateral approach" on illegal migration, including on disrupting traffickers' operations before they reach France.

Similar Stances: The goal is universally persued

They're also set to meet their Group of Seven counterparts in Frankfurt later this week.

The ministers said the two countries' existing deal has already seen the prevention of more than 23,000 small boat crossings in 2021 and more than 30,000 crossings this year, as well as the dismantling of 55 organised crime groups and more than 500 arrests.

Counteracting Crime: Existing efforts have achieved good results

Downing Street stated that the increase in beach patrols in northern France would "increase early detection," while the presence of UK staff in French control rooms would boost understanding of the "threat" at hand and help inform deployments.

Policy Details: The policy is promising and likely to yield good results

But Enver Solomon, chief executive of the Refugee Council, claimed that the deal fails to address the factors behind people choosing to put themselves at risk by trying to reach the UK in the first place and will, therefore, "do little to end the crossings."

Expert Opinion: Someone disagreed, but they are only "claiming" that.

Figure 3.6: The Subframe-level Dissection of the News Article from a Right-wing News Agency.

This discrepancy in the news article structures motivates us to hypothesize that the article structure reflects the writer's political stance, and this preference in the article structure, as well as subframe choices, can be modeled by a generative language model. In the next section, we elaborate on our `GenCo` details and explain how it achieves this goal.

3.3.2 GenCo Details

The architecture of `GenCo` is shown in Figure 3.7. The framework starts with an input configuration vector, where the user gets to specify different dimensions of framing, such as political stances and emotional intensity. The vector is then input to a controllable generator which is a generative language model such as `T5`, `BART`, and `GPT`. Existing Information Extraction tools are then applied to extract the event structure of the generated news. We follow [42] to extract the subframes and leverage AMR graphs (*e.g.*, Figure 4.5 and Figure 4.6) with `amrlib`[6] to construct article event graphs. Two levels of event graphs are involved: 1) the inter-subframe graphs which capture the coarse-grained semantics such as paragraphs, and 2) the intra-subframe graphs which capture the fine-grained semantics such as sentences. The generator then generates an event graph which is compared to event graphs sampled from corresponding news pools from the dataset for contrastive learning with a classifier. The generator and the classifier are collectively trained and mutually enhancing each other.

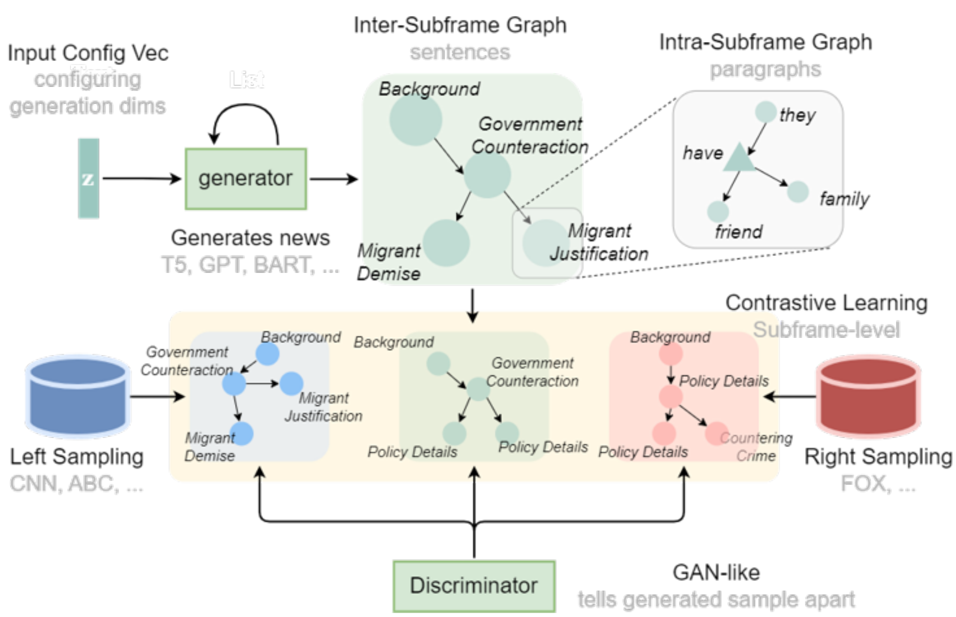


Figure 3.7: The Architecture of `GenCo`.

[6]https://github.com/bjascob/amrlib

Chapter 4

Empirical Study and Analysis

We provide more empirical study results on the `MultiAgencyNews` dataset by comparing news articles from left- and right-wing news agencies. We present a word cloud visualization of the news article contents in §4.1, a topic modeling visualization with LDA in §4.2, an AMR graph visualization in §4.3, and a PVI baseline with a BERT backbone in §4.4.

For the word cloud, LDA visualization, and AMR visualization, the topic of their corpus is gun control[1]. For the BERT PVI baseline, the whole dataset is used.

4.1 Word Cloud by Frequency

The news article content of a gun control news[2] is modeled with word cloud[3] and shown in Figure 4.1. On the Left side, the discussion is inclined towards the assault weapons themselves and their consequences, while on the Right side discussion is inclined towards the bill itself, the opponents' partisanship, and political concepts.

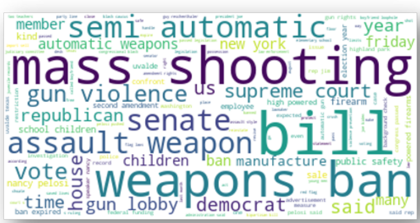


Figure 4.1: Wordcloud of Left-wing News Articles.

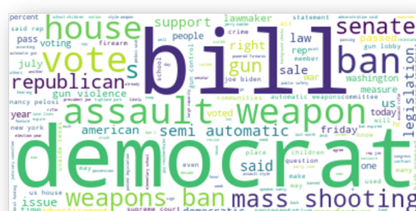


Figure 4.2: Wordcloud of Right-wing News Articles.

[1] https://ground.news/interest/gun-control
[2] https://tinyurl.com/2nzw6c3m
[3] https://pypi.org/project/wordcloud/

4.2 Topic Modeling with LDA

We also apply Latent Dirichlet Allocation (LDA) topic modeling on the dataset to compare the topics on both sides. The results are shown in Figure 4.3 and Figure 4.4. On the Left side, topics are more dispersed, and the discussion on the ban itself is equivalent to weapons, while on the Right side topics are more focused, and the largest topic emphasizes the ban itself more than the weapons.

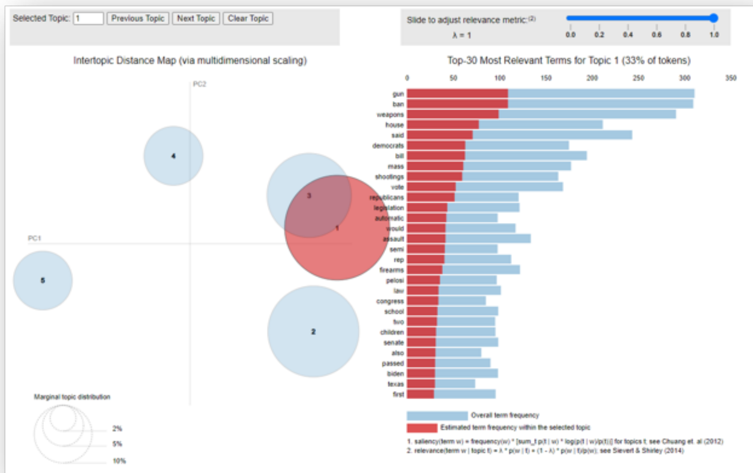


Figure 4.3: LDA Topic Modelling Result of Left-wing News Articles.

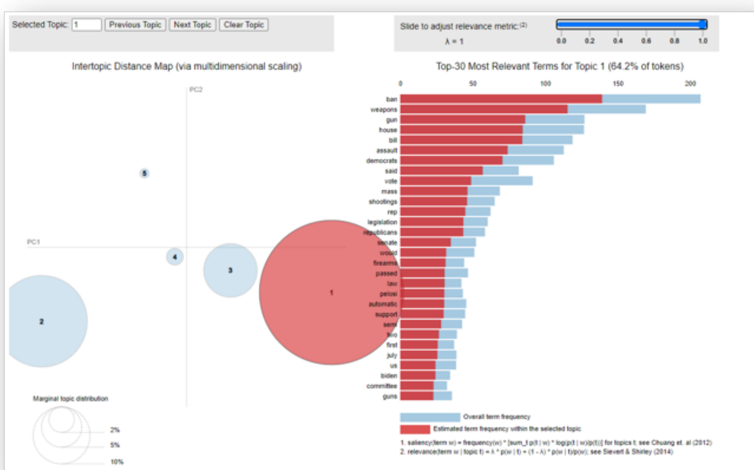


Figure 4.4: LDA Topic Modelling Result of Right-wing News Articles.

4.3 AMR Graph Modeling

The Abstract Meaning Representation (AMR) graphs are also extracted to compare the article structures on both sides. The results are shown in Figure 4.5 and Figure 4.6. In addition to the basic facts (shooter age, place of incident, *etc.*), the news article on the Left side pointed out the emotions (“sad” / “anger”), while the news article on the Right side emphasizes the critical injury to the officer (“situation” / “critical”).

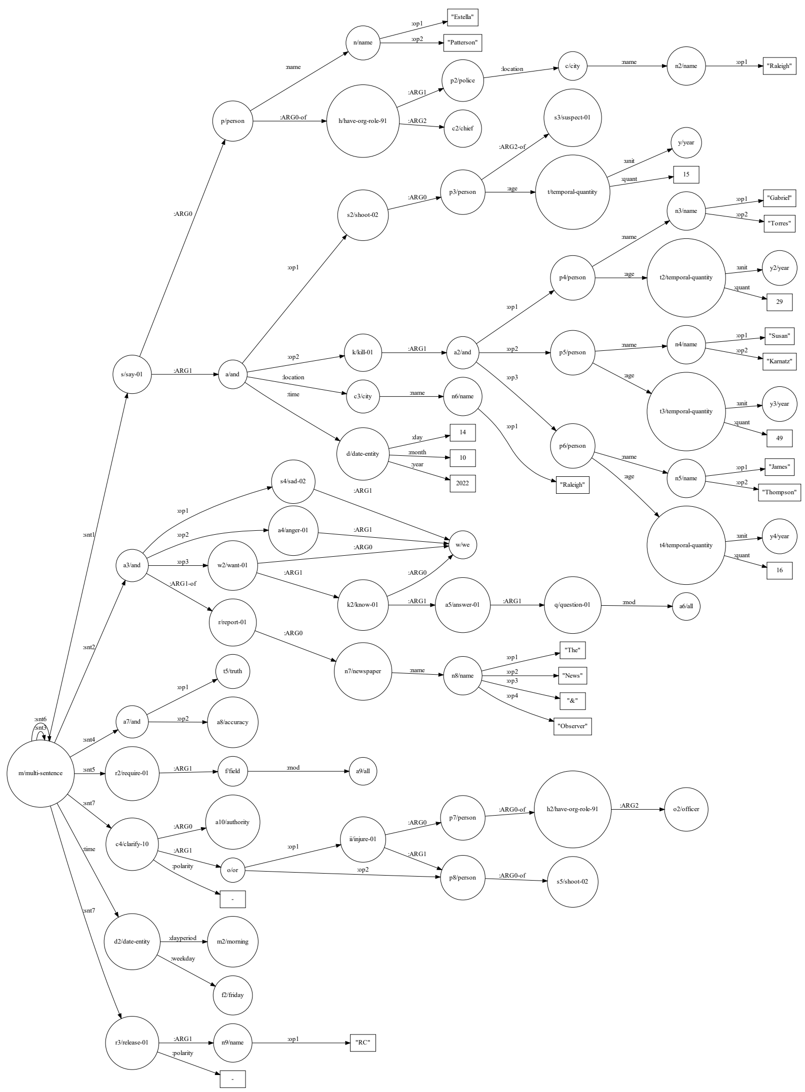


Figure 4.5: The AMR Graph of Left-wing News Articles.

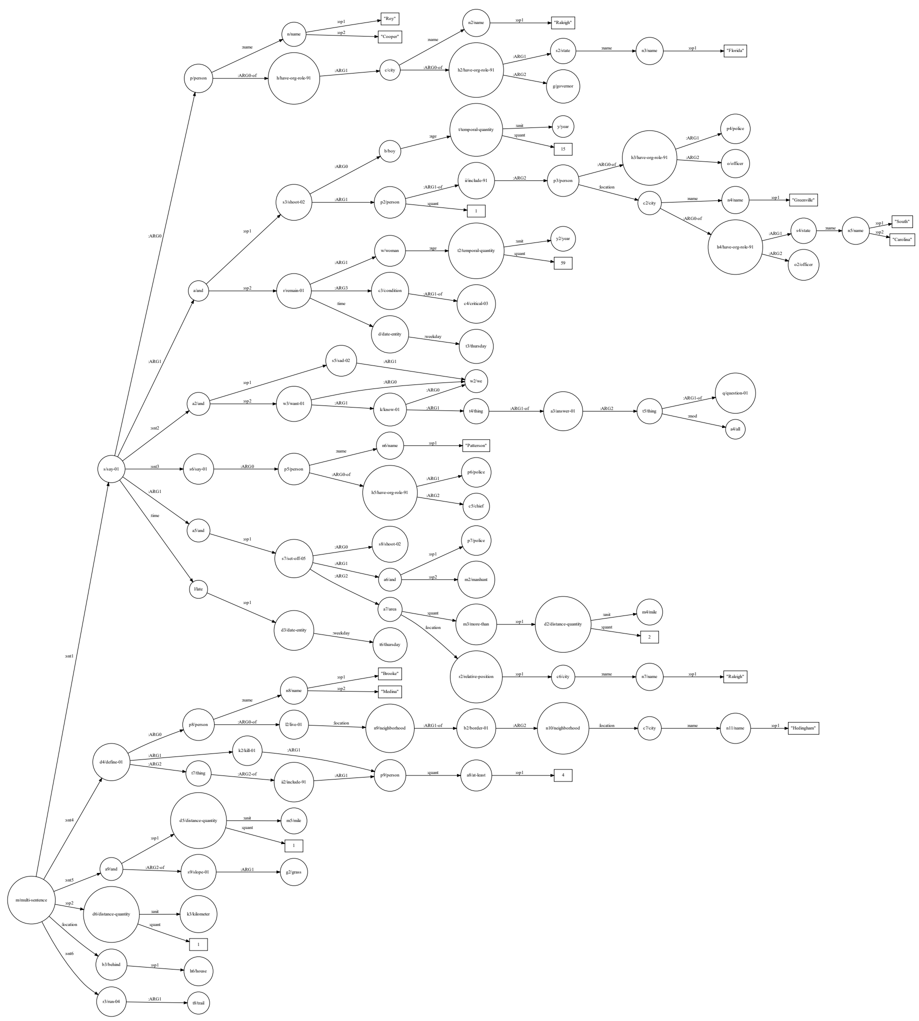


Figure 4.6: The AMR Graph of Right-wing News Articles.

4.4 BERT PVI Baseline

To evaluate how challenging the dataset is for Political Viewpoint Identification (PVI), we finetuned a BERT model for sequence classification. The finetuning started with a vanilla bert-base-uncased checkpoint from HuggingFace Transformers[4]. The task is formulated as a 2-way classification with binary cross entropy loss. The dataset was split into training, validation, and test sets at the ratio of 0.7/0.1/0.2. The results are shown in Figure 4.7. The baseline model achieved only 59.19% accuracy on the test set, which is only marginally higher than random guessing. This implies that PVI on the `MultiAgencyNews` dataset is still a challenging task.

Figure 4.7: The AMR Graph of Left-wing News Articles.

[4]https://huggingface.co/bert-base-uncased

Chapter 5

Interactive Demo Application

We designed and implemented an interactive demo application[1] hosted on an AWS Cloud server to demonstrate our framing analysis functionalities. The demo application is based on Streamlit[2]. In the following sections, we elaborate on two functionalities of the demo application: 1) Text generation controlled by user-specified Left-Right stance position in §5.1, and 2) Left-Right stance categorization given text input in §5.2.

5.1 Stance-guided Generation

A screenshot of the interface for stance-guided generation is shown in Figure 5.1. A continuous slide bar controls the left-right position of text generation, and the user can specify the random seed and the max/min generation length for more generation control. The user can then input prefix text for the model to continue writing. After the "Generate!" button is clicked, the generated text will be displayed.

5.2 Stance Categorization

A screenshot of the interface for stance categorization is shown in Figure 5.2. An input box allows the user to put in the text to be analyzed. After clicking on the "Analyze!" button, two results will be output and displayed: 1) distribution of the probability across all 7 different stance categories, in the form of a histogram chart, and 2) a list-out of text spans that serve as evidence for the stance categorization and their evidence scores.

[1] `http://switch.blenderdemo.com:8501/`
[2] `https://streamlit.io/`

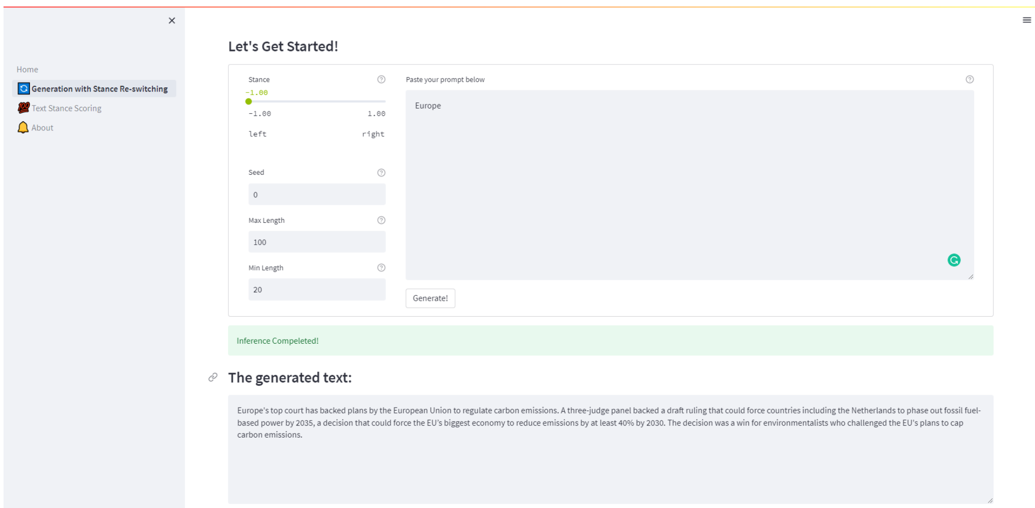


Figure 5.1: The interface of the Stance-guided Generation functionality.

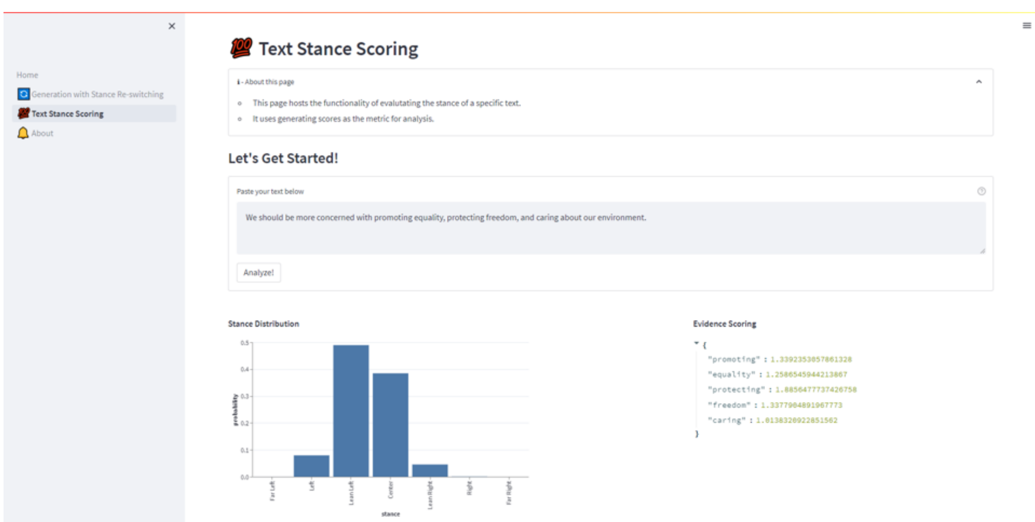


Figure 5.2: The interface of the Stance Categorization functionality.

Chapter 6

Conclusion

In this paper, we propose a novel large-scale, multi-agency news dataset with crowd-sourced political stances and factuality labels to facilitate framing analysis. We show through empirical study and baseline training that the dataset reveals the discrepancy in linguistic features of the different news agencies with different political stances. To conduct framing analyses on this dataset, two methods are proposed. The first is via learning a "switch" in the embedding space to latently edit the word embeddings, and the second utilizes a generative contrastive learning framework. An interactive website is further created to directly demonstrate our pipelines.

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