GENERATIVE CONTRASTIVE LEARNING FOR STRUCTURAL FRAMING ANALYSIS

BY

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THESIS

Submitted in partial fulfillment of the requirements
for the degree of Bachelor of Science in Electrical and Computer Engineering
in the Undergraduate College of the
University of Illinois Urbana-Champaign, 2022

Urbana, Illinois

Adviser:

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Abstract

Framing is the act “to select some aspects of a perceived reality and make 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 for her priceless feedback and inspiration. She has been the perfect advisor providing more support and guidance than I can 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 the entertainment and emotional support.

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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 which 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, which is 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.

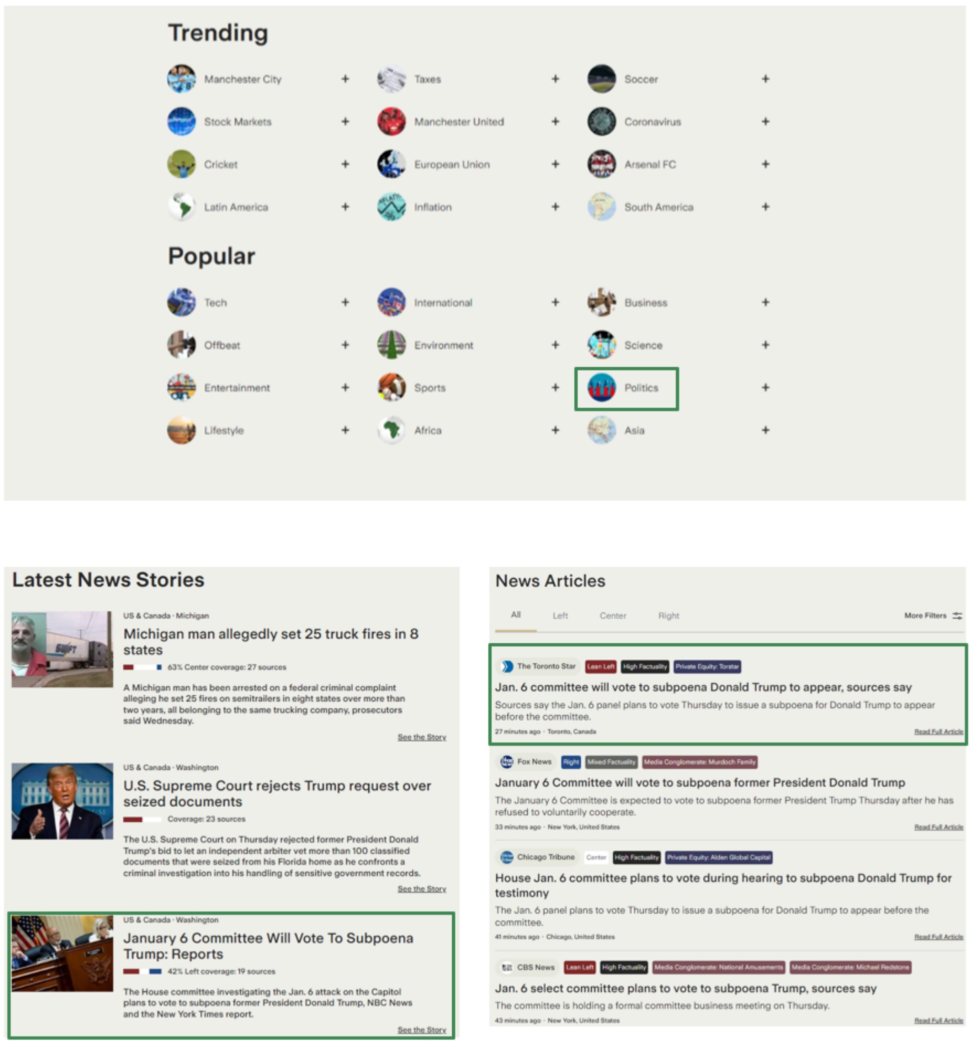

Figure 3.1: A Screeshot of `ground.news` (https://ground.news). The top figure displays a non-exhaustive list of the topics covered. The left bottom figure displays a list of *stories* under the topic *Politics*. The right bottom figure displays a list of news *articles* from different news agencies 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 scrapper[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 scrapper 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].

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

Table 3.1: The Statistics of the Collected Dataset

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.

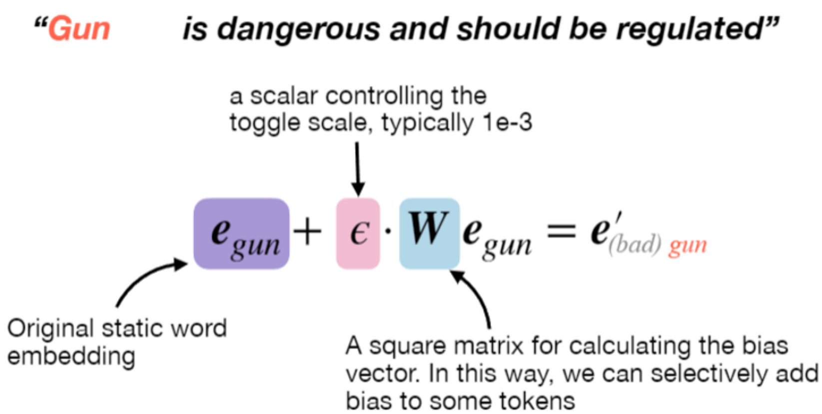

Figure 3.2: Learning a projection matrix for switching generative language models allows selective addition of stance shifts.

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.

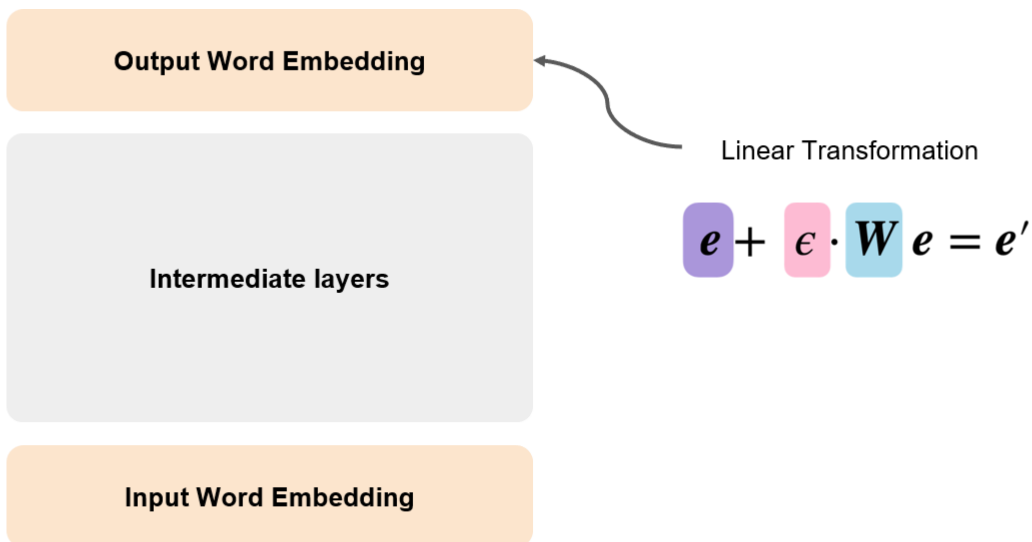

Figure 3.3: The Model Architecture of `SwitchLM`.

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-

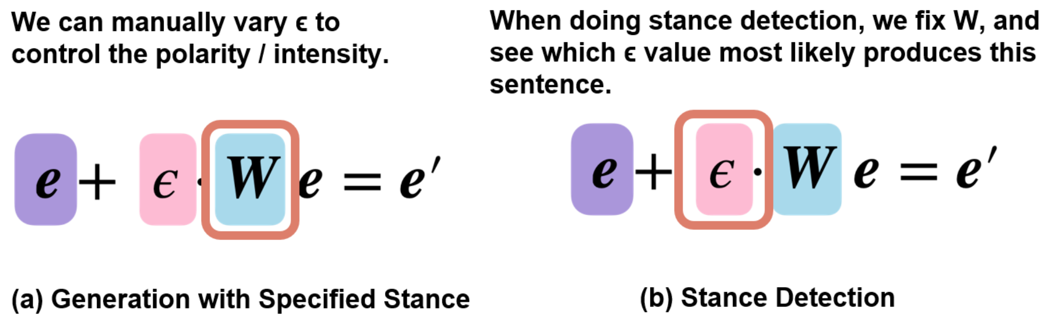

Figure 3.4: The Two Modes of `SwitchLM`.

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

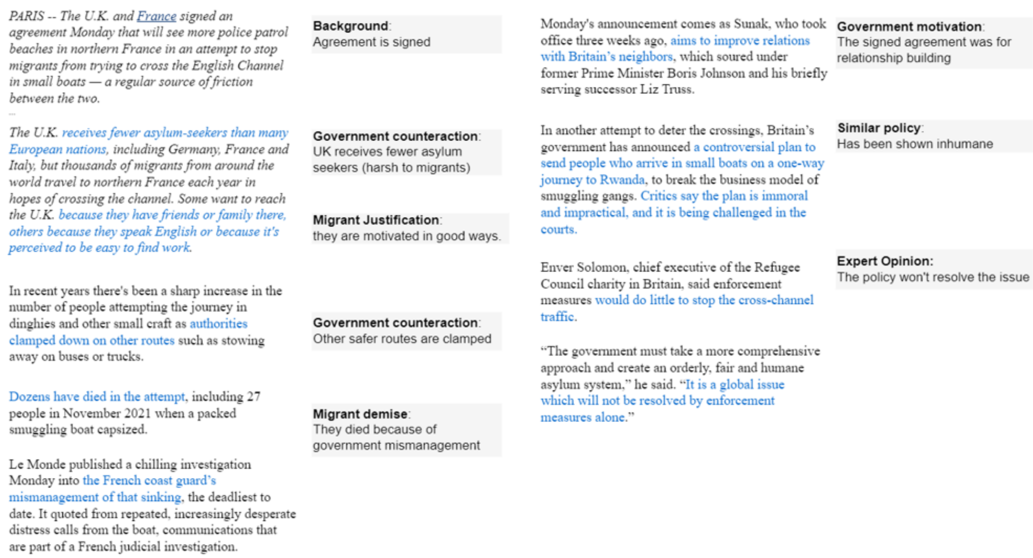

Figure 3.5: The Subframe-level Dissection of the News Article from a Left-wing News Agency.

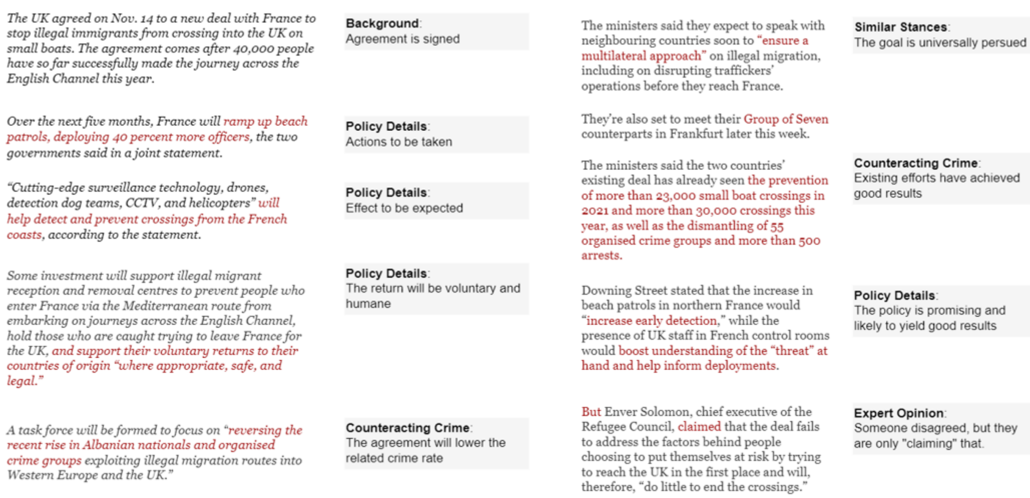

Figure 3.6: The Subframe-level Dissection of the News Article from a Right-wing News Agency.

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 [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.

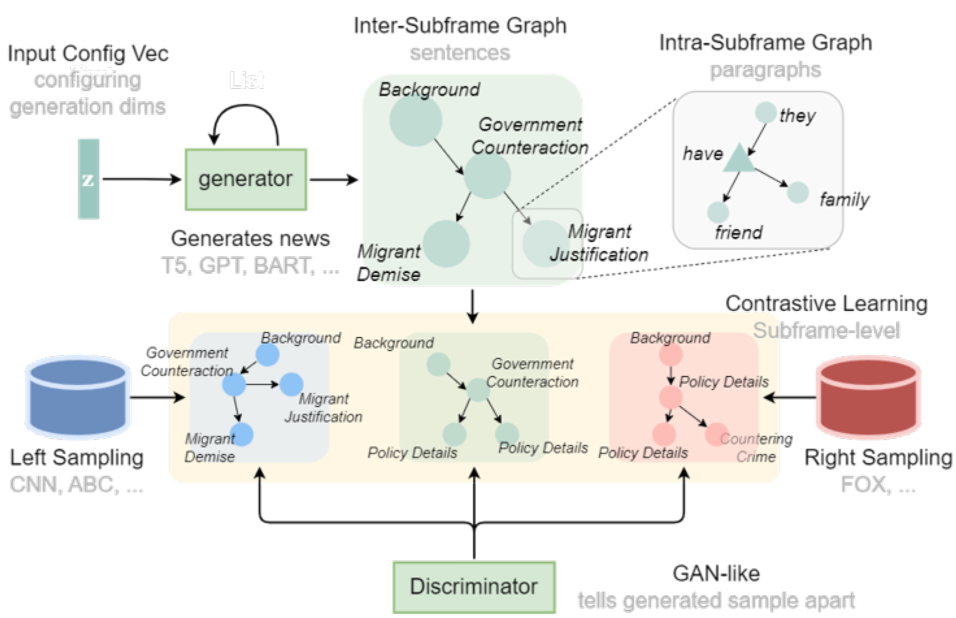

Figure 3.7: The Architecture of `GenCo`.

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

Chapter 4

Empirical Study and Analysis

4.1 Naive Word Cloud by Frequency

4.2 Topic Modeling with LDA

4.3 AMR Graph Modeling

4.4 BERT PVI Baseline

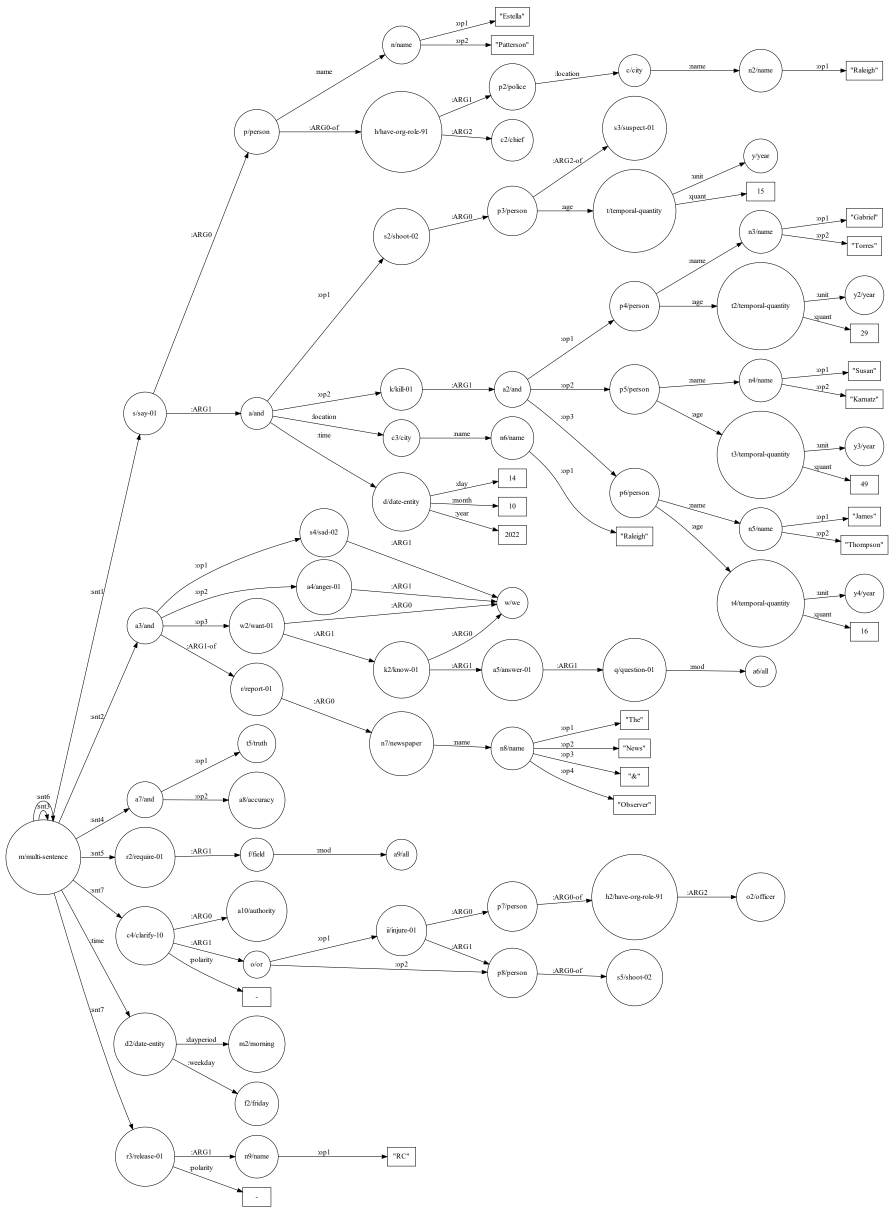

Figure 4.1: The Architecture of `GenCo`.

Chapter 5

Interactive Demo Application

This is the place for the app.

Chapter 6

Conclusion

I think our paper is good.

Appendix A

Hierarchy of the `Ground.News` Website

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